Expectations with Endogenous Information Acquisition: An Experimental Investigation*

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Abstract

Information frictions play an important role in many theories of expectation formation and macroeconomic fluctuations. We use a survey experiment to generate direct evidence on how people acquire and process information, in the context of national home price expectations. Participants can buy different pieces of information that could be relevant for the formation of their expectations about the future median national home price. We use an incentive-compatible mechanism to elicit their maximum willingness to pay. We also introduce exogenous variation in the value of information by randomly assigning individuals to rewards for the ex-post accuracy of their expectations. Consistent with rational inattention, individuals are willing to pay more for information when they stand to gain more from it. However, underscoring the importance of limits on information processing capacity, individuals disagree on which signal they prefer to buy. Individuals with lower education and numeracy are less likely to demand information that has ex-ante higher predictive power. As a result of the disagreement, lowering the information acquisition cost does not decrease the cross-sectional dispersion of expectations. We show that a model with rational inattention and heterogeneous prior beliefs about information sources can match almost all of our empirical results. Our findings also have implications for the design of information interventions.

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1 Introduction

Given the centrality of expectations in decision-making under uncertainty, consumer expectations have been the focus of much research, particularly in macroeconomics. Studies have found considerable dispersion in consumers' expectations (Mankiw, Reis, and Wolfers, 2003). The literature has theorized that this dispersion results from "rational inattention,"[1] which may arise due to the costs of acquiring information, as in the sticky information models of Mankiw and Reis (2002) and Reis (2006), or due to constraints on individuals' information processing capacity, as in Sims (2003) and Woodford (2003). However, there is little *direct* empirical micro evidence that shows how individuals acquire and process information in the real world.[2] In this paper, we present a survey experiment to study the causes and consequences of information acquisition and processing decisions.

We study information acquisition in the context of expectations about national home prices. Our interest in home prices stems from the fact that home price expectations play a prominent role in many accounts of the housing boom that occurred during the mid-2000s in the United States (e.g., Shiller, 2005; Glaeser and Nathanson, 2015). These home price expectations have been measured with survey data, and these survey measures have been shown to be associated with real behavior such as buying or making investments in a home (Armona, Fuster, and Zafar, 2017; Bailey et al., 2018). Given the prominence of housing in household portfolios, these decisions can have substantial welfare consequences.

We design a survey experiment to test a series of predictions of the inattention models. The main survey we use was conducted through the Federal Reserve Bank of New York in February 2017, as part of a regular online survey on housing issues. The experimental design has four main stages. In the first stage, respondents report their expectations about the national median home price for the end of the year (their "prior belief"). In the second stage, which occurs much later in the survey, respondents are informed that their forecast will be re-elicited and incentivized: if it falls within 1% of the realized price, the respondent is eligible for a monetary reward. Half of the subjects are randomly assigned to a reward that pays \$100 with a probability of 10%, and the other half is assigned to a reward that pays \$10 with a probability of 10%.

Before the belief re-elicitation, respondents are given the opportunity to choose among different pieces of information that could be potentially useful for their forecasts: the average expert forecast of home price growth during 2017 (this forecast was +3.6% at the time of the survey), the national home price change over the past one year (+6.8%), or the national home price change over the past ten years (-0.9%, or -0.1% annually). Respondents also can choose no information at all.

[1] We use "rational inattention" in the broad sense of referring to all models where there is some trade-off between expectations incorporating all available information optimally and some cost of doing so (as opposed to the narrower entropy-based approach of Sims, 2003).

[2] In a recent survey article, Gabaix (2017) makes the case for more experimental evidence on the determinants of attention, and the consequences of inattention.

These information pieces differ markedly in terms of their informativeness. For instance, one reasonable criterion, although certainly not the only one, is the information's ex-ante predictive power during the years leading up to the survey. Based on this criterion, the expert forecast is the most informative (RMSE of 2.8), followed by the past one-year change (RMSE of 3.2), and the ten-year change (RMSE of 7.9). This ranking of informativeness is consistent with findings from the real estate literature. For instance, the fact that past one-year price changes perform better than ten-year changes is consistent with the well-documented momentum in home prices over short horizons (Case and Shiller, 1989; Guren, 2016; Armona et al., 2017).

In the third stage, we elicit the respondent's maximum willingness to pay (WTP) for the most preferred information type. We use a multiple-price-list variation of the method of Becker, DeGroot, and Marschak (BDM): we ask individuals to choose either information or a payment between \$0.01 and \$5 in eleven scenarios. One scenario is then randomly chosen, and the corresponding choice is implemented. Finally, the survey concludes with the re-elicitation of home price expectations (the "posterior belief").

This experiment was designed to capture some important features of models of endogenous information acquisition and processing. On the one hand, sticky information models (e.g., Mankiw and Reis, 2002; Reis, 2006) propose that information frictions arise due to costs of information acquisition. Agents update their information sets at a given point in time when the expected benefit exceeds a fixed cost of updating. Conditional on updating, agents have full-information rational expectations. On the other hand, noisy information models (e.g., Sims, 2003; Woodford, 2003; Mackowiak and Wiederholt, 2009) highlight the importance of limited information processing capacity – in other words, even if information is freely available and agents continuously update their information sets, individuals may not use all of it or may use it inefficiently. To explore these features, our experimental design creates exogenous variation in the cost of acquiring information and exogenous variation in the reward to holding an accurate posterior. Moreover, in the experiment, individuals can choose between different pieces of information with different levels of informativeness. To explore the sticky information mechanism, we study how the information-acquisition cost affects posterior beliefs. To explore the noisy information mechanism, we investigate how the size of the reward and numeracy/financial literacy (our proxy for attention cost) affect the choice of the piece of information and the processing of the piece of information conditional on information being displayed.

Our first result, with regards to preferences over pieces of information, indicates that individuals disagree on which piece of information to use: 45.5% chose the forecast of housing experts, 28% chose the past one-year home price change, and 22% chose the past ten-year home price change. The remaining 4.5% reported to prefer no information at all. Thus, less than half of the sample chose the option that was most informative according to ex-ante predictive power. Some of this heterogeneity could be due to respondents using other criteria.[3] However, sophisticated

[3]This finding could be partly driven by the fact that some respondents distrust experts (Silverman, Slemrod,

respondents, as measured by their education or numeracy, were substantially more likely to choose the expert forecast than less sophisticated respondents. This finding suggests that at least part of the variation was due to cognitive limitations in identifying informative signals.

Our second result indicates that individuals demonstrate significant WTP for their favorite information: the average individual was willing to forego \$4.39. This WTP suggests that individuals expect to benefit from this information beyond the accuracy rewards provided in the survey. Interestingly, individuals are willing to pay a significant amount of money for information that is publicly available for free. Furthermore, we find strong support for a basic prediction of models of endogenous information acquisition and processing: the average WTP is significantly higher in the \$100-reward condition than in the \$10-reward condition (\$4.80 and \$3.99, respectively). This difference is statistically significant (p-value$<$0.01) and economically meaningful. In addition, we find that the amount of time spent choosing and processing information is weakly higher in the high-reward condition. However, we do not find that the ranking of pieces of information varies significantly by reward size. This suggests that individuals would need some form of guidance on which information is most useful.

Our third result exploits the information-provision experiment to study how the information acquired by the individuals affects their expectations. Our research design does not distinguish between rational expectations and some of its alternatives.[4] Instead, our design measures whether individuals incorporate certain pieces of information into their forecasts. Consistent with a genuine interest in information, individuals incorporate the information that they were willing to pay for into their forecast: they form posterior beliefs by putting, on average, 38% weight on the signal bought and 62% on their prior belief. As evidence of genuine learning, we show that the information provided in the baseline survey had a persistent effect on a follow-up survey conducted four months later. The rate of learning was similar across all three pieces of information, which confirms that the disagreement about the ranking of pieces of information was meaningful. However, we find patterns that at first sight run counter to the basic model of Bayesian updating. In particular, we find no evidence that individuals who had more uncertain prior beliefs put more weight on the purchased information.

Our final result is about the effect of endogenous information acquisition on the cross-sectional dispersion in beliefs. We measure the effect of the effective price of information (which was randomly assigned) on the dispersion of expectations. We find that a lower cost of information acquisition does not cause lower cross-sectional dispersion in expectations. To understand the

and Uler, 2014; Cavallo, Cruces and Perez-Truglia, 2016; Cheng and Hsiaw, 2017). We provide direct evidence about this mechanism using an auxiliary survey.

[4]In recent years, several models of expectation formation have been put forward that deviate from rational expectations or Bayesian updating, such as experience-based learning (Malmendier and Nagel, 2016), natural expectations (Fuster, Hebert, and Laibson, 2012), and diagnostic expectations (Bordalo, Gennaioli, and Shleifer, 2017). This has also led to a literature, discussed below, that investigates the updating of expectations in stylized information experiments. These papers all provide evidence on how signals are incorporated in revisions of expectations, but abstract away from the process of acquiring the signals – the focus of this paper.

reason, we divide respondents into groups, based on their preferred information piece. On the one hand, exposure to information tends to reduce the dispersion in posterior beliefs *within* a group. For example, among individuals who preferred the expert forecast (a signal of 3.6%), exposure to it results in their posterior beliefs becoming more compressed around 3.6%. On the other hand, exposure to information increases the dispersion in beliefs *across* these three groups, because each group acquires a different signal and the signals were far apart. These opposing effects are similar in magnitude, and thus end up canceling each other out.[5] Additionally, we show that this result is not an artifact of respondents being able to view only one piece of information – in an auxiliary survey with a similar set-up except that individuals are allowed to view multiple pieces of information simultaneously, we confirm that exposure to information does not cause lower cross-sectional dispersion. Finally, contrary to the prediction of sticky information models, dispersion in beliefs remains high within each group of individuals who acquire the same information.

We next show that most of our experimental findings can be explained by a model of rational inattention with cross-sectional heterogeneity in the cost of the attention, and where agents have heterogeneous beliefs about the precision of information sources. For example, with rational inattention, the model can match the empirical result that time spent on processing information is positively related to the reward size. The heterogeneity in perceived precision of information sources can explain why our respondents choose different information sources. In addition, under the assumption that the precision of prior beliefs is positively correlated with tastes for information (that is, respondents who enter the experiment with more precise beliefs intrinsically value information more), we can reconcile the seemingly puzzling experimental finding that individuals with more precise (that is, less uncertain) beliefs put more weight on the displayed information.

This paper is related to various strands of literature. First and most importantly, it is related to a growing body of work on rational inattention models (Mankiw and Reis, 2002; Sims, 2003; Woodford, 2003; Reis, 2006). We contribute to this literature by providing *direct* empirical micro evidence on how individuals acquire and process information in the real world. Our results are broadly consistent with these models. Specifically, the finding that cross-sectional dispersion does not decrease when the cost of information is lowered suggests that noisy information models (opposed to sticky information models) are a better characterization of the expectation formation process of consumers. In that sense, our conclusion is consistent with Coibion and Gorodnichenko (2012), who exploit the relationship of disagreement to shocks to distinguish between inattention models. Their setup is quite different since it does not involve the endogenous process of information acquisition, and uses observational data (opposed to experimental variation, as in our case).

[5] This finding has some parallels with the literature on media bias and political attitudes, according to which dispersion in beliefs can be persistent because voters self-select into different information sources (Mullainathan and Shleifer, 2005). The underlying mechanisms, however, are different: in the political economy literature the differences in information choices arise due to self-serving biases, while in our context the differences in choices seem to arise due to differences in preferences over information sources and/or cognitive limitations.

This paper is also related to a literature on the sources of dispersion in consumer expectations. For example, Figure 1 shows the distribution of housing expectations among consumers and experts. Consistent with the evidence for other types of macroeconomic (Mankiw et al., 2003; Cavallo et al., 2017), this figure shows that housing expectations are substantially more dispersed among consumers than among experts. Our findings shed some light on the sources of this dispersion. Our evidence suggests that constraints in information processing play a big role in explaining this dispersion: the dispersion in expectations arises because individuals differ in how much they are willing to pay for information as well as what type of information they want to acquire. As a result, even if the acquisition cost of information went down to zero, our findings imply that we would still observe substantial dispersion in consumers' expectations. This finding may explain why dispersion in expectations among consumers tends to be much larger than it is among experts even though the estimated information acquisition costs are not larger for consumers (Coibion and Gorodnichenko, 2012).

Our approach is related to a recent literature on information-provision experiments. Particularly relevant for our purposes are papers that employ information experiments in surveys to understand expectation formation in the context of inflation (Armantier et al., 2017; Cavallo et al., 2017; Coibion, Gorodnichenko, and Kumar, 2015) or housing (Armona et al., 2017). The experiments in the context of inflation find that when individuals are provided with official statistics, the dispersion in expectations substantially decreases.[6] The evidence from the information-provision literature provides suggestive evidence in favor of costly information acquisition models: once a piece of information is provided by the experimenter for free, the dispersion in expectations is reduced. However, information-provision experiments ignore a crucial aspect of the real world: individuals have to choose from multiple information sources, and *where* they look for information can be even more important than *how frequently* they look for information. Our findings indicate that, once respondents are allowed to choose information endogenously, reducing the cost of information may fail to reduce dispersion in expectations.

Finally, our results have implications for the design of information interventions. A growing body of research shows that, in a wide range of contexts, providing individuals with accurate information can have substantial effects on their beliefs and decisions (e.g., Duflo and Saez, 2003; Allcott, 2011; Cruces, Perez-Truglia, and Tetaz, 2013; Wiswall and Zafar, 2015). One of the policy implications often drawn from this literature is that entities should make more information widely available and easily accessible. Our evidence suggests that this strategy may not be sufficient, because individuals may not know which of the different pieces of information to focus on. Our findings imply that these interventions should either be targeted (providing consumers with limited but relevant information) or that they should guide consumers to help them interpret and weigh

[6]Endogenous information acquisition has been studied in other contexts, such as hiring decisions (Bartoš et al., 2016) and tax filing (Hoopes, Reck and Slemrod, 2015). Additionally, some laboratory experiments have been used to study demand for information in stylized settings (e.g., Gabaix et al., 2006).

the various pieces of information.

The rest of the paper proceeds as follows. Section 2 introduces the research design and survey and outlines the testable hypotheses. Section 3 presents the results. The following Section 4 describes the theoretical model and discusses how its predictions compare to the experimental findings. The last section concludes.

2 Survey Design

We designed a survey module to be embedded into the 2017 housing supplement of the Federal Reserve Bank of New York's Survey of Consumer Expectations (hereon, SCE Housing Survey). This survey has been fielded annually every February since 2014 and contains multiple blocks of questions, some of which distinguish between owners and renters.[7] Among other things, the survey asks about perceptions of past local home price changes, expectations for future local home price changes, and past and future intended housing-related behavior (e.g., buying a home, refinancing a mortgage). Respondents also provide information about their locations and many other demographic variables.

The SCE Housing Survey is run under the Survey of Consumer Expectations, an internet-based survey of a rotating panel of approximately 1,400 household heads from across the United States. The survey, as its name suggests, elicits expectations about a variety of economic variables, such as inflation and labor market conditions. Respondents participate in the panel for up to twelve months, with a roughly equal number rotating in and out of the panel each month.[8] Active panel members who participated in any SCE monthly survey in the prior eleven months were invited to participate in the housing module. Out of 1,489 household heads on the panel that were invited, 1,161 participated, implying a response rate of 78%. Item non-response is extremely uncommon and rarely exceeds 1% for any question. The total survey time for the median respondent was 37 minutes; we will later report time spent on specific questions analyzed here as a measure of effort spent on acquiring and processing information.

2.1 Research Design

Appendix D provides screenshots of the relevant module. The broad organization of the module was as follows:

[7] See Armona et al. (2017) and https://www.newyorkfed.org/microeconomics/sce/housing#main.

[8] The survey is conducted over the internet by the Demand Institute, a non-profit organization jointly operated by The Conference Board and Nielsen. The sampling frame for the SCE is based on that used for the Conference Board's Consumer Confidence Survey (CCS). Respondents to the CCS, itself based on a representative national sample drawn from mailing addresses, are invited to join the SCE internet panel. The response rate for first-time invitees hovers around 55%. Respondents receive \$15 for completing each survey. See Armantier et al. (2016) for additional information.

1. **Stage 1- Prior Belief**: This stage elicits individuals' expectations of future national home price changes. Respondents were informed that, according to Zillow, the median price of a home in the United States was $193,800 as of December 2016.[9] The respondents were asked for a point forecast: "*What do you think the value of the typical home in the U.S. will be at the end of this year (in December 2017)?*" To prevent typos in the responses, the survey environment calculated and reported the implied percentage change after individuals entered the value. Individuals could confirm the number and proceed to the next screen or revise their guess. We refer to the response to this question as the respondent's "prior belief." The survey also elicited the respondents' probability distribution over outcomes around their own point estimate: specifically, they were asked to assign probabilities to five intervals of future year-end home price changes: more than 10% below their point forecast; between 10% and 1% below their forecast; within +/-1% of their forecast; between 1% and 10% above their forecast; and more than 10% above their forecast.

2. **Stage 2- Information Preferences**: After answering a block of other housing-related questions for roughly 15 minutes, respondents entered the second stage. They were notified that the same questions about future national home prices that were asked earlier in the survey would be asked again, except this time their responses would be incentivized: "*This time, we will reward the accuracy of your forecast: you will have a chance of receiving $[X]. There is roughly a 10% chance that you will be eligible to receive this prize: we will select at random 60 out of about 600 people answering this question. Then, those respondents whose forecast is within 1% of the actual value of a typical U.S. home at the end of this year will receive $[X].*" We randomly assigned half of the respondents to X=$100 ("High Reward") and the other half to X=$10 ("Low Reward").

   Before providing their forecast, respondents were given an opportunity to see a potentially relevant piece of information: "*Before you report your forecast, you will have the opportunity to see only one of the following pieces of information that may help you with forecasting future year-ahead U.S. home prices. Please rank the following pieces of information on a 1 to 4 scale, where 1 is "Most Preferred" and 4 is the "Least Preferred"*:

   - *Change in the value of a typical home in the U.S. over the last one year (2016).*
   - *Change in the value of a typical home in the U.S. over the last ten years (2007-2016).*
   - *Forecasts of a panel of housing experts about the change in U.S. home prices over this coming year (2017).*
   - *None of the above – I would not like to see any information.*"

[9] They were then asked how the price changed over the prior one year (since December 2015) and the prior ten years (since December 2006). They also were asked to rate their recall confidence on a 5-point scale.

Respondents were asked to drag and drop each of their selected rankings into a table with labels from "1=Most Preferred" to "4=Least Preferred."

3. **Stage 3- Willingness-to-Pay for Information**: This stage, which immediately followed the second stage, elicited the respondents' maximum willingness-to-pay (WTP) for their highest-ranked information type. Respondents who ranked "*None of the above*" as their most preferred information in Stage 2 skipped this stage. To assess WTP, we used the list price method (e.g., Andersen et al., 2006) with eleven scenarios. In each scenario, respondents chose between seeing their preferred piece of information (i.e., the one they ranked highest in Stage 2) or receiving extra money in addition to their compensation for completing the survey. The amount of money offered in these scenarios was predetermined and varied in $0.50 increments, from $0.01 (in Scenario 1) to $5 (in Scenario 11). Respondents were told that one of these eleven scenarios would be drawn at random and the decision in that randomly chosen scenario would be implemented.

4. **Stage 4- Posterior Belief**: In this stage, the respondent may have seen their highest-ranked information choice, depending on the randomly chosen scenario in Stage 3 and their choice to see or not see the information in that scenario.[10] Year-ahead home price expectations (the point estimate and the subjective belief distribution) that were elicited in Stage 1 were re-elicited from all respondents. We used the Zillow Home Value Index (ZHVI) as the source for prices of the typical (median) home in the U.S. over the last one or ten years.[11] According to the ZHVI, U.S. home prices decreased by 0.1% per year on average (or 0.9% in total) over the ten years 2007-2016 and increased by 6.8% over the last one year (2016). The Zillow Home Price Expectations Survey, a quarterly survey of about 100 economists, real estate experts, and market strategists, was the source for expert forecast.[12] On average, experts forecasted an increase of 3.6% in home prices during 2017. Note that these information sources are publicly available.

   A paragraph providing the information followed a similar structure in all three cases. The raw information was provided, followed by a naive projection of home prices in December 2017 based on the annual growth rate implied by the information. For instance, respondents who chose expert forecast were presented with "*The average forecast of a distinguished panel of housing market experts who participate in the Zillow Home Price Expectations Survey is that home values in the U.S. will increase by 3.6% over the next year. If home values were to increase at a pace of 3.6% next year, that would mean that the value of a typical home*

[10] In Stage 3, the scenarios 1-11 were picked with probabilities 0.15, 0.14, 0.13, 0.12, 0.11, 0.10, 0.09, 0.07, 0.05, 0.03, and 0.01, respectively.

[11] For more information on the construction of the ZHVI, see http://www.zillow.com/research/ zhvi-methodology-6032/ (accessed on December 8, 2017). We used the ZHVI as of December 2016.

[12] For details, see https://pulsenomics.com/Home-Price-Expectations.php. We used the average forecast as of the fourth quarter of 2016.

would be 200,777 dollars in December 2017." At the bottom of this same screen, expectations about year-end home prices were re-elicited. Respondents were reminded about their prior belief. As in Stage 1, both the point estimate and subjective belief distribution were elicited. We refer to the point estimate from this stage as the "posterior belief."

Afterwards, respondents were picked at random to be eligible for the incentive, as indicated in Stage 2, and eligible respondents were informed at the end of the survey that they would be paid the \$10 (or \$100) reward in case of a successful forecast (within 1% of the December 2017 ZHVI) in early 2018.[13] At the end, respondents are also asked whether they used any external sources (such as Google or Zillow) when answering any question in the survey.

This summarizes the experimental setup. Four months after the initial survey, a short follow-up was fielded to active panelists in the June 2017 SCE monthly survey. As in Stages 1 and 4 of the main experiment, respondents were asked to report their expectations about year-end U.S. median home prices. We kept the identical frame of reference in the follow-up survey: we provided individuals with the median U.S. home price as of December 2016 and asked them to forecast the value in December 2017. Both the point estimate and subjective density were re-elicited. Of the 1,162 respondents who took the SCE Housing Survey, 762 were still in the panel in June and hence eligible to take the follow-up survey. Of those, 573 did so, implying a response rate of 75.2%.

An additional module was fielded in the 2018 SCE Housing Survey. Since the main purpose of the module is some robustness checks and because that sample has no overlap with the sample in the original study, we defer the details to Appendix B.

2.2 Discussion of the Experimental Design

Our design tries to mimic real-world information acquisition and processing, albeit in a stylized setting. Before turning to the empirical analysis, it is useful to discuss the features of the experimental design and to outline the main hypotheses. Unless otherwise stated, the null is that expectations are formed according to a combination of a sticky information model, as in Reis (2006), and a rational inattention model, as in Sims (2003). The model is presented formally in Section 4.

A key feature of our setup is that respondents are presented with three possible pieces of information, which they are asked to rank in terms of their preference, including a no-information option. We make it clear to respondents that they can see their top-ranked choice. Ideally, we want to test whether individuals have some reasonable idea or consensus about the usefulness of the information. However, no single criterion can measure informativeness. One reasonable metric of information usefulness is how well it has historically predicted past year-ahead home price changes in the United States.

[13]Payments to those who qualified and met the reward criterion were made in March 2018. 14 respondents received a payout (half of them \$100, the others \$10).

Let HPA_t denote the actual home price change during year t. Let HPA_t^F be the mean forecast of experts about home price changes for year t, HPA_{t-1} the annualized home price change over the past 1 year, and HPA_{t-10} the annualized home price change over the past 10 years. For each piece of information $I_t \in \{HPA_t^F,\ HPA_{t-1},\ HPA_{t-10}\}$, we define its informativeness as the root mean squared error (RMSE) of a model $HPA_t = I_t$. Thus, for the empirical analysis, we test a weaker version of the ideal hypothesis that is based on this specific metric of informativeness:

> ***Hypothesis 1 (Preference for Informative Signals):*** *The demand for an information source increases with its ex-ante predictive power.*

To calculate the RMSE of each piece of information, we use the Zillow Home Value Index as the outcome (that is, as our estimate of HPA_t), because it is the same outcome that we are asking the subjects to forecast in our survey, and regress it onto each of the potential sources of information. Using this data, the RMSE for experts' forecast is 2.8, the RMSE for past one-year changes is 3.2, and the RMSE for past ten-year changes is 7.9 when using the longest available series (the experts' forecast is available since 2010, and the ZHVI since 1996). Based on these results, the expert forecast has been the most informative in predicting year-ahead home price changes, followed by past one-year change, and then the ten-year change. This ranking remains the same when we use only data since 2010 for all three series (in this case, the one-year RMSE is 3.3, and the ten-year RMSE is 5.2). Using a longer home price index series from CoreLogic (starting in 1976), the ranking also remains consistent.[14]

This criterion for ranking the informativeness of the signals is broadly consistent with basic insights from the real estate literature. First, the fact that the forecasts are ranked highest is consistent with the view that forecasters use all available information in past home price changes optimally when providing a forecast.[15] Additionally, this criterion is consistent with the model of Carroll (2003), in which consumers periodically update their expectations based on reports of expert forecasts, which are assumed to be rational. Second, the higher ranking of past one-year home price change relative to past ten-year change is consistent with the well-documented momentum in home prices over short horizons (Case and Shiller, 1989; Guren, 2016; Armona et al., 2017). For instance, for the nominal CoreLogic national home price index from 1976–2017, the AR(1) coefficient of annual growth is 0.73 and highly statistically significant, with an R^2 of 0.57. This serial correlation is only slightly weaker if we calculate price growth in real terms (the coefficient falls to 0.66 but remains highly significant).[16] In contrast, regressing one-year growth

[14]Using the CoreLogic series, the RMSE is 4.6 for the average expert forecast (6 observations), 5.0 for the past one-year change (39 observations), and 7.8 for the past ten-year change (30 observations).

[15]This should be true at least for the consenus forecast, even though individual forecasters may have incentives to deviate for strategic reasons (e.g. Laster et al., 1999).

[16]It is also robust to using alternative home price indices, such as Case-Shiller. Further, momentum is similarly strong at a more local level: Armona et al. (2017) find that in a regression of one-year home price changes on lagged one-year home price changes at the zip code level, the average estimate (across the zip codes in the U.S.) is 0.53 (statistically significant with $p < 0.01$).

on growth over the previous ten years yields a small and insignificant negative coefficient.

Although reasonable, our criterion is not the only one that can determine the usefulness of information. For example, according to the ZHVI, U.S. home prices increased by 6.5% during 2017. Thus, based on ex-post accuracy, using the past one-year change would have led to the most accurate expectation. By this same ex-post metric, however, it is hard to rationalize picking home price change over the past ten years over either of the other two pieces of information.

Turning to our next hypothesis, rational inattention predicts that, in the absence of an incentive (such as the lack of a direct stake in the housing market), individuals in the real world may invest fewer resources in acquiring housing-relevant information and having more informed home price expectations.[17] The randomization of the accuracy incentive in Stage 2 provides a direct test of this hypothesis: that is, whether higher stakes causes the respondents to be willing to pay more for information or to spend more time processing it. Moreover, rational inattention models with constraints on information processing capacity (Sims, 2003; Woodford, 2003; Mackowiak and Wiederholt, 2009) predict that, when the stakes are high, respondents think carefully about the usefulness of potential information and hence rank information differently than their counterparts (in particular, they rank "None of the Above" lower). This leads to our second hypothesis:

> ***Hypothesis 2 (Attention and Stakes):*** *When the accuracy incentive is higher, individuals are more willing to pay for information and spend more time processing it; also, the higher accuracy incentive should make the individuals more likely to choose the more informative sources.*

Another feature of the design is that in Stage 4, some respondents get to see one of the pieces of information. Whether a respondent sees their top-ranked information depends on the WTP and the randomly picked scenario from Stage 3. This randomization generates random variation in the provision of information, because for two individuals with identical WTPs in Stage 3, whether the information is shown in Stage 4 is determined at random. We exploit this aspect of the design to investigate whether respondents incorporate the signal into their posterior beliefs, as would be expected if individuals were willing to pay for the information. Rational updating also implies that individuals who have uncertain prior beliefs put more weight on the information they receive.[18] This leads to our third hypothesis:

> ***Hypothesis 3 (Rational Updating):*** *If individuals are willing to pay for a signal, they should incorporate that signal into their expectation formation once they get access*

[17] This would follow from most sticky information models. For example, in the sticky updating model of Reis (2006), agents are modeled as maximizing utility subject to constraints, which also include costly information. Increasing the payoff for more informed expectations would lead more agents to incur the cost of acquiring housing-relevant information.

[18] Under Bayesian updating, the weight put on the signal is positively related to the uncertainty in the prior belief, and inversely related to the (perceived or actual) noise in the signal. As long as the perceived noise in the signal is independent of one's uncertainty in the prior belief, Bayesian updating predicts that individuals with more uncertain priors put more weight on the signal.

to it. The weight on the signal should be higher for those with higher prior uncertainty.

The last hypothesis is framed such that the null is the pure sticky information model (Reis, 2006). In this model, cross-sectional dispersion in beliefs arises only because some individuals update their information sets to perfect information, while other individuals do not update their information sets. If all individuals updated at a given point in time, there would be no cross-sectional dispersion in beliefs. When only some individuals update at a given point in time, there is no cross-sectional dispersion in beliefs among those who update. This leads to our final hypothesis:

> ***Hypothesis 4 (Information Acquisition and Dispersion of Expectations):*** *Cross-sectional dispersion in beliefs arises mainly because some individuals acquire information, while other individuals do not acquire information.*

2.3 Sample Characteristics

Of the 1,162 valid responses, we trimmed the sample by dropping 43 respondents: those with prior beliefs below the 2.5th percentile (an annual growth rate of -7.1%) or above the 97.5th percentile (an annual growth rate of 16.1%). These extreme beliefs may be the product of typos or lack of attention. As the prior belief was reported before the treatments, dropping these extreme prior beliefs should not contaminate the experimental analysis. For the posterior beliefs, these typos may also show up, but dropping individuals based on post-treatment outcomes could contaminate the experimental analysis. Instead, we winsorize the post-treatment outcomes using the same extreme values presented above (-7.1% and 16.1%).[19] In any case, we use graphical analysis whenever possible to certify that the results are not driven by outliers.

Column (1) of Table 1 shows characteristics of the sample for the main survey. Most dimensions in the sample align well with average demographic characteristics of the United States. For instance, the average age of our respondents is 50.8 years, and 47.6% are females, which is similar to the corresponding 45.5 years and 48.0% among U.S. household heads in the 2016 American Community Survey. Also, 74.8% of respondents in our sample are homeowners, compared to a national homeownership rate in the first quarter of 2017 of 63.6%, according to the American Community Survey. Our sample, however, has significantly higher education and income: 55.2% of our respondents have at least a bachelor's degree, compared to only 37% of U.S. household heads. Likewise, the median household income of respondents in the sample is $67,500, which is substantially higher than the U.S. 2016 median of $57,600. This may be partly due to different internet access and computer literacy across income and education groups in the U.S. population. Respondents expect national home prices to increase by 2.2%, on average, over the next year.

Columns (2) and (3) of the table show average characteristics for the subsamples assigned to the low- and high-reward treatments, respectively; in turn, columns (5) and (6) show the char-

[19] For the beliefs from the follow-up survey, we winsorize the values in the same way. Results are robust under alternative thresholds.

acteristics for the subsamples assigned to the low- and high-price treatments. Columns (4) and (7) present p-values for the test of the null hypothesis that the characteristics are balanced across treatment groups. The differences in pre-treatment characteristics are always small, and statistically insignificant in 19 out of the 20 tests. This is not surprising, because random assignment should preserve balance between the two groups. Additionally, the last row of Table 1 reports the response rate to the follow-up survey. The evidence rules out selective attrition: the response rate does not differ by reward or price treatments.

Table 2 provides additional information on how the follow-up sample compares with the initial sample. Column (1) show the average characteristics for the whole sample. Columns (2)–(4) break down the average observables by eligibility for the follow-up sample: the evidence shows that the subsample that was eligible to be invited to the follow-up survey was similar to the ineligible group of respondents who were phased out of the panel, with the differences being statistically and economically insignifciant. The final three columns of the table also are reassuring, as we see no evidence that, conditional on being invited to the follow-up, the individuals who responded to this survey are significantly different from the ones who did not.

3 Empirical Analysis

3.1 Hypothesis 1: Preference for Informative Signals

To understand how respondents acquire information, it is useful to describe the distribution of expectations prior to the information acquisition. Figure 2.a shows a histogram of the point estimates provided by respondents. In terms of the implied annual growth rates, the mean (median) value is 2.2% (1.7%), with substantial dispersion across respondents: the cross-sectional standard deviation of prior beliefs is 3.1%. To assess if individuals felt confident about their expectations, Figure 2.b shows the probability distribution of beliefs around the individual's own point estimate, averaged over all individuals. On average, individuals thought there was a 51% chance that the true price would fall within 1% of their guesses. Moreover, there was high dispersion in the degree of certainty. For example, 13% of the sample thought that there was a 90% chance or higher of year-end home prices being within 1% of their guess, and 16% of the sample thought that there was a 20% chance or lower.[20]

What happens when individuals with uncertain beliefs are offered the chance to acquire information? The median respondent spent 2.17 minutes choosing between the information sources (and reading the associated instructions), with 10th percentile at 1.23 minutes and 90th percentile at 4.85 minutes. Figure 3.a shows the ranking distribution for the different information types

[20]Ex post, only 3.5% of respondents had a prior forecast within 1% of the realized ZHVI price as of December 2017, which was $206,300 (according to Zillow in January 2018), corresponding to realized growth over 2017 of 6.5%. For the posterior forecast, this fraction increased to 11.5%.

over the whole population. Individuals disagreed on which of the three pieces of information they would want to see: 45.5% chose forecasts of housing experts, 28.1% chose the last-one-year home price change, 22.1% chose the last-ten-year home price change, and the remaining 4.3% preferred no information. The past predictive power criterion indicated that expert forecast was most informative, followed by the last-one-year home price change and then the last-ten-year home price change. Thus, the popularity of the choice is increasing with its informativeness. However, this correlation is far from perfect: less than half of the sample chose the most informative choice (i.e., expert forecast).

This heterogeneity in the ranking of information could be driven by consumers' lack of knowledge about the relative informativeness of the signals or by respondents using different criteria to determine the informativeness of the signals. Systematic differences in ranking by education or numeracy of respondents, which are reasonable proxies for ability to filter signals, would suggest evidence of the former.[21] Figure 3.c and 3.d thus break down the information choices by respondents' numeracy and education, respectively, and show that individuals with more education or with higher numeracy were substantially more likely to choose the "best" information: college graduates chose the expert forecast 50% of the time, compared with non-graduates who chose it 40% of the time (p-value$<$0.01).[22]

Table 3 further explores the heterogeneity and reports univariate relationships between the choice of information and various individual- and location- specific characteristics.[23] The dependent variables in columns (1)–(3) correspond to dummy variables indicating the highest ranked piece of information.[24] Besides numeracy and education of respondents, only a handful of variables are significant, suggesting that observable characteristics (at the individual or location level) cannot explain most of the heterogeneity in how individuals rank information. Homeowners are more likely to choose the past-one-year information and less likely to choose the expert forecast, perhaps because they are curious to learn about how their housing wealth has evolved. Higher income respondents and white respondents are more likely to choose the expert forecast, although these coefficients are only marginally significant.

One might expect respondents who have high confidence in their perceptions of past home price changes to be more likely to choose the expert forecast (since they think they know the past realized growth already); however, if anything we see the opposite. Likewise, one might expect respondents residing in states with volatile housing prices (as measured by the standard deviation in monthly home prices over the past 24 months) to be less likely to choose past home price changes. We do not find evidence of that.

[21] Numeracy is evaluated based on 5 questions taken from Lipkus et al. (2001) and Lusardi (2009). The rank correlation between education and numeracy in our sample is +0.31.

[22] Similarly, Burke and Manz (2014) find that respondents with higher levels of economic literacy choose more relevant information when forming inflation forecasts.

[23] The results are similar using multivariate regressions, as reported in Appendix Table A.1.

[24] The results are also robust if instead of a linear probability model we use a multinomial logit model.

In column (4), we study as an alternative outcome whether a respondent ranked the one-year realized growth higher than the 10-year realized growth (as would be optimal based on past predictive performance); we see little relation with observables, except that younger respondents are more likely to prefer the longer-term data. College-educated and higher-numeracy respondents are about 3 percentage points more likely to prefer one-year information, though neither estimate is very precise.

The supplementary survey that was conducted in 2018 provides some additional insights, which are discussed in detail in Appendix B. First, we validate the finding that subjects disagree in terms of the information that they acquire, and that those disagreements are correlated with education and numeracy. Second, the supplementary survey included a couple of additional questions to explore the role of trust in experts as a driving factor for preferences over information sources. Overall levels of trust in the credibility of experts and their ability to forecast accurately is moderate, and we do find that less-educated respondents exhibit lower levels of trust in experts. However, while a relevant explanation, distrust of experts is not the main factor driving the information choices of our respondents: for instance, we find that these differences in trust can explain less than a quarter of the education gap in preferring experts.

We can summarize our first result as follows:

> ***Result 1****: The information with the highest ex-ante predictive power, expert forecast, is the modal choice. The information with the second highest ex-ante predictive power is the second most frequent choice. Considerable disagreement exists across households on the ranking of information. The ranking is systematically related to measures of respondent ability, which suggests that cognitive limitations in deciphering informative signals partially drives the heterogeneity.*

3.2 Hypothesis 2: Attention and Stakes

Before we can test if higher stakes change the willingness to pay for information, it is useful to understand the distribution of WTP for the whole sample. Using responses to the eleven scenarios, we identify the range of an individual's WTP. For example, if an individual chose information instead of any amount up to \$3 and then chose the money from \$3.50 on, it means that the individual's WTP must be in the range \$3 to \$3.5. Around 5% of respondents provided inconsistent responses; for example, they chose information instead of \$3 but then chose \$2.5 instead of information. This inconsistency is within the range of other studies using this list method for elicitation of WTP for information. For instance, the share of inconsistent respondents was about 2% in Allcott and Kessler (2015) and 15% in Cullen and Perez-Truglia (2017).

Figure 4.a shows the histogram of WTP based on this approach. We find that individuals have significant WTP for their favorite information, with a median maximum WTP between \$4.5

and \$5.[25] This is fairly high WTP, given that the information we provide is publicly and readily available using a search tool like Google. This finding indicates that most individuals are either unaware of the availability of this information or they expect a high search cost. Also, the median WTP (\$4.5-\$5) is high, compared to the expected reward for perfect accuracy (\$1 for half of the sample and \$10 for the other half). This evidence suggests that individuals value the information beyond the context of the survey. They may want to use this information for real-world housing decisions. In this context, having incorrect expectations about house prices can translate into thousands of dollars in losses, relative to which the experimental incentive pales in comparison.[26]

We next test Hypothesis 2, i.e., whether WTP, time spent choosing and processing information, and ranking of information systematically varies with reward size. Figure 4.b conducts a non-parametric test of this hypothesis by comparing the distribution of WTP between the two reward groups. This figure suggests that, consistent with the rational inattention hypothesis, individuals in the higher-reward treatment are willing to pay more. The Mann-Whitney-Wilcoxon (henceforth MWW) test indicates that this difference is statistically significant (p-value$<$0.01).

To better understand the economic magnitude of this difference, column (1) of Table 4 presents the rational inattention test in regression form. The constant reported in column (1) can be interpreted as the mean WTP for the low-reward condition (\$10 with 10% probability). This average valuation is estimated to be \$3.99 (95% CI from 3.68 to 4.31). The coefficient on High Reward indicates that, relative to the \$10 reward, individuals assigned to the \$100 reward are willing to pay an additional \$0.80 for their favorite information (or 20% more). Note that the expected reward goes from \$1 to \$10, because the reward is given only with 10% probability. The \$0.80 difference in WTP then implies that for each additional dollar of expected reward, the WTP for information goes up by 8.9 cents.

Another way to interpret the result is as follows:

$$WTP_i = U_{Info} + 0.1 \cdot Reward_i \cdot \left[P_i\left(Accurate|Info\right) - P_i\left(Accurate|NoInfo\right)\right] + \varepsilon_i. \qquad (1)$$

The first term, U_{Info}, represents the expected real-world benefit from having the information (e.g., because one expects to make better choices when deciding whether to buy a house).

[25] An alternative estimate is given by means of an interval regression model. This is a maximum likelihood model that assumes that the latent WTP is normally distributed. The constant in this model is estimated to be \$4.39 (95% CI from 4.16 to 4.63). This coefficient can be interpreted as the mean WTP under the implicit assumption that WTP can take negative values; if we instead assume that the WTP must be non-negative, then the mean would be even higher.

[26] Additionally, we can compare the median WTP in our study (\$4.5-\$5) with the results from a few other papers that elicit WTP for information using similar methods. Those studies find lower valuations: \$0.40 for travel information (Khattak, Yim, and Prokopy, 2003), \$0.80 for food certification information (Angulo, Gil, and Tamburo, 2005), and \$3 for home energy reports (Allcott and Kessler, 2015). Hoffman (2016), in a field experiment about guessing the price and quality of actual websites, finds that business experts tend to underpay (overpay) for information when signals are informative (uninformative).

The second term reflects the benefits of information from the survey reward, under the simplifying assumption that the respondent is risk-neutral for small amounts. We can infer the value of $P_i\,(Accurate|Info) - P_i\,(Accurate|NoInfo)$ from a regression of WTP_i on $0.1 \cdot Reward_i$. Indeed, we do not even need to run a new regression. We can recover that parameter from the coefficients on column (1) of Table 4.[27] This estimator suggests that $P_i\,(Accurate|Info) - P_i\,(Accurate|NoInfo) = 0.089$. In other words, by acquiring the information, the average individual expects that the probability of being accurate (i.e., being within 1% of the realization) will increase by 8.9 percentage points, or 17% of the baseline probability.[28]

It is worth asking whether the level of attention varies systematically with respondents' abilities, as would be predicted under models of information rigidities due to cognitive limitations. Columns (2) and (3) of Table 4 investigate whether higher numeracy and higher education individuals are more rationally attentive (i.e., more reactive to the higher reward). In column (2), the High-Reward dummy is interacted with a standardized measure of numeracy. In column (3), the High-Reward dummy is interacted with a dummy for college graduate. In column (2), the effect of high reward is more than 50% larger (and statistically significant at the 10% level) for individuals with a one-standard-deviation higher numeracy. In column (3), the effect of high reward is 70% larger for college graduates relative to non-graduates, although the difference is imprecisely estimated and thus statistically insignificant.[29] We already showed that highly educated and highly numerate respondents are more likely to choose the expert forecast. So, not only are respondents with low education and numeracy less likely to rank information optimally, they also are less responsive to higher rewards.

Given that individuals pay more for information when the stakes are high, the next question is whether individuals choose information types differently when the stakes are high. Figure 3.b breaks down the information choice by reward type. The choices are almost identical across both groups; the p-value of the difference is 0.89. Column (4) of Table 4 presents this same test in regression form. It corresponds to a linear probability model where the dependent variable is whether the individual chooses the expert forecast (i.e., the "best" information type according to past predictive power). Column (4) implies that individuals are not more likely to choose expert forecast under the high reward. Additionally, Columns (5) and (6) of Table 4 show that the effect of the large reward on choosing the expert forecast does not differ by numeracy or education.

We can use the time spent making choices as an alternative measure of attention effort. Columns (7) through (9) use the time spent choosing between the information sources as the dependent vari-

[27]The coefficient on the High Reward dummy indicates that increasing $0.1 \cdot Reward_i$ by 9 (i.e., $0.1 \cdot 100 - 0.1 \cdot 10$) increases the WTP by \$0.80. Thus, increasing $0.1 \cdot Reward_i$ by 1 would increase the WTP by 0.089 ($= \frac{0.80}{9}$).

[28]The average individual responded that there was a 51.3% chance that their guess is within 1% of the true price. We use this as an estimate of the average $P_i\,(Accurate|NoInfo)$. Thus, the 8.9 percentage point effect translates into a 17% (=8.9/51.3) effect.

[29]Note the estimate for the High Reward dummy is no longer significant. On the other hand, the impact of the High Reward for college-educated respondents, which is the sum of the two estimates is a precisely estimated \$0.98. Thus, the impact of the higher rewards on the WTP is primarily driven by college-educated respondents.

able.[30] The results from column (7) indicate that, consistent with rational inattention, individuals assigned to the higher reward spent an additional 0.18 minutes choosing between information sources (from a baseline of 2.65 minutes in the lower-reward condition), though the difference is not quite statistically significant at conventional levels. Columns (8) and (9) show that more numerate and more educated respondents take less time to respond, but are not differentially sensitive to the higher reward.

Columns (10) through (12) use the time spent on the screen used to report the posterior beliefs. Due to the design of the survey, this variable includes the time spent looking at the information. As a result, in these regressions we control for a dummy indicating whether the individual was provided with information. The median time spent on reporting the posterior belief is 1.76 minutes for the lower-reward group. The results from column (10) suggest that the higher reward condition had a marginally significant positive effect on the time spent on this task (an additional 0.21 minutes, $p<0.1$). Again, we see no differential sensitivity to the rewards by education or numeracy.

This leads to our second result:

> ***Result 2***: *Consistent with rational inattention, the WTP for information is higher when the incentive is higher. Time spent choosing and processing information is also weakly higher when the incentive is higher. However, the ranking of information sources does not systematically differ by reward size.*

Figure 4.a shows considerable heterogeneity in WTP. We next investigate the drivers of this heterogeneity. Column (5) of Table 3 uses the interval regression model to estimate the effect of a set of factors on WTP, with the impact of each factor investigated one at a time. We see that higher income respondents, older respondents, and homeowners have economically and statistically significantly higher WTP for information. For instance, respondents with incomes above $60,000 are willing to pay about 50 cents more than those with lower incomes. Gender, education, and numeracy are not systematically related to WTP.

The expected effect of past search efforts on WTP is ambiguous. On the one hand, individuals who looked for information in the past may be willing to pay less for the information, because they have good information already. On the other hand, individuals who acquired more information in the past may have the highest revealed demand for information and thus could be more willing to buy additional information. Our evidence suggests that the second channel dominates: individuals who looked for housing-related information in the past were willing to pay an additional 57 cents, relative to those who did not. Likewise, we can study how the uncertainty in prior belief correlates with WTP. To measure uncertainty at the individual level, we use the responses to the probability bins. We fit these binned responses to a normal distribution for each individual and use the estimated standard deviation of the fitted distribution as a measure of individual-level

[30] We winsorize this time at 10 minutes, which is about the 98th percentile.

uncertainty, with higher values denoting higher uncertainty.[31] When looking at the relationship between uncertainty of prior beliefs and WTP, we again find evidence for the selection channel: individuals with a one-standard deviation higher uncertainty in their prior beliefs were, on average, willing to pay \$0.32 less.[32] Similarly, individuals who are more confident in their perceptions of past home price growth are willing to pay more for information.

The expected effect of local volatility in home prices on WTP also is ambiguous. On the one hand, updating more often is valuable for such respondents, and hence they should value information more. On the other hand, past changes in home prices are less informative. We have seen that respondents in these areas do not choose expert forecast more often. Here, we see that these respondents in fact value information more: increasing the home price volatility by 1 standard deviation increases the WTP by 25 cents.

Finally, we know that experts' forecasts historically have predicted home price changes more accurately than the other two information pieces. Under this metric, individuals then should be willing to pay more for expert forecasts. However, if individuals select a given information source because they erroneously believe it to be the most accurate/predictive one, then the WTP should not differ by information source. In an interval regression similar to the ones above, average WTP is highest for the 10-year information, followed by the expert forecast and the 1-year information; the difference between 10-year and 1-year information is significant at $p<0.05$ (while the coefficient on the expert forecast is not significantly different from either of the others). That is, there is no evidence that individuals pay more for information that has higher ex-ante predictive power. Panels c and d of Figure 4 break down the WTP by information type, showing how WTP for the expert forecast compares with that for past-one-year and past-ten-year home price changes, respectively. The panels also report results from an MWW test of the null that the distributions are identical, which is not rejected at conventional levels of significance.

3.3 Hypothesis 3: Rational Updating

Recall that our design generates random variation in whether a respondent saw information. For two individuals with identical WTP (and conditional on top-ranked information), whether information was shown to them was determined by chance. We use this random variation in the information provision to estimate the rate at which individuals use the signal to update their forecast. Furthermore, we calculate this learning rate for different sub-populations, particularly for sub-groups choosing different pieces of information.

[31] For instance, consider an individual with a 2% house price growth point forecast who has an uncertainty of 1 percentage point. It means that the individual's 95% confidence interval for house price growth is [0.04%, 3.96%] $(= [2 - (1 * 1.96), 2 + (1 * 1.96)])$.

[32] Note that the correlation of prior uncertainty with education/numeracy as well as with looking up housing-related information in the past is negative. This further suggests that the selection channel – of people genuinely interested in information having more precise priors and willing to pay more for information – being the dominating factor.

We use a simple learning model that naturally separates learning from the signal shown from other sources of signal-reversion.[33] Let b^{prior} denote the mean of the prior belief, b^{signal} the signal, and $b^{posterior}$ the mean of the corresponding posterior belief. When priors and signals are normally distributed, Bayesian learning implies that the mean of the posterior belief should be a weighted average between the signal and the mean of the prior belief:

$$b^{posterior} = \alpha \cdot b^{signal} + (1 - \alpha) \cdot b^{prior}. \tag{2}$$

The degree of learning can be summarized by the weight parameter α. In a Bayesian framework, the weight is proportional to the uncertainty (i.e., the variance) of the prior and inversely related to the uncertainty and noise in the signal. This parameter can take a value from 0 (individuals ignore the signal) to 1 (individuals fully adjust to the signal). Re-arranging this expression, we get the following:

$$b^{posterior} - b^{prior} = \alpha \cdot \left(b^{signal} - b^{prior}\right). \tag{3}$$

That is, the slope between the perception gaps ($b_k^{signal} - b_k^{prior}$) and revisions ($b_k^{posterior} - b_k^{prior}$) can be used to estimate the learning rate.[34] However, it is possible that individuals will revise their beliefs towards the signal even if they are not provided with the signal. For instance, consider someone who makes a typo when entering her prior belief and reports an estimate that differs significantly from the signals. If that person does not commit the typo again when reporting the posterior belief, it will look like she is reverting to the signal despite not being shown information. Also, it is possible that individuals think harder the second time they are asked about their home price expectation, especially since the posterior belief is incentivized but the prior belief is not. Additionally, it is plausible that some individuals searched for more housing-related information online during the survey. At the end of the survey, we asked respondents whether they had searched for information online during the survey, explaining that doing so was permitted, and 14.1% reported doing so. Interestingly, the search rate did not differ between respondents who saw information (14.3%) and those who did not (13.6%). Also, the simple act of taking a survey about housing may make respondents think more carefully about their responses and may lead them to revise their expectations even if they are not provided with any new information (see Zwane et al.,

[33] Similar learning models are used in Cavallo et al. (2017).

[34] There is an alternative specification for this learning model. Consider the case when the information chosen is the past 10 year home price change. b^{signal} is the actual past 10 year change, and $b_i^{\widehat{signal}}$ is i's prior belief about the past 10 year home price change, that was also elicited in the first stage of the survey. $b^{signal} - b_k^{\widehat{signal}}$ is then the difference between the actual change and the perceived change. The revision in expectations can be regressed onto this metric (this kind of learning model has been used in Amantier et al., 2016, and Armona et al., 2017). We do not use this alternative model for two reasons. First, this alternative model cannot be estimated for one of the data sources, because we did not elicit the prior belief about the signal of professional forecasters. Second, when considered simultaneously in the regression analysis, our baseline model fits the data better than this alternative specification.

2011, for a discussion of how surveying people may change their subsequent behavior).

Thus, we need to use the random variation in information provision to separate true learning from mean-reversion. Consider the dummy S_i that takes the value 1 if the individual was shown the signal. Let WTP_i be a set of dummies corresponding to the "threshold price" chosen by the individual in the scenarios. Conditional on this threshold, whether the individual received the information (S_i) depends on the randomly chosen scenario. Thus, we use the following regression specification:

$$b_i^{posterior} - b_i^{prior} = \alpha \cdot \left(b_i^{signal} - b_i^{prior}\right) \cdot S_i + \beta \cdot \left(b_i^{signal} - b_i^{prior}\right) + WTP_i\delta + \varepsilon_i. \quad (4)$$

The parameter of interest is still α, which measures the true learning rate (i.e., the effect of being randomly shown information on the updates). β reflects the degree of spurious mean-reversion. Figure 5.a shows the results from this regression. The y-axis indicates the revision in the forecast (i.e., posterior belief minus prior belief). The x-axis shows the "gap" between the signal and the prior belief, interacted by the treatment assignment dummy. For instance, if the respondent had a prior belief of 1% and was shown the expert forecast (which was 3.6%), the x-axis would take the value of 2.6%. Intuitively, the x-axis shows the potential for revision, and the y-axis shows the actual revision. If individuals fully incorporated the signals, then all dots should lie on the 45-degree line. If individuals did not incorporate any information, then the dots should lie on a horizontal line. The slope of the line is 0.38, which is highly statistically significant (p-value<0.001) and economically substantial: the average individual puts 38% weight on the signal and 62% on their prior belief.[35]

One potential concern with survey experiments is that, instead of inducing genuine learning, the information provided in the experiment elicits spurious reactions—for instance, due to unconscious numerical anchoring (Tversky and Kahneman, 1974) or experimenter demand (Goffman, 1963). Following Cavallo et al. (2017) and Armona et al. (2017), we use the follow-up survey to address this potential concern: if the reaction to the information was completely spurious, then the experimental effects should not persist for months after the information provision. To do this, Figure 5.b reproduces Figure 5.a, but instead of using $b_i^{posterior} - b_i^{prior}$ as the y-axis, we use $b_i^{follow\text{–}up} - b_i^{prior}$, where $b_i^{follow\text{–}up}$ is the belief reported four months later (i.e., in the follow-up survey).

Figure 5.b shows that the effects of the information persisted four months after the information provision, suggesting that a significant part of the reaction to the information was not spurious. The estimated slope (0.171) is smaller than the short-term equivalent (0.380), but it is still economically meaningful and statistically significant at the 10% level. Also, note that the slope is expected to be lower in the medium-term, because individuals may have been exposed to additional signals

[35] It is worth noting that the average learning rate does not differ by education, but it is the case that respondents with higher numeracy put more weight on the signal than those with low numeracy (Appendix Figure A.4).

during the interim four months, thus gradually diluting the effect of the signal provided during our experiment.

Figure 6.a investigates whether the learning rates differ across the three pieces of information. Ex ante, there is little reason for rates to differ: once respondents reveal their information preference, they should be equally responsive to it. This is confirmed in the figure. Panels b and c of Figure 6 investigate whether the learning rate differs by WTP for information or by uncertainty in prior belief. Under Bayesian updating, respondents who were more uncertain should have put more weight on the signal. Likewise, individuals who valued the information more arguably should have put more weight on it. While we do not find evidence of differential learning for high vs. low WTP respondents, we see from panel c that respondents with higher prior uncertainty, if anything, tend to update *less*. Our next result thus is as follows:

> ***Result 3***: *Respondents incorporate information that they buy, and the weight that respondents put on the information does not vary by information type. However, contrary to rational updating, we do not find the weight to be higher for individuals with higher prior uncertainty.*

3.4 Hypothesis 4: Information Acquisition and Dispersion of Expectations

In this subsection, we study how information acquisition affects dispersion in beliefs. We begin by investigating the effect of an exogenous reduction in the cost of information. In Stage 3, a scenario is picked at random. Thus, the experimental setup induces exogenous variation in the cost of information. We exploit this and compare how beliefs evolve when "low-price" ($0.01–$1.5) scenarios are picked at random, versus "high-price" ($2–$5) scenarios. Table 5 presents the results from this test. First of all, notice from the first row of the table that the lower cost of information did result in more information acquisition: the share of individuals acquiring information is 21 percentage points higher in the low-price group relative to the high-price group.

The rest of the rows from Table 5 show how beliefs evolved for the low- and high-price groups. As expected (due to the scenario being picked at random), the distribution of prior beliefs for the two groups is similar. At the final stage, due to the belief updating of those who saw the signal (as studied above), the mean forecast increased and uncertainty decreased. However, even though a significantly higher share of respondents in the low-price group saw a signal, the dispersion in beliefs remains similar across the two groups. In particular, we do not find evidence that the mean absolute deviation (MAD) is lower for the low-price group: in fact, it is slightly higher, at 2.21, than for the high-price group, which has a mean absolute deviation of 2.13 (the difference is not statistically significant at conventional levels; p-value=0.59).

We also study an additional measure of disagreement, defined as follows: for each respondent, we construct a 95% confidence interval for their forecast based on their point forecast along with the reported uncertainty.[36] We then form all possible pairs of respondents within a group (here, the low-price and high-price groups) and define a disagreement as occurring for a pair if the two respondents' constructed confidence intervals do not overlap. This measure thus reflects effects of information both on the dispersion in point forecasts and on respondents' uncertainty. In Table 5, we see that the fraction of disagreements roughly doubled from the prior stage to the posterior stage, primarily because respondents' uncertainty went down. However, we again see that disagreement is almost exactly at the same level for the group with a low cost of information, which was much more likely to obtain the signal, than for the group with a high cost of information.

How is it that more information does not induce higher consensus? Figures 7 and 8 explore this question. Figure 7 shows the distribution of prior beliefs for individuals who were not shown the information (Figure 7.a) versus individuals who were shown the information (Figure 7.b). Comparing the two indicates that these two groups started with similar distributions of beliefs. Figure 8 shows the comparison of posterior beliefs between individuals who were not shown information (Figure 8.a) versus individuals who were shown the information (Figure 8.b). Figure 8.a shows that, among individuals who were not shown information, the distribution of posterior beliefs is the same regardless of whether the individuals preferred the expert forecast, past-one-year home price change, or past-ten-year home price change.[37]In contrast, Figure 8.b shows that, for individuals who saw the information, posterior beliefs were substantially different across the three information groups. In each group, posterior beliefs moved towards the values of the respective signals: that is, -0.1% for the ten-year price change, 3.6% for the expert forecast, and 6.8% for the one-year price change. Within a group, the revelation of information tended to decrease dispersion of expectations. However, because those groups moved towards differing signals, the dispersion in beliefs across those three groups increased. The net effect of information acquisition on belief dispersion depends on the combination of these two channels, which end up canceling each other out.

Table 6 provides a more quantitative version of the previous graphical argument. The first two columns of Table 6 describe prior and posterior beliefs, respectively. It is worth remembering that whether or not a respondent sees information is endogenous to their WTP, which in turn may reflect other characteristics. Therefore, the comparison here is not as "clean" as the one in Table 5, which relies on experiment-induced variation in whether a respondent saw the information.

We are primarily interested in one feature of these beliefs: the dispersion, measured by the mean absolute deviation (MAD) across individuals. The first thing that we can corroborate is that, within information groups, information provision tended to reduce belief dispersion (but

[36]Note that our results are qualitatively unchanged if we use confidence intervals with different coverage, e.g. 90% or 50%.

[37]Consistent with the evidence discussed above that subjects in the no-information group may have searched for information or thought harder about the question, a comparison of Figure 7.a versus Figure 8.a indicates that the distribution of beliefs changed from prior to posterior even for individuals who were not shown information ($p<0.01$, MWW test).

belief dispersion remained high). For instance, for individuals who preferred the forecast and were shown the information, the MAD decreased from 2.19 to 1.14 percentage points. In contrast, for individuals who preferred the expert forecast but did not get to see the information, the MAD in beliefs increased from 1.93 percentage points for prior beliefs to 2.38 for posterior beliefs. These qualitative differences are consistent inside the group of individuals who chose the 10-year information, while for those who chose the 1-year information, MAD even increased for those who saw the info (perhaps because the signal was rather "extreme"), though less so than for those who did not see the info.

Now we turn to the sample that pools the individuals across all three information sources. In this pooled sample, the group that saw the information did not see a decline in the mean absolute deviation of beliefs: this measure of dispersion is 2.04 percentage points for the prior beliefs and 2.05 percentage points for the posterior beliefs.[38] And since respondents became more confident in their forecast, disagreement substantially increases, from 10.7% to 19.7% of all pairs. Disagreement also increases, though somewhat less strongly, in the no-information group; the difference-in-differences across groups is not statistically significant. Regarding confidence in expectations, mean uncertainty in posterior beliefs is lower than that in prior beliefs for both groups (those who saw the information and those who did not). However, consistent with the notion that information should make individuals more certain, we see that uncertainty declines more for the group that is shown information (from 3.9 to 2.8 percentage points, or more than 1 percentage point) than for the group that is not shown information (from 4.1 to 3.6 percentage points).

The table also shows how the cross-sectional dispersion evolves in the medium term. Ex-ante, the medium-term impact on dispersion is unclear – in the interim four months, individuals may have received various signals. Depending on the heterogeneity in these signals, the cross-sectional dispersion may go up or down. Additionally, because individuals are being asked about year-end home prices, some uncertainty may have resolved over the interim four months. The last column in Table 6 shows how these statistics evolved for the information-shown and not-shown groups. Comparing the follow-up belief with the posterior belief, the mean absolute deviation in expectations increases for both the information-shown and not-shown groups, though somewhat more so for the former group, which also sees a slight increase in disagreement.

One potential concern is that the cross-sectional dispersion does not decrease when information is cheaper just because respondents could buy, at most, one of the three information pieces. Could allowing individuals to view multiple pieces of information reverse this result? To investigate this, we fielded a supplementary module in the 2018 SCE Housing Survey. Details of this module and the analysis are presented in Appendix B. In this supplementary study, respondents can choose between two pieces of information. Then, we randomize them into three groups: they get to observe either no information, their preferred information, or both pieces of information. The comparison

[38]The mean absolute deviation in the pooled sample that does not see information does go up (from 2.27 to 2.61), but that difference is statistically insignificant (p-value=0.15).

between no information and their preferred information is equivalent to the comparison from the main experiment (i.e., randomizing the price of the preferred information between zero or infinity). We corroborate the finding from the main survey: cross-sectional dispersion does not decline when subjects get to see either their preferred information or both pieces of information. We find that randomly providing two signals at the same time has effects similar to providing just one piece of information, and that cross-sectional dispersion (measured either by the MAD or the disagreement metric) does not go down.

The fourth set of findings can be summarized as follows:

> ***Result 4****: A lower cost of information does not lead to a decrease in the cross-sectional dispersion of beliefs. This finding arises for two reasons. First, individuals choose to acquire different pieces of information and put significant weight on the acquired information. Second, within groups of individuals who acquire the same information, dispersion in beliefs remains high.*

4 Theory

We present a simple model that can match most of the experimental findings. The model is a combination of a sticky information model, as in Reis (2006), and a rational inattention model, as in Sims (2003). The model also features heterogeneous prior beliefs about the quality of different information sources.

4.1 Model

The timing is as follows:

1. Individuals report their prior beliefs over the fundamental.
2. Individuals can acquire access to one of three information sources at cost c or no information ("information acquisition").
3. The selected information is displayed and individuals choose the amount of attention allocated to the displayed information ("information processing").
4. Individuals report posterior beliefs over the fundamental and receive a payoff.

Individual i has the prior belief that the fundamental θ is normally distributed with mean $\mu_\theta(i)$ and variance $\sigma_\theta^2(i)$, where the i indicates that the prior belief over the fundamental may differ across individuals. In the experiment, the fundamental is house price growth during the calendar year.

Individuals have the common prior belief that each information source $j \in \{1,2,3\}$ is a noisy signal on the fundamental

$$x_j = \theta + \varepsilon_j,$$

where x_j is the displayed information and the noise ε_j is normally distributed with mean zero, but individuals may have heterogeneous prior beliefs over precisions. Individual i believes that the precisions of the three information sources equal $\tau_1(i) \equiv (1/\sigma^2_{\varepsilon,1}(i))$, $\tau_2(i) \equiv (1/\sigma^2_{\varepsilon,2}(i))$, and $\tau_3(i) \equiv (1/\sigma^2_{\varepsilon,3}(i))$, where the i indicates that the prior belief over precisions may differ across individuals. In the appendix, we solve a model with a common prior belief over precisions. In that model, individuals can process information about precisions before selecting an information source. Heterogeneity in beliefs over precisions arises ex post due to idiosyncratic processing mistakes. In that model, additional features of the experimental data arise endogenously. Here we focus on the simpler model with heterogeneous priors over precisions and no information processing before selecting an information source.

If an individual acquires access to an information source, the information is displayed. Paying attention to this information is modeled as a noisy signal on the displayed information

$$s(i) = x_j + \psi(i),$$

where j is the information source that the individual selected, x_j is the displayed information, and $\psi(i)$ is noise that arises due to limited attention to the displayed information. That is, limited attention creates a noisy perception of the displayed information. The noise $\psi(i)$ is assumed to be normally distributed with mean zero and variance $\sigma^2_\psi(i)$. Paying more attention to the displayed information is formalized as a smaller variance of noise, $\sigma^2_\psi(i)$. Individuals choose the amount of attention allocated to the displayed information, i.e., they choose $\sigma^2_\psi(i)$.

Posterior beliefs follow from Bayesian updating. If individual i selected information source $j \in \{1,2,3\}$ and chose the variance of noise $\sigma^2_\psi(i)$, her posterior belief is given by combining her prior belief with the signal

$$s(i) = \theta + \varepsilon_j + \psi(i).$$

The posterior mean of the fundamental is

$$E[\theta|s(i)] = \mu_\theta(i) + \frac{\sigma^2_\theta(i)}{\sigma^2_\theta(i) + \sigma^2_{\varepsilon,j}(i) + \sigma^2_\psi(i)}[\theta + \varepsilon_j + \psi(i) - \mu_\theta(i)]. \tag{5}$$

The weight on the displayed information is an increasing function of the perceived precision of the selected information source and the attention allocated to the displayed information.[39] The

[39] In Gabaix's (2014) model of sparsity, the weight on information is also an increasing function of attention to the information, as in Sims' (2003) model of rational inattention. One difference between these theories is that in Sims' (2003) model of rational inattention the weight on information can be viewed as the optimal response to a noisy perception of the information. The noisy perception of information in turn helps to match heterogeneity in

posterior variance of the fundamental is

$$\sigma_{\theta|s}^{2}(i) = \frac{1}{\frac{1}{\sigma_{\theta}^{2}(i)} + \frac{1}{\sigma_{\varepsilon,j}^{2}(i)+\sigma_{\psi}^{2}(i)}}.$$

The payoff received by individual i at the end equals

$$-\phi\left(\theta - E\left[\theta|s(i)\right]\right)^{2},$$

where the parameter ϕ controls the incentive to have an accurate posterior.

The optimal information strategy of an individual consists of an acquisition strategy ($j \in \{1,2,3\}$ or no information) and an attention strategy ($\sigma_{\psi}^{-2}(i) \geq 0$) that maximize the expected payoff net of the costs of acquiring and processing information:

$$-\phi\sigma_{\theta|s}^{2}(i) - cz - d\left(\sigma_{\psi}^{-2}(i)\right),$$

where c is the cost of acquiring information, z is an indicator variable which takes the value one if information is acquired, and $d\left(\sigma_{\psi}^{-2}(i)\right)$ denotes the cost of paying attention to the displayed information. One can think of the cost c as the sticky information aspect of the model (Mankiw and Reis, 2002), because in micro-founded versions of sticky information models there is a fixed cost of acquiring information (Reis, 2006).

Following Sims (2003), the cost of paying attention to displayed information is assumed to be an increasing function f of the uncertainty reduction about the displayed information

$$d\left(\sigma_{\psi}^{-2}(i)\right) = f\left(H(x_j) - H(x_j|s(i))\right),$$

where $H(x_j)$ denotes the entropy of displayed information and $H(x_j|s(i))$ denotes the conditional entropy of the displayed information given the signal on the displayed information. Since entropy is simply a measure of uncertainty, the argument of the function f simply measures the uncertainty reduction about the displayed information due to the signal on the displayed information. The entropy of a normally distributed random variable x with variance σ_x^2 equals a constant plus $\frac{1}{2}\ln(\sigma_x^2)$, and hence, the last equation reduces to

$$d\left(\sigma_{\psi}^{-2}(i)\right) = f\left(\frac{1}{2}\ln\left(\frac{\sigma_{x,j}^{2}(i)}{\sigma_{x,j|s}^{2}(i)}\right)\right) = f\left(\frac{1}{2}\ln\left(\frac{\sigma_{x,j}^{2}(i)}{\frac{\sigma_{x,j}^{2}(i)\sigma_{\psi}^{2}(i)}{\sigma_{x,j}^{2}(i)+\sigma_{\psi}^{2}(i)}}\right)\right) = f\left(\frac{1}{2}\ln\left(1+\frac{\sigma_{x,j}^{2}(i)}{\sigma_{\psi}^{2}(i)}\right)\right).$$

The cost of paying attention to displayed information is an increasing function of the signal-to-noise ratio in the signal on the displayed information. In the rational inattention literature following

reported posterior beliefs among individuals who see the same information.

Sims (2003), it is quite common to assume that f is a linear function, in which case the last equation reduces to

$$d\left(\sigma_{\psi}^{-2}(i)\right)=\mu\frac{1}{2}\ln\left(1+\frac{\sigma_{x,j}^{2}(i)}{\sigma_{\psi}^{2}(i)}\right),$$

where $\mu>0$ denotes the marginal cost of attention. All results presented in the following subsection also hold for any function f that is strictly increasing, convex, twice continuously differentiable, and has a non-zero derivative at zero.

4.2 Solution and comparison to experimental findings

The following proposition characterizes the solution to the model.

Proposition 1 *Individual i's optimal information strategy is to select the information source of the highest perceived precision,*

$$j^{*}(i)=\underset{j\in\{1,2,3\}}{\arg\max}\left(\frac{1}{\sigma_{\varepsilon,j}^{2}(i)}\right),$$

and to choose the precision of the signal on the displayed information that maximizes the net benefit of paying attention to the displayed information:

$$\frac{1}{\sigma_{\psi}^{2,*}(i)}=\underset{\left(1/\sigma_{\psi}^{2}(i)\right)\geq 0}{\arg\max}\left\{\phi\left(\sigma_{\theta}^{2}(i)-\frac{1}{\frac{1}{\sigma_{\theta}^{2}(i)}+\frac{1}{\sigma_{\varepsilon,j^{*}}^{2}(i)+\sigma_{\psi}^{2}(i)}}\right)-\frac{\mu}{2}\ln\left(1+\frac{\sigma_{\theta}^{2}(i)+\sigma_{\varepsilon,j^{*}}^{2}(i)}{\sigma_{\psi}^{2}(i)}\right)\right\}. \tag{6}$$

More attention yields a more accurate posterior but is also more costly. If the willingness to pay for access to the preferred information source (the max in (2)) exceeds the cost c, the individual acquires access to the preferred information source and the posterior mean of the fundamental is given by equation (1) with $j=j^{*}(i)$ and $\sigma_{\psi}^{2}(i)=\sigma_{\psi}^{2,*}(i)$.

The maximization problem (2) has the following properties. First, there exists a unique solution. Second, for sufficiently low ϕ/μ, high $\sigma_{\theta}^{-2}(i)$, and low $\sigma_{\varepsilon,j^{*}}^{-2}(i)$, the solution is a corner solution. In this case, it is optimal to pay no attention to the displayed information and the willingness to pay for access to the information therefore equals zero. Third, in the case of an interior solution, the optimal precision $\sigma_{\psi}^{-2,*}(i)$ is strictly increasing in ϕ/μ and $\sigma_{\varepsilon,j^{*}}^{-2}(i)$.

Before turning to a comparison of model predictions and experimental findings, we make three assumptions about heterogeneity.

Assumption 1: There is cross-sectional heterogeneity in $\underset{j\in\{1,2,3\}}{\arg\max}\left(\frac{1}{\sigma_{\varepsilon,j}^{2}(i)}\right)$.

Assumption 2: There is cross-sectional heterogeneity in the marginal cost of attention μ, and the marginal cost of attention μ is negatively correlated with numeracy in the cross section. This assumption seems natural since individuals with higher numeracy presumably find it less costly to pay attention to quantitative information and all displayed information is quantitative information.

Assumption 3: There is cross-sectional heterogeneity in the taste for information ϕ, and the precision of the prior $\sigma_\theta^{-2}(i)$ is positively correlated with the taste for information ϕ in the cross section. This assumption also seems natural because experimental subjects had the possibility to acquire and process information already before the experiment.

Finally, we compare model predictions and experimental findings.

First, due to corner solutions in the allocation of attention, the model can match the experimental finding that some individuals choose to acquire no information even before learning the cost of information acquisition. There is no point in acquiring information that one will not pay attention to anyway.

Second, with heterogeneous priors over precisions (Assumption 1), the model can match the experimental finding that individuals select different information sources. Furthermore, the fact that the average willingness to pay and the average weight on the displayed information do not differ across the three information groups suggests that $\max_{j\in\{1,2,3\}}\left(\frac{1}{\sigma_{\varepsilon,j}^2(i)}\right)$ does not differ systematically across the three information groups. That is, individuals rank information sources differently but think equally highly of their preferred information source.

Third, the model can match the experimental finding that individuals in the higher-reward treatment have a higher willingness to pay and thus are more likely to acquire the information.

Fourth, with costly attention ($\mu > 0$), the model can match the experimental finding that numeracy and reward matter *conditional* on information being displayed. Under Assumption 2 the model can match the experimental finding that individuals with higher numeracy react more to the displayed information (because they pay more attention to the displayed information) and the experimental finding that they select the alternative "I would not like to see any information" less frequently (because the optimal allocation of attention is less likely to be a corner solution). Under Assumption 3 the model can match the experimental finding that individuals with higher precision of the prior react more to the displayed information. Bayesian updating implies that agents with higher precision of the prior put a smaller weight on the signal. Endogenous attention implies that agents with a stronger taste for information pay more attention to the displayed information, implying a larger weight on the signal. Hence, if the precision of the prior and ϕ are positively correlated in the cross section, individuals with higher precision of the prior may end up putting a larger weight on the signal. Furthermore, the model can match the experimental finding that individuals in the higher-reward treatment spend more time on processing the displayed information.

Fifth, Bayesian updating under rational information acquisition and rational inattention implies that individuals with strictly positive willingness to pay put a strictly positive weight on the signal. A strictly positive willingness to pay implies that the preferred information source is perceived to be useful and the individual plans to pay attention to the displayed information, which in turn implies that the weight on the signal is strictly positive. Hence, the posterior beliefs of individuals who acquire access to different information sources should diverge, which matches the experimental finding that the posterior beliefs of individuals who select different information sources move towards different signals. Finally, within a group, access to the information source decreases dispersion in beliefs if and only if the fact that individuals put weight on the same displayed information dominates the fact that there is individual-specific noise in the signal on the displayed information and the fact that individuals may have heterogeneous signal weights. Thus, the model can also match the experimental finding that dispersion in beliefs falls within some groups and increases within other groups once information is displayed.[40]

Table 7 summarizes the predictions of the following versions of the model: (i) common prior over precisions and costless attention, (ii) heterogeneous priors over precisions and costless attention, (iii) heterogeneous priors over precisions and costly attention. These predictions hold for any level of the cost of information acquisition, $c \geq 0$. In sum, the special case of the model with a common prior over precisions and costless attention can match only a small subset of the findings. The benchmark version of the model with heterogeneous priors over precisions and costly attention can match almost all of the findings.

In the appendix, we solve a model where we replace the assumption of heterogeneous priors over precisions by the assumption of a common prior over precisions and the assumption that individuals can process information about the quality of information sources before selecting an information source. Heterogeneity in beliefs over precisions arises ex post due to idiosyncratic information-processing mistakes. In that model, additional features of the experimental data arise endogenously. In particular, the highest-precision information source is endogenously the modal choice, and under Assumption 2, high numeracy individuals are endogenously more likely to select the highest-precision information source.

5 Discussion and Conclusion

Using an innovative experimental setup that makes the information acquisition process endogenous, this paper attempts to understand the role of information frictions in explaining the heterogeneity in consumers' expectations about home price changes. Consumers exhibit substantial demand for information and, consistent with rational inattention, the demand for information is high when the stakes are high. Although information acquisition costs do seem to matter, our findings indicate that the main drivers of heterogeneity in consumer expectations are constraints on information processing. Consumers disagree on what information is most informative, with less sophisticated agents less likely to choose "informative" signals. Importantly, we see that the cross-sectional variance of the expectations distribution does not decrease because of endogenous information

[40] In the literature on noisy rational expectations models of financial markets following Grossman and Stiglitz (1980), there also exist models in which heterogeneity in beliefs arises because agents select different pieces of information. However, in that literature, agents select different pieces of information because equilibrium prices partially reveal information, while here agents select different pieces of information because of heterogeneity in beliefs over precisions.

acquisition, which would be expected in a setting with rational acquisition and information processing.

Endogenous information acquisition may thus increase disagreement across individuals, even though the opinions of people who look at the same signals tend to converge. Disagreement is thought to be an important driver of trade in asset markets (e.g. Harrison and Kreps 1978, Scheinkman and Xiong 2003, Hong and Stein 2007). In the context of the housing market, Bailey et al. (2017) show that counties with higher disagreement (which in their case is driven by different house price experiences of out-of-town friends) see higher trading volumes. Thus, to the extent that different households vary in the information sources they rely on, as our evidence suggests, differing signals from these sources may have important consequences for activity and prices in the housing market.

On the modeling front, many models with information frictions assume that individuals process information in a rational way. Our results suggest that this may be a misleading assumption and instead support models wherein consumers have heterogeneous beliefs about the precision of information sources, and have limited information processing capacity and process information at a finite rate (e.g., Sims, 2003). In that sense, our conclusion is similar to Coibion and Gorodnichenko (2012) who find that noisy information models are better at characterizing the expectations formation process. Our findings also suggest that consumers may not know which pieces of information to choose. In fact, we find that less sophisticated individuals (as proxied by education or numeracy) are less likely to pick informative signals. Thus, our results help explain why consumers tend to have so much dispersion in their expectations.

Disagreement in (inflation) expectations has been shown to vary over time, and the levels tend to be larger among consumers than among experts. For instance, Mankiw, Reis and Wolfers (2003) try to explain this finding through the lens of a sticky-information model, where some people form expectations based on outdated information. While their model can fit the survey data better than models of rational expectations, it is unable to match other features of the data, such as the positive relationship between the level of inflation and disagreement in expectations, or the higher level of disagreement during recessions. Our findings offer an alternative potential explanation for these patterns: consumers all update at regular frequencies but simply look at different information. Future work that tries to understand the dynamics of information acquisition would be valuable. With that goal in mind, it seems important that, in addition to collecting survey measures of expectations, we start collecting high-frequency data on the information sources that consumers are paying attention to.

We show that a rational inattention model with heterogeneity amongst consumers in the cost of attention and in beliefs about precision of information sources best characterizes our empirical results. Besides its implications for modeling of expectation formation, our findings have some direct policy implications. There is a debate in the literature about the optimal level of information disclosure by government agencies such as central banks and statistics agencies. For instance, most government agencies have the choice of releasing data such as official statistics on inflation, unemployment, and gross domestic product, among others. Some authors have argued that information disclosure is optimal (Hellwig 2005), whereas others argue that it can be harmful (Morris and Shin 2002). These models always assume that individuals process all the available information optimally. Implicitly, these models are assuming that more information cannot be worse for consumers, in the sense that that they can choose to ignore bad signals. Our evidence indicates that this assumption may be heroic. Instead, our findings imply that it is especially important for the government (and, for that matter, non-government) entities to disclose the information in a careful manner. Policy makers may want to act paternalistically by disclosing only the "good signals," by making the best signals more salient, or by guiding the customers on how to interpret and weigh all the available information.

References

[1] Allcott, H. (2011). "Social Norms and Energy Conservation." Journal of Public Economics, Vol. 95(9-10), pp. 1082-1095.

[2] Allcott, H., and Kessler, J. B. (2015). "The welfare effects of nudges: A case study of energy use social comparisons," NBER Working Paper No. 21671.

[3] Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2006). "Elicitation using multiple price list formats". Experimental Economics, Vol. 9(4), pp. 383-405.

[4] Angulo, A. M., Gil, J. M., and Tamburo, L. (2005). "Food safety and consumers' willingness to pay for labelled beef in Spain". Journal of Food Products Marketing, Vol. 11(3), pp. 89-105.

[5] Armantier, O., Nelson, S., Topa, G., van der Klaauw, W. and Zafar, B. (2016). "The Price Is Right: Updating of Inflation Expectations in a Randomized Price Information Experiment," Review of Economics and Statistics, forthcoming.

[6] Armona, L., A. Fuster, B. Zafar (2017). "Home Price Expectations and Behavior: Evidence from a Randomized Information Experiment," Review of Economic Studies, forthcoming.

[7] Bailey, M., R. Cao, T. Kuchler, and J. Stroebel (2017). "Social Networks and Housing Markets," NBER Working Paper No. 22258.

[8] Bailey, M., R. Cao, T. Kuchler, and J. Stroebel (2018). "The Economic Effects of Social Networks: Evidence from the Housing Market," Journal of Political Economy, forthcoming.

[9] Bartoš, V.; Bauer, M.; Chytilová, J.; Matějka, F. (2016). "Attention Discrimination: Theory and Field Experiments with Monitoring Information Acquisition," American Economic Review, Vol. 106(6), pp. 1437-1475.

[10] Burke, M., and M. Manz (2014). "Economic literacy and inflation expectations: evidence from an economic experiment," Journal of Money, Credit, and Banking, Vol. 46(7), pp. 1421-1456.

[11] Bordalo, P.; N. Gennaioli, and A. Shleifer (2018). "Diagnostic Expectations and Credit Cycles," Journal of Finance, forthcoming.

[12] Carroll, C. (2003). "Macroeconomic Expectations of Households and Professional Forecasters," Quarterly Journal of Economics, Vol. 118(1), pp. 269-298.

[13] Case, K. and R. Shiller (1989). "The Efficiency of the Market for Single-Family Homes," American Economic Review, Vol 79(1), pp. 125–137.

[14] Cavallo, A.; Cruces, G. and Perez-Truglia, R. (2016), "Learning from Potentially Biased Statistics," Brookings Papers on Economic Activity, Spring 2016, pp. 59–108.

[15] Cavallo, A.; Cruces, G. and Perez-Truglia, R. (2017). "Inflation Expectations, Learning and Supermarket Prices: Evidence from Survey Experiments," American Economic Journal: Macroeconomics, Vol 9(3), pp. 1–35.

[16] Cheng, I. and A. Hsiaw (2017). "Distrust in Experts and the Origins of Disagreement." Working Paper.

[17] Coibion, O. and Gorodnichenko, Y. (2012). "What can survey forecasts tell us about informational rigidities?" Journal of Political Economy, Vol. 120, pp. 116-159.

[18] Coibion, O., Gorodnichenko, Y. and Kumar, S. (2015). "How Do Firms Form Their Expectations? New Survey Evidence." NBER Working Paper No. 21092.

[19] Cruces, G., Perez-Truglia, R. and Tetaz, Martin (2013). "Biased Perceptions of Income Distribution and Preferences for Redistribution: Evidence from a Survey Experiment". Journal of Public Economics, Vol 98, pp. 100-112.

[20] Cullen, Z. and Perez-Truglia, R. (2017). "How Much Does Your Boss Make? The Effects of Salary Comparisons," Working Paper.

[21] Duflo, E. and Saez, E. (2003). "The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment," Quarterly Journal of Economics, Vol 118(3), pp. 815-842.

[22] Fuster, A., B. Hebert, and D. Laibson (2012). "Natural expectations, macroeconomic dynamics, and asset pricing," NBER Macroeconomics Annual, Vol 26 (1), pp. 1-48.

[23] Gabaix, X. (2017). "Behavioral Inattention," NBER Working Paper No. 24096.

[24] Gabaix, X.; Laibson, D.; Moloche, G. and Weinberg, S. (2006). "Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model," American Economic Review, Vol 96(4), pp.1043-1068.

[25] Glaeser, E., and C. Nathanson. (2015). "Housing Bubbles," in Handbook of Regional and Urban Economics, Volume 5. Eds. Gilles Duranton, Vernon Henderson, and William Strange. 701-751.

[26] Goffman, E. 1963. Stigma: Notes on the Management of Spoiled Identity. Englewood Cliffs, NJ: Prentice-Hall.

[27] Guren, A. (2016): "House Price Momentum and Strategic Complementarity," Journal of Political Economy, forthcoming

[28] Harrison, J.M. and D.M. Kreps (1978). "Speculative investor behavior in a stock market with heterogeneous expectations," Quarterly Journal of Economics, Vol 92(2): 323–336.

[29] Hellwig, C. (2005). "Heterogeneous Information and the Welfare Effects of Public Information Disclosures." UCLA Economics Working Paper No. 283.

[30] Hoffman, M. (2016). "How is Information Valued? Evidence from Framed Field Experiments." The Economic Journal, Vol 126(595): 1884-1911.

[31] Hong, H. and J.C. Stein (2007). "Disagreement and the stock market," Journal of Economic Perspectives, Vol 21(2): 109–128.

[32] Hoopes, J.; Reck, D. and Slemrod, J. (2015). "Taxpayer Search for Information: Implications for Rational Attention," American Economic Journal: Economic Policy, Vol 7(3), pp. 177-208.

[33] Khattak, A. J., Yim, Y., and Prokopy, L. S. (2003). "Willingness to pay for travel information," Transportation Research Part C: Emerging Technologies, Vol 11(2), pp. 137-159.

[34] Laster, D., Bennett, P., and Geoum, I. S. (1999). "Rational Bias in Macroeconomic Forecasts," The Quarterly Journal of Economics, Vol 114(1), pp. 293-318.

[35] Maćkowiak, B., and Wiederholt, M. (2009). "Optimal sticky prices under rational inattention," The American Economic Review, Vol 99(3), pp. 769-803.

[36] Malmendier, U. and Nagel, S. (2016). "Learning from Inflation Experiences," The Quarterly Journal of Economics, Vol 131(1), pp. 53-87.

[37] Mankiw, N.G. and Reis, R. (2002). "Sticky Information Versus Sticky Prices: A Proposal To Replace The New Keynesian Phillips Curve," Quarterly Journal of Economics, Vol 117(4), pp. 1295-1328.

[38] Mankiw, N.G., Reis, R. and Wolfers, J. (2003). "Disagreement About Inflation Expectations." In NBER Macroeconomics Annual 2003, ed. by M. Gertler, and K. Rogoff.

[39] Morris, S. and H.S. Shin (2002). "The Social Value of Public Information," American Economic Review, Vol. 92 (5), pp. 1521–34.

[40] Mullainathan, S. and A. Shleifer. (2005). "The Market for News," American Economic Review, Vol 95(4), pp. 1031-1053.

[41] Reis, R. (2006). "Inattentive consumers," Journal of monetary Economics, Vol 53(8), pp. 1761-1800.

[42] Scheinkman, J.A and W. Xiong (2003). "Overconfidence and speculative bubbles," Journal of Political Economy, Vol 111(6), pp. 183–1220.

[43] Shiller, R. (2005). "Irrational Exuberance," Second Edition, Princeton: Princeton University Press.

[44] Silverman, D.; J. Slemrod and N. Uler (2014). "Distinguishing the Role of Authority 'In' and Authority 'To'," Journal of Public Economics, Vol 113, pp. 32-42.

[45] Sims, C. (2003). "Implications of rational inattention," Journal of monetary Economics, Vol 50(3), pp. 665-690.

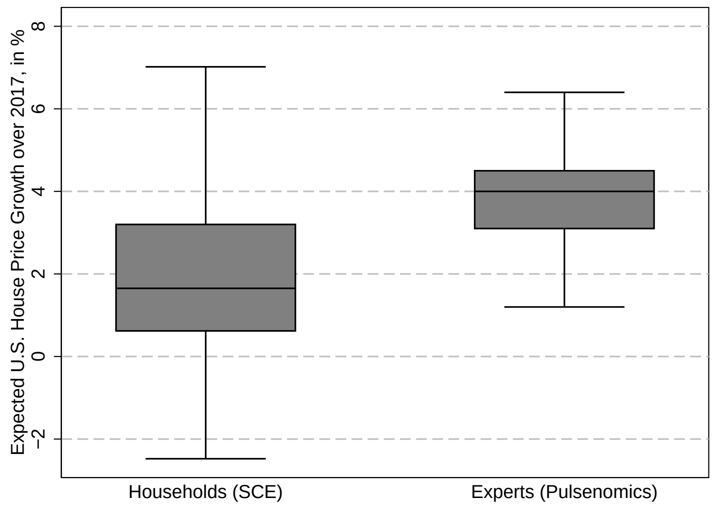
[46] Tversky, A. and D. Kahneman. 1974. "Judgment under Uncertainty: Heuristics and Biases." Science 185 (4157): 1124–31.

[47] Wiswall, M., and B. Zafar. (2015). "Determinants of College Major Choices: Identification from an Information Experiment." Review of Economic Studies, Vol 82(2), pp. 791-824.

[48] Woodford, M. (2003). "Imperfect Common Knowledge and the Effects of Monetary Policy," In Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund Phelps, edited by P. Aghion, R. Frydman, J. Stiglitz, and M. Woodford. Princeton, NJ: Princeton Univ. Press.

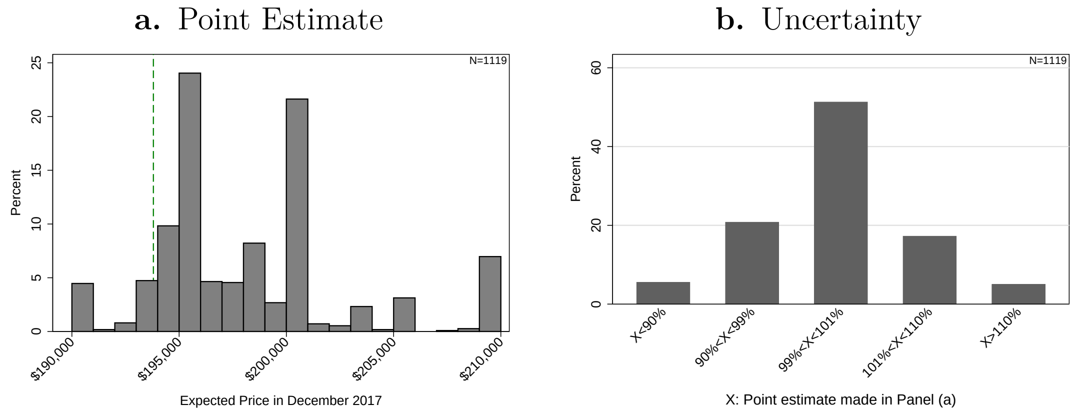
[49] Zwane, A.; Zinman, J.; Van Dusen, E.; Pariente, W.; Null, C.; Miguel, E.; Kremer, M.; Karlan, D.; Hornbeck, R.; Gine, X.; Duflo, E.; Devoto, F.; Crepon, B. and Banerje, A. (2011). "Being surveyed can change later behavior and related parameter estimates," Proceedings of the National Academy of Sciences, Vol 108, pp. 1821–1826.

Figure 1: Comparison of House Price Expectations: Households versus Experts



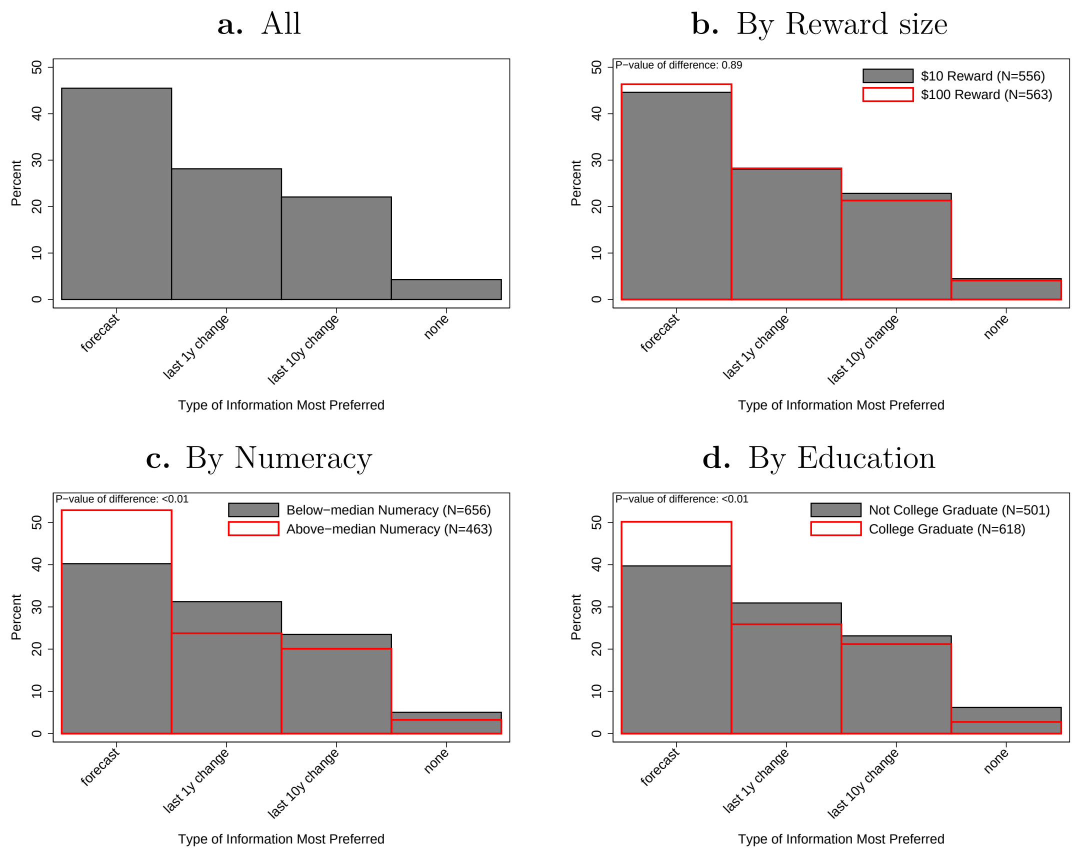
Notes: Box plots of the distribution of expected change (in percentage points) in the median house price value (Zillow Home Value Index) from December 2016 to December 2017. The left plot corresponds to the responses in the Survey of Consumer Expectations collected in February 2017 (N=1,119). The right plot corresponds to the responses of experts from the Pulsenomics panel in 2016:Q4 (N=105).

Figure 2: Prior Beliefs: Expectations about Median House Price



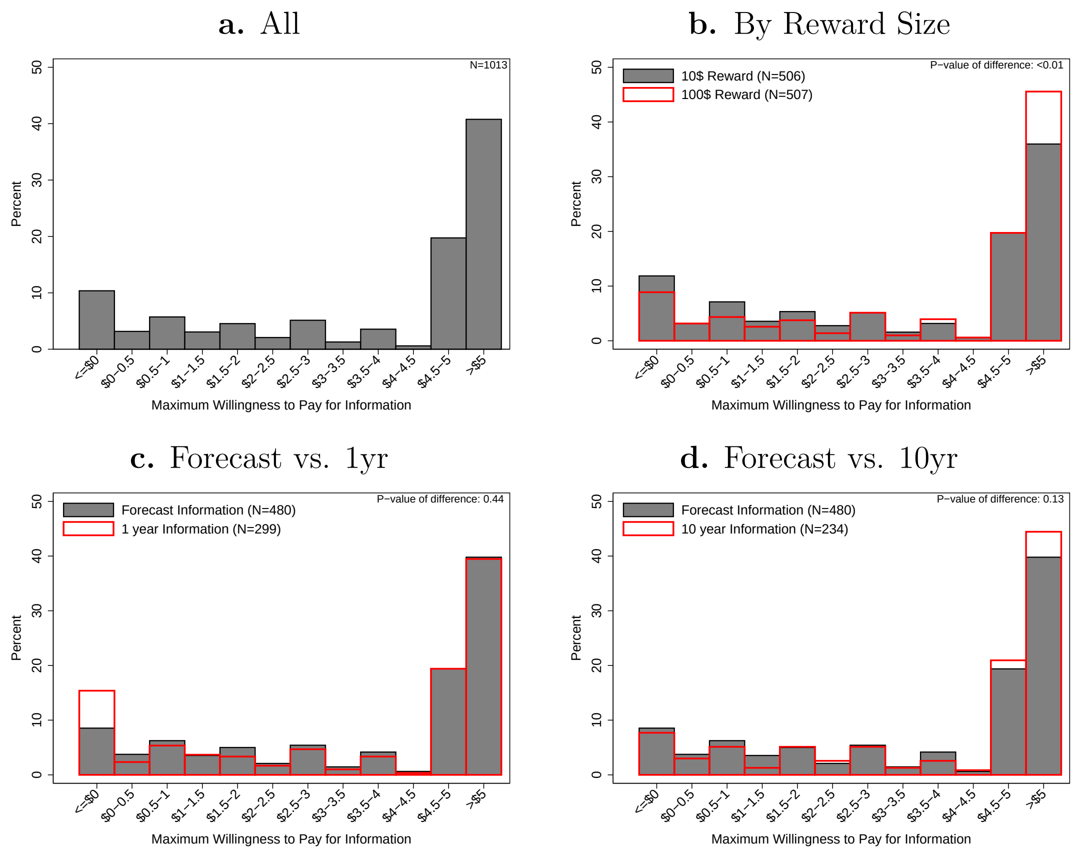
Notes: Panel (a) shows the distribution of the expected value of the typical home in the U.S. at the end of 2017 (as of February 2017, when the survey took place). The green line corresponds to the median house value in U.S. in December 2016 according ot the Zillow Home Value Index (this value was shown to respondents). The histogram is censored at $190,000 and $210,000. Panel (b) corresponds to the distribution of the confidence about the forecast made in Panel (a) by individuals.

Figure 3: Type of Information Most Preferred



Notes: Panel (a) shows the distribution of the type of information most preferred by individuals that may help them with forecasting future year-ahead U.S. home prices. Panel (b) provides the same information according the size of the reward, panel (c) according to the level of numeracy, and panel (d) according to the level of education. P-value of difference tests the joint significance of the estimates of a multinomial logit regression.

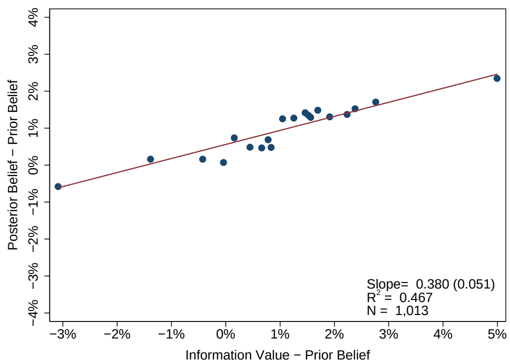
Figure 4: Willingness to Pay for Favorite Information



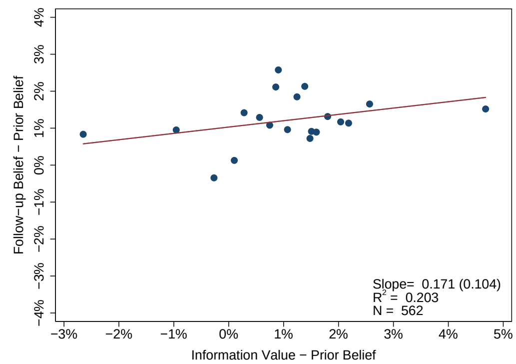
Notes: This sample does not include respondents who chose "None" as their most favorite information source and respondents with non-monotonic choices across the BDM scenarios. Panel (a) shows the distribution of maximum willingness to pay for favorite information in the whole sample. Panel (b) shows the distribution of maximum willingness to pay for information according the size of the reward. Panel (c) compares the distribution of WTP between individuals who preferred forecasts information and individuals who preferred information over the last one year. Panel (d) compares the distribution of WTP between individuals who preferred forecasts information and individuals who preferred information over the last ten years. P-value of difference refers to the Mann-Whitney-Wilcoxon test of the equality of two distributions.

Figure 5: Short and Medium-Term Learning Rates

a. Short Term



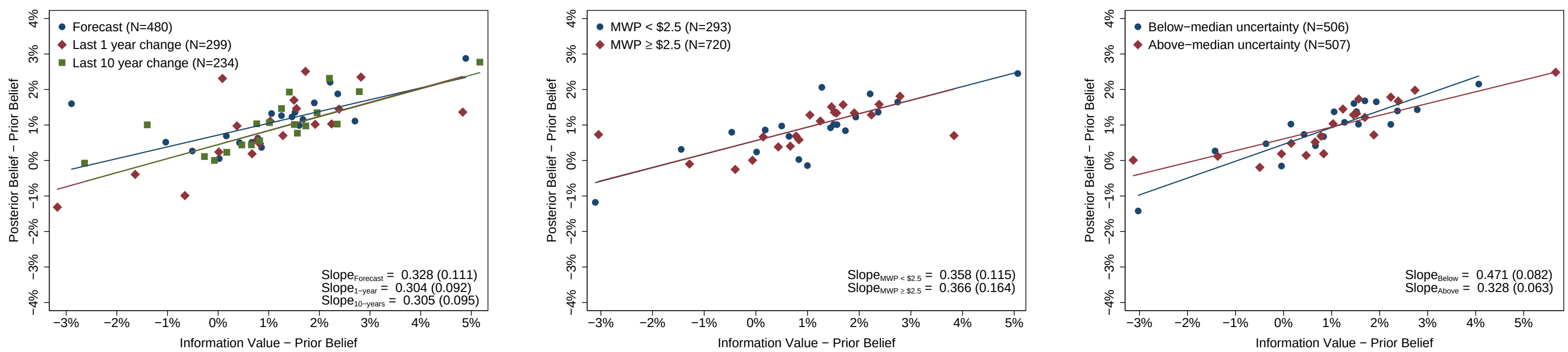
b. Medium-Term



Notes: Learning rates are estimated using equation (4) from section 3.3. The graphs show a binned-scatter plot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., posterior belief minus the prior belief) on the signal gap (i.e., signal value minus the prior belief) interacted by a dummy that takes the value 1 if the individual was shown the signal. The regressions control for the signal gap (i.e., without the interaction), dummies for maximum willingness to pay and the prior belief. We winsorize the dependent variables at the bottom/top 2.5%. Panel a. presents the results for the Short-Term (i.e., the dependent variable is the belief update during the baseline survey) and panel b. presents the results for the Medium-Term (the dependent variable is the difference between the posterior belief from the follow-up survey and the prior belief from the baseline survey).

Figure 6: Learning from Feedback

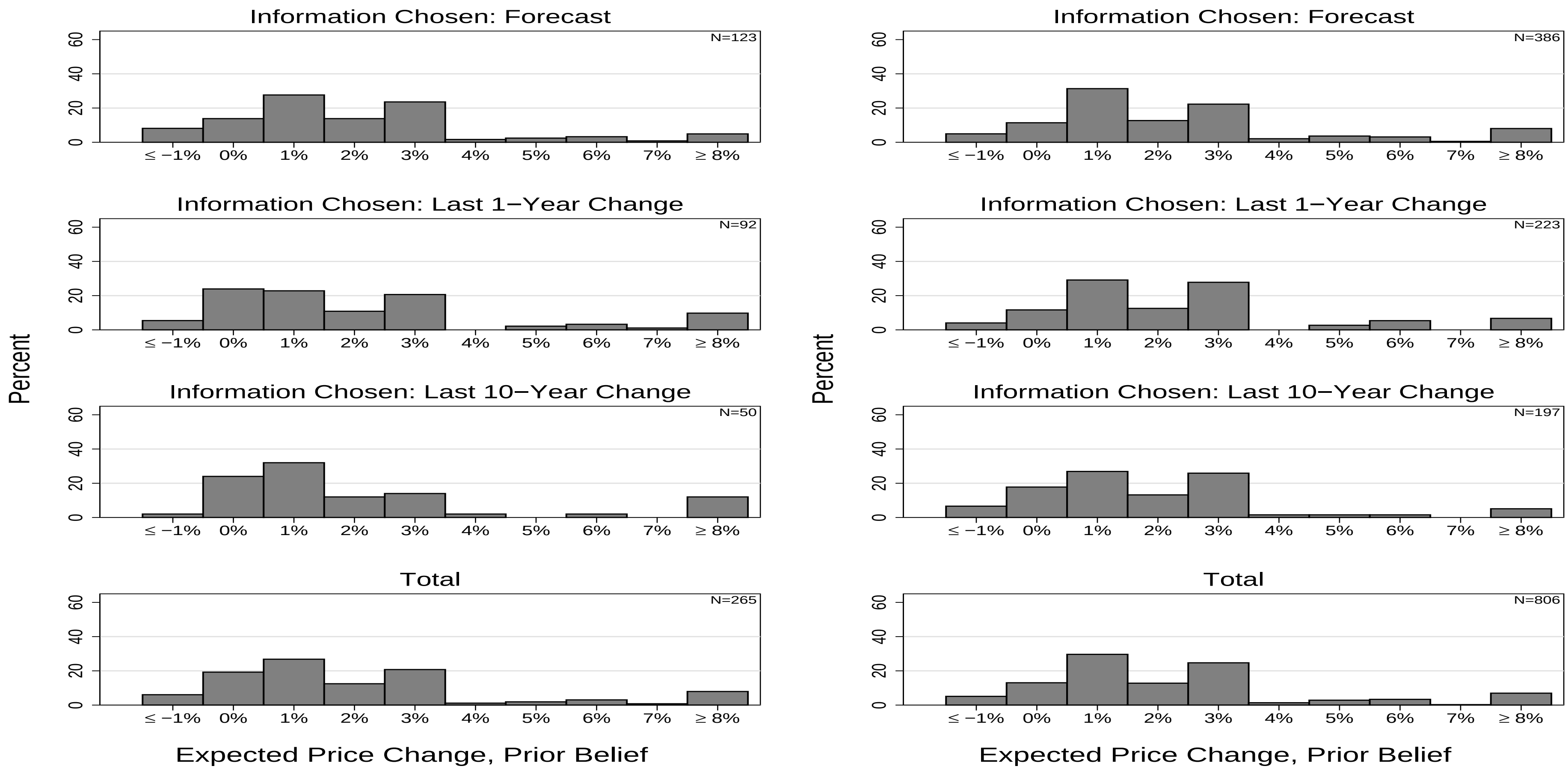
a. By Info Chosen **b.** By WTP **c.** By Uncertainty in Priors



Notes: This sample does not include respondents who chose "None" as their most favorite information source and respondents with non-monotonic choices across the BDM scenarios. Learning rates are estimated using equation (4) from section 3.3. The graphs show a binned-scatter plot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., the dependent variable is the belief update during the baseline survey) on the signal gap (i.e., signal value minus the prior belief) interacted by a dummy that takes the value 1 if the individual was shown the signal. The regressions control for the signal gap (i.e., without the interaction), dummies for maximum willingness to pay and the prior belief. We winsorize the dependent variables at the bottom/top 2.5%. . Panel a. presents the results according info chosen (i.e., forecast, last 1-year change, and last 10-year change). Panel b. presents results according WTP (i.e., above and below the median WTP). Finally, panel c. presents the results according the uncertainty (i.e., above and below the median uncertainty).

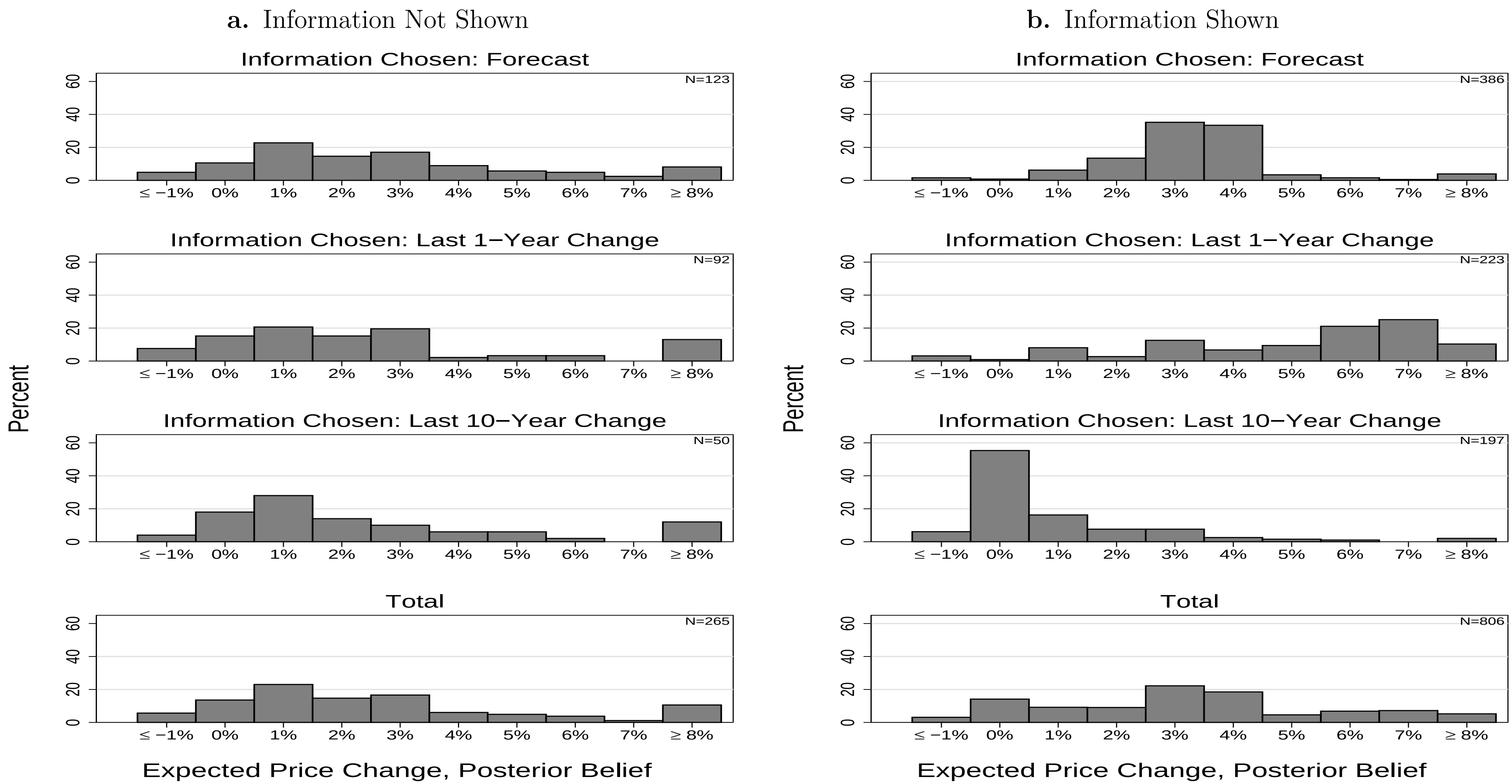
Figure 7: Prior Beliefs: Individuals Who Will not be Shown Information vs. Individuals Who Will

a. Information not to be Shown **b.** Information to be Shown



Notes:The distribution of the prior beliefs according the type of information most preferred (this sample does not include respondents who chose “None” as their most favorite information source). Panel (a) shows the distribution when individuals will not be shown information. Panel (b) shows the distribution when individuals will be shown information.

Figure 8: Posterior Beliefs: Individuals Who Were Shown Information vs. Individuals Who Were Not



Notes: The distribution of the posterior beliefs according the type of information most preferred (this sample does not include respondents who chose "None" as their most favorite information source). Panel (a) shows the distribution of individuals who were not shown the information. Panel (b) shows the distribution of individuals who were shown the information.

Table 1: Descriptive Statistics and Randomization Balance by Reward Size

	All (1)	Low Reward (2)	High Reward (3)	F-test P-value (4)	Low Price (5)	High Price (6)	F-test P-value (7)
Prior Belief ($1,000s)	198.1	198.2	197.9	0.374	198.1	198.2	0.662
	(0.178)	(0.258)	(0.246)		(0.254)	(0.266)	
Prior Belief (% change)	0.0220	0.0230	0.0210	0.374	0.0220	0.0230	0.662
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	
Income > $60,000 (0/1)	0.555	0.577	0.533	0.135	0.583	0.547	0.244
	(0.015)	(0.021)	(0.021)		(0.021)	(0.022)	
College Graduate (0/1)	0.552	0.550	0.554	0.898	0.577	0.543	0.264
	(0.015)	(0.021)	(0.021)		(0.021)	(0.022)	
Age	50.83	51.18	50.48	0.450	50.71	50.76	0.965
	(0.462)	(0.663)	(0.644)		(0.663)	(0.677)	
Female (0/1)	0.476	0.471	0.481	0.735	0.456	0.494	0.219
	(0.015)	(0.021)	(0.021)		(0.021)	(0.022)	
Married (0/1)	0.634	0.656	0.611	0.115	0.636	0.644	0.790
	(0.014)	(0.020)	(0.021)		(0.020)	(0.021)	
White (0/1)	0.811	0.784	0.837	0.0250	0.803	0.825	0.356
	(0.012)	(0.017)	(0.016)		(0.017)	(0.017)	
Homeowner (0/1)	0.748	0.752	0.744	0.771	0.757	0.746	0.689
	(0.013)	(0.018)	(0.018)		(0.018)	(0.019)	
Resp. Follow-Up Survey (0/1)	0.552	0.550	0.554	0.898	0.545	0.569	0.438
	(0.015)	(0.021)	(0.021)		(0.021)	(0.022)	
Observations	1,119	556	563		563	508	

Notes: Individual characteristics obtained from baseline survey. Column (1) corresponds to all respondents; columns (2) and (3) correspond to treatment groups for reward size treatment; columns (5) and (6) correspond to the price treatments (Low Price correspond to scenarios 1-4, while High-Price corresponds to scenarios 5-11). Column (4) and (7) present p-values for the test of the null hypothesis that the mean characteristic is equal the corresponding pair of treatment groups. All variables constructed from the survey data.

Table 2: Descriptive Statistics by Follow-Up Invitation and Response

		Invited to Follow-Up			Responded Follow-Up invitation		
	All	No	Yes	F-test P-value	No	Yes	F-test P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prior Belief ($1,000s)	198.1	197.9	198.2	0.534	198.7	198.1	0.331
	(0.178)	(0.293)	(0.224)		(0.673)	(0.234)	
Prior Belief (% change)	0.0220	0.0210	0.0230	0.534	0.0260	0.0220	0.331
	(0.001)	(0.002)	(0.001)		(0.003)	(0.001)	
Income > $60,000 (0/1)	0.555	0.533	0.566	0.285	0.617	0.557	0.218
	(0.015)	(0.026)	(0.018)		(0.045)	(0.020)	
College Graduate (0/1)	0.552	0.543	0.557	0.665	0.583	0.552	0.523
	(0.015)	(0.026)	(0.018)		(0.045)	(0.020)	
Age	50.83	51.10	50.69	0.681	49.22	50.98	0.214
	(0.462)	(0.823)	(0.558)		(1.279)	(0.618)	
Female (0/1)	0.476	0.501	0.463	0.230	0.517	0.453	0.203
	(0.015)	(0.026)	(0.018)		(0.046)	(0.020)	
Married (0/1)	0.634	0.635	0.633	0.938	0.608	0.638	0.548
	(0.014)	(0.025)	(0.018)		(0.045)	(0.019)	
White (0/1)	0.811	0.816	0.808	0.724	0.817	0.806	0.780
	(0.012)	(0.020)	(0.015)		(0.035)	(0.016)	
Homeowner (0/1)	0.748	0.753	0.745	0.769	0.750	0.744	0.896
	(0.013)	(0.022)	(0.016)		(0.040)	(0.018)	
Observations	1,119	381	738		120	618	

Notes: Individual characteristics obtained from baseline survey. Column (1) corresponds to all respondents, column (2) corresponds to individuals who were not invited to the follow-up survey, column (3) corresponds to individuals who where invited to the follow-up survey. Column (4) presents p-value for the test of the null hypothesis that the mean characteristic is equal across (2) and (3). Column (5) corresponds to individuals who were invited to the follow-up survey but did not respond. Column (6) corresponds to individuals who were invited to the follow-up survey and responded. Finally, column (7) presents p-value for the test of the null hypothesis that the mean characteristic is equal across (5) and (6). All variables constructed from the survey data.

Table 3: Factors Associated to Information Choice and Willingness to Pay

	Indicator: chose...				
	Forecast (1)	1-yr (2)	10yr (3)	1yr>10yr (4)	WTP (5)
Income > $60,000	0.056*	-0.021	0.007	0.036	0.491**
	(0.030)	(0.027)	(0.025)	(0.030)	(0.242)
College Graduate (0/1)	0.104***	-0.050*	-0.020	0.031	0.108
	(0.030)	(0.027)	(0.025)	(0.030)	(0.240)
Age	-0.001	0.003***	-0.002**	0.003***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)
Female (0/1)	0.013	-0.011	-0.009	-0.003	-0.256
	(0.030)	(0.027)	(0.025)	(0.029)	(0.235)
Married (0/1)	-0.025	0.009	0.040	-0.006	0.244
	(0.031)	(0.028)	(0.025)	(0.030)	(0.250)
White (0/1)	0.072*	-0.037	-0.019	0.014	0.082
	(0.037)	(0.035)	(0.032)	(0.038)	(0.324)
High Numeracy (0/1)	0.127***	-0.075***	-0.034	0.026	-0.071
	(0.030)	(0.027)	(0.025)	(0.030)	(0.232)
Uncertainty in Prior Belief (Std)	0.001	0.002	0.007	-0.011	-0.321***
	(0.015)	(0.014)	(0.012)	(0.015)	(0.118)
Median House Value in State (Std)	0.027*	-0.010	-0.008	0.007	0.171
	(0.015)	(0.013)	(0.012)	(0.014)	(0.118)
House Value Volatility in State (Std)	-0.001	-0.006	0.007	-0.005	0.248**
	(0.015)	(0.013)	(0.013)	(0.015)	(0.116)
Looked for Info in Past (0/1)	0.009	0.024	-0.007	0.013	0.569**
	(0.030)	(0.027)	(0.025)	(0.030)	(0.238)
Homeowner (0/1)	-0.058*	0.088***	-0.003	0.065*	0.690**
	(0.034)	(0.029)	(0.029)	(0.034)	(0.272)
Conf. in past Recall (1-5)	-0.021	0.021	0.001	0.004	0.239**
	(0.015)	(0.014)	(0.012)	(0.015)	(0.122)
Mean	0.45	0.28	0.22	0.60	4.39
Observations	1119	1119	1119	1119	1013

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each coefficient comes from a separate univariate regression. Interval regressions are estimated in columns (5), using willingness to pay as the dependent variable. In columns (1) through (4), OLS regression are estimated using a dummy variable (=1) if the individual preferred the forecast information, 1 year information, 10 years information, or 1 year information over 10 years information as the dependent variable.

Table 4: Effect of Reward Size on Information Choice and Willingness to Pay

	Max. Willingness to Pay			Indicator: Chose Forecast			Min Ranking Info			Min. Spent Posterior Belief		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High Reward (0/1)	0.805***	0.776***	0.575	0.018	0.017	-0.006	0.175	0.178	0.232	0.206*	0.210*	0.365**
	(0.232)	(0.234)	(0.378)	(0.030)	(0.030)	(0.044)	(0.112)	(0.111)	(0.170)	(0.120)	(0.120)	(0.175)
High Reward*Std. Numeracy		0.425*			0.008			-0.087			-0.133	
		(0.249)			(0.029)			(0.120)			(0.119)	
High Reward*College			0.402			0.041			-0.101			-0.285
			(0.476)			(0.060)			(0.225)			(0.240)
Std. Numeracy		-0.115			0.063***			-0.154*			0.011	
		(0.170)			(0.020)			(0.079)			(0.075)	
College Graduate (0/1)			-0.082			0.084**			-0.309**			0.065
			(0.332)			(0.042)			(0.151)			(0.170)
Feedback Shown (0/1)										0.795***	0.807***	0.803***
										(0.121)	(0.121)	(0.121)
Constant	3.993***	3.997***	4.039***	0.446***	0.446***	0.400***	2.651***	2.650***	2.822***	1.762***	1.753***	1.719***
	(0.162)	(0.163)	(0.265)	(0.021)	(0.021)	(0.031)	(0.076)	(0.075)	(0.109)	(0.112)	(0.112)	(0.147)
Mean		4.39			0.45			2.74			2.41	
Observations	1013	1013	1013	1119	1119	1119	1119	1119	1119	1071	1071	1071

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns (1) through (3) report results for interval regressions with maximum willingness to pay as the dependent variable (this sample does not include respondents who chose "None" as their most favorite information source and respondents with non-monotonic choices across the BDM scenarios). Columns (4) through (6) report OLS regressions where the dependent variable is a dummy indicating if the individual preferred the forecast information. Columns (7) to (9) report OLS regressions where the dependent variables is the minutes spent on ranking the information sources (this variable is upper censored at 10 minutes, which is roughly the 99th percentile of the variable). Columns (10) to (12) report OLS regressions where the dependent variables is the minutes spent on reporting the posterior beliefs (this variable is upper censored at 10 minutes, which is roughly the 99th percentile of the variable). For these last three columns the sample does not include respondents who chose "None" as their most favorite information source. The variable *College* equals 1 if the level of the education of the individual is equal or greater than a Bachelor degree. The variable *Std. Numeracy Score* indicates the level of ability in numeracy, with higher values indicating higher numeracy and normalized to have a mean of 0 and a standard deviation of 1. The variable *Feedback Shown* equals 1 if the individual was shown the information.

Table 5: Cost of Information and Dispersion of Expectations

		Low Price (1)	**High Price** (2)	P-value Diff (3)
Obtained Signal (%)		86.19 (1.057)	65.41 (1.545)	0.00
Expectations:				
Prior	Mean	2.15 (0.133)	2.22 (0.137)	0.74
	MAD	2.06 (0.098)	2.04 (0.100)	0.88
	Uncertainty	3.94 (0.124)	3.81 (0.130)	0.61
	Disagreement (%)	9.66 (0.92)	10.49 (1.00)	0.54
Posterior	Mean	3.24 (0.141)	3.02 (0.143)	0.26
	MAD	2.21 (0.104)	2.13 (0.104)	0.59
	Uncertainty	2.87 (0.109)	2.96 (0.117)	0.68
	Disagreement (%)	19.03 (1.29)	19.51 (1.40)	0.80
Observations		536	477	

Notes: This sample does not include respondents who chose “None” as their most favorite information source and respondents with non-monotonic choices across the BDM scenarios. The group Low-Price corresponds to individuals randomly assigned to scenarios 1-4 (corresponding to prices from \$0.01 to\$1.5), while the group High-Price corresponds to individuals randomly assigned to scenarios 5-11 (corresponding to prices from \$2 to \$5). The average level, the dispersion (measured as mean absolute deviation, MAD), the uncertainty, and the fraction of disagreements within group is presented for the prior and posterior belief. The prior belief refers to the expected change for home prices to the end of the year before the information, that may help with forecasting, was presented to individuals. Posterior belief refers to the expected change after the information was shown to individuals. Both in the prior and posterior belief the survey elicited the respondent’s subjective belief distribution about home prices. To measure uncertainty at the individual level, we fit these binned responses to a normal distribution for each individual, and use the estimated standard deviation of the fitted distribution as a measure of individual-level uncertainty, with higher values denoting higher uncertainty. A disagreement is defined as non-overlap of two respondents’ constructed 95% confidence interval; the table reports the fraction of all pairwise meetings that would result in a disagreement so defined. Columns (1) and (2) present the information for individuals who were randomly assigned to the Low and High Price respectively. Column (3) presents p-value for the test of the null hypothesis that the mean characteristic is equal across (1) and (2). Numbers in parentheses in each cell are standard errors.

Table 6: Effect of Information-Acquisition on the Distribution of Expectations

		Baseline Sample		Follow-Up Sample
		Prior	Posterior	Follow-Up
		(1)	(2)	(3)
Information Shown				
All	Mean	2.27 (0.106)	3.28 (0.107)	3.36 (0.191)
N=806 (450)	MAD	2.04 (0.077)	2.05 (0.078)	2.73 (0.141)
	Uncertainty	3.86 (0.101)	2.76 (0.087)	3.13 (0.135)
	Disagreem. (%)	10.68 (0.79)	19.74 (1.08)	20.34 (1.46)
Forecast	Mean	2.41 (0.164)	3.38 (0.124)	3.72 (0.282)
N=386 (205)	MAD	2.19 (0.121)	1.14 (0.109)	2.80 (0.203)
	Uncertainty	3.82 (0.142)	2.78 (0.125)	3.33 (0.212)
	Disagreem. (%)	10.36 (1.10)	7.75 (1.06)	17.58 (2.01)
1 Year Change	Mean	2.42 (0.198)	5.17 (0.209)	3.77 (0.389)
N=223 (131)	MAD	2.01 (0.145)	2.25 (0.145)	3.14 (0.275)
	Uncertainty	3.61 (0.201)	3.09 (0.179)	3.51 (0.272)
	Disagreem. (%)	14.97 (1.86)	17.80 (2.08)	21.89 (2.76)
10 Year Change	Mean	1.82 (0.179)	0.92 (0.164)	2.23 (0.317)
N=197 (114)	MAD	1.79 (0.125)	1.35 (0.132)	2.15 (0.244)
	Uncertainty	4.22 (0.209)	2.34 (0.160)	2.32 (0.201)
	Disagreem. (%)	6.66 (1.19)	10.30 (1.60)	22.03 (3.09)
Information Not Shown				
All	Mean	2.15 (0.208)	2.77 (0.237)	3.16 (0.354)
N=265 (146)	MAD	2.27 (0.154)	2.61 (0.174)	2.83 (0.266)
	Uncertainty	4.06 (0.176)	3.59 (0.176)	3.52 (0.270)
	Disagreem. (%)	8.81 (1.19)	16.19 (1.73)	15.69 (2.29)
Forecast	Mean	1.97 (0.247)	2.99 (0.311)	2.60 (0.372)
N=123 (75)	MAD	1.93 (0.175)	2.38 (0.225)	2.27 (0.263)
	Uncertainty	4.05 (0.262)	3.28 (0.250)	2.81 (0.334)
	Disagreem. (%)	9.48 (1.74)	17.29 (2.68)	18.92 (3.26)
1 Year Change	Mean	2.32 (0.403)	2.56 (0.475)	4.08 (0.812)
N=92 (45)	MAD	2.61 (0.296)	2.97 (0.358)	3.91 (0.558)
	Uncertainty	4.58 (0.319)	4.22 (0.323)	5.07 (0.616)
	Disagreem. (%)	7.76 (2.01)	13.88 (2.68)	9.09 (2.80)
10 Year Change	Mean	2.29 (0.549)	2.60 (0.484)	3.17 (0.898)
N=50 (26)	MAD	2.55 (0.411)	2.48 (0.331)	3.20 (0.630)
	Uncertainty	3.10 (0.338)	3.21 (0.384)	2.89 (0.457)
	Disagreem. (%)	7.92 (2.45)	18.04 (4.16)	17.85 (7.88)

Notes: This sample does not include respondents who chose "None" as their most favorite information source. The average level, the dispersion, the uncertainty, and the fraction of disagreements within group is presented for the prior, posterior, and follow-up belief conditional on seeing the information and the most-preferred information source. The prior belief refers to the expected change for home prices to the end of the year before the information, that may help with forecasting, was presented to individuals. Posterior belief refers to the expected change after the information was shown to individuals, and follow-up belief refers to the expected change for home prices between the follow-up survey (4 months after the baseline survey) and the end of the year. See notes to Table 5 for additional notes on definitions of various measures. The first number in N corresponds to the number observations in the baseline survey. The number in parentheses corresponds to the number of observations in the Follow-Up survey. In columns (1) and (2) we present the results for the Baseline Sample. In columns (3), the sample includes individuals who were invited and responded the Follow-up survey. Numbers in parentheses in each cell are standard errors.

Table 7: Empirical Findings and Model Predictions

	All individuals choose the same information source?	Relationship between prior precision and learning rate?	Is numeracy and reward relevant? (conditionally on info displayed)
Data	No	Positive	Yes
Model			
Common prior about information sources	Yes	Negative	No
Heterogeneous priors about information sources	No	Negative	No
Heterogeneous priors about information sources & rational inattention	No	Non-Negative	Yes

Notes: This table refers to the theory presented in Section 4.

Online Appendix: For Online Publication Only

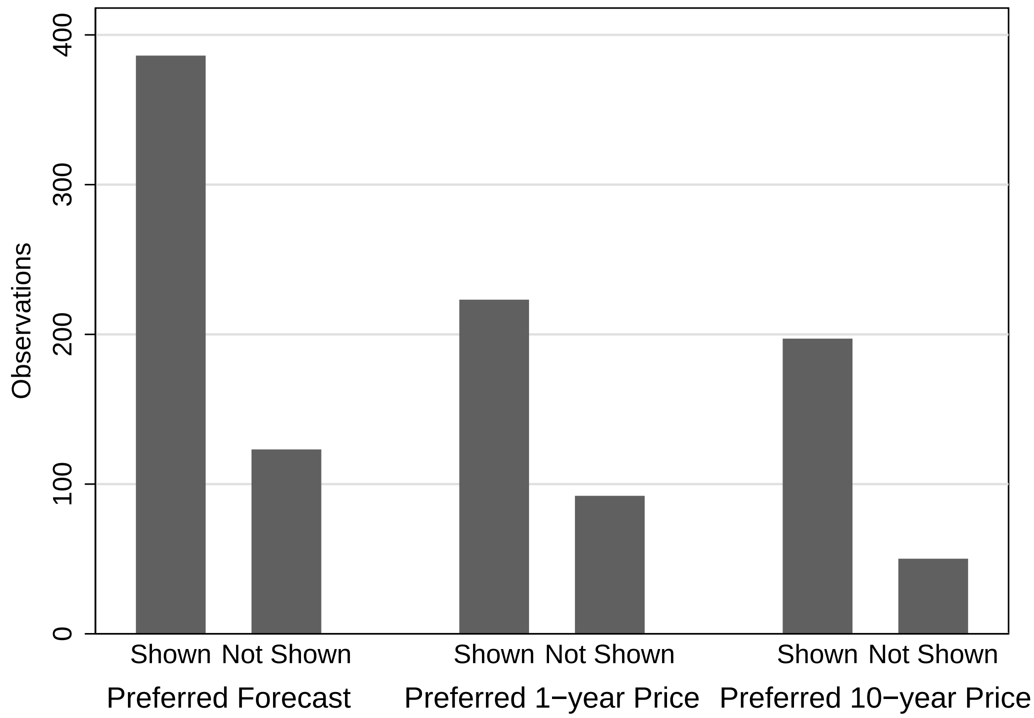
A Additional Results

A.1 Decomposition of learning rates

In this section, we give more details about the identification of the learning rates. Figure A.3.a shows how the beliefs evolved after the information was provided. The y-axis indicates the revision in national home price beliefs, i.e., posterior belief *minus* prior belief. The x-axis shows the "gap" between the signal and the prior belief. For instance, if the respondent had a prior belief of 1% and was shown the forecast of experts (which was 3.6%), the x-axis would take the value of 2.6%. Intuitively, the x-axis shows how much potential for revision there is, and the y-axis shows the actual revision. If individuals fully reacted to the signal shown, we would expect all dots to lie on the 45-degree line. If individuals did not react to the information, we would expect the dots to lie in a horizontal line. The slope of the line is 0.561, which is not only highly statistically significant (p-value<0.001), but also economically substantial: it is closer to the case where individuals fully react to the information (slope of 1) than the case where individuals fully ignore the information (slope of 0).

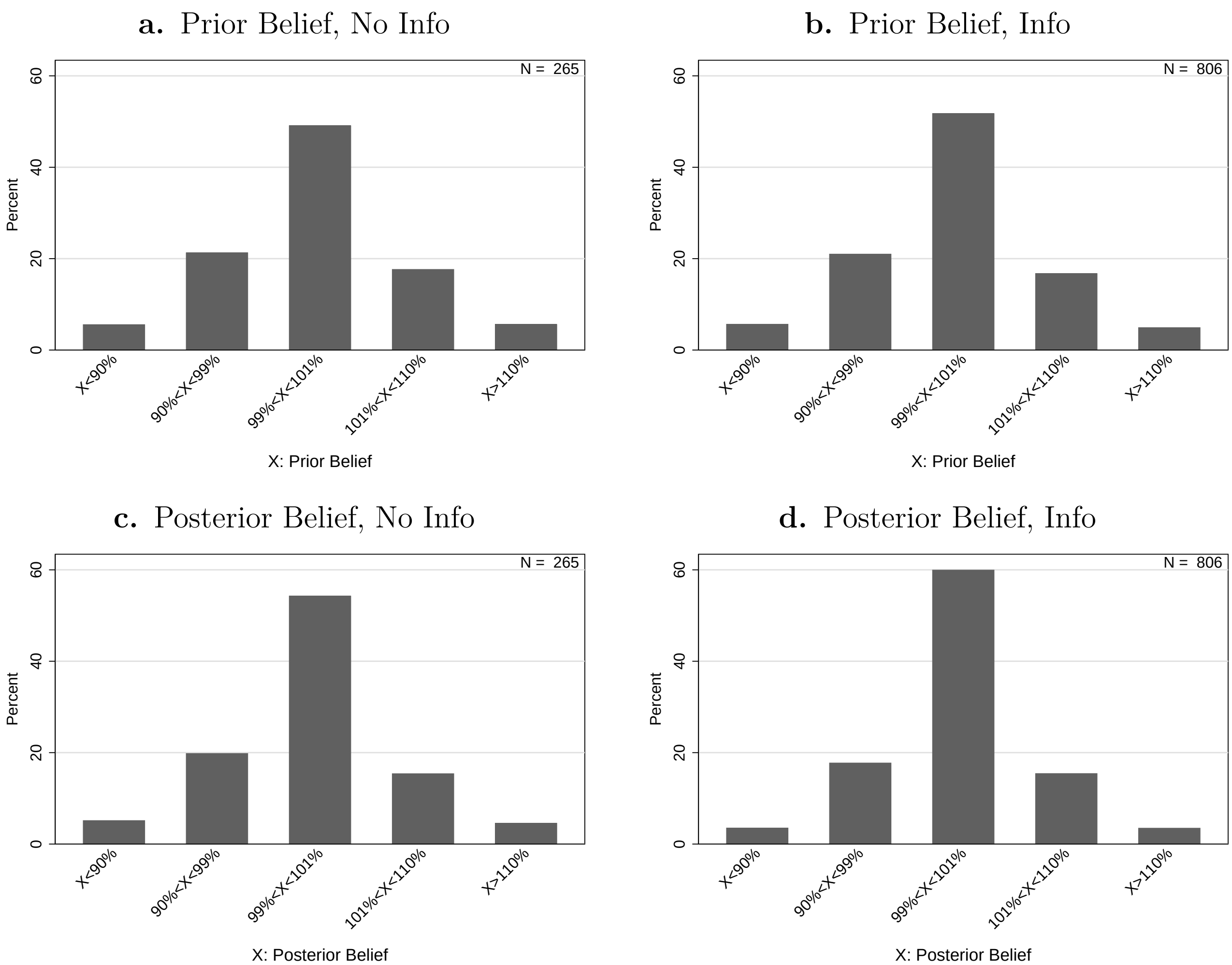
Figure A.3.b is identical to Figure A.3.a, except that instead of corresponding to individuals who were shown the signal, it corresponds to individuals who were not shown the signal. Consistent with the typos and/or information search, there is reversion to the signal when the signal was not shown. However, the magnitude of this reversion to the signal is substantially lower than the corresponding magnitude of the reversion when information is actually shown (0.163 versus 0.561). Figure 5.a presents the estimated learning rates (estimates of α), which roughly correspond to the difference between the slopes in Figure A.3.a and A.3.b (i.e., the incremental convergence towards the signal due to the signal provision).

Figure A.1: Distribution of Groups for Information Provision Experiment



Notes: The figure presents the distribution of the information provided to individuals in the experiment according to the type of information most preferred. This sample excludes the 43 individuals who ranked “No information” first.

Figure A.2: Certainty in Prior and Posterior Beliefs, By Information Provision

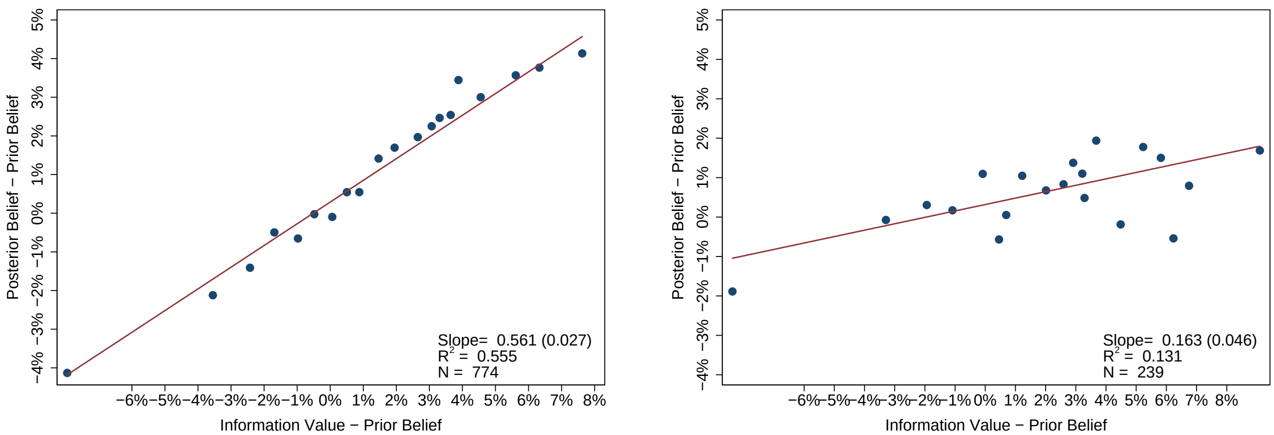


Notes: This sample does not include respondents who chose "None" as their most favorite information source. Certainty in Prior and Posterior Beliefs according information provision. It measures how confident are individuals in their beliefs. The x-axis presents the range of possible variations in the estimation. And the y-axis presents the estimation of the percent chance of the possible variations.

Figure A.3: Changes from Prior to Posterior Beliefs

a. Revisions if Signal Shown

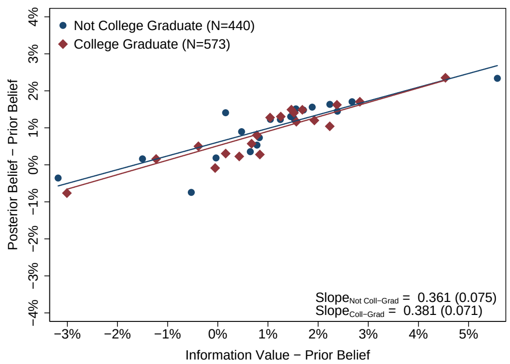
b. Revisions if Signal not Shown



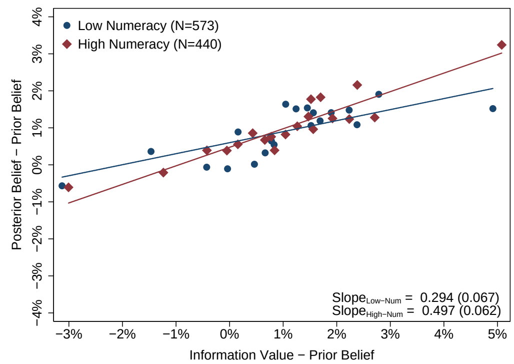
Notes: This sample does not include respondents who chose “None” as their most favorite information source and respondents with non-monotonic choices across the BDM scenarios. The figures measure how individuals revise their estimations of the expected value of a typical home 1 year forward according to the information shown. Panel a. presents the results for the subsample that received information and panel b. presents the results for the subsample that did not receive information. The dots correspond to the binned-scatterplot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., posterior belief minus the prior belief) on the signal gap (i.e., signal value minus the prior belief), controlling for maximum willingness to pay dummies. We winsorize the dependent variables at the bottom/top 2.5%.

Figure A.4: Learning Rates according Education and Numeracy

a. Education



b. Numeracy



Notes: This sample does not include respondents who chose "None" as their most favorite information source and respondents with non-monotonic choices across the BDM scenarios. Learning rates are estimated using equation (4) from section 3.3. The graphs show a binned-scatter plot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., the dependent variable is the belief update during the baseline survey) on the signal gap (i.e., signal value minus the prior belief) interacted by a dummy that takes the value 1 if the individual was shown the signal. The regressions control for the signal gap (i.e., without the interaction) and dummies for maximum willingness to pay. Panel a. presents the results according education (i.e., individuals who graduate from college or not) and panel b. presents the results according numeracy (i.e., individuals who have high or low numeracy).

Table A.1: Factors Associated to Information Choice and Willingness to Pay – Multivariate Results

	Indicator: chose...				
	Forecast	1-yr	10yr	1yr>10yr	WTP
	(1)	(2)	(3)	(4)	(5)
Income > $60,000	0.040	-0.012	-0.004	0.041	0.496*
	(0.035)	(0.032)	(0.030)	(0.035)	(0.274)
College Graduate (0/1)	0.067**	-0.027	-0.017	0.028	0.053
	(0.032)	(0.029)	(0.027)	(0.032)	(0.252)
Age	-0.000	0.002**	-0.002***	0.003***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)
Female (0/1)	0.036	-0.011	-0.021	0.025	0.019
	(0.032)	(0.028)	(0.027)	(0.032)	(0.252)
Married (0/1)	-0.035	0.003	0.039	-0.023	-0.058
	(0.036)	(0.032)	(0.029)	(0.035)	(0.278)
White (0/1)	0.070*	-0.044	-0.011	-0.008	-0.181
	(0.039)	(0.036)	(0.034)	(0.039)	(0.332)
High Numeracy (0/1)	0.110***	-0.069**	-0.038	0.019	-0.289
	(0.032)	(0.028)	(0.027)	(0.032)	(0.243)
Uncertainty in Prior Belief (Std)	0.006	0.004	0.005	-0.005	-0.257**
	(0.015)	(0.014)	(0.013)	(0.015)	(0.119)
Median House Value in State (Std)	0.024	-0.006	-0.010	0.007	0.097
	(0.015)	(0.014)	(0.013)	(0.015)	(0.125)
House Value Volatility in State (Std)	-0.009	-0.006	0.012	-0.009	0.195*
	(0.016)	(0.014)	(0.013)	(0.016)	(0.119)
Looked for Info in Past (0/1)	-0.008	0.033	-0.011	0.006	0.463*
	(0.031)	(0.028)	(0.026)	(0.031)	(0.249)
Homeowner (0/1)	-0.059	0.069**	0.014	0.027	0.125
	(0.039)	(0.032)	(0.032)	(0.039)	(0.303)
Conf. in past Recall (1-5)	-0.012	0.011	0.001	-0.002	0.080
	(0.015)	(0.014)	(0.013)	(0.015)	(0.128)
Mean	0.45	0.28	0.22	0.60	4.39
Observations	1119	1119	1119	1119	1013

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column corresponds to a separate multivariate regression. An interval regression is estimated in columns (using willingness to pay as the dependent variable. In columns (1) through (4), OLS regressions are estimated using a dummy variable (=1) if the individual preferred the forecast information, 1 year information, 10 years information, or 1 year information over 10 years information as the dependent variable.

B Supplementary Study

As a robustness check, we fielded a supplementary module one year later in the February 2018 SCE Housing Survey. The sample that takes this module has no overlap with the original study, since respondents are phased out of the SCE panel after 12 months. The main purpose of the module was to investigate whether our result that the cross-sectional dispersion fails to go down in the group that is exogenously exposed to information (relative to the group that does not see information) is an artifact of the fact that respondents could not choose to buy multiple information sources.

In the supplementary survey, respondents were randomized into seeing no, one, or two pieces of information. Snapshots of this survey can be found in Appendix E. We next briefly summarize the study design:

1. **Stage 1- Prior Belief** : This stage is identical to that in the main survey. Respondents report their year-end 2018 home price expectation as well as their subjective uncertainty.

2. **Stage 2- Information Preferences:** This stage is also quite similar to that in the main survey. As in the main survey, respondents were randomized into a "High Reward" or "Low Reward" group, and told that their home price expectation would be re-elicited. They were next informed that they may have the opportunity to see some information before the re-elicitation. They were then asked: *"If you had the choice of seeing one of the following two pieces of information, which one would you prefer to see?*

    (a) *The change in the value of a typical home in the US over the last one year (2017).*

    (b) *The change in the value of a typical home in the US over the last ten years (2008-2017).*

    (c) *Neither of the above -- I would not like to see any information"*

    In addition, conditional on choosing option a (option b), they were also asked if they would like to *additionally* see the information of option b (option a).

3. **Stage 3- Posterior Belief:** Depending on the stated preference for the information source in stage 2, respondents possibly saw additional information in this stage. Of those who said they preferred to see option a (that is, past one year home price change), a third were given no information, a third were given information about home price change in the past year, and the remaining third were given information on both the past one and ten year change in home prices.[41] For example, those who got to see both pieces of information were shown:

    "We will next inform you about the change in the value of a typical home in the US over the last one year, and over the last ten years.

[41] Those who chose option b were similarly randomly allocated to a no-info group, a group that saw only the past 10 year home price change, or a group that saw both changes. Those who chose option c did not see any information.

According to the Zillow Home Value Index, the value of a typical home in the US increased by 6.5% over the last one year (December 2016 - December 2017) and by 0.7% per year on average over the last ten years (December 2007 - December 2017). That means a typical home in the US that currently has a value of ***206,300*** *dollars would have had a value of* ***193,700*** *dollars in December 2016 and* ***191,700*** *dollars in December 2007.*

If home values were to increase at a pace of 6.5% next year (that is, last year's pace), that would mean that the value of a typical home would be ***219,710*** *dollars in December 2018.*

If home values were to increase at a pace of 0.7% next year (that is, the average annual pace over the last 10 years), that would mean that the value of a typical home would be ***207,744*** *dollars in December 2018.*

Earlier in the survey, you reported that you thought the value of the typical home in the US at the end of this year (in December 2018) would be 222,222 dollars. We would now like to ask you again about the future value of a typical home in the US ***at the end of this year****. What do you think the value of the typical home in the US will be at the end of this year (in December 2018)?"*

Home price expectations were then re-elicited from everyone.

At the very end of the survey, all respondents were asked whether they would have opted to see the forecast of housing experts for year-end home prices instead of their preferred information source. In addition, respondents were asked to report their belief (on a 5-point scale) about (1) the ability of experts to forecast house price growth accurately, and (2) the credibility of experts in general.

B.1 Empirical Analysis

A total of 1,144 respondents took the module. After applying the same sample selection criteria as in the main survey, we are left with 1,091 respondents. The sample is remarkably (and unsurprisingly) similar in observable characteristics to the main survey sample (shown in Table 1): 56.2% have household income of more than $60,000, 55.9% have a college degree or more, the mean age is 51.0 years, 45.6% are female, 64.6% are married, 84.6% are white, and 75.3% are homeowners. We next discuss the main results.

B.1.1 Cross-Sectional Dispersion

Table B.1 describes the prior and posterior beliefs for the three groups: the group that saw both pieces of information, the group that saw one piece of information, and the control group that saw no information. Recall that, conditional on one's reported preference for information, assignment to the three groups was random. Therefore, we can see how information – and more specifically being able to see multiple pieces of information – impacts the evolution of beliefs.

Information leads to a noticeable shift in mean beliefs, with the posterior belief significantly different from the prior. However, beliefs shift even in the control group. Relative to the no-info group, the average posterior uncertainty declines quite a bit in the two groups that saw information, indicating that information led respondents to become more certain. However, dispersion – as measured by the mean absolute deviation of beliefs across individuals – does not decline for the groups that saw information. In fact, the MAD goes up more for the information groups than for the control group: the MAD increases by 0.15 percentage points for the control group and by 0.44 (0.37) percentage points for the one- (two-) information group. We also see that our other measure of disagreement, based on whether a pair's constructed confidence interval overlaps or not, also increases a lot more for the information groups. For example, while a similar proportion of pairs disagreed at the prior stage in the two-information group and the control group (13.5% and 13.1%, respectively), at the posterior stage, a substantially higher proportion of pairs disagreed in the two-information group (22.9% versus 16.1% in the control group). This corroborates the finding in the main survey that information does not lead to a convergence in beliefs. Here we see that randomly providing two signals at the same time has effects similar to providing just one signal.

B.1.2 Other results

Table B.2 shows some useful patterns in the data. Column (1) shows that 92 percent of the respondents, when presented with the choice of seeing information in Stage 2, opted for some information (opposed to choosing the "Neither" option). We see that higher-education respondents and those with higher numeracy are significantly more likely to opt to see some information.

Conditional on wanting to see information, column (2) shows that 46 percent of the respondents preferred the past one year home price change, with the remaining 54 percent preferring the past ten year home price change. Given the serial dependence in home price movements, as discussed in the paper, the past one year home price change is arguably a more useful resource. Column (3) shows that the vast majority of respondents – 85 percent – reported wanting to see both sources of information if that were an option. In both columns (2) and (3), we see a clear difference by education and numeracy along the lines that one would expect.

Finally column (4) validates the finding in the main experiment that lower-numeracy and less-educated respondents are significantly less likely to prefer the forecast of experts over these alternative sources. Note, however, that here the vast majority – 68 percent – of respondents reported that they would have preferred experts' forecast over information about past home price changes, a substantially higher fraction than in the main experiment. This could be because the two studies differ in their specific setup.

Experts' forecast, as we discuss in the paper, should be the optimal information source. To dig deeper into why respondents may not choose the experts' forecast, the module included two questions about the perceived ability of experts to give accurate forecasts, and their credibility. The last two columns of the table show statistics for these two variables. 49 percent of the respondents agreed or somewhat agreed (answered 4 or 5 on a 5-point scale) with the statement *"Housing market experts can forecast future house price growth with high accuracy."* Likewise, 49 percent of the respondents agreed or somewhat agreed with the statement "*In general, I trust the credibility of people referred to as experts*." The last column shows that lower-educated respondents in fact have a lower level of trust in experts (44 percent of them trusting experts versus 53 percent of higher-educated respondents); they are also less likely to believe in the ability of experts to forecast accurately. In regression analysis (not presented here), we see that the 12 percentage point education gap in preferring experts (in column 4) declines by 2.5 points once we control for the perceived ability and trust in experts. This suggests that at least some of the differences by education in preferring experts are driven by perceptions about experts' credibility and ability.

Table B.1: Effect of Information-Acquisition on the Distribution of Expectations (Analogue of Table 6 in main text)

		Prior	Posterior
Both Pieces of Info			
	Mean	2.42 (0.176)	3.86 (0.200)
N=338	MAD	2.17 (0.130)	2.54 (0.145)
	Uncertainty	3.68 (0.155)	2.67 (0.134)
	Disagreem. (%)	13.48 (1.42)	22.89 (1.67)
One Piece of Info			
	Mean	2.35 (0.190)	3.28 (0.194)
N=327	MAD	2.11 (0.150)	2.55 (0.133)
	Uncertainty	3.90 (0.156)	2.83 (0.146)
	Disagreem. (%)	11.56 (1.31)	22.67 (1.61)
Control			
	Mean	2.58 (0.210)	3.00 (0.216)
N=338	MAD	2.39 (0.165)	2.54 (0.166)
	Uncertainty	3.63 (0.154)	3.29 (0.149)
	Disagreem. (%)	13.11 (1.39)	16.06 (1.54)

Notes: Table excludes respondents who report a preference for no information. The average level, the dispersion, the uncertainty, and the fraction of disagreements within group is presented for the prior, and posterior belief for the three groups (those who see two pieces of information, those who see one piece of information, and those who see neither (control).. The prior belief refers to the expected change for home prices to the end of the year before the information, that may help with forecasting, was presented to individuals. Posterior belief refers to the expected change after the information was shown to individuals. See notes to Table 5 for additional notes on definitions of various measures. Numbers in parentheses in each cell are standard errors.

Table B.2: Information Preferences and Beliefs

		Information Preferences				Perceptions	
	Obs	Prefer Any Info	Prefer 1yr | Info	Prefer Both | Info	Prefer Expert	Find Experts Accurate	Trust Experts
		(1)	(2)	(3)	(4)	(5)	(6)
All	1091	0.92	0.46	0.85	0.68	0.49	0.49
High Reward	546	0.92	0.47	0.86	0.68	0.51	0.49
Low Reward	545	0.92	0.45	0.85	0.67	0.47	0.49
P-value		0.993	0.589	0.585	0.683	0.155	0.785
College Graduate	610	0.94	0.44	0.89	0.73	0.52	0.53
Not College Grad	481	0.89	0.49	0.81	0.61	0.46	0.44
P-value		0.001	0.128	0.001	0.000	0.064	0.005
High Numeracy	469	0.96	0.50	0.87	0.71	0.48	0.48
Low Numeracy	622	0.89	0.43	0.84	0.65	0.51	0.50
P-value		0.000	0.017	0.140	0.023	0.312	0.393

Notes: High reward corresponds to 100 dollar prize. High numeracy corresponds to no incorrect answers. Column variable definitions are as follows: *Prefer Any Info*: Equals one if the respondent selected either 1 or 10 year info (opposed to no info); *Prefer 1 year | Info*: Conditional on selecting an information source, indicator that equals 1 if the respondent selected past 1 year info (those who selected no info are dropped here); *Prefer Both Info*: Indicator that equals 1 is respondent reported she would like to see both pieces of info (those who selected no info are dropped); *Prefer Expert*: Indicator that equals 1 if respondent reports that she would have chosen expert forecast, if it had been a choice; *Find Experts Accurate*: Indicator for reporting a belief of expert accuracy of 4 or 5 on a 5-point scale; *Trust Experts*: Indicator for reporting a belief of expert credibility of 4 or 5 on a 5-point scale.

C Model with a common prior over precisions

In the model in the paper, individual i has the prior belief that the precision of information source $j \in \{1,2,3\}$ equals $\tau_j(i) \equiv \left(1/\sigma^2_{\varepsilon,j}(i)\right)$. That τ_j is a function of i means that the prior belief about the precision of information source j may differ across individuals. In the model in this appendix, all individuals instead share the same prior belief about the precision of the information sources. Cross-sectional heterogeneity in beliefs over precisions arises ex post.

Common prior over precisions. Individuals have the prior belief that each information source j is a noisy signal about the fundamental

$$x_j = \theta + \varepsilon_j,$$

where x_j is the displayed information, θ and ε_j are mutually independent, and the noise ε_j is normally distributed with mean zero. Individuals have the prior belief that one information source has high precision, τ_H, and two information sources have low precision, τ_L, with $\tau_H > \tau_L$.[42] The three information sources are homogenous *a priori*, that is, for any information source $j \in \{1,2,3\}$, individuals assign probability 1/3 to information source j being the one with the high precision.

Processing information and posterior over precisions. The state of nature is the identity of the information source with high precision. Let $j^* \in \{1,2,3\}$ denote this information source. Individuals have imperfect information about the state of nature. As explained before, individuals have a uniform prior over j^*. Before selecting an information source, individuals can process information. Processing information is costly and processing more information is more costly. Processing information is modeled as receiving a noisy signal on the state. The signal announces the information source with the high precision and is correct with probability $\lambda \in [1/3, 1]$, where $\lambda = 1/3$ is a completely uninformative signal and $\lambda = 1$ is a perfectly informative signal. If the signal is incorrect, it announces one of the two suboptimal information sources with equal probability. Let $z(i) \in \{1,2,3\}$ denote the signal received by individual i. For any two individuals i and i', the signals $z(i)$ and $z(i')$ are conditionally independent given j^*, which captures the idea that information-processing mistakes arise on the level of the individual. It follows from Bayes' rule that for any individual i posterior beliefs are given by

$$\Pr\left(j = j^* | z(i) = j\right) = \frac{\lambda\frac{1}{3}}{\lambda\frac{1}{3} + (1-\lambda)\frac{1}{2}\frac{1}{3} + (1-\lambda)\frac{1}{2}\frac{1}{3}} = \lambda,$$

and

$$\Pr\left(j = j^* | z(i) \neq j\right) = \frac{(1-\lambda)\frac{1}{3}}{(1-\lambda)\frac{1}{3} + \left[\lambda + (1-\lambda)\frac{1}{2}\right]\frac{1}{3} + \left[\lambda + (1-\lambda)\frac{1}{2}\right]\frac{1}{3}} = \frac{1-\lambda}{2}.$$

Processing more information amounts to a higher λ. The precise cost function for processing

[42] The assumption that two information sources have the same low precision is only for ease of exposition.

information will be specified below and will have the property that signals with a higher λ are more costly.

First Action: Selecting an information source: The optimal choice of the information source given the realization of the signal on precisions is to follow the recommendation of the signal. That is, the optimal action is to select information source j if and only if $z(i) = j$ for any $\lambda > (1/3)$ ("informative signal"). Intuitively, individuals have a uniform prior over j^* and the signal on the state is informative. Formally, $\lambda > (1/3) \Leftrightarrow \lambda > \frac{1-\lambda}{2}$. This has three implications. First, since there is idiosyncratic noise in the signal, individuals arrive at heterogeneous posteriors over precisions and take heterogeneous actions, even though individuals have a common prior over precisions. Second, for any sufficiently large group of individuals choosing to process information (i.e., for any sufficiently large group of individuals choosing $\lambda > (1/3)$), the information source with the high precision will be the modal choice with a high probability. Third, once λ becomes a choice variable (see the paragraph on rational inattention below) the probability of selecting the high-precision information source will depend on household characteristics.

Conditional expectation of the fundamental: After selecting an information source and acquiring the information (more on that below), the information is displayed. Paying attention to the displayed information is modeled as receiving a noisy signal on the displayed information

$$s(i) = x_j + \psi(i) = \theta + \varepsilon_j + \psi(i),$$

where j is the selected information source, x_j is the displayed information, and $\psi(i)$ is noise that arises due to limited attention to the displayed information. The noise $\psi(i)$ is assumed to be normally distributed with mean zero and variance $\sigma_\psi^2(i)$. Paying more attention to the displayed information is formalized as a smaller $\sigma_\psi^2(i)$. For the moment, we assume that this variance of noise is exogenous. For example, one could set $\sigma_\psi^2(i) = 0$ ("perfect attention to displayed information"). In an extension, we will solve the case where this variance of noise is endogenous, as in Section 4 of the paper. Individuals assign probability λ to having acquired the right information source and probability $1-\lambda$ to having acquired a wrong information source. The conditional expectation of the fundamental thus equals

$$\begin{aligned} E[\theta|s(i), z(i)] &= \lambda E[\theta|s(i), \tau_j = \tau_H] + (1-\lambda) E[\theta|s(i), \tau_j = \tau_L] \\ &= \lambda [\mu_\theta(i) + K(i, \tau_H)(s(i) - \mu_\theta(i))] + (1-\lambda)[\mu_\theta(i) + K(i, \tau_L)(s(i) - \mu_\theta(i))], \end{aligned}$$

with

$$K(i, \tau_H) \equiv \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \frac{1}{\tau_H} + \sigma_\psi^2(i)} \text{ and } K(i, \tau_L) \equiv \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \frac{1}{\tau_L} + \sigma_\psi^2(i)}.$$

The second line follows from the fact that the fundamental and the signal $s(i)$ have a multivariate normal distribution for a given precision of the information source. The equation for the conditional expectation can also be written as

$$E\left[\theta|s\left(i\right),z\left(i\right)\right]=\mu_{\theta}\left(i\right)+\underbrace{\left[\lambda K\left(i,\tau_{H}\right)+\left(1-\lambda\right)K\left(i,\tau_{L}\right)\right]}_{\equiv K\left(i,\lambda\right)}\left(s\left(i\right)-\mu_{\theta}\left(i\right)\right).$$

The weight that individual i puts on the displayed information, $K\left(i,\lambda\right)$, is a weighted average of the weight appropriate for the high-precision information source and the weight appropriate for a low-precision information source, reflecting the fact that the individual is unsure whether he or she has selected the high-precision information source. Individuals who process more information before selecting an information source (i.e., individuals with a higher λ) select the high-precision information source with a higher probability and put more weight on the displayed information, because they are more confident that they have selected the high-precision information source.[43]

Second Action: Reporting a forecast of the fundamental: Each individual is assumed to report the forecast of the fundamental that minimizes the mean square error

$$E\left[\left(\theta-y\right)^{2}|s\left(i\right),z\left(i\right)\right],$$

where θ is the fundamental and y denotes the reported forecast. The optimal action for any realization of the signals is then to report the conditional expectation of the fundamental

$$y=E\left[\theta|s\left(i\right),z\left(i\right)\right].$$

The mean square error of individual i can be written as[44]

$$\begin{aligned}MSE\left(i,\lambda\right)&\equiv E\left[\left(\theta-E\left[\theta|s\left(i\right),z\left(i\right)\right]\right)^{2}|s\left(i\right),z\left(i\right)\right]\\&=\lambda\underbrace{E\left[\left(\theta-E\left[\theta|s\left(i\right),z\left(i\right)\right]\right)^{2}|s\left(i\right),z\left(i\right)=j^{*}\right]}_{\equiv MSE\left(i,\tau_{j}=\tau_{H},K\left(i\right)=K\left(i,\lambda\right)\right)}\\&\quad+\left(1-\lambda\right)\underbrace{E\left[\left(\theta-E\left[\theta|s\left(i\right),z\left(i\right)\right]\right)^{2}|s\left(i\right),z\left(i\right)\neq j^{*}\right]}_{\equiv MSE\left(i,\tau_{j}=\tau_{L},K\left(i\right)=K\left(i,\lambda\right)\right)},\end{aligned}\tag{C.1}$$

where $MSE\left(i,\tau_{j}=\tau_{H},K\left(i\right)=K\left(i,\lambda\right)\right)$ denotes the mean square error conditional on having selected the high-precision information source and putting weight $K\left(i,\lambda\right)$ instead of $K\left(i,\tau_{H}\right)$ on the displayed information; and $MSE\left(i,\tau_{j}=\tau_{L},K\left(i\right)=K\left(i,\lambda\right)\right)$ denotes the mean square error conditional on having selected the low-precision information source and putting weight $K\left(i,\lambda\right)$ instead of $K\left(i,\tau_{L}\right)$ on the displayed information. Note that the mean square error of individual i

[43]Note that the conditional expectation of the fundamental depends on the realization and the properties of the signal on precisions, $z\left(i\right)$. The realization of this signal affects the choice of the information source through $j=z\left(i\right)$. The properties of this signal (i.e., λ) affect the weight on the displayed information.

[44]The mean square error of individual i depends on precision of the prior, $\left(1/\sigma_{\theta}^{2}\left(i\right)\right)$, as well as λ and $\left(1/\sigma_{\psi}^{2}\left(i\right)\right)$. In the notation $MSE\left(i,\lambda\right)$, we highlight the dependence on λ and subsume the rest in the index i.

depends on λ for two reasons: λ affects the probability of selecting the high-precision information source and the weight on the displayed information. One can show that the mean square error of individual i is strictly decreasing in λ and twice continuously differentiable on $(1/3, 1)$.

Rational Inattention: Rationally inattentive individuals choose how much information to process before taking an action. Here they choose how much information to process before selecting an information source. The benefit of processing information about precisions is the implied reduction in the mean square error, $MSE\,(i, 1/3) - MSE\,(i, \lambda)$. The cost of processing information is assumed to be increasing in the *amount* of information processed. The decision problem of the rationally inattentive individual reads

$$\max_{\lambda\in[1/3,1]} \left\{\phi\left(MSE\,(i, 1/3) - MSE\,(i, \lambda)\right) - \mu I\,(\lambda)\right\},$$

where the parameter ϕ controls the incentive to have an accurate forecast of the fundamental, the parameter $\mu > 0$ is the marginal cost of processing information, and $I\,(\lambda)$ measures the amount of information processed by the individual.

We assume that the function $I\,(\lambda)$ is strictly increasing on $[1/3, 1]$ and twice continuously differentiable on $(1/3, 1)$. To give an example, in the rational inattention literature following Sims (2003), it is common to quantify the amount of information processed by an individual by uncertainty reduction, where uncertainty is measured by entropy. In this case

$$\begin{aligned} I\,(\lambda) &= H\,(j^*) - H\,(j^*|z\,(i)) \\ &= \left[-3\frac{1}{3}\ln\left(\frac{1}{3}\right)\right] - \left[-\lambda\ln\left(\lambda\right) - 2\left(\frac{1-\lambda}{2}\right)\ln\left(\frac{1-\lambda}{2}\right)\right], \end{aligned}$$

where $H\,(j^*)$ denotes the entropy of j^* before processing information, $H\,(j^*|z\,(i))$ denotes the conditional entropy of j^* given knowledge of the signal $z\,(i)$, and the difference between the two measures the uncertainty reduction about j^* due to knowledge of the signal. The second line follows from the fact that the entropy of a discrete random variable with probability mass function p_i, $i \in \{1, 2, \ldots, N\}$, equals $-\sum_{i=1}^{N} p_i \ln\left(p_i\right)$, with the convention that $0\ln\left(0\right) = 0$. See Cover and Thomas (1991), Chapter 2.

Individuals with a lower μ/ϕ choose to process more information before selecting an information source, i.e., they choose a higher λ, for any function $I\,(\lambda)$ that is strictly increasing on $[1/3, 1]$ and twice continuously differentiable on $(1/3, 1)$. To see this, divide the objective in the optimization problem by ϕ and note that the resulting objective satisfies strictly increasing differences in λ and μ/ϕ. It follows that any selection of the arg max set must be strictly increasing in λ (Milgrom and Shannon, 1994). Hence, individuals with a lower marginal cost of processing information or a higher preference for an accurate forecast of the fundamental will choose a higher λ. As a result, they are more likely to select the high-precision information source and they put a larger weight on the displayed information because they are more confident that they have selected the right information source. Under the natural assumption that numeracy is negatively correlated with the marginal cost of processing information in the cross section, the model can match the experimental findings that high numeracy individuals are more likely to select the expert forecast and put a higher weight on the displayed information.

Comparison to standard discrete choice under rational inattention: The first-order condition for λ when $I(\lambda)$ is given by the last equation reads

$$\phi\frac{\partial\left[MSE\left(i,1/3\right)-MSE\left(i,\lambda\right)\right]}{\partial\lambda}-\mu\ln\left(\frac{\lambda}{\frac{1-\lambda}{2}}\right)=0.$$

Rearranging yields

$$\frac{\lambda}{\frac{1-\lambda}{2}}=e^{\frac{\phi}{\mu}\frac{\partial\left[MSE\left(i,1/3\right)-MSE\left(i,\lambda\right)\right]}{\partial\lambda}}.$$

The probability of selecting the high-precision information source compared to the probability of selecting a specific low-precision information source is related to the derivative of the benefit of processing information with respect to λ and the marginal cost of processing information, μ. The problem of selecting an information source is a discrete choice problem and the last equation can be compared to celebrated results on discrete choice under rational inattention (Matějka and McKay, 2015, Caplin and Dean, 2015). The difference to standard discrete choice under rational inattention is that processing information before selecting an option increases both the probability of *selecting* the best option (captured through the weights λ and $1-\lambda$ in equation (C.1)) and the *use* of the option (captured through the variable $K(i,\lambda)$ in equation (C.1)). The *use* of the option improves because the agent can be more confident of having selected the best option. As a result, the expression for the derivative of the benefit of processing information with respect to λ is more complicated than in standard discrete choice under rational inattention. The same issue may arise in other contexts (think of selecting and using a wine or selecting and using a car).

Summary: Even though individuals share a common prior over precisions, individuals arrive at heterogeneous posteriors over precisions and select different information sources. The high-precision information source is the modal choice. High numeracy individuals are more likely to select the high-precision information source and put a larger weight on the displayed information because they are more confident that they have selected the high-precision information source.

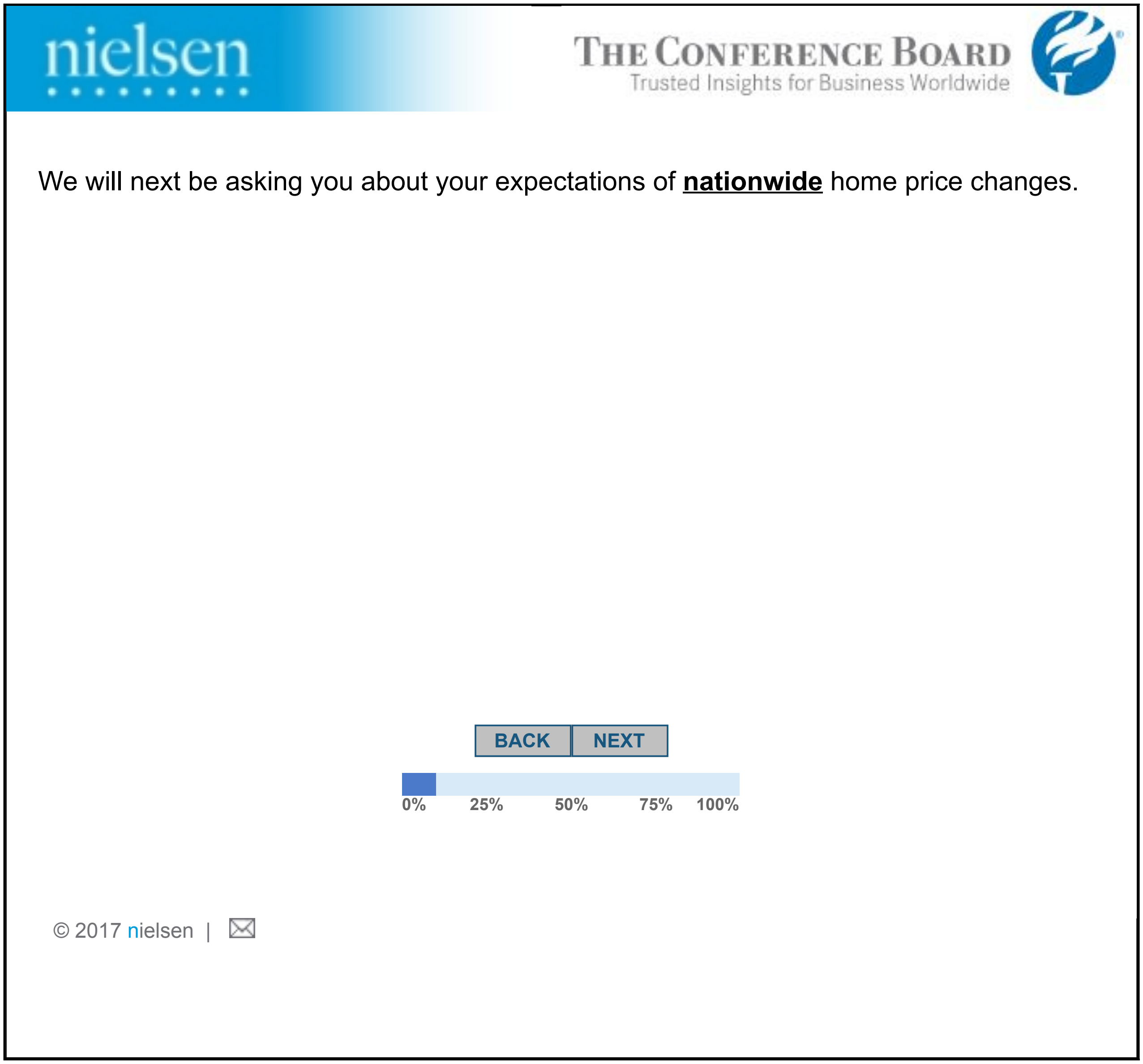
Extensions: One can allow individuals to choose the amount of information processed before selecting an information source and the amount of information processed before reporting a forecast of the fundamental

$$\max_{\lambda\in[1/3,1],\left(1/\sigma_{\psi}^{2}(i)\right)\in\mathbb{R}_{+}}\left\{\phi\left(MSE\left(i,1/3,0\right)-MSE\left(i,\lambda,1/\sigma_{\psi}^{2}\left(i\right)\right)\right)-\mu I\left(\lambda,\sigma_{\psi}^{2}\left(i\right)\right)\right\}.$$

In the benefit term, we now simply highlight the fact that the mean square error depends on λ and $\sigma_{\psi}^{2}(i)$. In the cost term, we now measure the quantity of information processed about j^{*} and the quantity of information processed about the displayed information x_j. The total quantity of information processed depends on λ and $\sigma_{\psi}^{2}(i)$.

One can also introduce the fixed cost of acquiring access to the information source. As pointed out in Section 4 of the paper, the willingness to pay for access to the selected information source equals the benefit of access to the information source, $\phi\left(MSE\left(i,1/3,0\right)-MSE\left(i,\lambda,1/\sigma_{\psi}^{2}(i)\right)\right)$, net of the cost of processing the displayed information at the optimal λ and $\sigma_{\psi}^{2}(i)$. The individual acquires access to the information source if this willingness to pay exceeds the cost.

D Survey Instrument: Main Study



As of December 2016, the value of the median or "typical" home in the US was **193,800** dollars (according to Zillow.com). Now, think about how the value of the typical home in the US has changed over time. (By value, we mean how much that typical home would approximately sell for.)

What do you think the value of such a home was

Please provide your best guess in each box below.

one year earlier (in December 2015)? 193000 dollars

ten years earlier (in December 2006)? 190000 dollars

How confident are you in your answers?

Please select only one.

Not at all confident		**Somewhat confident**		**Very confident**
1	2	3	4	5
○	○	○	○	○

BACK NEXT

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We would now like you to think about the **future** value of the typical home in the US. As mentioned earlier, according to Zillow.com, the value of the typical home in the US was **193,800** dollars as of December 2016.

What do you think the value of the typical home in the US will be **at the end of this year** (in December 2017)?

Please enter a number in the box below.

[ ] dollars

BACK NEXT

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We would now like you to think about the **future** value of the typical home in the US. As mentioned earlier, according to Zillow.com, the value of the typical home in the US was **193,800** dollars as of December 2016.

What do you think the value of the typical home in the US will be **at the end of this year** (in December 2017)?

Please enter a number in the box below.

194000 dollars

*You said that you expect the value of a typical home in the US to be $194,000 at the end of this year. That is, you expect home prices to change by **0.10%** over the course of the year 2017.*

If not, please change your answer.

BACK NEXT

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You estimated the value of the typical home in the US to be 194,000 dollars at the end of this year. Now we want to ask you about how confident you are about this forecast.

What do you think is the percent chance (or chances out of 100) that the value of such a home **at the end of this year (in December 2017)** will be...

*(Please note: The numbers need to add up to **100**.)*

Less than 174,600 dollars		percent chance
Between 174,600 and 192,100 dollars		percent chance
Between 192,100 and 195,900 dollars		percent chance
Between 195,900 and 213,400 dollars		percent chance
More than 213,400 dollars		percent chance
TOTAL	0	

BACK NEXT

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Earlier in the survey, we asked you to forecast the value of a typical home in the US at the end of this year. Later in this survey, we will ask you to do so again.

This time, we will reward the accuracy of your forecast: you will have a chance of receiving **$100**. There is roughly a 10% chance that you will be eligible to receive this prize: we will select at random 60 out of about 600 people answering this question. Then, those respondents whose forecast is within 1% of the actual value of a typical US home at the end of this year will receive $100.

Your payment will depend on your answer, so consider this question carefully. You will be informed at the end of the survey if you have been chosen for this potential prize.

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Before you report your forecast, you will have the opportunity to see only one of the following pieces of information that may help you with forecasting future year-ahead US home prices. Please rank the following pieces of information on a 1-4 scale, where 1 is "Highest ranked/Most Preferred" and 4 is the "Least Preferred".

Please click on each piece of information on the left, and drag it to the right hand side of the screen.

Change in the value of a typical home in the US over the last one year (2016).	1=Most preferred
Change in the value of a typical home in the US over the last ten years (2007-2016).	2
Forecasts of a panel of housing experts about the change in US home prices over this coming year (2017).	3
None of the above -- I would not like to see any information	4=Least preferred

BACK NEXT

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You said that you would most prefer seeing information on the change in the value of a typical home in the US over the last one year (2016). Now we want to assess how much you would value this information.

You will next be presented with 11 scenarios. In each scenario, you will be given the choice of either seeing information about the change in the value of a typical home in the US over the last one year (2016) OR receiving extra money with the check that you will be getting for completing this survey. The amount of money that you will be offered in these scenarios is pre-determined, and goes from $0.01 to $5. For instance, in *Scenario 1*, you will need to choose between seeing information or receiving $0.01; and in *Scenario 11*, you will need to choose between seeing information or receiving $5.

We will draw one of these 11 scenarios at random for you. Your choice in the randomly chosen scenario will then be implemented. That is, you will have to make 11 choices, but only one of those choices will be implemented.

Since one scenario will be picked at random, your choices will not affect which scenario will be chosen.

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You will now be asked to make a decision for each of the **11 scenarios**.

Scenario 1:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $0.01?

Note: if this scenario is chosen for you, your choice will be implemented. If you choose the information, you will see it on the next page. Instead if you choose the money, you will receive $0.01 in your check.

◉ see information ○ receive $0.01

Scenario 2:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $0.50?

◉ see information ○ receive $0.50

Scenario 3:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $1?

◉ see information ○ receive $1

Scenario 4:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $1.50?

◉ see information ○ receive $1.50

Scenario 5:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $2?

◉ see information ○ receive $2

Scenario 6:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $2.50?

◉ see information ○ receive $2.50

Scenario 7:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $3?

- see information
- receive $3

Scenario 8:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $3.50?

- see information
- receive $3.50

Scenario 9:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $4?

- see information
- receive $4

Scenario 10:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $4.50?

- see information
- receive $4.50

Scenario 11:
Would you like to see information about the change in the value of a typical home in the US over the last one year (2016) OR receive $5?

- see information
- receive $5

BACK NEXT

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We would now like to ask you again about the future value of a typical home in the US **at the end of this year**.

Remember you will now have a chance of receiving **$100** for the accuracy of your forecast. There is roughly a 10% chance that you will be eligible to receive this prize. About 600 people are answering this question, of whom 60 will be randomly picked for this potential prize.

If you are picked, you will receive $100 if your forecast is within 1 percent of the actual median home value in the US in December 2017 (according to the Zillow Home Value Index).

Your payment will depend on your answer, so consider this question carefully. You will be informed at the end of the survey if you have been chosen for this potential prize.

NEXT

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Scenario 1 was picked at random for you.

You had chosen to receive information about the change in the value of a typical home in the US over the last one year (2016).

According to the Zillow Home Value Index, the value of a typical home in the US increased by 6.8% over the last one year (December 2015 - December 2016). That means a typical home in the US that currently has a value of **193,800** dollars would have had a value of **181,500** dollars in December 2015. If home values were to increase at a pace of 6.8% next year, that would mean that the value of a typical home would be **206,978** dollars in December 2017.

Earlier in the survey, you reported that you thought the value of the typical home in the US at the end of this year (in December 2017) would be 194,000 dollars.

We would now like to ask you again about the future value of a typical home in the US **at the end of this year**.

NEXT

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According to the Zillow Home Value Index, the value of a typical home in the US increased by 6.8% over the last one year (December 2015 - December 2016). That means a typical home in the US that currently has a value of **193,800** dollars would have had a value of **181,500** dollars in December 2015. If home values were to increase at a pace of 6.8% next year, that would mean that the value of a typical home would be **206,978** dollars in December 2017.

Earlier in the survey, you reported that you thought the value of the typical home in the US at the end of this year (in December 2017) would be 194,000 dollars.

We would now like to ask you again about the future value of a typical home in the US **at the end of this year**.

What do you think the value of the typical home in the US will be at the end of this year (in December 2017)?

Please enter a number in the box below.

[ ] dollars

NEXT

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According to the Zillow Home Value Index, the value of a typical home in the US increased by 6.8% over the last one year (December 2015 - December 2016). That means a typical home in the US that currently has a value of **193,800** dollars would have had a value of **181,500** dollars in December 2015. If home values were to increase at a pace of 6.8% next year, that would mean that the value of a typical home would be **206,978** dollars in December 2017.

Earlier in the survey, you reported that you thought the value of the typical home in the US at the end of this year (in December 2017) would be 194,000 dollars.

We would now like to ask you again about the future value of a typical home in the US **at the end of this year**.

What do you think the value of the typical home in the US will be at the end of this year (in December 2017)?

Please enter a number in the box below.

200000 dollars

*You said that you expect the value of a typical home in the US to be $200,000 at the end of this year. That is, you expect home prices to change by **3.20%** over the course of the year 2017.*

If not, please change your answer.

NEXT

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You estimated the value of the typical home in the US to be 200,000 at the end of this year (in December 2017). Now we want to ask you about how confident you are about this forecast.

What do you think is the percent chance (or chances out of 100) that the value of such a home **at the end of this year (in December 2017)** will be...

*(Please note: The numbers need to add up to **100**.)*

Less than 180,000 dollars		percent chance
Between 180,000 and 198,000 dollars		percent chance
Between 198,000 and 202,000 dollars		percent chance
Between 202,000 and 220,000 dollars		percent chance
More than 220,000 dollars		percent chance
TOTAL	0	

BACK NEXT

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It was ok to refer to other sources (such as Google, Zillow, etc.) when taking the survey. Did you use any such sources when answering any question in the survey?

Please select only one.

- ◯ Yes
- ◯ No

BACK NEXT

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E Survey Instrument: Supplementary Study

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We will next be asking you about your expectations of **nationwide** home price changes.

BACK NEXT

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As of December 2017, the value of the median or "typical" home in the US was **206,300** dollars (according to Zillow.com). Now, think about how the value of the typical home in the US has changed over time. (By value, we mean how much that typical home would approximately sell for.)

What do you think the value of such a home was

Please provide your best guess in each box below.

one year earlier (in December 2016)? ____ dollars

ten years earlier (in December 2006)? ____ dollars

How confident are you in your answers?

Please select only one.

Not at all confident		**Somewhat confident**		**Very confident**
1	2	3	4	5
○	○	◉	○	○

BACK NEXT

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We would now like you to think about the **future** value of the typical home in the US. As mentioned earlier, according to Zillow.com, the value of the typical home in the US was **206,300** dollars as of December 2017.

What do you think the value of the typical home in the US will be **at the end of this year** (in December 2018)?

Please enter a number in the box below.

210000 dollars

*You said that you expect the value of a typical home in the US to be $210,000 at the end of this year. That is, you expect home prices to change by **1.79%** over the course of the year 2018.*

If not, please change your answer.

BACK NEXT

0% 25% 50% 75% 100%

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You estimated the value of the typical home in the US to be 210,000 dollars at the end of this year. Now we want to ask you about how confident you are about this forecast.

What do you think is the percent chance (or chances out of 100) that the value of such a home **at the end of this year (in December 2018)** will be...

*(Please note: The numbers need to add up to **100**.)*

Less than 189,000 dollars	0	percent chance
Between 189,000 and 207,900 dollars	10	percent chance
Between 207,900 and 212,100 dollars	80	percent chance
Between 212,100 and 231,000 dollars	10	percent chance
More than 231,000 dollars	0	percent chance
TOTAL	100	

BACK NEXT

0% 25% 50% 75% 100%

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Earlier in the survey, we asked you to forecast the value of a typical home in the US at the end of this year. Later in this survey, we will ask you to do so again.

This time, we will reward the accuracy of your forecast: you will have a chance of receiving **$100**. There is roughly a 10% chance that you will be eligible to receive this prize: we will select at random 60 out of about 600 people answering this question. Then, those respondents whose forecast is within 1% of the actual value of a typical US home at the end of this year will receive $100.

Your payment will depend on your answer, so consider this question carefully. You will be informed at the end of the survey if you have been chosen for this potential prize.

BACK NEXT

0% 25% 50% 75% 100%

Before you report your forecast, you will possibly have the opportunity to see some information that may help you with forecasting future year-ahead US home prices.

If you had the choice of seeing one of the following two pieces of information, which one would you prefer to see?

I would prefer to see:

Please select only one.

- The change in the value of a typical home in the US over the last one year (2017).
- The change in the value of a typical home in the US over the last ten years (2008-2017).
- Neither of the above -- I would not like to see any information

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You stated that your preferred information is about the change in home values over the last one year. If possible, would you additionally want to see information about the change in home values over the last ten years as well?

Please select only one.

- Yes, I would like to see this additional information.
- No, I would prefer not to see this additional information.

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We would now like to ask you again about the future value of a typical home in the US **at the end of this year**.

Remember you will now have a chance of receiving **$100** for the accuracy of your forecast. There is roughly a 10% chance that you will be eligible to receive this prize. About 600 people are answering this question, of whom 60 will be randomly picked for this potential prize.

If you are picked, you will receive $100 if your forecast is within 1 percent of the actual median home value in the US in December 2018 (according to the Zillow Home Value Index).

Your payment will depend on your answer, so consider this question carefully. You will be informed at the end of the survey if you have been chosen for this potential prize.

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We will next inform you about the change in the value of a typical home in the US over the last one year.

According to the Zillow Home Value Index, the value of a typical home in the US increased by 6.5% over the last one year (December 2016 - December 2017). That means a typical home in the US that currently has a value of **206,300** dollars would have had a value of **193,700** dollars in December 2016. If home values were to increase at a pace of 6.5% next year, that would mean that the value of a typical home would be **219,710** dollars in December 2018.

Earlier in the survey, you reported that you thought the value of the typical home in the US at the end of this year (in December 2018) would be 210,000 dollars.

We would now like to ask you again about the future value of a typical home in the US **at the end of this year**.

What do you think the value of the typical home in the US will be at the end of this year (in December 2018)?

Please enter a number in the box below.

230000 dollars

Click here to view the official rules for the game.

*You said that you expect the value of a typical home in the US to be $230,000 at the end of this year. That is, you expect home prices to change by **11.49%** over the course of the year 2018.*

If not, please change your answer.

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You estimated the value of the typical home in the US to be 230,000 at the end of this year (in December 2018). Now we want to ask you about how confident you are about this forecast.

What do you think is the percent chance (or chances out of 100) that the value of such a home **at the end of this year (in December 2018)** will be...

*(Please note: The numbers need to add up to **100**.)*

Less than 207,000 dollars	0	percent chance
Between 207,000 and 227,700 dollars	5	percent chance
Between 227,700 and 232,300 dollars	90	percent chance
Between 232,300 and 253,000 dollars	5	percent chance
More than 253,000 dollars	0	percent chance
TOTAL	100	

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If you had been offered the opportunity to see the forecast of a panel of housing experts about year-end home prices before you reported your expectation, would you have chosen to do so (instead of seeing information about past home price changes)?

Please select only one.

- (•) Yes
- ( ) No

On a scale from 1 to 5, how strongly do you agree with the following statements:

Housing market experts can forecast future house price growth with high accuracy.

Please select only one.

- (•) 5 - Strongly agree: I think housing experts can definitely forecast prices with high accuracy.
- ( ) 4
- ( ) 3 - Neither agree nor disagree.
- ( ) 2
- ( ) 1 - Strongly disagree: I think housing experts can definitely NOT forecast prices with high accuracy.

In general, I trust the credibility of people referred to as experts.

Please select only one.

- (•) 5 -- Strongly agree: I generally trust the credibility of experts.
- ( ) 4
- ( ) 3 - Neither agree nor disagree.
- ( ) 2
- ( ) 1 -- Strongly disagree: I generally DON'T trust the credibility of experts.

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