Expectations with Endogenous Information Acquisition: An Experimental Investigation[*]

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Abstract

We use a survey experiment to generate direct evidence on how people acquire and process information. Participants can buy different information signals that could help them forecast the future median national home price. Participants put substantial value on their preferred signal and, when acquired, use the signal in the formation of their expectations. However, they disagree on which signal to buy. As a result, making information cheaper does not decrease the cross-sectional dispersion of expectations. We provide a model with costly acquisition and processing of information, and show that it can match almost all of our empirical results.

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1 Introduction

Consumer expectations play a central role in modern macroeconomics and finance. As a result, a growing literature studies empirical properties of expectations. One of the robust findings in this literature is that there is considerable dispersion in consumers' expectations (e.g., Mankiw, Reis, and Wolfers, 2003). This disagreement is important for a number of reasons. For example, belief disagreements may drive trade in asset markets (e.g., Harrison and Kreps, 1978; Hong and Stein, 2007), explain heterogeneity in household portfolios (Meeuwis et al., 2018; Giglio et al., 2019), reduce the effectiveness of policy announcements (Angeletos and Lian, 2018), and have received the attention of policy-makers (Bernanke, 2007).

Various models of information frictions have been advanced to explain the dispersion in consumer expectations. For example, sticky information models (e.g., Mankiw and Reis, 2002; Reis, 2006) propose that information frictions arise due to fixed costs of updating information sets, broadly interpreted as the costs of acquiring, absorbing and processing information. Conditional on paying this cost, agents have full-information rational expectations. On the other hand, noisy information models (e.g., Sims, 2003; Woodford, 2003; Maćkowiak and Wiederholt, 2009) highlight the importance of partial updating and noisy perceptions due to limited information-processing capacity.

Inspired by these models, a recent empirical literature studies information frictions through information provision experiments. This method has been applied to understanding expectation formation for a number of macroeconomic variables such as inflation (Armantier et al., 2016; Cavallo, Cruces, and Perez-Truglia, 2017; Coibion, Gorodnichenko and Kumar, 2018), house prices (Armona, Fuster and Zafar, 2017), and GDP growth (Roth and Wohlfart, 2018). These papers tend to find that when individuals are provided with objective statistics, the dispersion in expectations decreases, thereby providing suggestive support for costly information acquisition models. Extrapolating from these findings, one might conclude that as information becomes easier to access (for instance, due to the Internet), disagreement in expectations should decrease. However, these studies ignore a crucial aspect of the real world: individuals choose which information sources to consult, and *where* they look for information can be even more important than *how frequently* they look for information.

To fill this gap in the empirical literature, we consider the formation of expectations when the acquisition of information is endogenous. Specifically, we present a survey experiment to study the choice, valuation and use of information, and investigate whether expectations across individuals converge in a setting where information acquisition is endogenized. While our method can be applied to other contexts, we provide an application to the context of home price expectations. Our choice of this application is motivated by 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; Kaplan, Mitman, and Violante, 2019).[1]

The main survey underlying our study was conducted in February 2017 on a nationwide sample of households broadly representative of the U.S. population, as part of a regular online survey on the topic of housing run by the Federal Reserve Bank of New York. The experimental design has four 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 participants 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 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 can also state that they do not want to see any information. In the third stage, we elicit each respondent's willingness to pay (WTP) for their most preferred information source. We use a multiple-price-list variation of the Becker-DeGroot-Marschak (BDM) method: 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, so that some respondents get to see their preferred piece of information. Finally, the survey concludes with the re-elicitation of home price expectations (the "posterior belief").

The experiment was designed to capture some important features of the existing models of endogenous information acquisition and processing such as sticky information (e.g., Mankiw and Reis, 2002; Reis, 2006) and noisy information (e.g., Sims, 2003; Woodford, 2003; Maćkowiak and Wiederholt, 2009). Our design creates exogenous variation in some key variables, such as the costs and benefits of acquiring information. These sources of variation allow us to test some basic predictions of these models and to provide novel facts on how consumers acquire and use information.[2]

Our headline empirical result is that in our setting with endogenous information acquisition, lowering the cost of information does not cause lower cross-sectional dispersion in expectations. To understand why this happens, it is useful to go through the findings in the various stages of

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[1]Home price expectations have been measured with survey data, and these measures have been shown to be associated with real behavior such as buying or making investments in a home (Armona et al., 2017; Bailey et al., 2018). Given the prominence of housing in household portfolios, these decisions can have substantial welfare consequences.

[2]Our goal is not to run a horse-race between different "rational inattention" models. Also, our experiment was not designed to disentangle between the existing rational inattention models and alternative "behavioral" departures from full-information rational expectations such as experience-based learning (Malmendier and Nagel, 2016), natural expectations (Fuster, Hebert, and Laibson, 2012), diagnostic expectations (Bordalo, Gennaioli, and Shleifer, 2018), or sparsity (Gabaix, 2014).

the experiment.

The first finding is that individuals differ in their preferences over available information sources. The information sources that we offered in our experiment vary markedly in terms of their informativeness. One reasonable way to rank them, although certainly not the only one, is based on their ex-ante predictive power during the years leading up to the survey. Based on this criterion, the expert forecast is the most informative, followed by the past one-year change, and then the ten-year change. However, individuals display substantial disagreement 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 the heterogeneity in information preferences could be due to respondents using other criteria.[3] However, we find that sophisticated respondents, as measured by their education or numeracy, are substantially more likely to choose the expert forecast than less sophisticated respondents. This finding suggests that at least part of the variation is due to cognitive limitations in identifying informative signals.

The second finding is that respondents are willing to pay for the information and, once they acquire it, they incorporate it into their expectations. The average individual was willing to forego $4.16 to see their preferred piece of information, which is larger than the expected accuracy reward and thus suggests that individuals want to acquire information beyond their interest in our experiment. We find strong support for a basic prediction of models of endogenous information acquisition: the average willingness to pay is significantly higher in the $100-reward condition than in the $10-reward condition ($4.58 and $3.75, respectively).[4] We also find that individuals incorporate the information they acquire in their posterior belief – indeed, the information learned persists months after the information was acquired.

Jointly, these two findings explain why lowering the cost of information did not cause lower cross-sectional dispersion in expectations. On the one hand, exposure to information tends to reduce the dispersion in posterior beliefs *within* a group that obtains the same signal. For example, the beliefs of individuals who chose and obtained the expert forecast (a signal of 3.6%) become more compressed around 3.6%. On the other hand, exposure to information increases the dispersion in beliefs *across* the 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. Moreover, using a second experiment in an auxiliary survey, we show that this result persists even when individuals are allowed to see more than one piece of information at a time.

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[3]For instance, some respondents may distrust experts (Silverman, Slemrod, 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]As a measure of effort spent on information processing and updating, we use the time spent on the relevant survey screens. We find that this time spent increases in the possible reward and the revealed valuation for the information.

We also document some interesting and seemingly puzzling heterogeneity. Respondents that are more confident in their existing knowledge of the housing market, as indicated by low uncertainty in their prior forecast or them indicating that they have previously looked up house-price information, have significantly *higher* WTP for the information (contrary to what one might have hypothesized). With regards to updating, we also find patterns that at first sight run counter to the basic Bayesian model: individuals who have less uncertain prior beliefs put *more* weight on the purchased information and spend more time on processing the information. Similar patterns obtain for high-numeracy respondents when compared to low-numeracy ones.

Finally, we interpret our experimental findings through the lens of a novel rational inattention model with some ex-ante heterogeneity. Agents in the model have a choice among different pieces of information. They face a fixed cost of acquiring information and a variable cost of processing information (i.e., paying more attention to displayed information is costlier). Agents differ in terms of the marginal cost of processing information and the incentive to have an accurate posterior. Under the assumption that this incentive is negatively correlated with prior uncertainty (i.e., respondents who enter the experiment with more precise beliefs tend to value information more), the model can match all experimental findings that at first seem puzzling: respondents with lower prior uncertainty have a higher willingness to pay for information, spend more time processing the information, and revise their beliefs more. Similarly, if low numeracy is a proxy for a high marginal cost of processing information, the model is consistent with low-numeracy individuals having lower willingness to pay for information and them putting less weight on purchased information. Finally, agents in the model rank pieces of information differently because they have heterogeneous beliefs about the precision of different pieces of information. In the simplest version of the model that illustrates the main channels, this heterogeneity in beliefs over precisions is simply taken as given. In an extension, individuals have a common prior over precisions, and heterogeneous beliefs arise endogenously due to cognitive limitations at the stage where agents select pieces of information.

Our paper makes three main contributions. First, it shows that disagreement about what sources of information to rely on can play an important role in explaining the dispersion in consumer expectations. Our findings imply that even if the cost of acquiring information went down to zero, we would still observe substantial dispersion in consumers' expectations. Disagreement about information sources may also explain why dispersion in expectations among consumers tends to be much larger than it is among experts (who are likely more similar in terms of information they look at), even though the estimated information acquisition costs are not larger for consumers (Coibion and Gorodnichenko, 2012). Furthermore, our findings suggest that what one can learn from randomized information experiments that do not endogenize the information acquisition process may be limited.[5]

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[5]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).

Second, we provide direct empirical micro evidence to inform theoretical work on inattention models.[6] By measuring choice, valuation, and use of information, we collect data at each stage of the expectation formation process. We find that the first stage and the third stage are particularly important. A model that combines a choice of which information to look at and an endogenous information-processing margin is needed to match the patterns in the data. Existing models typically do not combine these two features, and hence may only offer an incomplete picture of the expectation formation process.

Third, we show that an individual's prior uncertainty is correlated with behavior at each stage of the expectation formation process. Somewhat surprisingly, individulals with low prior uncertainty have a higher willingness to pay for information, spend more time processing the displayed information, and incorporate the information more strongly in their beliefs. We interpret this as evidence of a selection effect: such individuals care more about having accurate beliefs on house prices. They likely acquired and processed more information on house prices before the experiment (hence, the low prior uncertainty), and they acquire and process more information on house prices during the experiment. The model that we outline is able to rationalize this with such individuals having a higher "taste" for information.

This finding has one immediate implication: reduced-form approaches that investigate the relationship between prior uncertainty and expectation updating may not be informative tests of Bayesian updating. However, we note that existing evidence on the relationship between prior uncertainty and updating are somewhat mixed. In the context of inflation expectations, individuals with higher prior certainty tend to respond less to the provided information (Armantier et al., 2016; Cavallo et al., 2017; Coibion, Gorodnichenko and Kumar, 2018), while in the context of house price and labor market expectations, Armona et al. (2017) and Conlon et al. (2018) do not find that to be the case.[7] One speculative explanation, which should be examined in future work, is that prior uncertainty is more likely to be endogenous in cases where the variables over which expectations are being formed are of first-order importance to the individual (housing or labor market).

Regarding policy, our findings suggest that in the case of public information provision, less can be more if the aim is to reduce dispersion of beliefs. Providing one piece of information is more likely to reduce belief dispersion than providing multiple pieces of information. In addition, our heterogeneity results imply that information provision interventions will have differential effects across the population. At least in the context of house prices that we study, high-numeracy individuals and low-prior-uncertainty individuals will move their beliefs more in response to information.

The rest of the paper proceeds as follows: Section 2 introduces the research design and survey, and provides an outline of the empirical analysis. Section 3 presents the results. Section 4 describes the theoretical model and discusses how its predictions compare to the experimental findings. The

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[6]For a textbook treatment of the literature on information acquisition and processing, including inattention models, see Veldkamp (2011).

[7]In our auxiliary survey, which is based on a completely separate sample of respondents, we also replicate our finding that respondents with higher prior uncertainty update less when receiving information.

last section concludes.

2   Research Design

Our main survey module was embedded in 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 housing-related questions, some of which distinguish between owners and renters.[8]

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 U.S. The survey, as its name suggests, elicits expectations about various 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.[9] Active panel members who had 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 that were invited, 1,162 participated, implying a response rate of 78%. Item non-response is extremely uncommon and rarely exceeds 1% for any question. The median total survey time was 37 minutes.

2.1   Survey Module

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

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 U.S. was $193,800 as of December 2016.[10] 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

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

[9]The survey is conducted 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 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.

[10]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.

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.*"

   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 - Valuation of Information**: This stage, which immediately followed the second stage, elicited the respondents' valuation, or "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 version of the BDM 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 of whether to see the information in that scenario or not.[11] 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.[12] 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 prior 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 the expert forecast.[13] On average, experts forecasted an increase of 3.6% in home prices during 2017. Note that all 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 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.[14] At the end of the survey, respondents were also asked whether they had used any

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[11]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.

[12]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.

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

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

external sources (such as Google or Zillow) when answering any question in the survey.

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 that 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 and Outline of Analysis

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 how our analysis will proceed.

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. 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 the source has historically predicted past year-ahead home price changes in the United States.

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 $HPA_t = I_t$.

To calculate the RMSE of each piece of information, we use the Zillow Home Value Index as the outcome (that is, as our measure of HPA_t), because it is the same outcome that we are asking the subjects to forecast in our survey. 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.[15]

This criterion for ranking the informativeness of the signals is consistent with existing literature. First, the fact that the forecasts are ranked highest is consistent with the view that experts use all available information in past home price changes optimally when providing a forecast.[16] 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, 2018; 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).[17] In contrast, regressing one-year growth 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 remains hard to rationalize picking home price change over the past ten years over either of the other two pieces of information.

Finally, note that our design elicits beliefs about national home prices. An alternative would have been to elicit beliefs about local home prices instead, such as the median price in the zip code or county where the respondent resides. Beliefs about local prices have the advantage that they may be of more direct relevance to the household's decision-making. However, we decided to elicit national home price expectations for two main reasons. The first is related to data availability: while surveys like the Zillow survey ask experts for national price forecasts, to the best of our knowledge, there is no comparable data where the same experts are asked for price forecasts at a local level. Second, using national home prices simplifies the research design enormously, because we do not have to deal with local heterogeneity.[18]

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[15]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).

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

[17]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 $p < 0.01$).

[18]For example, when two individuals report different expectations about national prices, that difference can be interpreted directly as disagreement, because they are forecasting the same random variable. This is not the case when individuals report their own local home price expectations, because individuals living in different locations would be making forecasts about different random variables.

2.2.1 Outline of Analysis

Our analysis will begin with a description of the sample and the distribution of prior beliefs in the initial stage of the survey module. Then, we will proceed in three stages. First, we will study what information sources people rank highest, and whether there is systematic heterogeneity. As discussed above, an ex-ante evaluation would prescribe that the expert forecast should be the preferred choice, and that ten-year past growth should be least preferred.

Second, we will investigate what determines people's valuation of the information, and how they use the information if they obtain it. In terms of valuation, rational inattention predicts that individuals invest more resources in acquiring and processing house-price-related information if they have a stronger incentive to have accurate expectations.[19] The randomization of the accuracy incentive in Stage 2 provides a direct test of this prediction. In addition, we will study how the valuation of information relates to other (non-randomly-allocated) proxies for stakes, such as a high likelihood of a purchase of a home in the near future, and to measures of confidence in one's existing knowledge of the housing market.

We will further study how those respondents who get to see information use it. Here, we will exploit that our design generates random variation in the provision of information, since whether a respondent gets to see their preferred piece of information depends on their valuation but also on which scenario from Stage 3 is randomly picked. We will test whether respondents incorporate the signal into their posterior beliefs, as would be expected if individuals were willing to pay for the information. Standard Bayesian updating also implies that individuals who have uncertain prior beliefs put more weight on the information they receive.[20] As an alternative metric for how people use information, we will further rely on the time spent on forming the posterior belief.

Third, we will investigate how a change in the price of information affects the cross-sectional dispersion of expectations. In a pure sticky information model (Reis, 2006), cross-sectional dispersion 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 among those who update. Thus, one might expect that, as the price of information decreases, more people update and the dispersion of expectations decreases. Since our design randomly varies the effective price of information (due to randomness in which scenario is picked), we can directly test this hypothesis.

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[19]This would follow from most "rational inattention" 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 accurate expectations would lead more agents to incur the cost of acquiring information.

[20]This holds as long as the (perceived) noise in the signal is independent of one's uncertainty in the prior belief.

2.3 Sample Characteristics

Of the 1,162 valid responses, we trim 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. Typos may also be present in posterior beliefs, 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%).[21] 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 U.S. demographic characteristics. For instance, the average age of our respondents is 50.8 years, and 47.4% 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 (ACS). Also, 74.8% of respondents in our sample are homeowners, somewhat higher than the national homeownership rate of 63.6% in the first quarter of 2017, according to the ACS. 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. The survey also included a battery of 5 questions taken from Lipkus, Samsa, and Rimer (2001) and Lusardi (2008) that measure the respondent's numeracy (see Appendix A.1 for the questions). On average, respondents answer 4 questions correctly. The rank correlation between education and numeracy in the sample is +0.31. Underscoring the fact that home prices are something that individuals actively think about, more than half of the sample – 56.3% – reports looking up home price information over the past 12 months. The average reported probability of moving and buying a different home over the next 3 years in the sample is 20 percent.

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 characteristics for the subsamples assigned to low and high realized prices of information. Columns (4) and (7) present p-values for the test of the null hypothesis that the characteristics are balanced across groups. The differences in pre-treatment characteristics are always small, and statistically insignificant in 31 out of the 34 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

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

rate to the follow-up survey. There is no evidence for selective attrition: the response rate does not differ by reward or price treatments. Table A.1 provides additional information on how the follow-up sample compares with the initial sample. There is no evidence of selection in terms of who is invited to the follow-up, or 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

Figure 1.a shows a histogram of the point estimates provided by respondents in the initial stage of the survey module, that is, prior to the information acquisition stages. 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 1.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 percent 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 percent 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 percent chance or lower.[22] We use the responses to the probability bins to measure prior uncertainty at the individual level, which we use in the analysis below. We fit the 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 corresponding to higher uncertainty.[23]

3.1   Ranking of Information Sources

What happens when individuals with uncertain prior beliefs are offered the chance to acquire information? Figure 2.a shows the ranking distribution for the different information types over the whole sample. Individuals disagreed on which of the three pieces of information they would want to see: 45.5% chose the expert forecast, 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.[24] The past predictive power criterion indicated that expert forecast was most informative, followed

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[22]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%.

[23]For instance, consider an individual with a 2% house price growth point forecast who has an uncertainty (i.e., fitted standard deviation) of 1 percentage point. It means that the individual's 95% confidence interval for house price growth is $[0.04\%, 3.96\%]$ $(= [2 - (1 * 1.96), 2 + (1 * 1.96)])$. In cases, where the respondent puts all mass in one bin or equal mass in two adjacent bins, a uniform distribution is fit. We are unable to fit a density for 4 individuals because of missing data. We winsorize prior uncertainty at the 98.5th percentile.

[24]The median respondent spent 2.17 minutes choosing between the information sources (and reading the associated instructions), with the 10th percentile at 1.23 minutes and 90th percentile at 4.85 minutes.

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 signal (i.e., expert forecast), and more than a quarter chose no information or a signal that in the past had little predictive power.

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. Figure 2.b and 2.c 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).[25] They are also substantially less likely to choose not to see any information, or choose the past ten-year home price change, the least informative signal.

Table 2 further explores the heterogeneity and reports univariate relationships between the choice of information and various individual- and location-specific characteristics. The dependent variables in columns (1)–(4) correspond to dummy variables indicating the highest ranked piece of information.[26] 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 much of the heterogeneity in how individuals rank information. Homeowners and individuals who are likely to be active housing market participants, as measured by the reported probability of moving and buying a home within the next 3 years, are less likely to choose no information source (column 4). Conditional on choosing an information source, homeowners are 8.8 percentage points 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. On the other hand, active housing market participants are much more likely to choose the forward-looking signal: they are 16 percentage points more likely to choose the expert forecast (and significantly less likely to choose the past one-year information). Individuals who report looking up information during the survey are significantly more likely to choose the expert forecast – the information source that would arguably be the hardest to find.[27] We also see that individuals who report having looked up information about home prices in the past 12 months (and hence

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

[26]The results are qualitatively similar using multivariate regressions, as reported in Appendix Table A.2. Fewer estimates are, however, statistically significant in the multivariate set-up due to the dependence between the covariates. The results are also robust if instead of a linear probability model we use a multinomial logit model.

[27]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. 14% of the sample reported doing so. Interestingly, the search rate was not statistically different for respondents who were assigned the high reward treatment (14.7%) and those assigned the low reward treatment (13.3%); p-value=0.49.

are arguably better informed) are in fact less likely to choose no information, suggesting that such individuals have a positive taste for information. Notably, we see that being assigned to the high-reward treatment does not have any systematic impact on the ranking of information sources; this is also shown in Figure 2.d.

Since both the expert forecast and the past one-year home price change could be argued to be the most informative signals, in column (5), as an alternative outcome we study whether a respondent ranked either the expert forecast or the one-year realized growth as their top choice. Other than education and numeracy, we see little relation with observables.

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 the informativeness of signals partially drives the heterogeneity.*

3.2 Valuation and Use of Information

3.2.1 Valuation of Information

Using responses to the eleven scenarios in Stage 3, we identify the range of an individual's valuation or willingness to pay (WTP). For example, if an individual chose information instead of any amount up to $3 and then chose the money from $3.5 on, it means that the individual's WTP must be in the range $3 to $3.5.[28] Around 5% of respondents provided inconsistent responses; for example, they chose information instead of $3 but then chose $2.5 instead of information.[29]

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[28]Individuals who ranked "no information" highest in Stage 2 are assigned a WTP in the interval [-infinity, 0].

[29]This inconsistency is within the range of other studies using this 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 3.a shows the histogram of WTP for the whole sample (excluding inconsistent respondents). We find that individuals have significant WTP for their favorite information, with a median WTP between $4.5 and $5. An alternative estimate is given by means of an interval regression model. This model assumes that the latent WTP is normally distributed. The constant in this model is estimated to be $4.16 (95% CI from 3.94 to 4.40). 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. This is a fairly high WTP, given that the information we provide is public and readily available using a search tool like Google. It is also very 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 are either unaware of the availability of this information or they expect a high search cost, and that they value the information beyond the context of the survey. They may want to use this information for real-world housing decisions, where having incorrect expectations can translate into thousands of dollars in losses, relative to which the experimental incentive pales in comparison.[30]

We next study whether WTP systematically varies with reward size and other factors. To directly test the effect of stakes, Figure 3.b compares the distribution of WTP between the two reward groups. This figure shows that, as expected, individuals in the higher-reward treatment are willing to pay significantly more. A Mann-Whitney-Wilcoxon (henceforth MWW) test indicates that the difference is significant at p<0.01.

To better understand the economic magnitude of this difference, we regress the WTP onto a constant and a high-reward dummy. The constant in this regression can be interpreted as the mean WTP for the low-reward condition ($10 with 10% probability). This average valuation is estimated to be $3.75 (95% CI from 3.50 to 4.10). The estimated coefficient on high reward is 0.83 (95% CI from 0.34 to 1.32), indicating that, relative to the $10 reward, individuals assigned to the $100 reward are willing to pay an additional $0.83 for their favorite information (or 22% more). Note that the expected reward goes from $1 to $10, because the reward is given only with 10% probability. The $0.83 difference in WTP then implies that for each additional dollar of expected reward, the WTP for information goes up by 9.2 cents. Equivalently, under the assumption of risk neutrality, the average individual expects that the probability of being accurate (i.e., being within 1% of the realization) will increase by 9.2 percentage points, or 18% of the baseline probability, if they acquire the information.

Column (1) in Table 3 shows the univariate relationship between the WTP and various correlates. Here, we discuss the more notable and interesting ones. The expected effect of past information acquisition effort 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 already have

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[30]We can also 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).

good information. On the other hand, individuals who acquired more information in the past may have the highest revealed demand or "taste" 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 77 cents, relative to those who did not.

Likewise, we can study how the uncertainty in prior belief correlates with 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 $0.28 less. Similarly, individuals who are more confident in their perceptions of past home price growth are willing to pay more for information. In sum, the evidence strongly points to heterogeneity in the taste for information, and this channel will be a key element of the model presented in Section 4.

Finally, we study whether WTP differs depending on the information source a respondent chose. We argued earlier that based on past performance, individuals should value experts' forecasts most highly and ten-year growth least highly. However, if individuals select a given information source because they erroneously believe it to be the most accurate/predictive one, then WTP would not differ by information source. Indeed, panels c and d of Figure 3 show that it is not the case that individuals pay more (less) for information that has higher (lower) ex-ante predictive power.[31]

The first two columns of Table A.3 show the correlates of the WTP in a multivariate framework. When we simultaneously control for other variables in column (2) of Table A.3, we see that the WTP is significantly higher for those respondents who chose the ten-year information. The other patterns are qualitatively similar to those shown in the first column of Table 3.

3.2.2 Use of Information

We now turn to the question of how people incorporate their preferred information, if they obtain it, in their posterior forecast. To do so, we first study the updating in the point forecast, and then use the time spent on reporting the posterior forecast as an additional measure of updating effort.

To study updating, we use a simple learning model that naturally separates learning from the signal shown from other sources of reversion toward the signal.[32] 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:

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

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[31]In a simple interval regression similar to the ones above, average WTP is highest for the ten-year information, followed by the expert forecast and the one-year information; the difference between ten-year and one-year information is significant at $p<0.05$ (while the coefficient on the expert forecast is not significantly different from either of the others).

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

In a Bayesian framework, the weight parameter α increases in the uncertainty (i.e., the variance) of the prior and decreases in 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:

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

That is, the slope between the perception gaps ($b_i^{signal} - b_i^{prior}$) and revisions ($b_i^{posterior} - b_i^{prior}$) can be used to estimate the learning rate. However, it is possible that individuals will revise their beliefs towards the signal even if they are not provided with it.[33] Recall that our design generates random variation in whether a respondent saw information. We can use this variation to separate true learning from mean-reversion. Denote by S_i a dummy that takes the value 1 if the individual was shown the signal, and 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 ($S_i = 1$) depends on the randomly chosen scenario. Thus, we use the following regression specification:

$$b_i^{posterior} - b_i^{prior} = \alpha \cdot \left(b_i^{signal} - b_i^{prior} \right) \cdot S_i + \beta \cdot \left(b_i^{signal} - b_i^{prior} \right) + WTP_i \delta + \varepsilon_i. \tag{3}$$

The parameter of interest is still α, which measures the true learning rate (i.e., the effect of being randomly shown information). β reflects the degree of spurious mean-reversion. Figure 4.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%. 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.[34]

One potential concern with survey experiments is that, instead of inducing genuine learning, the information provided affects forecasts 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 concern: if the reaction to the information was completely spurious, then the experimental effects should not persist for months after the information provision. Figure 4.b thus reproduces Figure 4.a, but using $b_i^{follow-up} - b_i^{prior}$ on the y-axis, where $b_i^{follow-up}$ is the belief reported four months later. We see that the estimated slope in the follow-up (0.173) is smaller than in the main survey (0.380), but it is still economically

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[33]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.

[34]Appendix A presents additional details on the estimation.

meaningful and statistically significant at the 10% level. This suggests that a significant part of the reaction to the information was not spurious. Also, the lower slope in the follow-up is expected, because individuals may have been exposed to additional signals during the interim four months, thus gradually diluting the effect of the signal provided during our experiment.

We next study heterogeneity in learning rates. Figure 5.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 5 investigate whether the learning rate differs by WTP for information or by the reward size. One might expect respondents who valued the information more to put greater weight on the signal; however, we do not find evidence for differential slopes. Similarly, while the slope in the high reward treatment is directionally stronger, the difference is far from statistically significant.

In contrast, we do find significant differences in updating depending on the uncertainty in respondents' prior belief. Under Bayesian updating, respondents who were more uncertain should put more weight on the signal (as long as the prior uncertainty is orthogonal to the perceived signal noise). However, Figure 5.d shows that respondents with higher prior uncertainty tend to update *less*. This result is also replicated in the supplementary study described in Appendix B (see Figure B.1). While this is surprising based on the standard Bayesian intuition, it is arguably consistent with the earlier result that respondents with higher prior uncertainty have a lower WTP for information. We will return to this in the theory in Section 4. Another result that the theory will be able to rationalize is that high-numeracy respondents tend to update more strongly than low-numeracy respondents (panel e). In contrast, updating rates do not differ by respondent education (panel f).

As an alternative measure of how people allocate effort and use information, we rely on the time spent reporting the posterior belief. Column (2) of Table 3 uses the log time spent on the screen used to report the posterior belief as the dependent variable.[35] Due to the design of the survey, this variable includes the time spent looking at the information, and therefore respondents who get to see information would mechanically take more time reporting the posterior belief. Thus, in column (3), we restrict to the sample that actually got to see information. We see that individuals assigned to the higher reward spent significantly more time reporting their posterior belief: an additional 11% when comparing to the full sample (column 2), and 12% more when just looking at respondents who saw information (column 3). Similarly, higher WTP for information is associated with significantly more time spent on forming the posterior, even when we just look at respondents who saw information. These two variables thus do seem to correlate with effort spent on updating, even though they were not associated with differential updating above.

Reinforcing the earlier finding that lower-uncertainty individuals may be those who have a

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[35]We winsorize this variable at the 1.5th percentile (0.46 minutes) and at the 98.5th percentile (18.79 minutes) of the distribution.

taste for information, and that they update more strongly in response to the information, we see that they also spend significantly more time reporting their posterior belief. This remains true in a multivariate version of the same analysis, shown in Table A.3. Higher numeracy or education are not associated with time spent on the posterior forecast. In terms of other variables, we see that higher-income individuals spend less time on the screen, while the 14% of participants who later report having looked up other sources during the survey spent substantially more time (about 30%) on the screen—this suggests that they looked up the information during this time.

We summarize the findings in this subsection as follows:

> **Result 2**: *Respondents put value on information that can help them form more accurate forecasts, and incorporate signals if they obtain them. The valuation of information increases with incentives for accuracy, but is lower for people with higher prior uncertainty. Furthermore, contrary to standard models of rational updating, individuals with higher prior uncertainty put less weight on the signal (and spend less time on forming their posterior belief).*

3.3 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 4 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 4 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,

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

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 4, 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 6 and 7 explore this question. Figure 6 shows the distribution of prior beliefs for individuals who were not shown the information (Figure 6.a) versus individuals who were shown the information (Figure 6.b). Comparing the two indicates that these two groups started with similar distributions of beliefs. Figure 7 shows the comparison of posterior beliefs between individuals who were not shown information (Figure 7.a) versus individuals who were shown the information (Figure 7.b). Figure 7.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 7.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 the three groups moved towards differing signals, the dispersion in beliefs across 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 5 provides a more quantitative version of the previous graphical argument. The first two columns of Table 5 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 4, 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 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

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90% or 50%.

[37]A comparison of Figure 6.a versus Figure 7.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), suggesting that the re-elicitation by itself (and the other housing-related questions they answered between the two stages) may have led respondents to think differently about future price growth.

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 increased even 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 11.6% to 20.8% of all pairs. Disagreement also increases similarly 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 declined more for the group that was shown information (from 4.0 to 2.9 percentage points, or more than 1 percentage point) than for the group that was not shown information (from 4.3 to 3.8 percentage points).

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 (for free). The comparison 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 third set of findings can be summarized as follows:

> **Result 3**: *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*

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[38]The mean absolute deviation in the pooled sample that does not see information does go up (from 2.17 to 2.64), with the difference statistically significant (p-value<0.01).

information. Second, within groups of individuals who acquire the same information, dispersion in beliefs remains high.

4   A Model of Information Acquisition and Processing

In this section, 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). Agents in the model have a choice among different pieces of information. They face a fixed cost of acquiring information and a variable cost of processing information.

4.1   Model

The timing of the model is as follows:

1. Individuals can acquire access to one of three information sources at cost c, or choose no information ("information acquisition").

2. The purchased information is displayed and individuals choose the amount of attention to allocate to the displayed information ("information processing").

3. 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 $\mu_\theta\left(i\right)$ and variance $\sigma_\theta^2\left(i\right)$. In the experiment, the fundamental is one-year future house price growth. The i indicates that the prior belief over the fundamental may differ across individuals.

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

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

where x_j is the displayed information and ε_j is normally distributed noise with mean zero. Individuals may have heterogeneous priors over precisions. Individual i believes that the precisions of the three information sources equal $\tau_1\left(i\right) \equiv (1/\sigma_{\varepsilon,1}^2\left(i\right))$, $\tau_2\left(i\right) \equiv (1/\sigma_{\varepsilon,2}^2\left(i\right))$, and $\tau_3\left(i\right) \equiv (1/\sigma_{\varepsilon,3}^2\left(i\right))$, where the i indicates that the prior belief over precisions may differ across individuals. While the model presented here allows for heterogeneous priors about precisions, we show in Appendix D that the main predictions are the same even with a common prior belief about the precisions – moreover, the Appendix model can match additional features of the experimental data. Here we present the version of the model with heterogeneous prior beliefs just because it can provide the basic intuitions with less notation.

Paying attention to displayed information is modeled as a noisy signal about the displayed information

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

where $s\left(i\right)$ is the signal on the displayed information, j is the information source that the individual selected, and $\psi\left(i\right)$ 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 $\psi\left(i\right)$ is assumed to be normally distributed with mean zero and variance $\sigma_\psi^2\left(i\right)$. Paying more attention to the displayed information is formalized as a smaller variance of noise, $\sigma_\psi^2\left(i\right)$. Individuals choose the amount of attention allocated to the displayed information, i.e., they choose $\sigma_\psi^2\left(i\right)$.

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

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

The posterior mean of the fundamental is

$$E\left[\theta|s\left(i\right)\right] = \mu_\theta\left(i\right) + \frac{\sigma_\theta^2\left(i\right)}{\sigma_\theta^2\left(i\right) + \sigma_{\varepsilon,j}^2\left(i\right) + \sigma_\psi^2\left(i\right)}\left[\theta + \varepsilon_j + \psi\left(i\right) - \mu_\theta\left(i\right)\right].$$

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 posterior variance of the fundamental is

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

The payoff received by individual i at the end equals

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

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 ($\sigma_\psi^{-2}\left(i\right) \geq 0$) that maximize the expected payoff net of the costs of acquiring and processing information:

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

where c is the cost of acquiring information, z is an indicator variable which takes the value one if information is acquired, and $d\left(\sigma_\psi^{-2}\left(i\right)\right)$ 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

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[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 reported posterior beliefs among individuals who see the same information.

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 reduction in uncertainty about the displayed information:

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

where $H\left(x_{j}\right)$ denotes the entropy of the displayed information and $H\left(x_{j}|s\left(i\right)\right)$ 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 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 $\frac{1}{2}\ln\left(\sigma_{x}^{2}\right)$, and hence, the last equation reduces to

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

In the rational inattention literature following Sims (2003), it is 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 qualitative 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. Note that the cost of paying attention is an increasing function of the signal-to-noise ratio in the signal about the displayed information.

4.2 Solution of the Model and Comparison to Experimental Findings

The following proposition gives the solution of the model.

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

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

The closed-form solution for the optimal $\sigma_{\psi}^{-2}(i)$ is given in Appendix C. The willingness to pay

for access to the preferred piece of information equals

$$WTP(i) = \max \left\{ 0, \phi \sigma_\theta^2(i) \left(\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_{\varepsilon,j^*}^2(i)} - \frac{\mu}{2\phi\sigma_\theta^2(i)} \right) - \frac{\mu}{2} \ln \left(\frac{2\phi\sigma_\theta^2(i)}{\mu} \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_{\varepsilon,j^*}^2(i)} \right) \right\}.$$

(4)

The weight on the displayed information is given by

$$E\left[\theta | s(i)\right] = \mu_\theta(i) + \alpha(i)\left[\theta + \varepsilon_{j^*} + \psi(i) - \mu_\theta(i)\right],$$

where

$$\alpha(i) = \max \left\{ 0, \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_{\varepsilon,j^*}^2(i)} - \frac{\mu}{2\phi\sigma_\theta^2(i)} \right\}.$$

(5)

The proof of Proposition 1 is in Appendix C. The term $\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_{\varepsilon,j^*}^2(i)}$ in equation (5) is the full-attention Bayesian weight on the displayed information. The variable $\alpha(i)$ is the rational-inattention Bayesian weight on the displayed information. The difference between the two is governed by the cost and benefit of paying attention, as captured by the term $\frac{\mu}{\phi\sigma_\theta^2(i)}$. The willingness to pay for access to the preferred piece of information equals the gain from a more accurate posterior, $\phi\sigma_\theta^2(i)\alpha(i)$, minus the cost of paying attention to the displayed information at the optimal amount of attention to the displayed information. In this simplest version of the model, the choice of the piece of information is simply governed by the prior beliefs over precisions.

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 $\arg\max_{j \in \{1,2,3\}} \left(\frac{1}{\sigma_{\varepsilon,j}^2(i)} \right)$.

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; all displayed information in the experiment is quantitative.

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 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, the model can match the finding that some individuals choose the option "I would not like to see any information" before even learning the cost of information acquisition. There is simply no point in acquiring information that one will not pay attention to anyway – the corner solution in equations (4)-(5). Moreover, the model is consistent with low-numeracy individuals selecting this option more frequently, because their cost of processing information is higher.

Second, the model matches the finding that individuals in the high-reward treatment have a higher willingness to pay. $WTP(i)$ is increasing in ϕ. The model also matches the finding that willingness to pay for information is increasing in numeracy. High-numeracy individuals anticipate that processing information is cheaper for them and that they will incorporate the displayed information more into their beliefs. Furthermore, the model can match the finding that willingness to pay is increasing in the precision of the prior (rather than decreasing in the precision of the prior, as one may have expected). The intuition is explained below. Moreover, the finding that the average willingness to pay does not differ across the group of individuals who select the expert forecast and the group of individuals who select the last-one-year home price change can be easily interpreted in terms of the model: $\underset{j \in \{1,2,3\}}{arg\max} \left(\frac{1}{\sigma^2_{\varepsilon,j}(i)} \right)$ differs across these groups but $\underset{j \in \{1,2,3\}}{\max} \left(\frac{1}{\sigma^2_{\varepsilon,j}(i)} \right)$ does not differ systematically across these two groups. That is, individuals rank information sources differently but think equally highly of their preferred information source.

Third, the model matches the finding that the weight on the displayed information is increasing in numeracy. See equation (5). Furthermore, under Assumption 3, the model can match the finding that individuals with a higher precision of the prior put more weight on the information. Standard Bayesian updating implies that the weight on the information is decreasing in the precision of the prior, contrary to our experimental findings. Formally, the full-attention Bayesian weight $\frac{\sigma^2_\theta(i)}{\sigma^2_\theta(i)+\sigma^2_{\varepsilon,j^*}(i)}$ is strictly decreasing in $\sigma^{-2}_\theta(i)$. However, the rational-inattention Bayesian weight $\alpha(i) = \frac{\sigma^2_\theta(i)}{\sigma^2_\theta(i)+\sigma^2_{\varepsilon,j^*}(i)+\sigma^2_\psi(i)} = \frac{\sigma^2_\theta(i)}{\sigma^2_\theta(i)+\sigma^2_{\varepsilon,j^*}(i)} - \frac{\mu}{2\phi\sigma^2_\theta(i)}$ is increasing in the incentive to have an accurate posterior, ϕ. If the selection effect formalized by Assumption 3 is sufficiently strong, the rational-inattention Bayesian weight $\alpha(i)$ is increasing in the precision of the prior. In this case, the model can simultaneously match the three empirical findings that individuals with a higher precision of the prior report a higher willingness to pay for information, exert more effort on processing the displayed information, and put more weight on the displayed information.

Fourth, the model matches the finding of diverging posterior beliefs of individuals who rank pieces of information differently, because information acquisition is optimal only if an agent plans to put positive weight on the information.[40] Moreover, 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, $\psi(i)$, and the fact that individuals have heterogeneous signal weights, $\alpha(i)$. Hence, the model can also match the experimental finding that dispersion in beliefs remains high in all groups, falls within some groups, and increases within other groups once information is displayed.

Table 6 summarizes the predictions of three versions of the model: (i) common prior over

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[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.

precisions and costless information processing, (ii) heterogeneous priors over precisions and costless information processing, (iii) heterogeneous priors over precisions and costly information processing. 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 with heterogeneous priors over precisions and costly information processing can match almost all of the findings.

In Appendix D, we solve a model where we replace the assumption of heterogeneous priors over precisions by the assumption that agents face the cost of information processing also at the stage where they rank pieces of information. Agents have a common prior over precisions. Heterogeneity in beliefs over precisions arises ex post due to idiosyncratic information-processing mistakes at the stage where agents rank pieces of information. In that model, additional features of the experimental data arise endogenously: the highest-precision information source is endogenously the modal choice, and high-numeracy individuals are endogenously more likely to select the highest-precision information source.

5   Discussion and Conclusion

Using an innovative experimental setup measuring agents' choice, valuation and use of information, this paper attempts to understand the role of information frictions in explaining the heterogeneity in consumers' expectations. Our main empirical result is that with endogenous information acquisition, lowering the cost of information does not cause lower cross-sectional dispersion in expectations, because respondents choose to look at different pieces of information.

Our findings have a number of implications for modeling expectation formation. First, given that dispersion in expectations is such a pervasive feature of survey data, it seems important to incorporate this dispersion in economic models, but probably the focus should shift somewhat from heterogeneity in the timing of updating to heterogeneity in the type of information that agents look at. A second important dimension of heterogeneity in posterior beliefs is heterogeneity in the beliefs among agents who see the same information. The fact that precision of the prior and numeracy increase the extent to which information is incorporated into posterior beliefs suggests the importance of an endogenous information-processing margin. Third, heterogeneity in the cost of processing information also seems to be key to understand cross-sectional differences in information acquisition.

These implications are well aligned with existing findings of numeracy and cognitive abilities being associated with the accuracy of (inflation) expectations and the link between expectations and behavior (Armantier et al., 2015; D'Acunto et al., 2019). We are able to provide direct insights into these relationships, and find that numeracy matters at all stages of belief formation: (1) whether to consider acquiring information at all; (2) what information to acquire; (3) the valuation of the information; and (4) the weight that is put on the acquired signal. Under the plausible assumption that low-numeracy individuals have a higher cost of processing information,

the theoretical model we outline in Section 4 can rationalize these empirical findings. Future work that tries to understand the dynamics of information acquisition and expectation heterogeneity would be valuable, and might benefit from collecting high-frequency data on the information sources that consumers are paying attention to.

Besides their implications for modeling expectation formation, 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 weigh and interpret the various pieces of information.

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Figure 1: Prior Beliefs: Expectations about Median House Price

a. Point Estimate

b. Uncertainty
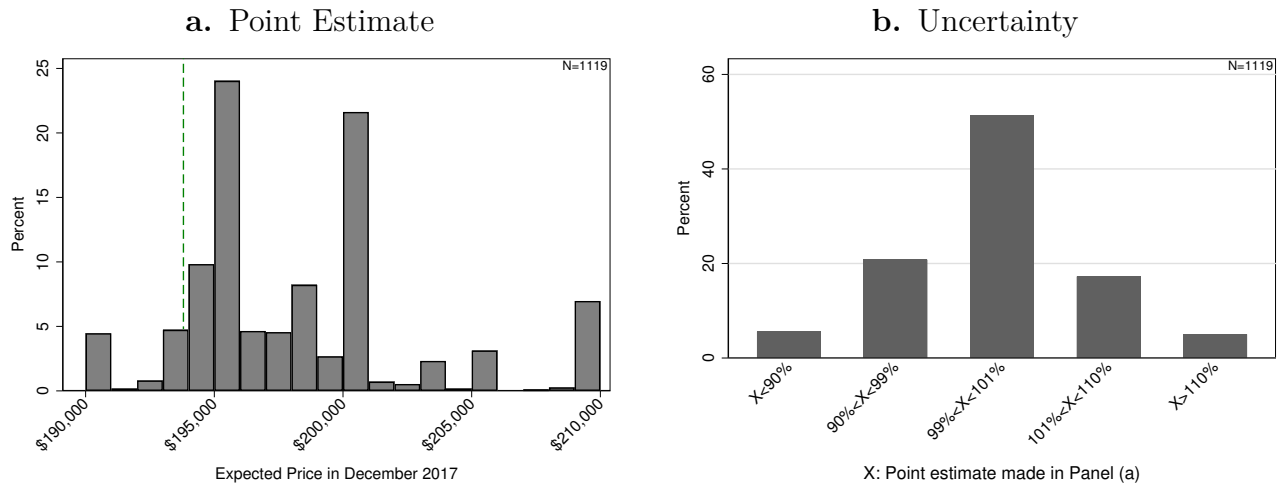
Notes: Panel (a) shows the distribution of the expected value of the typical home in the U.S. at the end of 2017 (as of February 2017, when the survey took place). The vertical dotted line corresponds to the median house value in U.S. in December 2016 according to the Zillow Home Value Index (this value 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 2: Type of Information Most Preferred

a. All

b. By Numeracy

c. By Education

d. By Reward Size
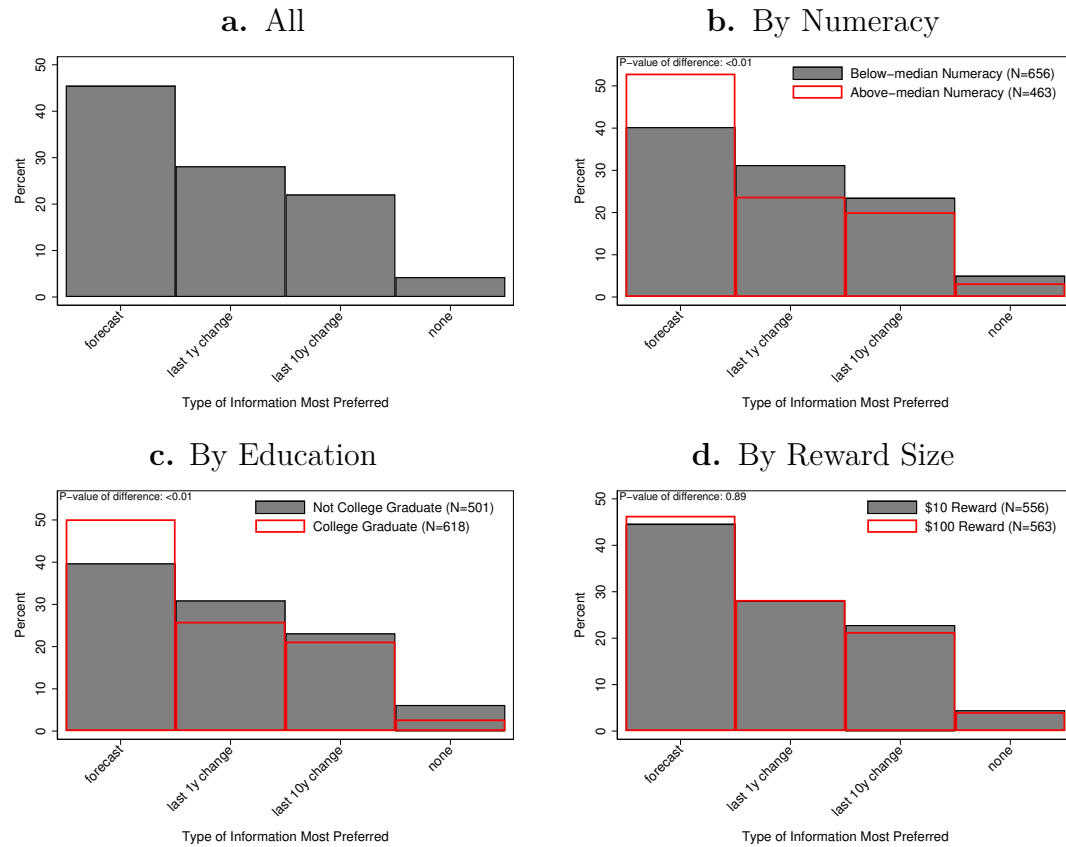
Notes: Panel (a) shows the distribution of the type of information most preferred by individuals that may help them with forecasting future year-ahead U.S. home prices; Panel (b) provides the same information according to the level of numeracy, panel (c) according to the level of education, and panel (d) according to the size of the reward. P-value of difference (in last three panels) tests for whether the distribution of most preferred information source differs by that characteristic.

Figure 3: Willingness to Pay for Favorite Information
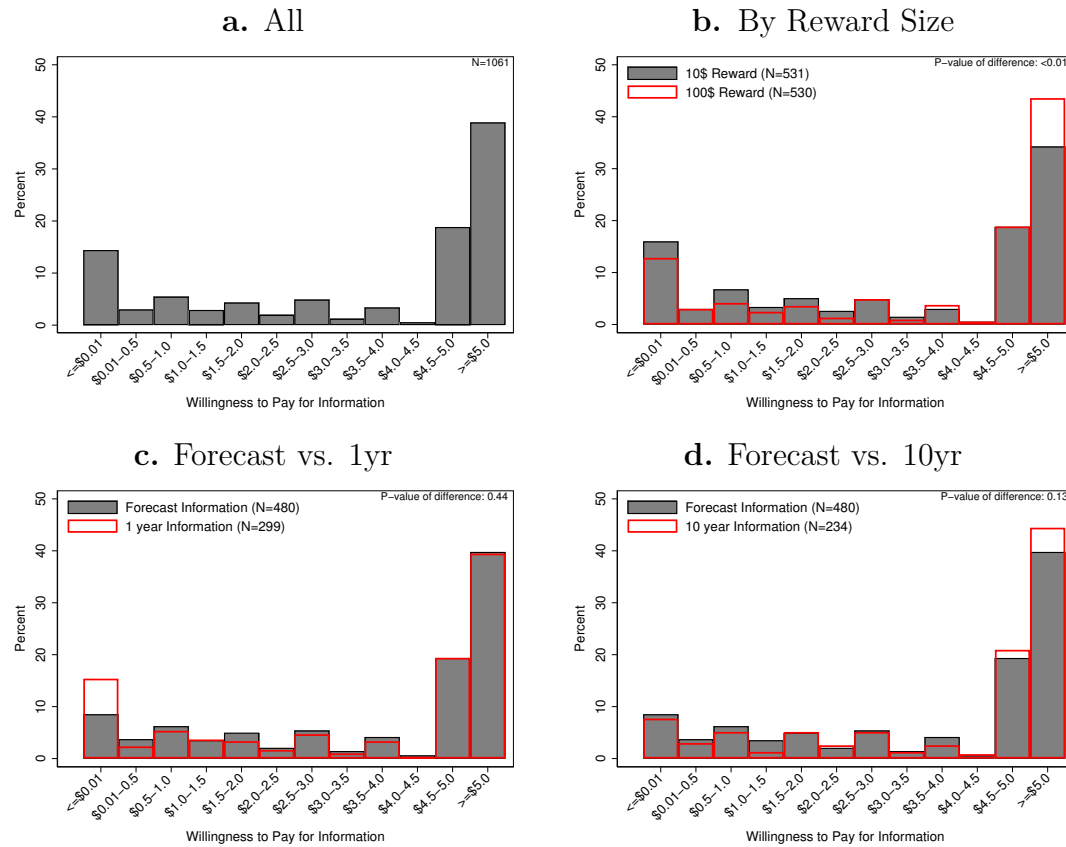
a. All

b. By Reward Size

c. Forecast vs. 1yr

d. Forecast vs. 10yr

Notes: This sample does not include respondents with non-monotonic choices across the BDM scenarios. Panel (a) shows the distribution of willingness to pay (WTP) for favorite information in the whole sample. Panel (b) shows the distribution of WTP 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 4: Learning Rates from Information

a. Main Survey

b. Follow-Up Survey
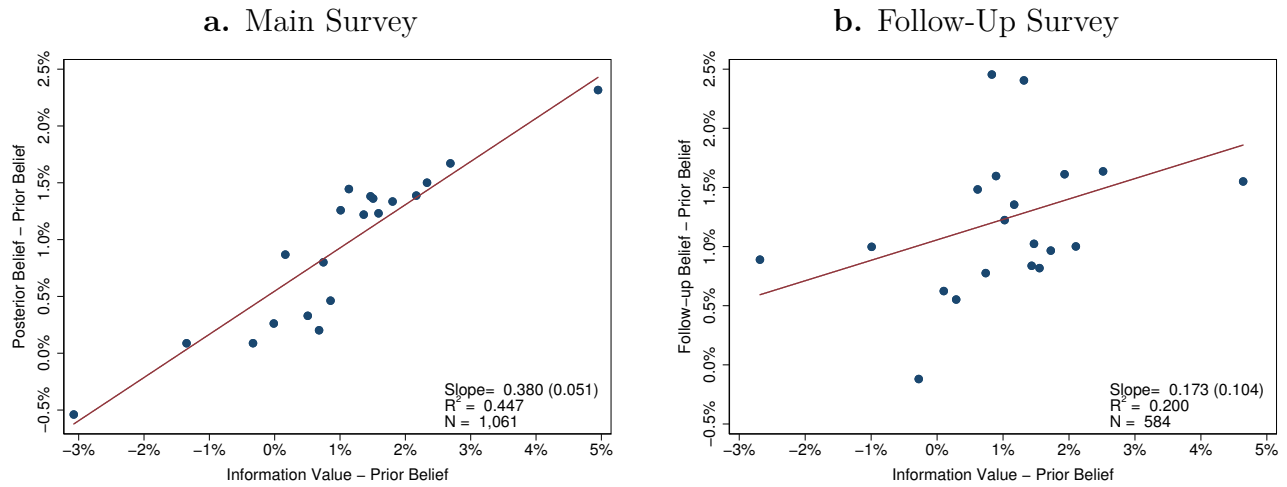
Notes: Learning rates are estimated using equation (3) from Section 3.2.2. The graphs show a binned-scatter plot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., posterior belief minus the prior belief) on the signal 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 willingness to pay and the prior belief. Panel a. presents the results for the main survey (i.e., the dependent variable is the belief update during the main survey in February 2017) and panel b. presents the results for the follow-up survey (the dependent variable is the difference between the posterior belief from the follow-up survey and the prior belief from the main survey).

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Figure 5: Learning Rates: Heterogeneity

a. By Info Chosen

- Forecast (N=480)
- Last 1 year change (N=299)
- Last 10 year change (N=234)

$Slope_{Forecast} = 0.328 \ (0.111)$
$Slope_{1-year} = 0.304 \ (0.092)$
$Slope_{10-years} = 0.305 \ (0.095)$
P–value = 0.983

x-axis: Information Value – Prior Belief
y-axis: Posterior Belief – Prior Belief

b. By WTP

- MWP < \$2.5 (N=341)
- MWP ≥ \$2.5 (N=720)

$Slope_{MWP < \$2.5} = 0.357 \ (0.114)$
$Slope_{MWP \geq \$2.5} = 0.366 \ (0.164)$
P–value = 0.963

x-axis: Information Value – Prior Belief
y-axis: Posterior Belief – Prior Belief

c. By Reward Size

- Low Reward (N=531)
- High Reward (N=530)

$Slope_{Low} = 0.377 \ (0.067)$
$Slope_{High} = 0.409 \ (0.090)$
P–value = 0.775

x-axis: Information Value – Prior Belief
y-axis: Posterior Belief – Prior Belief

d. By Uncertainty in Priors

- Below–median uncertainty (N=532)
- Above–median uncertainty (N=529)

$Slope_{Below} = 0.496 \ (0.080)$
$Slope_{Above} = 0.318 \ (0.064)$
P–value = 0.076

x-axis: Information Value – Prior Belief
y-axis: Posterior Belief – Prior Belief

e. By Numeracy

- Low Numeracy (N=606)
- High Numeracy (N=455)

$Slope_{Low-Num} = 0.294 \ (0.067)$
$Slope_{High-Num} = 0.497 \ (0.062)$
P–value = 0.024

x-axis: Information Value – Prior Belief
y-axis: Posterior Belief – Prior Belief

f. By Education

- Not College Graduate (N=471)
- College Graduate (N=589)

$Slope_{Not\ Coll-Grad} = 0.361 \ (0.075)$
$Slope_{Coll-Grad} = 0.380 \ (0.071)$
P–value = 0.854

x-axis: Information Value – Prior Belief
y-axis: Posterior Belief – Prior Belief

Notes: Same as in Figure 4, except that now the different panels estimate separate learning rates depending on (a) the chosen information (i.e., forecast, last 1-year change, and last 10-year change); (b) WTP (i.e., above and below the median WTP); (c) reward size (high or low reward); (d) uncertainty in prior beliefs (i.e., above and below the median uncertainty); (e) numeracy (i.e., above or below median numeracy); and (f) respondent education (at least a college degree or not).

Figure 6: Prior Beliefs: Individuals Who Will not be Shown Information vs. Individuals Who Will

a. Information not to be Shown

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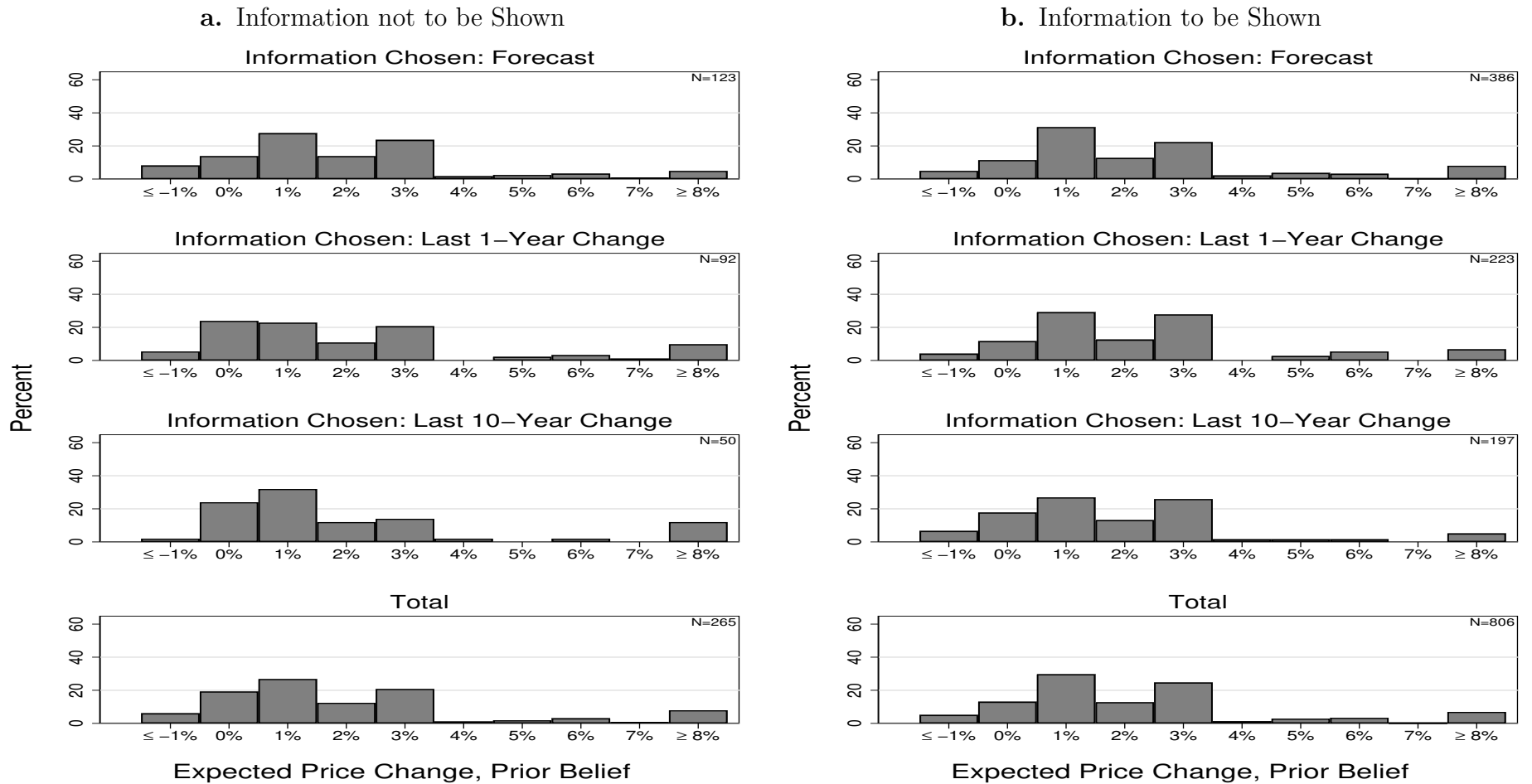
Notes: The distribution of the prior beliefs according the type of information most preferred (this sample does not include respondents who chose "None" as their most favorite information source). Panel (a) shows the distribution when individuals will not be shown information. Panel (b) shows the distribution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

Figure 7: Posterior Beliefs: Individuals Who Were Shown Information vs. Individuals Who Were Not

a. Information Not Shown

b. Information Shown
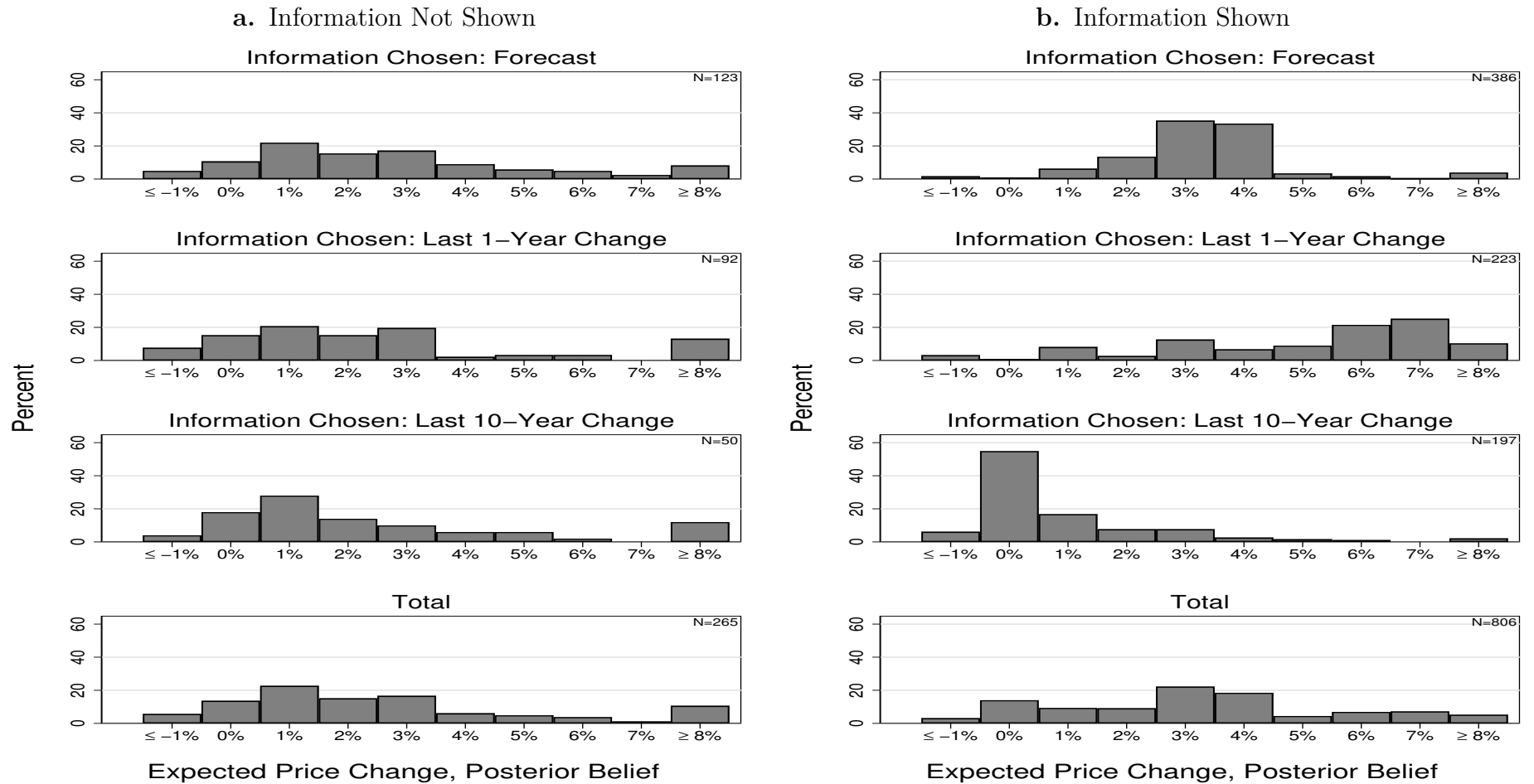
Notes: The distribution of the posterior beliefs according the type of information most preferred (this sample does not include respondents who chose "None" as their most favorite information source). Panel (a) shows the distribution of individuals who were not shown the information. Panel (b) shows 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
	(5.969)	(6.095)	(5.843)		(6.022)	(5.986)	
Prior Belief (% change)	0.022	0.023	0.021	0.374	0.022	0.023	0.662
	(0.031)	(0.031)	(0.030)		(0.031)	(0.031)	
Income > 60,000 (0/1)	0.553	0.574	0.532	0.164	0.583	0.544	0.201
	(0.497)	(0.495)	(0.499)		(0.494)	(0.499)	
College Graduate (0/1)	0.552	0.550	0.554	0.877	0.577	0.543	0.275
	(0.498)	(0.498)	(0.497)		(0.495)	(0.499)	
Age	50.83	51.18	50.48	0.450	50.71	50.76	0.965
	(15.458)	(15.637)	(15.286)		(15.743)	(15.262)	
Female (0/1)	0.474	0.467	0.481	0.641	0.454	0.493	0.197
	(0.500)	(0.499)	(0.500)		(0.498)	(0.500)	
Married (0/1)	0.634	0.656	0.611	0.115	0.636	0.644	0.790
	(0.482)	(0.475)	(0.488)		(0.482)	(0.479)	
White (0/1)	0.813	0.788	0.837	0.039	0.806	0.826	0.383
	(0.390)	(0.409)	(0.370)		(0.396)	(0.379)	
Homeowner (0/1)	0.748	0.752	0.744	0.771	0.757	0.746	0.689
	(0.434)	(0.432)	(0.437)		(0.429)	(0.436)	
Numeracy (0-5)	4.013	4.005	4.020	0.824	4.069	4.000	0.278
	(1.062)	(1.096)	(1.029)		(1.034)	(1.053)	
Uncertainty in Prior Belief (Normalized)	0.041	0.044	0.038	0.065	0.042	0.041	0.881
	(0.049)	(0.051)	(0.045)		(0.048)	(0.049)	
Median House Value in State (1,000s)	225.235	226.613	223.872	0.674	233.383	218.550	0.026
	(108.080)	(107.852)	(108.384)		(114.023)	(102.627)	
House Value Volatility in State (Normalized)	0.037	0.037	0.036	0.316	0.037	0.037	0.699
	(0.015)	(0.015)	(0.015)		(0.015)	(0.015)	
Looked for Info in Past (0/1)	0.563	0.561	0.565	0.901	0.570	0.569	0.967
	(0.496)	(0.497)	(0.496)		(0.495)	(0.496)	
Conf. in Past Recall (1-5)	2.873	2.875	2.871	0.937	2.866	2.883	0.744
	(0.847)	(0.855)	(0.840)		(0.846)	(0.838)	
Probability Move and Buy in 3yr	0.200	0.196	0.205	0.572	0.204	0.204	0.967
	(0.280)	(0.275)	(0.285)		(0.278)	(0.287)	
Resp. Follow-Up Survey (0/1)	0.552	0.550	0.554	0.898	0.545	0.569	0.438
	(0.497)	(0.498)	(0.497)		(0.498)	(0.496)	
Observations	1,119	556	563		563	508	

Notes: Individual characteristics obtained from main 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 to the corresponding pair of treatment groups. All variables constructed from the survey data. Uncertainty is the standard deviation derived from the individual-level subjective density (this variable is winsorized above the 98.5th percentile), normalized by the home price level at the end of 2016. House price volatility in state is the standard deviation of median home prices in the state of residence over the last 2 years, ending in December 2016, normalized by the average home price over the past 2 years.

Table 2: Factors Associated with Information Choice

	Indicator: chose...				
	Forecast (1)	1yr (2)	10yr (3)	None (4)	Forecast or 1yr (5)
High Reward (0/1)	0.018	0.002	-0.015	-0.004	0.019
	(0.030)	(0.027)	(0.025)	(0.012)	(0.026)
Income > 60,000 (0/1)	0.056*	-0.018	0.008	-0.045***	0.038
	(0.030)	(0.027)	(0.025)	(0.013)	(0.027)
College Graduate (0/1)	0.105***	-0.052*	-0.019	-0.034***	0.054**
	(0.030)	(0.027)	(0.025)	(0.013)	(0.027)
Age	-0.001	0.003***	-0.002**	0.000	0.002*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Female (0/1)	0.016	-0.013	-0.012	0.008	0.004
	(0.030)	(0.027)	(0.025)	(0.012)	(0.026)
Married (0/1)	-0.025	0.009	0.040	-0.025*	-0.016
	(0.031)	(0.028)	(0.025)	(0.013)	(0.027)
White (0/1)	0.071*	-0.032	-0.022	-0.018	0.040
	(0.038)	(0.035)	(0.033)	(0.017)	(0.035)
Numeracy (0-5)	0.063***	-0.042***	-0.001	-0.020***	0.021*
	(0.014)	(0.013)	(0.011)	(0.007)	(0.012)
Uncertainty in Prior Belief (Std)	-0.001	0.009	0.000	-0.008	0.008
	(0.015)	(0.014)	(0.012)	(0.006)	(0.013)
Median House Value in State (Std)	0.027*	-0.010	-0.008	-0.010**	0.017
	(0.015)	(0.013)	(0.012)	(0.005)	(0.013)
House Value Volatility in State (Std)	-0.001	-0.006	0.007	0.000	-0.008
	(0.015)	(0.013)	(0.013)	(0.006)	(0.014)
Looked for Info in Past (0/1)	0.009	0.024	-0.007	-0.026**	0.033
	(0.030)	(0.027)	(0.025)	(0.013)	(0.027)
Homeowner (0/1)	-0.058*	0.088***	-0.003	-0.028*	0.030
	(0.034)	(0.029)	(0.029)	(0.016)	(0.031)
Conf. in Past Recall (1-5)	-0.025	0.025	0.001	-0.001	-0.000
	(0.018)	(0.016)	(0.015)	(0.008)	(0.016)
Prob Move and Buy Home in 3 Years	0.158***	-0.094**	-0.020	-0.044**	0.064
	(0.053)	(0.047)	(0.044)	(0.018)	(0.046)
Look at Info During Survey (0/1)	0.130***	-0.113***	-0.012	-0.005	0.018
	(0.043)	(0.034)	(0.035)	(0.017)	(0.037)
Mean	0.45	0.28	0.22	0.04	0.74
Observations	1119	1119	1119	1119	1119

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each coefficient comes from a separate univariate regression. In columns (1) through (5), OLS regression are estimated using a dummy variable (=1) if the individual preferred the forecast information, 1 year information, 10 years information, None, and forecast or 1 year information as the dependent variable, respectively. Variables with a (Std) are standardized to have a mean of zero and standard deviation of 1.

Table 3: Factors Associated with WTP and Response Times

	Willingness To Pay	Log Min Posterior Belief	Log Min Posterior Belief | See Info
	(1)	(2)	(3)
High Reward (0/1)	0.828***	0.107**	0.124**
	(0.250)	(0.043)	(0.049)
Income > 60,000 (0/1)	0.862***	-0.086**	-0.176***
	(0.259)	(0.044)	(0.050)
College Graduate (0/1)	0.398	-0.002	-0.040
	(0.257)	(0.043)	(0.049)
Age	0.031***	0.007***	0.007***
	(0.008)	(0.001)	(0.002)
Female (0/1)	-0.289	0.022	0.067
	(0.254)	(0.043)	(0.049)
Married (0/1)	0.445*	-0.036	-0.118**
	(0.268)	(0.045)	(0.052)
White (0/1)	0.300	-0.045	-0.026
	(0.350)	(0.058)	(0.066)
Numeracy (0-5)	0.244*	0.029	0.009
	(0.126)	(0.021)	(0.025)
Uncertainty in Prior Belief (Std)	-0.276**	-0.078***	-0.069***
	(0.136)	(0.021)	(0.025)
Median House Value in State (Std)	0.254**	-0.018	-0.032
	(0.126)	(0.020)	(0.022)
House Value Volatility in State (Std)	0.249**	0.009	-0.012
	(0.125)	(0.022)	(0.024)
Looked for Info in Past (0/1)	0.773***	0.040	-0.025
	(0.256)	(0.043)	(0.050)
Homeowner (0/1)	0.906***	0.110**	0.055
	(0.293)	(0.051)	(0.059)
Conf. in Past Recall (1-5)	0.288*	-0.016	-0.047
	(0.154)	(0.027)	(0.033)
Prob Move and Buy Home in 3 Years	0.172	-0.003	-0.050
	(0.437)	(0.074)	(0.086)
Look at Info During Survey (0/1)	0.067	0.320***	0.263***
	(0.351)	(0.064)	(0.077)
WTP		0.104***	0.056***
		(0.010)	(0.018)
Mean	4.16	0.65	0.77
Observations	1061	1119	806

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column (1) reports results for interval regressions with willingness to pay as the dependent variable (this sample does not include respondents with non-monotonic choices across the BDM scenarios). Columns (2)-(3) report OLS regressions where the dependent variables is the log minutes spent on reporting the posterior beliefs (this variable is winsorized at the top and bottom 1.5th percentile).

Table 4: 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	4.16 (0.147)	4.09 (0.161)	0.83
	Disagreement (%)	10.18 (0.95)	11.87 (1.07)	0.24
Posterior	Mean	3.24 (0.141)	3.02 (0.143)	0.26
	MAD	2.21 (0.104)	2.13 (0.104)	0.59
	Uncertainty	3.03 (0.132)	3.24 (0.145)	0.45
	Disagreement (%)	20.45 (1.34)	20.39 (1.43)	0.98
Observations		536	477	

Notes: This sample does not include respondents who chose "None" as their 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 year-end home prices reported in Stage 1. Posterior belief refers to the expected home price change reported in Stage 4. To measure uncertainty at the individual level, we fit these binned responses to a normal distribution for each individual (or to a uniform distribution if the respondent puts all mass in one bin or equal mass in two adjacent bins), 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-values 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 5: Effect of Information-Acquisition on the Distribution of Expectations

		Prior	Posterior
		(1)	(2)
Information Shown			
All	Mean	2.27 (0.106)	3.28 (0.107)
N=806	MAD	2.04 (0.077)	2.05 (0.078)
	Uncertainty	4.02 (0.117)	2.95 (0.104)
	Disagreem. (%)	11.59 (0.83)	20.77 (1.10)
Forecast	Mean	2.41 (0.164)	3.38 (0.124)
N=386	MAD	2.19 (0.121)	1.14 (0.109)
	Uncertainty	3.99 (0.167)	2.97 (0.149)
	Disagreem. (%)	11.46 (1.17)	7.84 (1.05)
1 Year Change	Mean	2.42 (0.198)	5.17 (0.209)
N=223	MAD	2.01 (0.145)	2.25 (0.145)
	Uncertainty	3.85 (0.239)	3.48 (0.234)
	Disagreem. (%)	15.25 (1.89)	18.33 (2.09)
10 Year Change	Mean	1.82 (0.179)	0.92 (0.164)
N=197	MAD	1.79 (0.125)	1.35 (0.132)
	Uncertainty	4.27 (0.226)	2.28 (0.162)
	Disagreem. (%)	7.98 (1.29)	12.01 (1.73)
Information Not Shown			
All	Mean	2.07 (0.185)	2.66 (0.225)
N=313	MAD	2.17 (0.139)	2.64 (0.168)
	Uncertainty	4.32 (0.211)	3.78 (0.205)
	Disagreem. (%)	9.61 (1.15)	18.64 (1.75)
Forecast	Mean	1.97 (0.247)	2.99 (0.311)
N=123	MAD	1.93 (0.175)	2.38 (0.225)
	Uncertainty	4.41 (0.336)	3.49 (0.295)
	Disagreem. (%)	9.64 (1.76)	18.26 (2.75)
1 Year Change	Mean	2.32 (0.403)	2.56 (0.475)
N=92	MAD	2.61 (0.296)	2.97 (0.358)
	Uncertainty	5.23 (0.424)	4.84 (0.468)
	Disagreem. (%)	9.65 (2.23)	18.37 (3.18)
10 Year Change	Mean	2.29 (0.549)	2.60 (0.484)
N=50	MAD	2.55 (0.411)	2.48 (0.331)
	Uncertainty	3.47 (0.469)	3.39 (0.419)
	Disagreem. (%)	8.33 (2.55)	17.88 (4.14)

Notes: The average level, the dispersion, the uncertainty, and the fraction of disagreements within group is presented for the prior and posterior belief conditional on seeing the information and the most-preferred information source. The prior belief refers to the expected change for year-end home prices reported in Stage 1. Posterior belief refers to the expected home price change reported in Stage 4. See notes to Table 4 for additional details on definitions of various measures. Numbers in parentheses in each cell are standard errors.

Table 6: 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 over precisions	Yes	Negative	No
Heterogeneous priors over precisions	No	Negative	No
Heterogeneous priors over precisions & rational inattention	No	Positive or Negative	Yes

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

A Additional Results

A.1 Numeracy Questions

In the first survey that SCE panelists take, they are asked the following five questions, which form the basis of our numeracy measure:

1. In a sale, a shop is selling all items at half price. Before the sale, a sofa costs \$300. How much will it cost in the sale?

2. Let's say you have \$200 in a savings account. The account earns ten per cent interest per year. Interest accrues at each anniversary of the account. If you never withdraw money or interest payments, how much will you have in the account at the end of two years?

3. In the BIG BUCKS LOTTERY, the chances of winning a \$10.00 prize are 1%. What is your best guess about how many people would win a \$10.00 prize if 1,000 people each buy a single ticket from BIG BUCKS?

4. If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?

5. The chance of getting a viral infection is 0.0005. Out of 10,000 people, about how many of them are expected to get infected?

A.2 Decomposition of Learning Rates

In this section, we give more details about the identification of the learning rates. Figure A.1.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.1.b is identical to Figure A.1.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 discussion in the main text that typos and/or more careful consideration can lead to updating that looks like learning from a signal, 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 4.a presents the estimated learning rates (estimates of α), which roughly correspond to the difference between the slopes in Figure A.1.a and A.1.b (i.e., the incremental convergence towards the signal due to the signal provision).

Figure A.1: Changes from Prior to Posterior Beliefs
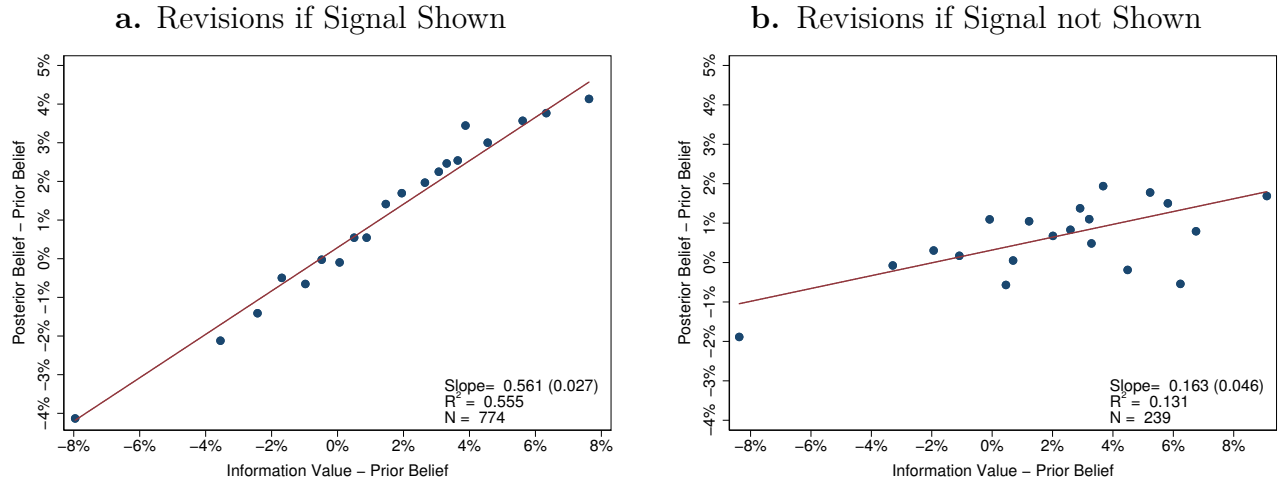
a. Revisions if Signal Shown

b. Revisions if Signal not Shown

Notes: This sample does not include respondents who chose "None" as their favorite information source and respondents with non-monotonic choices across the BDM scenarios. The figures measure how individuals revise their beliefs of the expected value of a typical home one-year forward, conditional on whether information is 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 willingness to pay dummies.

Table A.1: 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
	(5.969)	(5.714)	(6.098)		(7.367)	(5.821)	
Prior Belief (% change)	0.022	0.021	0.023	0.534	0.026	0.022	0.331
	(0.031)	(0.029)	(0.031)		(0.038)	(0.030)	
Income > 60,000 (0/1)	0.553	0.528	0.565	0.237	0.610	0.557	0.277
	(0.497)	(0.500)	(0.496)		(0.490)	(0.497)	
College Graduate (0/1)	0.552	0.543	0.556	0.679	0.580	0.552	0.571
	(0.498)	(0.499)	(0.497)		(0.496)	(0.498)	
Age	50.83	51.10	50.69	0.681	49.22	50.98	0.214
	(15.458)	(16.058)	(15.149)		(14.008)	(15.355)	
Female (0/1)	0.474	0.499	0.462	0.246	0.517	0.451	0.191
	(0.500)	(0.501)	(0.499)		(0.502)	(0.498)	
Married (0/1)	0.634	0.635	0.633	0.938	0.608	0.638	0.548
	(0.482)	(0.482)	(0.482)		(0.490)	(0.481)	
White (0/1)	0.813	0.816	0.811	0.826	0.831	0.807	0.539
	(0.390)	(0.388)	(0.392)		(0.377)	(0.395)	
Homeowner (0/1)	0.748	0.753	0.745	0.769	0.750	0.744	0.896
	(0.434)	(0.432)	(0.436)		(0.435)	(0.437)	
Numeracy (0-5)	4.013	3.995	4.022	0.688	4.075	4.011	0.535
	(1.062)	(1.061)	(1.064)		(1.022)	(1.072)	
Uncertainty in Prior Belief (Normalized)	0.041	0.041	0.041	0.961	0.047	0.040	0.132
	(0.049)	(0.051)	(0.047)		(0.047)	(0.048)	
Median House Value in State (1,000s)	225.235	224.432	225.645	0.861	239.850	222.878	0.137
	(108.080)	(108.782)	(107.792)		(115.701)	(106.063)	
House Value Volatility in State (Normalized)	0.037	0.037	0.037	0.938	0.039	0.036	0.076
	(0.015)	(0.016)	(0.015)		(0.014)	(0.015)	
Looked for Info in Past (0/1)	0.563	0.570	0.560	0.751	0.550	0.561	0.817
	(0.496)	(0.496)	(0.497)		(0.500)	(0.497)	
Conf. in Past Recall (1-5)	2.873	2.913	2.853	0.262	2.908	2.842	0.434
	(0.847)	(0.854)	(0.844)		(0.834)	(0.846)	
Probability Move and Buy in 3yr	0.200	0.191	0.205	0.424	0.230	0.200	0.310
	(0.280)	(0.277)	(0.282)		(0.295)	(0.279)	
High Reward (0/1)	0.503	0.486	0.512	0.399	0.550	0.505	0.364
	(0.500)	(0.500)	(0.500)		(0.500)	(0.500)	
Observations	1,119	381	738		120	618	

Notes: Individual characteristics obtained from main survey. Column (1) corresponds to all respondents, column (2) corresponds to individuals who were not invited to the follow-up survey, and 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 A.2: Factors Associated with Information Choice – Multivariate Results

	Indicator: chose...				
	Forecast (1)	1yr (2)	10yr (3)	None (4)	Forecast or 1yr (5)
High Reward (0/1)	0.011	0.008	-0.015	-0.005	0.020
	(0.030)	(0.027)	(0.025)	(0.012)	(0.027)
Income > 60,000 (0/1)	0.034	0.002	-0.009	-0.027**	0.036
	(0.036)	(0.033)	(0.030)	(0.014)	(0.032)
College Graduate (0/1)	0.066**	-0.023	-0.027	-0.016	0.043
	(0.032)	(0.029)	(0.028)	(0.012)	(0.029)
Age	0.000	0.002**	-0.002***	0.000	0.002**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Female (0/1)	0.037	-0.014	-0.017	-0.006	0.023
	(0.032)	(0.028)	(0.027)	(0.013)	(0.029)
Married (0/1)	-0.035	0.001	0.039	-0.005	-0.034
	(0.036)	(0.032)	(0.029)	(0.015)	(0.031)
White (0/1)	0.060	-0.031	-0.019	-0.009	0.028
	(0.040)	(0.037)	(0.035)	(0.019)	(0.037)
Numeracy (0-5)	0.058***	-0.043***	0.000	-0.015*	0.015
	(0.015)	(0.014)	(0.013)	(0.008)	(0.015)
Uncertainty in Prior Belief (Std)	0.014	0.002	-0.001	-0.015**	0.016
	(0.016)	(0.015)	(0.012)	(0.007)	(0.013)
Median House Value in State (Std)	0.027*	-0.009	-0.010	-0.008	0.018
	(0.016)	(0.014)	(0.013)	(0.005)	(0.013)
House Value Volatility in State (Std)	-0.007	-0.007	0.010	0.003	-0.013
	(0.016)	(0.014)	(0.014)	(0.006)	(0.014)
Looked for Info in Past (0/1)	-0.014	0.035	-0.010	-0.010	0.021
	(0.031)	(0.028)	(0.027)	(0.013)	(0.028)
Homeowner (0/1)	-0.049	0.070**	0.004	-0.025	0.021
	(0.040)	(0.033)	(0.033)	(0.018)	(0.036)
Conf. in Past Recall (1-5)	-0.019	0.011	0.006	0.001	-0.007
	(0.018)	(0.017)	(0.015)	(0.009)	(0.016)
Prob Move and Buy in 3 Years	0.129**	-0.038	-0.051	-0.040**	0.091*
	(0.057)	(0.050)	(0.048)	(0.020)	(0.050)
Mean	0.45	0.28	0.22	0.04	0.74
Observations	1119	1119	1119	1119	1119
R2	0.05	0.04	0.02	0.05	0.03

Notes: Heteroskedasticity-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Each column corresponds to a separate multivariate OLS regression. Unlike in Table 2, here we do not include the dummy variable "Look at Info During Survey", given its potential endogeneity with respect to the information source a respondent chose.

Table A.3: Factors Associated with Willingness to Pay and Response Times - Multivariate Results

	Willingness To Pay	Willingness To Pay	Log Min Posterior Belief	Log Min Posterior Belief	Log Min Posterior Belief | See Info	Log Min Posterior Belief | See Info
	(1)	(2)	(3)	(4)	(5)	(6)
High Reward (0/1)	0.843***	0.834***	0.096**	0.060	0.120**	0.106**
	(0.246)	(0.228)	(0.042)	(0.040)	(0.048)	(0.047)
Income > 60,000 (0/1)	0.719**	0.503*	-0.092*	-0.145***	-0.142**	-0.145***
	(0.298)	(0.273)	(0.049)	(0.048)	(0.057)	(0.056)
College Graduate (0/1)	0.184	0.104	0.009	-0.023	-0.005	-0.016
	(0.273)	(0.254)	(0.046)	(0.043)	(0.052)	(0.051)
Age	0.037***	0.039***	0.008***	0.007***	0.008***	0.008***
	(0.009)	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)
Female (0/1)	0.135	0.058	0.056	0.031	0.076	0.057
	(0.269)	(0.251)	(0.045)	(0.043)	(0.052)	(0.052)
Married (0/1)	-0.012	-0.074	-0.008	-0.019	-0.045	-0.050
	(0.298)	(0.276)	(0.050)	(0.048)	(0.058)	(0.057)
White (0/1)	-0.103	-0.263	-0.134**	-0.139**	-0.105	-0.103
	(0.361)	(0.334)	(0.060)	(0.056)	(0.066)	(0.065)
Numeracy (0-5)	0.066	-0.085	0.035	0.018	0.024	0.019
	(0.137)	(0.129)	(0.023)	(0.022)	(0.027)	(0.026)
Uncertainty in Prior Belief (Std)	-0.128	-0.249*	-0.078***	-0.079***	-0.080***	-0.076***
	(0.136)	(0.130)	(0.021)	(0.019)	(0.024)	(0.024)
Median House Value in State (Std)	0.166	0.096	-0.014	-0.023	-0.023	-0.024
	(0.134)	(0.126)	(0.021)	(0.020)	(0.024)	(0.024)
House Value Volatility in State (Std)	0.203	0.214*	0.010	-0.003	-0.010	-0.017
	(0.127)	(0.117)	(0.022)	(0.021)	(0.025)	(0.025)
Looked for Info in Past (0/1)	0.481*	0.464*	0.051	-0.005	0.015	-0.010
	(0.267)	(0.250)	(0.045)	(0.043)	(0.052)	(0.052)
Homeowner (0/1)	0.284	0.111	0.056	0.057	0.027	0.034
	(0.331)	(0.308)	(0.058)	(0.054)	(0.067)	(0.066)
Conf. in Past Recall (1-5)	0.087	0.094	-0.044	-0.035	-0.056*	-0.054*
	(0.160)	(0.150)	(0.028)	(0.025)	(0.034)	(0.033)
Prob Move and Buy in 3 Years	0.606	0.317	0.115	0.085	0.098	0.095
	(0.476)	(0.439)	(0.080)	(0.074)	(0.093)	(0.090)
Look at Info During Survey (0/1)		-0.118		0.350***		0.297***
		(0.327)		(0.064)		(0.078)
Choose 1yr. (0/1)		-0.412		-0.053		0.013
		(0.275)		(0.048)		(0.057)
Choose 10yr. (0/1)		0.530*		0.078		0.149**
		(0.285)		(0.052)		(0.059)
Choose None (0/1)		-21.954***		-0.449***		
		(0.703)		(0.106)		
WTP				0.081***		0.033*
				(0.011)		(0.018)
Mean	4.16	4.16	0.65	0.65	0.77	0.77
Observations	1061	1061	1119	1119	806	806
R2	.	.	0.06	0.17	0.08	0.11

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Interval regression is estimated in columns (1) and (2), using willingness to pay as the dependent variable. In columns (3) through (6), OLS regressions are estimated using the log of the time spent on reporting the posterior belief.

B Supplementary Study

To shed further light on the findings from our main study, 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 sample from the main 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 F. 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:

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[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.

"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.

*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 further 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 other interesting 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.

Finally, Figure B.1 replicates the finding in the main survey that individuals who are more certain (that is, those with below-median uncertainty) are in fact more responsive to the information. The set-up here is different from the main experiment. Thus, to make this comparison as similar to that in the main study, we restrict the sample to individuals who received one piece of information or no information (that is, we exclude individuals who received two pieces of information).

Figure B.1: Learning Rate By Uncertainty in Prior Beliefs
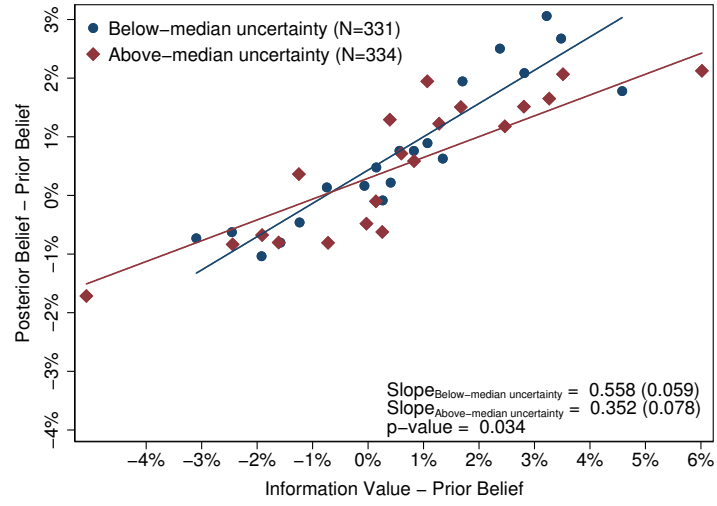
Notes: Same as in Panel d of Figure 5 in the main paper, except that this uses the supplementary survey. The figure shows the updating slope by uncertainty in prior beliefs (i.e., above and below the median uncertainty).

Table B.1: Effect of Information-Acquisition on the Distribution of Expectations (Analogue of Table 5 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 (0.154)	2.72 (0.136)
	Disagreem. (%)	12.09 (1.31)	22.32 (1.66)
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	3.91 (0.156)	2.83 (0.144)
	Disagreem. (%)	10.32 (1.20)	22.97 (1.65)
Control			
	Mean	2.58 (0.210)	3.00 (0.216)
N=338	MAD	2.39 (0.165)	2.54 (0.166)
	Uncertainty	3.66 (0.155)	3.28 (0.148)
	Disagreem. (%)	12.68 (1.40)	16.61 (1.57)

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 4 for additional notes on definitions of various measures. Numbers in parentheses in each cell are standard errors.

Table B.2: Information Preferences and Beliefs

	Obs	Information Preferences				Perceptions	
		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 if 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   Proof of Proposition 1

The net benefit of acquiring access to information source j at cost c and receiving a signal of precision $1/\sigma_\psi^2(i)$ on the displayed information equals

$$\phi\left(\sigma_\theta^2(i) - \sigma_{\theta|s}^2(i)\right) - c - \mu\frac{1}{2}\ln\left(1 + \frac{\sigma_\theta^2(i) + \sigma_{\varepsilon,j}^2(i)}{\sigma_\psi^2(i)}\right), \tag{C.1}$$

where

$$\sigma_{\theta|s}^2(i) = \begin{cases} \frac{1}{\frac{1}{\sigma_\theta^2(i)} + \frac{1}{\sigma_{\varepsilon,j}^2(i) + \sigma_\psi^2(i)}} & \text{if } \frac{1}{\sigma_\psi^2(i)} > 0 \\ \sigma_\theta^2(i) & \text{if } \frac{1}{\sigma_\psi^2(i)} = 0 \end{cases}.$$

The net benefit equals ϕ times the difference between prior and posterior variance of the fundamental minus the cost of information acquisition, c, minus the marginal cost of information processing, μ, times the uncertainty reduction about the displayed information.

To find the optimal signal precision, $1/\sigma_\psi^2(i)$, that maximizes objective (C.1) for a given information source j, it is useful to rewrite the maximization problem in terms of a different choice variable. Let α denote the weight on the signal implied by Bayesian updating

$$E\left[\theta|s(i)\right] = \mu_\theta(i) + \alpha\left[\theta + \varepsilon_j + \psi(i) - \mu_\theta(i)\right],$$

where

$$\alpha \equiv \begin{cases} \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_{\varepsilon,j}^2(i) + \sigma_\psi^2(i)} & \text{if } \frac{1}{\sigma_\psi^2(i)} > 0 \\ 0 & \text{if } \frac{1}{\sigma_\psi^2(i)} = 0 \end{cases}.$$

Rewriting the objective (C.1) in terms of α instead of $1/\sigma_\psi^2(i)$ yields the expression

$$\phi\alpha\sigma_\theta^2(i) - c - \mu\frac{1}{2}\ln\left(\frac{1}{1 - \frac{\sigma_\theta^2(i) + \sigma_{\varepsilon,j}^2(i)}{\sigma_\theta^2(i)}\alpha}\right).$$

Writing the maximization problem in terms of α instead of $1/\sigma_\psi^2(i)$ yields

$$\max_{\alpha\in\left[0,\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_{\varepsilon,j}^2(i)}\right)}\left\{\phi\alpha\sigma_\theta^2(i) - c - \mu\frac{1}{2}\ln\left(\frac{1}{1 - \frac{\sigma_\theta^2(i) + \sigma_{\varepsilon,j}^2(i)}{\sigma_\theta^2(i)}\alpha}\right)\right\}.$$

The unique solution is

$$\alpha^* = \max\left\{0, \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_{\varepsilon,j}^2(i)} - \frac{\mu}{2\phi\sigma_\theta^2(i)}\right\}. \tag{C.2}$$

It follows from the definition of α that the signal precision that yields the optimal α is

$$\left(\frac{1}{\sigma_\psi^2(i)}\right)^* = \max\left\{0, \left[2\frac{\phi}{\mu}\frac{\sigma_\theta^4(i)}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)}-1\right]\frac{1}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)}\right\}. \tag{C.3}$$

Substituting the optimal α back into the objective yields the net benefit of acquiring access to information source j at the solution

$$\max\left\{-c, \phi\frac{\sigma_\theta^4(i)}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)}-\frac{\mu}{2}-c-\frac{\mu}{2}\ln\left(2\frac{\phi}{\mu}\frac{\sigma_\theta^4(i)}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)}\right)\right\}. \tag{C.4}$$

Equations (C.2)-(C.4) complete the characterization of individual i's optimal amount of attention to the displayed information for information source j (equation (C.3)), optimal weight on the displayed information for information source j (equation (C.2)), and net benefit of acquiring access to information source j (equation (C.4)). The max operators in equations (C.2)-(C.4) simply reflect the fact that, in the case of $\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)} \leq \frac{\mu}{2\phi\sigma_\theta^2(i)}$, the optimal amount of attention to displayed information equals zero and the net benefit of acquiring access to information source j equals $-c$. Finally, in the case of an interior solution ($\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)} > \frac{\mu}{2\phi\sigma_\theta^2(i)}$), the partial derivative of expression (C.4) with respect to $\sigma_{\varepsilon,j}^2(i)$ is strictly negative, implying that the net benefit of acquiring access to an information source is strictly increasing in its perceived precision, $\sigma_{\varepsilon,j}^{-2}(i)$.

Comparing any two information sources for which the optimal amount of attention is strictly positive (i.e., comparing any two information sources for which expression (C.3) is strictly positive and thus expression (C.2) is strictly positive), individual i strictly prefers the information source with the higher perceived precision, $\sigma_{\varepsilon,j}^{-2}(i)$, because the net benefit of acquiring access to an information source is strictly increasing in its perceived precision, $\sigma_{\varepsilon,j}^{-2}(i)$.

Finally, an individual's willingness to pay for access to information source j equals the net benefit of access to information source j plus the cost of information acquisition, c. Hence, individual i's willingness to pay for access to information source j equals

$$WTP(i,j) = \max\left\{0, \phi\frac{\sigma_\theta^4(i)}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)}-\frac{\mu}{2}-\frac{\mu}{2}\ln\left(2\frac{\phi}{\mu}\frac{\sigma_\theta^4(i)}{\sigma_\theta^2(i)+\sigma_{\varepsilon,j}^2(i)}\right)\right\}. \tag{C.5}$$

D   Alternative Model with Common Prior over Signal 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 $\tau_j(i) \equiv \frac{1}{\sigma^2_{\varepsilon,j}(i)}$. τ_j being 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, $\tau_H = \frac{1}{\sigma^2_\varepsilon}$, and two information sources have low precision, $\tau_L = \frac{1}{\delta \sigma^2_\varepsilon}$, with $\delta > 1$.[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.

Cognitive effort 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 expend cognitive effort on figuring out the state of nature, which is modeled as receiving a noisy signal on the state. The signal announces the identity of the information source with high precision and is correct with probability $\lambda \in [1/3, 1]$, where $\lambda = 1/3$ corresponds to a completely uninformative signal and $\lambda = 1$ corresponds to a perfectly informative signal. More cognitive effort corresponds to a higher λ but comes at a higher cost. 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 cognitive mistakes arise on the level of the individual. It follows from Bayes' rule that for any individual i posterior beliefs are given by

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

---

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

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

The precise cost function for cognitive effort will be specified below and will have the property that a higher λ is 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. Formally, for any $\lambda > (1/3)$, we have $\lambda > \frac{1-\lambda}{2}$, and thus the optimal action is to select information source j if and only if $z(i) = j$. Intuitively, agents have a uniform prior and the signal is informative; hence the optimal action is to follow the recommendation of the signal. 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 expend cognitive effort (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 individual characteristics.

Prior beliefs and posterior beliefs over the fundamental. Individual i has the prior belief that the fundamental θ is normally distributed with mean $\mu_\theta(i)$ and variance $\sigma_\theta^2(i)$. Throughout this appendix, we set $\mu_\theta(i) = 0$ to simplify some of the equations and without affecting any of the qualitative results.

After selecting an information source and acquiring the information, 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 study the case where this variance of noise is endogenous, as in Section 4 of the paper.

Next, we derive the conditional density of the fundamental, θ, given the signal, $s(i)$. From the point of view of an individual, the signal on the fundamental is drawn from a mixture of two normal distributions. With probability λ the signal is drawn from a normal distribution with high precision. With probability $1-\lambda$ the signal is drawn from a normal distribution with low precision.

The posterior density can be written as a mixture density

$$p\left(\theta|s(i)\right) = p\left(\theta|s(i), j = j^*\right)p\left(j = j^*|s(i)\right)$$
$$+ p\left(\theta|s(i), j \neq j^*\right)p\left(j \neq j^*|s(i)\right).$$

The first term in each product is simple. The conditional distribution of θ given $s(i)$ and $j = j^*$ (high-precision information source) is a normal distribution with mean $\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i)+\sigma_\varepsilon^2+\sigma_\psi^2(i)}s(i)$ and variance $\frac{1}{\frac{1}{\sigma_\theta^2(i)}+\frac{1}{\sigma_\varepsilon^2+\sigma_\psi^2(i)}}$; and the conditional distribution of θ given $s(i)$ and $j \neq j^*$ (low-precision information source) is a normal distribution with mean $\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i)+\delta\sigma_\varepsilon^2+\sigma_\psi^2(i)}s(i)$ and variance $\frac{1}{\frac{1}{\sigma_\theta^2(i)}+\frac{1}{\delta\sigma_\varepsilon^2+\sigma_\psi^2(i)}}$. The second term in the first product is the posterior probability of having selected the high-precision information source given the realization of the signal $s(i)$. Using the fact that Bayes' rule implies that

$$p\left(j = j^*|s(i)\right) = \frac{p\left(s(i)|j = j^*\right)p\left(j = j^*\right)}{p\left(s(i)\right)},$$

and that

$$p\left(j = j^*\right) = \lambda,$$

$$p\left(s(i)|j = j^*\right) = \frac{1}{\sqrt{2\pi\left(\sigma_\theta^2\left(i\right) + \sigma_\varepsilon^2 + \sigma_\psi^2\left(i\right)\right)}}e^{-\frac{s(i)^2}{2\left(\sigma_\theta^2(i)+\sigma_\varepsilon^2+\sigma_\psi^2(i)\right)}},$$

$$p\left(s(i)\right) = \frac{\lambda}{\sqrt{2\pi\left(\sigma_\theta^2\left(i\right) + \sigma_\varepsilon^2 + \sigma_\psi^2\left(i\right)\right)}}e^{-\frac{s(i)^2}{2\left(\sigma_\theta^2(i)+\sigma_\varepsilon^2+\sigma_\psi^2(i)\right)}}$$
$$+ \frac{1-\lambda}{\sqrt{2\pi\left(\sigma_\theta^2\left(i\right) + \delta\sigma_\varepsilon^2 + \sigma_\psi^2\left(i\right)\right)}}e^{-\frac{s(i)^2}{2\left(\sigma_\theta^2(i)+\delta\sigma_\varepsilon^2+\sigma_\psi^2(i)\right)}},$$

yields

$$p\left(j = j^*|s(i)\right) = \frac{\lambda}{\lambda + (1-\lambda)\sqrt{\frac{\sigma_\theta^2(i)+\sigma_\varepsilon^2+\sigma_\psi^2(i)}{\sigma_\theta^2(i)+\delta\sigma_\varepsilon^2+\sigma_\psi^2(i)}}e^{\left[\frac{1}{2\left(\sigma_\theta^2(i)+\sigma_\varepsilon^2+\sigma_\psi^2(i)\right)}-\frac{1}{2\left(\sigma_\theta^2(i)+\delta\sigma_\varepsilon^2+\sigma_\psi^2(i)\right)}\right]s(i)^2}}.$$

The posterior probability of having selected the high-precision information source depends on λ and depends on the signal realization $s(i)$, because extreme signal realizations indicate that the low-precision information source has been selected. Combining results yields the conditional density of the fundamental, θ, given the signal, $s(i)$.

It is now straightforward to compute the conditional mean and the conditional variance of the

fundamental, θ, given the signal, $s(i)$. Standard results on mixture distributions yield

$$E\left[\theta|s(i)\right] = E\left[\theta|s(i), j = j^*\right] p\left(j = j^*|s(i)\right) + E\left[\theta|s(i), j \neq j^*\right] p\left(j \neq j^*|s(i)\right)$$

$$= \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_\varepsilon^2 + \sigma_\psi^2(i)} s(i)$$

$$\times \frac{\lambda}{\lambda + (1 - \lambda)\sqrt{\frac{\sigma_\theta^2(i) + \sigma_\varepsilon^2 + \sigma_\psi^2(i)}{\sigma_\theta^2(i) + \delta\sigma_\varepsilon^2 + \sigma_\psi^2(i)}}e^{\left[\frac{1}{2\left(\sigma_\theta^2(i) + \sigma_\varepsilon^2 + \sigma_\psi^2(i)\right)} - \frac{1}{2\left(\sigma_\theta^2(i) + \delta\sigma_\varepsilon^2 + \sigma_\psi^2(i)\right)}\right]s(i)^2}}$$

$$+ \frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \delta\sigma_\varepsilon^2 + \sigma_\psi^2(i)} s(i)$$

$$\times \left(1 - \frac{\lambda}{\lambda + (1 - \lambda)\sqrt{\frac{\sigma_\theta^2(i) + \sigma_\varepsilon^2 + \sigma_\psi^2(i)}{\sigma_\theta^2(i) + \delta\sigma_\varepsilon^2 + \sigma_\psi^2(i)}}e^{\left[\frac{1}{2\left(\sigma_\theta^2(i) + \sigma_\varepsilon^2 + \sigma_\psi^2(i)\right)} - \frac{1}{2\left(\sigma_\theta^2(i) + \delta\sigma_\varepsilon^2 + \sigma_\psi^2(i)\right)}\right]s(i)^2}}\right). \qquad \text{(D.1)}$$

For any signal realization $s(i)$ that differs from the prior mean of the fundamental, individuals respond more to the signal when λ is larger, because they can be more confident that they have selected the high-precision information source. Formally, the absolute difference between the posterior mean of the fundamental and the prior mean of the fundamental is strictly increasing in λ, because $p\left(j = j^*|s(i)\right)$ is strictly increasing in λ. In addition, standard results on mixture distributions yield

$$Var\left(\theta|s(i)\right) = \left(\left(\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \sigma_\varepsilon^2 + \sigma_\psi^2(i)}\right)^2 s(i)^2 + \frac{1}{\frac{1}{\sigma_\theta^2(i)} + \frac{1}{\sigma_\varepsilon^2 + \sigma_\psi^2(i)}}\right) p\left(j = j^*|s(i)\right)$$

$$+ \left(\left(\frac{\sigma_\theta^2(i)}{\sigma_\theta^2(i) + \delta\sigma_\varepsilon^2 + \sigma_\psi^2(i)}\right)^2 s(i)^2 + \frac{1}{\frac{1}{\sigma_\theta^2(i)} + \frac{1}{\delta\sigma_\varepsilon^2 + \sigma_\psi^2(i)}}\right) p\left(j \neq j^*|s(i)\right)$$

$$- \left(E\left[\theta|s(i)\right]\right)^2.$$

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

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

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

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

A closed-form expression for this conditional mean of the fundamental is given in the previous

paragraph.

Rational Inattention. So far we have derived the choice of the information source and the posterior beliefs over the fundamental for a given λ. Finally, we let individuals choose the probability with which they want to identify the high-precision information source. Individuals can choose how much cognitive effort they expend on identifying the high-precision information source.

The benefit of identifying the high-precision information source with a high probability is that it reduces the individual's mean square error:

$$E\left[\left(\theta - E\left[\theta|s(i)\right]\right)^2\right] = E\left[E\left[\left(\theta - E\left[\theta|s(i)\right]\right)^2|s(i)\right]\right] = E\left[Var\left(\theta|s\left(i\right)\right)\right].$$

It is straightforward to show that this mean square error is strictly decreasing in λ on $[1/3, 1]$ and twice continuously differentiable in λ on $(1/3, 1)$. In the following, let $MSE\left(i, \lambda\right)$ denote the mean square error of individual i, where the index i indicates that the mean square error depends on the variances $\sigma_\theta^2\left(i\right)$ and $\sigma_\psi^2\left(i\right)$, which may differ across individuals, and the argument λ indicates that the mean square error depends on λ.

The cognitive cost of identifying the high-precision information source with probability λ is assumed to equal $\mu I\left(\lambda\right)$, where $\mu > 0$ denotes the marginal cost of attention, as in Section 4 of the paper, and $I\left(\lambda\right)$ is the amount of attention that is required to identify the high-precision information source with probability λ. We assume that the function $I\left(\lambda\right)$ is strictly increasing on $[1/3, 1]$ and twice continuously differentiable on $(1/3, 1)$. In other words, attention is costly and identifying the best option among the three available options with a higher probability requires more attention.

We make no further assumptions about the function $I\left(\lambda\right)$, but it may be useful to give a concrete example. In the rational inattention literature following Sims (2003), it is common to quantify attention by uncertainty reduction, where uncertainty is measured by entropy. This is the modeling approach we took in Section 4 of the paper when we derived closed-form solutions. Applying the same modeling approach here yields

$$I\left(\lambda\right) = H\left(j^*\right) - H\left(j^*|z\left(i\right)\right),$$

where $H\left(j^*\right)$ denotes the entropy of the discrete state of nature j^* before receiving the signal $z\left(i\right)$ and $H\left(j^*|z\left(i\right)\right)$ denotes the conditional entropy of the discrete state of nature j^* after receiving the signal $z\left(i\right)$. The right-hand side of the last equation quantifies the amount of information processed by the agent. The cost function $\mu I\left(\lambda\right)$ then says that for a higher μ the same uncertainty reduction requires a higher cognitive effort. Using the fact that the entropy of a discrete random variable with probability mass function p_i, $i \in \{1, 2, 3\}$, equals $-\sum_{i=1}^{3} p_i ln(p_i)$, with the convention $0 \ln\left(0\right) = 0$,

(Cover and Thomas, 1991, Chapter 2) yields

$$I\left(\lambda\right) = \left[-3\frac{1}{3}\ln\left(\frac{1}{3}\right)\right] - \left[-\lambda\ln\left(\lambda\right) - 2\left(\frac{1-\lambda}{2}\right)\ln\left(\frac{1-\lambda}{2}\right)\right]. \qquad \text{(D.2)}$$

The function $I\left(\lambda\right)$ given by the last equation is strictly increasing on $[1/3, 1]$ and twice continuously differentiable on $(1/3, 1)$.

The decision problem of the rationally inattentive individual reads

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

where $MSE\left(i, 1/3\right) - MSE\left(i, \lambda\right)$ is the reduction in the mean square error that is achieved by identifying the high-precision information source with probability λ, $\mu I\left(\lambda\right)$ is the cognitive cost of identifying the high-precision information source with probability λ, and the parameter ϕ controls the incentive to have an accurate forecast of the fundamental.

Individuals with a higher ϕ/μ choose to identify the high-precision information source with a higher probability, i.e., they choose a higher λ. The proof is simple. Divide the objective in the decision problem by μ. The resulting transformed objective satisfies the strict single crossing property in $\left(\lambda; \frac{\phi}{\mu}\right)$. It follows from the Monotone Selection Theorem in Milgrom and Shannon (1994) that every selection from the set of solutions to the optimization problem is monotone nondecreasing in ϕ/μ. Furthermore, the partial derivative of the objective with respect to λ is strictly increasing in ϕ/μ, implying that interior solutions cannot remain unchanged as ϕ/μ changes.

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. Under the natural assumption that high-numeracy individuals need to expend less cognitive effort to identify the high-precision information source with a given probability (i.e., under the assumption that numeracy is negatively correlated with μ in the cross section), high-numeracy individuals choose to select the high-precision information source with a higher probability. As a result, they have a higher willingness to pay for their preferred piece of information and react more to the displayed information, because they can be more confident that they have selected the high-precision information source.

Comparison to standard discrete choice under rational inattention. It may be useful to compare the results in this appendix to well-known results in the literature on discrete choice under rational inattention (Matějka and McKay, 2015; Caplin and Dean, 2015). The first-order condition for λ when $I\left(\lambda\right)$ is given by equation (D.2) 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

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

The probability of selecting the high-precision information source divided by the probability of selecting any other information source is related to the partial derivative of the benefit term with respect to λ divided by the marginal cost of information flow, μ. The difference between the last equation and standard results on discrete choice under rational inattention (Matějka and McKay, 2015; Caplin and Dean, 2015) is that the expression for the partial derivative of the benefit term with respect to λ is more complicated than in the existing literature on static discrete choice under rational inattention. The reason is that processing more information before selecting an option changes both the probability of *selecting* the best option and the subsequent *use* of the selected option (captured through the weight λ in equation (D.1)). This model feature arises naturally in the context of choice of an information source, but may also arise in other contexts.

Extensions. One can allow individuals to choose the amount of attention allocated to selecting an information source and the amount of attention devoted to the displayed information

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

In the benefit term, we now 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 x_j. The total quantity of information processed depends on λ and $\sigma_\psi^{-2}(i)$.

One can also introduce the fixed cost of information acquisition. 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, $\phi \left(MSE\left(i, 1/3, 0\right) - MSE\left(i, \lambda, \sigma_\psi^{-2}\left(i\right)\right) \right)$, net of the cost of processing the displayed information x_j 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.

E Survey Instrument: Main Study

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

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0%   25%   50%   75%   100%

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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
○	○	○	○	○

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0%   25%   50%   75%   100%

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

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0%   25%   50%   75%   100%

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.

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0%   25%   50%   75%   100%

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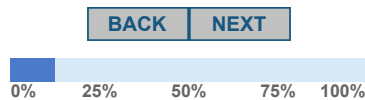
You estimated the value of the typical home in the US to be 194,000 dollars at the end of this year. Now we want to ask you about how confident you are about this forecast.

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	

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0%   25%   50%   75%   100%

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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0%   25%   50%   75%   100%

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

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

◀ ▶

1=Most preferred	
2	
3	
4=Least preferred	

▲
▼

BACK | **NEXT**

0%   25%   50%   75%   100%
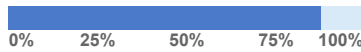
You said that you would most prefer seeing information on the change in the value of a typical home in the US over the last one year (2016). Now we want to assess how much you would value this information.

You will next be presented with 11 scenarios. In each scenario, you will be given the choice of either <u>seeing information</u> about the change in the value of a typical home in the US over the last one year (2016) OR receiving <u>extra money</u> 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 <u>at random</u> 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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0%   25%   50%   75%   100%
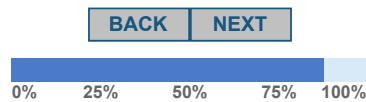
You will now be asked to make a decision for each of the **11 scenarios**.

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

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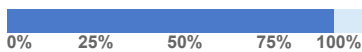
0%   25%   50%   75%   100%

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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

| 0% | 25% | 50% | 75% | 100% |
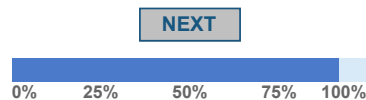
Scenario 1 was picked at random for you.

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

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**.

<div align="center">

NEXT

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| 0% | 25% | 50% | 75% | 100% |

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

0%   25%   50%   75%   100%

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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
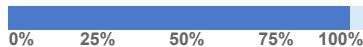
0%   25%   50%   75%   100%

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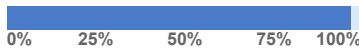
It was ok to refer to other sources (such as Google, Zillow, etc.) when taking the survey. Did you use any such sources when answering any question in the survey?

Please select only one.

○ Yes

○ No

BACK | NEXT

0%   25%   50%   75%   100%
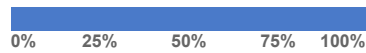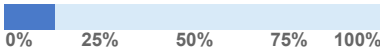
F Survey Instrument: Supplementary Study

We will next be asking you about your expectations of **<u>nationwide</u>** 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?
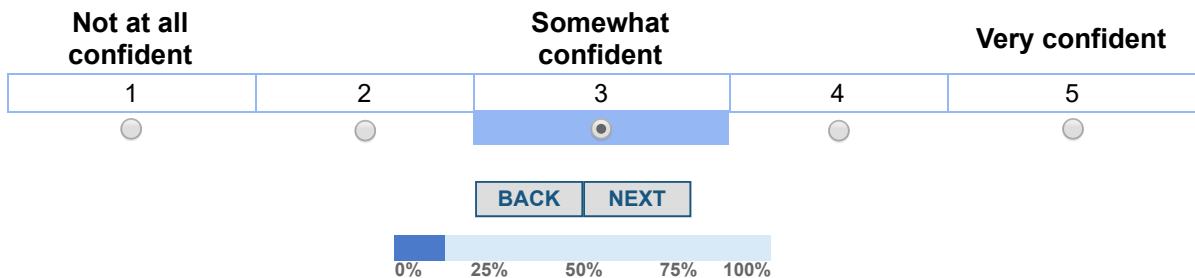
Please select only one.

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

BACK   NEXT

0%   25%   50%   75%   100%

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 <u>course of the year 2018</u>.*

If not, please change your answer.

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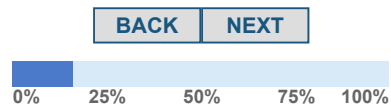
You estimated the value of the typical home in the US to be 210,000 dollars at the end of this year. Now we want to ask you about how confident you are about this forecast.

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%

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

| BACK | NEXT |

0%   25%   50%   75%   100%

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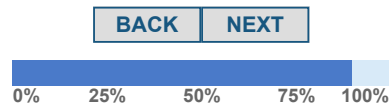
You stated that your preferred information is about the change in home values over the last one year. If possible, would you additionally want to see information about the change in home values over the last ten years as well?

Please select only one.

○ Yes, I would like to see this additional information.

○ No, I would prefer not to see this additional information.
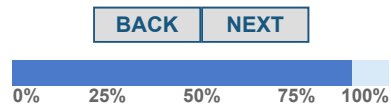
BACK | NEXT

0%   25%   50%   75%   100%

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** <u>for the accuracy of your forecast</u>. 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.

NEXT

0%   25%   50%   75%   100%
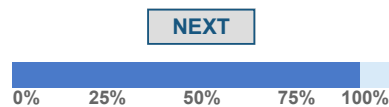
We will next inform you about the change in the value of a typical home in the US over the last one year.

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)?
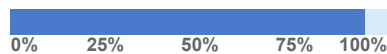
Please enter a number in the box below.

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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0%   25%   50%   75%   100%

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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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0%   25%   50%   75%   100%
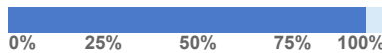
If you had been offered the opportunity to see the forecast of a panel of housing experts about year-end home prices before you reported your expectation, would you have chosen to do so (instead of seeing information about past home price changes)?

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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