Expectations with Endogenous Search

Evidence from an Information-Acquisition Experiment*

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Abstract

Information frictions are believed to play an important role in the expectations of households. There is, however, little *direct* empirical micro evidence on how individuals acquire information in the real world and process it. We conduct a survey experiment to address this question using the context of house price expectations. We let consumers buy different pieces of information that could be relevant for the formation of their expectations about the future median national home price. We use an incentive-compatible mechanism to elicit their maximum willingness to pay. We also introduce exogenous variation in the value of information by randomly assigning individuals to rewards for the ex-post accuracy of their expectations. This setup generates several testable hypotheses. Consistent with rational inattention, individuals are willing to pay more for information when they stand to gain more from it. However, underscoring the importance of limits on information processing capacity, individuals disagree on which signal they prefer to buy. Less sophisticated individuals, or those with lower education and financial numeracy, are less likely to demand information that has ex-ante higher predictive power, and this gap is not ameliorated when the stakes are higher. As a result, lowering the information acquisition cost does not decrease the cross-sectional dispersion of expectations. Our findings have implications for models of expectation formation and for the design of information interventions.

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1 Introduction

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

We study information acquisition in the context of expectations about national home prices. Our interest in home prices stems from the fact that home price expectations play a prominent role in many accounts of the housing boom that occurred during the mid-2000s in the United States (e.g., Shiller, 2005; Glaeser and Nathanson, 2015). In fact, Armona, Fuster, and Zafar (2017) and Bailey et al. (2017) show that home price expectations tend to affect housing-related behavior, such as buying or making investments in a home. Furthermore, in this high-stakes context, changes in housing prices can cause substantial wealth shocks.

We designed a survey experiment and embedded it in an online survey on housing issues conducted by the Federal Reserve Bank of New York. The experiment has three main stages. In the first stage, respondents report their expectations about the national median home price for the end of the year (their "prior belief"). In the second stage, which occurs much later in the survey, respondents are informed that their home price expectation will be re-elicited (their "posterior belief") and incentivized: if the expectation falls within 1% of the realized price, the respondent is eligible for a monetary reward. We create exogenous variation in the rewards: half of the subjects are randomly assigned to a reward that pays $100 with a probability of 10%, and the other half is assigned to a reward that pays $10 with a probability of 10%. Before respondents report their posterior beliefs and determine if they get the reward, they are given the opportunity to choose one of the following pieces of information that could be useful for their forecasts: the average year-end home price forecast from a panel of housing experts; the home price change over the past year; or the home price change over the past ten years. Respondents also can choose no information at all. In the third and final stage, we elicit the respondent's maximum willingness to pay (WTP) for the most preferred information type from the second stage. The experiment concludes with the re-elicitation of home price expectations (the posterior belief).

When eliciting WTP, we use a multiple-price-list variation of the Becker–DeGroot–Marschak method. In this incentive-compatible method, individuals choose either information or a pay-

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

ment between \$0.01 and \$5 in eleven scenarios. One scenario is then randomly chosen, and the corresponding choice is implemented. The random variation in the effective cost of information acquisition in turn generates random variation in whether the individual acquires the information. This experiment allows us to test features of two families of models from the literature on information frictions. In sticky information models (e.g., Mankiw and Reis, 2002; Reis, 2006; Carroll, 2003), agents update their information sets infrequently due to information acquisition costs. However, once they update their information sets, they process all information optimally to form expectations. Information frictions arise in these models because of the information acquisition costs. These models contrast with noisy information models (e.g., Sims, 2003; Woodford, 2003; Mackowiak and Wiederholt, 2009), in that even if information is freely available and agents continuously update their information, they may not use all of it or may use it inefficiently because of limited information processing capacity. Information frictions arise in these models because of limitations in information processing.

Our experimental design tests key predictions and differences among these two sets of rational inattention models. For example, the randomization of the accuracy rewards allows us to investigate whether subjects demand more information when the stakes are higher, as predicted by sticky information models. To distinguish between sticky and noisy information models, we randomize the cost of acquiring information. For sticky information models, lowering the cost of information acquisition should reduce the cross-sectional dispersion of expectations, but that need not be the case for noisy information models.

In our setup, respondents can choose one of three pieces of information: the average expert forecast for home price change during 2017 was 3.6%, national home prices increased by 6.8% during the past one year, and home prices decreased by 0.9% over the past ten years. Given a metric for informativeness, we can rank this information in terms of its informativeness. One reasonable criterion, although certainly not the only one, is the information's power for ex-ante prediction of U.S. home prices during the years leading up to the survey. Based on this criterion, the expert forecast is most informative, followed by past one-year change, and then ten-year change. This ranking is consistent with basic intuitions from the real estate literature. For instance, the fact that past one-year price changes are ranked higher than ten-year changes is consistent with the well-documented momentum in home prices over short horizons (Case and Shiller, 1989; Guren, 2016; Armona et al., 2017).

Our first result, with regards to information preference, indicates that individuals disagree on which piece of information to use: 45% chose forecasts of housing experts, 28% chose the past one-year home price change, and 22% chose the last ten-year home price change. The remaining 5% reported to prefer no information at all. Thus, less than half of the sample chose the option that was most informative according to ex-ante predictive power. Some of this heterogeneity could be due to respondents using other criteria, including the possibility that some respondents distrust experts (Silverman, Slemrod, and Uler, 2014; Cheng and Hsiaw, 2017). However, sophisticated

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

Our second result indicates that individuals demonstrated significant WTP for their favorite information: in the low-reward condition ($10 with 10% probability), the median individual was willing to pay $4.05. This WTP suggests that individuals expect to benefit from this information beyond the accuracy rewards provided in the survey. Furthermore, we find strong support for the rational inattention hypothesis: the median WTP is significantly higher in the $100-reward condition than in the $10-reward condition ($4.78 and $4.05, respectively). This difference is statistically significant (p-value<0.01) and economically meaningful. However, the information ranking does not vary by reward size. That is, respondents do not seem to think more carefully about the usefulness of the information when the stakes are higher, which suggests constraints in consumers' ability to decipher informative signals.

Our third result exploits the information-provision experiment to study how the information acquired by the individuals affects their expectations. It is important to note, however, that our research design does not distinguish between different expectation formation models, such as rational expectations and natural expectations.[2] Consistent with a genuine interest in information, individuals incorporate the information that they were willing to pay for into their expectation formation. Our findings suggest that individuals form posterior beliefs by putting 44.5% weight on the signal bought and 55.5% on their prior belief.

Four months after the baseline survey, we conducted a follow-up survey. Results from this survey show that the information had a persistent effect on respondents' beliefs. Also, the rate of learning was similar across all three pieces of information, which confirms that the disagreement about the information ranking was meaningful. However, we again observe violations of fully rational behavior. We find no evidence of individuals who had more uncertain prior beliefs or individuals who paid more for information by putting more weight on the purchased information.

Our final result is about the cross-sectional dispersion in expectations. If individuals only face costs of acquiring information but process information optimally (as in some sticky information models), the dispersion in beliefs should decrease when the information acquisition cost decreases. Contrary to this prediction, we show that being randomly assigned to a lower cost of information acquisition did not cause lower cross-sectional dispersion in expectations. If individuals acquired information at higher rates when the cost was lower, then why did cheaper information not induce higher consensus?

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

To understand the mechanisms behind this result, we divide respondents into three groups, based on their preferred information choice. On the one hand, exposure to information tended to reduce the dispersion in beliefs within each group. For example, among individuals who preferred the expert forecast, exposure to it resulted in their posterior beliefs becoming more compressed around the signal of 3.6%. On the other hand, exposure to information tended to increase the dispersion in beliefs across these three groups, because each group acquired a different signal and the different groups moved in different directions. These two channels tended to cancel each other out: thus, information acquisition did not lead to a decrease in the overall dispersion in expectations.[3]

Our results are broadly consistent with rational inattention models. However, information costs do not seem to be the main cause of disagreement across consumers. Even if the acquisition cost of information were zero, our findings imply that we would still observe substantial dispersion in consumers' expectations, because they choose to acquire different signals. Our two findings (i.e., information ranking did not change with the incentive and systematic differences based on consumer education and numeracy existed in the choices of information and remained persistent even when the stakes were varied) suggest that constraints on information processing were binding for a large part of the sample. Consumers do not know what information to pay attention to, which may explain why disagreement in expectations among consumers tends to be much larger than it is among experts, even when the estimated degrees of information rigidity are not larger (Coibion and Gorodnichenko, 2012).

Our approach is related to a recent literature on information-provision experiments. Particularly relevant for our purposes are papers that employ information experiments in surveys to understand expectation formation in the context of inflation (Armantier et al., 2017; Cavallo et al., 2017; Coibion, Gorodnichenko, and Kumar, 2015) or housing (Armona et al., 2016). The experiments in the context of inflation find that when individuals are provided with official statistics, the dispersion in expectations substantially decreases. However, these experiments exogenously expose respondents to pre-determined information and hence, by design, cannot shed light on information acquisition. Our paper complements this literature by endogenizing information acquisition.[4]

Finally, our results have implications for the design of information interventions. A growing body of research shows that, in a wide range of contexts, providing individuals with accurate information can have substantial effects on their beliefs and decisions (e.g., Duflo and Saez, 2003; Allcott, 2011; Cruces, Perez-Truglia, and Tetaz, 2013; Wiswall and Zafar, 2015). Our paper

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

[4]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).

speaks to this broader literature. 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 how to process the different pieces of information made available to them. Either these interventions should be narrowly targeted, in the sense that they provide consumers with limited but relevant information, or consumers need to be guided to help them interpret and weigh the various pieces of information.

The rest of the paper proceeds as follows. Section 2 introduces the research design and survey and outlines the testable hypotheses. Section 3 presents the results. The last section concludes.

2 Survey Design

We designed a survey module to be embedded into the 2017 Survey of Consumer Expectations (SCE) Housing Survey. The survey has been fielded annually every February since 2014 and contains multiple blocks of questions, some of which distinguish between owners and renters.[5] 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, housing debt). Respondents also provide information about their locations and many other demographic variables. Item non-response is extremely rare and rarely exceeds 1% for any question.

The SCE Housing Survey is part of the Federal Reserve Bank of New York's SCE, which is an internet-based survey of a rotating panel of approximately 1,400 household heads from across the United States. The survey, as its name suggests, elicits expectations about a variety of economic variables, such as inflation and labor market conditions. Respondents participate in the panel for up to twelve months, with a roughly equal number rotating in and out of the panel each month.[6] Active panel members who participated in any SCE monthly survey in the prior eleven months were invited to participate in the housing module. Out of 1,489 household heads on the panel that were invited, 1,161 participated, implying a response rate of 78%.

2.1 Research Design

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

[5]See https://www.newyorkfed.org/microeconomics/sce/housing#main

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

1. **Stage 1- Prior Belief** : This stage elicits individuals' expectations of future national home price changes. Respondents were informed that, according to Zillow, the median price of a home in the United States was $193,800 as of December 2016.[7] 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 go back to revise their guess. We refer to the response to this question as the respondent's "prior belief." The survey also elicited the respondents' subjective belief distributions about home prices at the end of year: specifically, they were asked to assign probabilities to five intervals of future year-end home price changes: less than -10%; between -10% and -1%; between -1% and 1%; between 1% and 10%; and more than 10%.

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 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=Most Preferred."

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

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

4. **Stage 4- Posterior Belief**: In this stage, the respondent may have seen their highest-ranked information choice, depending on the randomly chosen scenario in Stage 3 and their choice to see or not see the information in that scenario.[8] 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 median and typical U.S. home prices over the last one or ten years.[9] According to the ZHVI, U.S. home prices decreased by 0.1% per year on average (or 0.9% in total) over the last ten years and increased by 6.8% over the last one year. The Zillow Home Price Expectations Survey, a quarterly survey of 100 economists, real estate experts, and market strategists, was the source for expert forecast.[10] On average, experts forecasted an increase of 3.6% in home prices during 2017. Note that these information sources are publicly available.

   A paragraph providing the information followed a similar structure in all three cases. The raw information was provided, followed by a naive projection of home prices in December 2017 based on the annual growth rate implied by the information. For instance, respondents who chose expert forecast were presented with "*The average forecast of a distinguished panel of housing market experts who participate in the Zillow Home Price Expectations Survey is that home values in the US 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."

[8] In Stage 3, each of the scenarios 1-6 were picked with probability 15%, while each of scenarios 7-11 were picked with probability 2%.

[9] 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.

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

Respondents were picked at random with a 10% chance of being eligible for the incentive, and eligible respondents were informed at the end of the survey that they would be paid in January 2018, because the December 2017 ZHVI was used to determine the incentive.

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

2.2 Discussion of the Experimental Design

Our design tries to mimic real-world information acquisition and processing, albeit in a stylized setting. Before turning to the empirical analysis, it is useful to discuss the features of the experimental design and to outline the main hypotheses. 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, and a no-information option. Respondents understand that they can see their top-ranked choice. This setup allows us to test whether individuals have some reasonable idea or consensus about the usefulness of the information. Ideally, we want to test the hypothesis that the demand for information increases with its informativeness. However, no single criterion can measure informativeness. One reasonable metric of information usefulness is how it predicted past year-ahead home price changes in the United States.

Let $H\hat{P}A_t$ denote the predicted 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 $H\hat{P}A_t = I_t$. Thus, for the empirical analysis, we test a weaker version of the ideal hypothesis that is based on this specific metric of informativeness:

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

To calculate the RMSE of each piece of information, our baseline results are based on CoreLogic home price data, because it has a longer time series than Zillow. This yields a RMSE of 4.6 for the expert forecast, 7.83 for the past one-year change, and 8.37 for the past ten-year change. Based on this criterion, the expert forecast historically has been the most informative in predicting year-

ahead home price changes, followed by past one-year change, and then ten-year change.[11] These relative rankings are the same if we use Zillow instead of Corelogic data.[12]

This criterion for ranking the informativeness of the signals is broadly consistent with basic insights from the real estate literature. First, the fact that the forecasts are ranked highest is consistent with the efficient market hypothesis, which implies that forecasters use all available information in past home price changes optimally when providing a forecast. Additionally, this criterion is consistent with information acquisition models, such as Carroll (2003), in which consumers periodically update their expectations from reports of expert forecasts, which are assumed to be rational. Second, the higher ranking of past one-year home price change relative to past ten-year change is consistent with the well documented momentum in home prices over short horizons (Case and Shiller, 1989; Guren, 2016; Armona et al., 2017). For instance, for the nominal CoreLogic national home price index from 1976–2017, the AR(1) coefficient of annual growth is 0.73 and highly statistically significant, with an R^2 of 0.57. This serial correlation is only slightly weaker if we calculate price growth in real terms (the coefficient falls to 0.66 but remains highly significant).[13] 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 is hard to rationalize picking home price change over the past ten years over either of the other two pieces of information.

Rational inattention predicts that, in the absence of an incentive (such as the lack of a direct stake in the housing market), individuals in the real world may invest fewer resources in acquiring housing-relevant information and having more informed home price expectations.[14] The randomization of the accuracy incentive in Stage 2 provides a direct test of this hypothesis: that is, whether higher stakes causes the respondents to be willing to pay more for information. Moreover, rational inattention models with constraints on information processing capacity (Sims, 2003; Woodford, 2003; Mackowiak and Wiederholt, 2009) predict that, when the stakes are high, respondents think

[11] The CoreLogic series starts in 1976, so the RMSE for one-year (ten-year) changes is based on 38 (29) observations. The Zillow Home Price Expectations Survey started in 2009, and so the RMSE for experts' forecast is based on 6 data points. The RMSE continues to be the lowest for expers' forecast if we use data since 2009 for all three information sources.

[12] Using the Zillow Home Price Value Index, the RMSE for past one-year (ten-year) changes is 5.72 (8.25), and for experts' forecast is 2.9.

[13] 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 US) is 0.53 (statistically significant with $p < 0.01$).

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

carefully about the usefulness of potential information and hence rank information differently than their counterparts (in particular, they rank "None of the Above" lower). This leads to our second hypothesis:

> ***Hypothesis 2 (Rational Inattention):*** *When the accuracy incentive is higher, individuals are more willing to pay for information; also, the higher accuracy incentive should make the individuals more likely to choose the informative sources.*

Another aspect of the design that merits discussion is that, in Stage 4, some respondents may get to see one of the pieces of information. Whether a respondent sees the top-ranked information depends on the WTP and the randomly picked scenario from Stage 3. This randomization generates random variation in the provision of information, because for two individuals with identical WTPs in Stage 3, whether the information is shown in Stage 4 is determined at random. We exploit this scenario to investigate whether respondents incorporate the signal into their posterior beliefs, as would be expected if individuals were willing to pay for the information. Rational updating also implies that individuals who have uncertain prior beliefs and individuals who are willing to pay more for the information put more weight on the information that they receive.[15] This leads to our third hypothesis:

> ***Hypothesis 3 (Rational Updating):*** *If individuals are willing to pay for a signal, they should incorporate that signal into their expectation formation once they get access to it. The weight on the signal should be higher for those who pay more for the signal and whose prior uncertainty is higher.*

Finally, in models of costly search (e.g., Reis, 2006) where individuals process information optimally, expectations should be more likely to converge when the cost of acquiring information is low, because more individuals observe signals more often. We can test whether the price of information, which was randomly assigned in Scenarios 1 through 11, led to greater convergence in beliefs. Also, under optimal processing and acquisition of information, beliefs should converge upon receipt of information. We can test for this because, conditional on one's WTP, information provision in our setting was random. This leads to our final main hypotheses:

> ***Hypothesis 4 (Information-Acquisition and Dispersion of Expectations):*** *Lowering the cost of information reduces cross-sectional dispersion in expectations. Relative to the case with no information, information provision leads to a decrease in the dispersion of beliefs.*

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

2.3 Survey Implementation

Of the 1,162 valid responses, we trimmed the sample by dropping the top 5% and bottom 5% of responses to the prior belief. These 130 responses correspond to individuals who reported a prior belief of an annual growth rate below -1.96% (on average, -14.5%) or above 8.36% (on average, 26.5%).[16] These extreme beliefs are probably due to typos or people not paying attention to the survey question. As the prior belief was reported before the treatments, dropping these extreme prior beliefs should not contaminate the experimental analysis. For the posterior beliefs, we could not drop individuals, because that would contaminate the experimental analysis. Instead, we winsorized the post-treatment outcomes to minimize the sensitivity to outliers.[17] In any case, we use graphical analysis whenever possible to certify that the results are not driven by outliers.

Column (1) of Table 1 shows characteristics of the sample for the main survey. Most dimensions in the sample align well with average demographic characteristics of the United States. For instance, the average age of our respondents is 50.8 years, and 46.7% are females, which is similar to the corresponding 45.5 years and 48.0% among U.S. household heads in the 2016 American Community Survey. Also, 74.6% of respondents in our sample are homeowners, compared to a national homeownership rate in the first quarter of 2017 of 63.6%, according to the American Community Survey. Our sample, however, has significantly higher education and income: 56% of our respondents have at least a bachelor's degree, compared to only 37% of U.S. household heads. Likewise, the median household income of respondents in the sample is $67,500, which is substantially higher than the U.S. 2016 median of $57,600. This may be partly due to different internet access and computer literacy across income and education groups in the U.S. population. Respondents expect national home prices to increase by 2.1%, on average, over the next year.

Columns (2) and (3) of the table show the characteristics for the subsamples assigned to the low- and high-reward treatments, respectively. Column (4) shows that the characteristics (except for the proportion of Whites) do not statistically differ between the two treatments. This is not surprising, because random assignment should preserve balance between the two groups. Importantly, we see that the follow-up response rate does not differ according to the reward treatment. Appendix Table B.1 provides the same randomization balance analysis but for the assignment of the price-elicitation scenario in Stage 3 instead of the assignment of the reward size. Again, the evidence suggests that the randomization was successful.

Table 2 provides additional information on how the follow-up sample compares with the initial sample. Column (1) show the average characteristics for the whole sample. Columns (2)–(4) break down the average observables by eligibility for the follow-up sample: the evidence shows that the subsample that was eligible to be invited to the follow-up survey was similar to the ineligible group of respondents who were phased out of the panel, with the difference being statistically

[16] Results are robust under alternative less restrictive thresholds.

[17] For the posterior beliefs from the baseline survey and the beliefs from the follow-up survey, we winsorize the outcomes to take values in the range from -1% to +8%. Results are robust under alternative thresholds.

and economically insignifciant. The three columns of the table also are reassuring, as we see no evidence that, conditional on being invited to the follow-up, the individuals who responded to this survey are too different from the ones who did not.

3 Empirical Analysis

3.1 Hypothesis 1: Preferences over Informative Signals

To understand how respondents acquire information, it is useful to describe the distribution of expectations prior to the information acquisition. Figure 1.a shows a histogram of the point estimates provided by respondents. In terms of the implied annual growth rates, the mean (median) value is 2.1% (1.7%), with substantial disagreement across respondents: the cross-sectional standard deviation of prior beliefs is 2.0%. 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 knew that their guesses might be wrong: they thought there was only a 54% chance that the true price would fall within 1% of their guesses. Moreover, there was high dispersion in the degree of certainty. For example, 10.5% of the sample thought that there was a 90% chance or higher of year-end home prices being within 1% of their guess, and 12% of the sample thought that there was a 20% chance or lower.

What happens when individuals with uncertain beliefs are offered the chance to acquire information? Figure 2.a shows the ranking distribution for the different information types over the whole population. Individuals disagreed on which of the three pieces of information to buy: 45% chose forecasts of housing experts, 28% chose the last-one-year home price change, 22% chose the last-ten-year home price change, and the remaining 5% preferred no information. The past predictive power criterion indicated that expert forecast was most informative, followed by the last-one-year home price change and then the last-ten-year home price change. Thus, the popularity of the choice is increasing with its informativeness. However, this correlation is far from perfect: less than half of the sample chose the most popular choice (i.e., expert forecast).

This heterogeneity in the ranking of information could be driven by consumers' lack of knowledge about the relative informativeness of the signals or by respondents using different criteria to determine the informativeness of the signals. Systematic differences in ranking by education or numeracy of respondents, which are reasonable proxies for ability to filter signals, suggest evidence of the former. Figure 2.c and 2.d thus break down the information choices by respondents' numeracy and education, respectively, and show that individuals with more education or with higher numeracy were substantially more likely to choose the "best" information: college graduates chose the expert forecast 50% of the time, compared with non-graduates who chose it 40% of the time (p-value<0.01).[18]

[18]Similarly Burke and Manz (2014) find that respondents with higher levels of economic literacy choose more

Table 3 further explores the heterogeneity and reports both univariate and multivariate relationships between the choice of information and various individual- and location-specific characteristics. Columns (1)–(3) of the table report correlates of choosing each piece of information in a univariate framework. Besides numeracy and education of respondents, only a handful of variables are significant, suggesting that observable characteristics (at the individual or location level) cannot explain most of the heterogeneity in how individuals rank information. Homeowners were more likely to choose the past-one-year information and less likely to choose expert forecast. Respondents who reported checking external sources during the survey (about 14% of the sample) were 15 percentage points more likely to choose expert forecast. Consistent with a selection story, respondents who are savvy enough to look up other information also may be more sophisticated and adept at screening informative signals.

One might expect respondents who have high confidence in their perceptions of past home price changes to be more likely to choose expert forecast. In fact, we see the opposite: these respondents were more likely to choose past-one-year information and less likely to choose expert forecast. This finding is consistent with a selection channel, where individuals who are more certain about past home price changes likely overlooked that type of information and thus revealed a "preference" for it. Likewise, one might expect respondents residing in states with volatile housing prices (as measured by the standard deviation in monthly home prices over the past 24 months) to be less likely to choose past home price changes. We do not find evidence of that. Our conclusions remain unchanged in columns (5)–(7) of the table, which reports estimates from a multivariate regression. This leads to our first result:

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

3.2 Hypothesis 2: Rational Inattention

Before we can test if higher stakes change the willingness to pay for information, it is useful to understand the distribution of WTP for the whole sample. Using responses to the eleven hypothetical scenarios, we identify the range of an individual's WTP. For example, if an individual chose information instead of any amount up to \$3 and then chose the amount from \$3.50 on, it means that the individual's WTP must be in the range \$3 to \$3.5. Around 5% of respondents provided inconsistent responses; for example, they chose information instead of \$3 but then chose \$2.5 instead of information. This inconsistency is within the range of other studies using this list

relevant information when forming inflation forecasts.

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 based on this approach. We find that individuals have significant WTP for their favorite information, with a median maximum WTP between \$4.5 and \$5. [19] This is fairly high WTP, given that the information we provide is publicly and readily available using a search tool like Google. This finding indicates that most individuals are either unaware of the availability of this information or they expect a high search cost. Also, the median WTP (\$4.5-\$5) is high, compared to the expected reward for perfect accuracy (\$1 for half of the sample and \$10 for the other half). This evidence suggests that individuals value the information beyond the context of the survey. They may want to use this information for real-world housing decisions. In this context, having incorrect expectations about house prices can translate to thousands of dollars in losses, relative to which the experimental incentive pales in comparison. Additionally, we can compare the median WTP in our study (\$4.5-\$5) with the results from a few other papers that elicit WTP for information using similar methods. Those studies find lower valuations: \$0.40 for travel information (Khattak, Yim, and Prokopy, 2003), \$0.80 for food certification information (Angulo, Gil, and Tamburo, 2005), and \$3 for home energy reports (Allcott and Kessler, 2015).

We next test Hypothesis 2, whether the WTP and ranking of information systematically varies with reward size. Figure 3.b conducts a non-parametric test of this hypothesis by comparing the distribution of WTP between the two reward groups. This figure suggests that, consistent with the rational inattention hypothesis, individuals in the higher-reward treatment are willing to pay more when. The Epps-Singleton test suggests that this difference is statistically significant (p-value=0.02).[20]

To better understand the economic magnitude of this difference, column (1) of Table 4 presents the rational inattention test in regression form. The constant reported in column (1) can be interpreted as the median WTP for the low-reward condition (\$10 with 10% probability). This median valuation is estimated to be \$4.05 (95% CI from 3.73 to 4.38). The coefficient on High Reward indicates that, relative to the \$10 reward, individuals assigned to the \$100 reward are willing to pay an additional \$0.73 for their favorite information (or 18% more). Note that the expected reward goes from \$1 to \$10, because the reward is given only with 10% probability. The \$0.73 difference in WTP then implies that for each additional dollar of expected reward, the WTP for information goes up by 8.11 cents.

Another way to interpret the result is as follows:

[19] An alternative estimate is given by means of an interval regression model. This is a maximum likelihood model that assumes that the latent WTP is normally distributed. The median valuation, which is given by the constant in this model, is estimated to be \$4.41 (95% CI from 4.18 to 4.65).

[20] The Epss-Singleton test is a version of the Kolmogorov–Smirnov test of equality of distributions that is valid for discrete data (Goerg and Kaiser, 2009).

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

The first term, U_{Info}, represents the expected benefit value from real-world information (e.g., because one expects to make better choices when deciding whether to buy a house). The second term reflects the benefits of information from the survey reward, under the simplifying assumption that the respondent is risk-neutral for small amounts. We can infer the value of $P_i(Accurate|Info) - P_i(Accurate|NoInfo)$ from a regression of WTP_i on $0.1 \cdot Reward_i$. Indeed, we do not even need to run a new regression. We can recover that parameter from the coefficients on column (1) of Table 4.[21] This estimator suggests that $P_i(Accurate|Info) - P_i(Accurate|NoInfo) = 0.081$. In other words, by acquiring the information, the median individual expects that the probability of being accurate (i.e., being within 1% of the realization) will increase by 8.1 percentage points, or 15% of the baseline probability.[22]

It is worth asking whether the level of attention varies systematically with respondents' abilities. Columns (2) and (3) of Table 4 investigate whether higher numeracy and higher education makes one more rationally attentive (i.e., more reactive to the higher reward). In column (2), the High-Reward dummy is interacted with a standardized measure of numeracy. In column (3), the High-Reward dummy is interacted with a dummy for college graduate. In column (2), the effect of high reward is 80% larger (and statistically significant at the 5% level) for individuals with a one-standard-deviation higher numeracy. In column (3), the effect of high reward is 134% larger for college graduates relative to non-graduates, although the difference is imprecisely estimated and thus statistically insignificant.[23] We already show that highly educated and highly numerate respondents are more likely to choose expert forecast. So, not only are respondents with low education and numeracy less likely to rank information optimally, they also are less responsive to higher rewards.

Given that individuals pay more for information when the stakes are high, the next question is whether individuals choose information types differently when the stakes are high. Figure 2.b breaks down the information choice by reward type. The choices are almost identical across both groups; the p-value of the difference is 0.88. Column (4) of Table 4 presents this same test in regression form. It corresponds to a linear probability model where the dependent variable is whether the individual chooses the forecast (i.e., the "best" information type according to past

[21] The coefficient on the High Reward dummy indicates that increasing $0.1 \cdot Reward_i$ by 9 (i.e., $0.1 \cdot 100 - 0.1 \cdot 10$) increases the WTP by \$0.73. Thus, increasing $0.1 \cdot Reward_i$ by 1 would increase the WTP by 0.081 ($= \frac{0.73}{9}$).

[22] The median individual responded that there was a 54% chance that their guess is within 1% of the true price. We use this as an estimate of the median $P_i(Accurate|NoInfo)$. Thus, the 8.1 percentage point effect translates into a 15% (=8.1/54) effect.

[23] Note the estimate for the High Reward dummy is no longer significant. On the other hand, the impact of the High Reward for college-educated respondents, which is the sum of the two estimates is a precisely estimated \$0.96. Thus, the impact of the higher rewards on the WTP is primarily driven by college-educated respondents.

predictive power). Column (4) suggests that individuals are not more likely to choose expert forecast under the high reward. Additionally, Columns (5) and (6) of Table 4 show that the effect of the large reward on choosing the expert forecast does not differ by numeracy or education. This leads to our second result:

> ***Result 2****: Consistent with rational inattention, the WTP for information is higher when the incentive is higher, with greater responsiveness by more sophisticated respondents. However, the ranking of the information types does not systematically differ by reward size.*

Figure 3.a shows considerable heterogeneity in WTP. We next investigate the drivers of this heterogeneity. Column (4) of Table 3 uses the interval regression model to estimate the effect of a set of factors on WTP, with the impact of each factor investigated one at a time. Gender, education, and numeracy are not systematically related to WTP. We see that owners and individuals residing in states with high median home prices (i.e., those respondents who arguably have high stakes in the housing market) have economically and statistically significantly higher values for WTP. For example, increasing the median house value by 1 standard deviation increases the WTP by 22 cents.

The expected effect of past search efforts on WTP is ambiguous. On the one hand, individuals who looked for information in the past may be willing to pay less for the information, because they have good information already. On the other hand, individuals who acquired more information in the past may have the highest demand for information and thus are more willing to buy additional information. We find suggestive evidence that the second channel dominates: individuals who looked for housing-related information in the past were willing to pay an additional 59 cents, relative to those who did not. Likewise, we can study how the uncertainty in prior belief correlates to WTP. To measure uncertainty at the individual level, we use the responses to the probability bins. We fit these binned responses to a normal distribution for each individual and use the estimated standard deviation of the fitted distribution as a measure of individual-level uncertainty, with higher values denoting higher uncertainty. For instance, consider an individual with a 2% expectation who has an uncertainty of 1 percentage point. It means that the individual's 95% confidence interval for expectation is [0.04%, 3.96%] $(= [2 - (1 * 1.96), 2 + (1 * 1.96)])$. When looking at the relationship between uncertainty of prior beliefs and WTP, we again find evidence for the selection channel: individuals with high uncertainty in their prior beliefs were, on average, willing to pay \$.29 less.[24]

The expected effect of local volatility in home prices on WTP also is ambiguous. On the one hand, updating more often is valuable for such respondents, and hence they should value information more. On the other hand, past changes in home prices are less informative. We

[24]Note that the correlation of prior uncertainty with education/numeracy as well as with looking up housing-related information in the past is negative.

have seen that respondents in these areas do not choose expert forecast more often. Here, we see that these respondents in fact valued information more: increasing the home price volatility by 1 standard deviation increases the WTP by 31 cents. Column (8) of Table 3 is similar to column (4), except that it presents estimates from a multivariate regression. We see that, qualitatively, estimates continue to be similar.

Finally, we know that expert forecasts historically have predicted home price changes more accurately than the other two information pieces. Under this metric, individuals then should be willing to pay more for expert forecasts. Panels c and d of Figure 3 break down the WTP by information type, showing how WTP for expert forecast compares with that for past-one-year and past-ten-year home price changes, respectively. To establish whether these pairwise differences are statistically significant, these figures report the results from an Epps–Singleton two-sample test using the empirical characteristic function. These pairwise differences are statistically insignificant; that is, individuals in each of these three groups seemed to be equally willing to pay for the information.

3.3 Hypothesis 3: Rational Updating

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

We use a simple learning model that naturally separates learning from the signal shown from other sources of signal-reversion.[25] Let b^{prior} denote the mean of the prior belief, b^{signal} the signal, and $b^{posterior}$ the mean of the corresponding posterior belief. When priors and signals are normally distributed, Bayesian learning implies that the mean of the posterior belief should be a weighted average between the signal and the mean of the prior belief:

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

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

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

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

That is, the slope between the perception gaps ($b_k^{signal} - b_k^{prior}$) and revisions ($b_k^{posterior} - b_k^{prior}$) can be used to estimate the learning rate.[26] However, it is possible that individuals will revise their beliefs towards the signal even if they are not provided with the signal. For instance, consider someone who makes a typo when entering 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 or he is reverting to the signal despite not being shown information. Also, it is possible that individuals think harder the second time they are asked about their home price expectation, especially since the posterior belief is incentivized but the prior belief is not. Additionally, it is plausible that some individuals searched for more housing-related information online during the survey. At the end of the survey, we asked respondents whether they searched for information online during the survey, explaining that doing so was permitted, and 14.4% reported doing so. Interestingly, the search rate did not differ between respondents who saw information (14.6%) and those who did not (14.1%). Also, the simple act of taking a survey about housing may make respondents think more carefully about their responses and may lead them to revise their home price expectations even if they are not provided with any new information (see Zwane et al., 2011, for a discussion of how surveying people may change their subsequent behavior).

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

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

The parameter of interest is still α, which measures the true learning rate (i.e., the effect of being randomly shown information on the updates). β reflects the degree of spurious mean-reversion. Figure 4.a shows the results from this regression. 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, 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

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

x-axis would take the value of 2.6%. Intuitively, the x-axis shows the potential for revision, and the y-axis shows the actual revision. If individuals fully incorporated the signals, then all dots should lie on the 45-degree line. If individuals did not incorporate any information, then the dots should lie in a horizontal line. The slope of the line is 0.445, which is highly statistically significant (p-value<0.001) and economically substantial. It is midway between individuals fully reacting to the information (slope of 1) and individuals fully ignoring the information (slope of 0). In other words, the average individual puts 44.5% weight on the signal and 55.5% on their prior belief. It is worth pointing out that the average learning rate does not differ by either education or numeracy (Appendix figure B.4).

A natural question to ask is what the medium-term impact of information is on mean beliefs and cross-sectional dispersion. To test whether the effect on beliefs is persistent, Figure 4.b reproduces Figure 4.a, but instead of using $b_i^{posterior} - b_i^{prior}$ as the y-axis, we use $b_i^{follow-up} - b_i^{prior}$, where $b_i^{follow-up}$ is the belief reported four months later in the follow-up survey. There is good reason to believe that the slope will be lower in the medium-term horizon, 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. The result, shown in Figure 4.b, supports the hypothesis of persistent learning: the estimated slope (0.169) is smaller than the short-term equivalent (0.445), but it is still economically significant and statistically significant at the 10% level.

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. Panels b and c of Figure 5 investigate whether the learning rate differs by WTP for information or by uncertainty in prior belief. Under Bayesian updating, respondents who were more uncertain should have put more weight on the signal. Likewise, individuals who valued the information more arguably should have put more weight on it. We fail to find evidence of differential learning based on either prior uncertainty or WTP. Our next result thus is as follows:

> ***Result 3****: Subjects incorporate information that they buy, and the weight that respondents put on the information does not vary by information type. However, contrary to "rational" updating, the weight does not differ by one's WTP for the information or by prior uncertainty.*

3.4 Hypothesis 4: Information-Acquisition and Dispersion of Expectations

In a setting where individuals weight the signals optimally, more access to information (either due to reduced cost of the information or increased incentive for the accuracy of the beliefs) should reduce the cross-sectional dispersion in beliefs. We investigate this directly. 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" scenarios ($2–$5). Table 5 shows how beliefs in the full sample evolve 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, the mean posterior belief for the two groups is significantly different, a result of different exposure to information for the two groups. However, we do not find evidence that dispersion, as measured by the cross-sectional standard deviation, decreases more for the low-price group. The average standard deviation of the posterior is similar for both groups and in fact is higher than that for prior beliefs

How is it that more information does not induce higher consensus? This becomes clearer in Figures 6 and 7. 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.[27] In contrast, Figure 7.b shows that, for individuals who saw the information, posterior beliefs were dramatically different across the three information types. 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. Thus, within a certain information type, the revelation of information tended to decrease dispersion in expectations. However, because those groups moved towards differing signals, the dispersion of beliefs across those three groups increased. The net effect of information acquisition on belief dispersion depends on the combination of these two channels.

Table 6 summarizes the results from Figures 6 and 7. The first two columns of Table 6 provide statistics on how beliefs evolve, conditional on seeing the information and on the most-preferred information. We are primarily interested in how the dispersion in beliefs changed. As a measure of belief dispersion, we focus on the standard deviation of beliefs. The first thing that we can corroborate is that, within information types, information provision tended to reduce belief dispersion. For instance, for individuals who preferred the expert forecast but did not get to see the information, the standard deviation in beliefs increased from 2.0 percentage points for prior beliefs to 2.3 for posterior beliefs. In contrast, for individuals who preferred the forecast and were shown

[27] Consistent with the evidence discussed above that subjects in the no-information group may have searched for information or thought harder about the question, a comparison of Figure 6.a versus Figure 7.a indicates that the distribution of beliefs changed from prior to posterior beliefs even for individuals who were not shown information.

the information, the SD in beliefs decreased from 2.0 to 1.4 percentage points. The same is true for individuals who chose the past-10-year change but not for individuals who chose the past-1-year change (for whom, probably due to the extreme value of the signal, the dispersion went up).

It is also worth commenting on how uncertainty at the individual-level evolved, as reported in the last row in each panel in Table 6. Mean uncertainty in posterior beliefs is lower than that in prior beliefs for both groups (those who saw the information and those who did not). However, consistent with the notion that information should make individuals more certain, we see that uncertainty declines more for the group that is shown information (from 3.8 to 2.7 percentage points, or more than 1 percentage point) than for the group that is not shown (from 3.8 to 3.4 percentage points).

To see the net effect of information provision, we compare the evolution of belief dispersion for the entire sample. For the group that did not see the information, dispersion increases from 2.1 to 2.3 percentage points from prior to posterior. In comparison, dispersion increases by about the same amount for individuals who saw the information. This evidence suggests that the opportunity to acquire information acquisition does not lead to a decrease in dispersion of beliefs. However, information leads to significantly different average posterior beliefs for the two groups.

We also see how the cross-sectional dispersion evolves in the medium term. Ex-ante, the medium-term impact on dispersion is unclear. In the interim four months, individuals may have received various signals. Depending on the heterogeneity in these signals, the cross-sectional dispersion may go up or down. Additionally, because individuals are being asked about year-end home prices, some uncertainty may have resolved over the interim four months. The last column in Table 6 shows how these statistics evolved for the information-shown and not-shown groups. Comparing the follow-up belief with the posterior belief, the cross-sectional dispersion increases for both the information-shown and not-shown groups. Most important and consistent with persistent learning, the mean expectation for the information-shown group continues to be different from that of the information-not-shown group. These findings can be summarized as follows:

> ***Result 4*** *: A lower cost of information does not lead to a decrease in the cross-sectional dispersion of beliefs. Likewise, endogenous information-acquisition and information-processing do not lead to lower dispersion.*

4 Conclusion

Using an innovative experimental setup that makes the information acquisition process endogenous, this paper attempts to understand the role of information frictions in explaining the heterogeneity in consumers' expectations about home price changes. Consumers exhibit substantial demand for information and, consistent with rational inattention, the demand for information is high when the stakes are high. Although information acquisition costs do seem to matter, our

findings indicate that the main drivers of heterogeneity in consumer expectations are constraints on information processing. Consumers disagree on what information is most informative, with less sophisticated agents less likely to choose "informative" signals. Importantly, we see that the cross-sectional variance of the expectations distribution does not decrease because of endogenous information acquisition, which would be expected in a setting with rational acquisition and information processing. Although individuals respond to different information, they do not weigh the different pieces of information optimally. This finding has implications for modeling of expectation formation and for practical design of information interventions.

On the modeling front, most models with information frictions assume that individuals process information in a rational way. Our results suggest that this may be a misleading assumption and instead support models wherein consumers have limited information processing capacity and process information at a finite rate (e.g., Sims, 2003). Our findings also suggest that consumers may not know which pieces of information to choose. In fact, we find that less sophisticated individuals (as proxied by education or numeracy) are less likely to pick informative signals. Thus, our results help explain why consumers tend to have so much disagreement in their expectations.

On the practical front, our results underscore the need for better design of information campaigns. Our findings imply that it is not sufficient to provide more information. Instead, individuals must be guided on how to interpret and weigh the information. Policy makers may want to act paternalistically by disclosing only the "good signals" or by making the best signals more salient.

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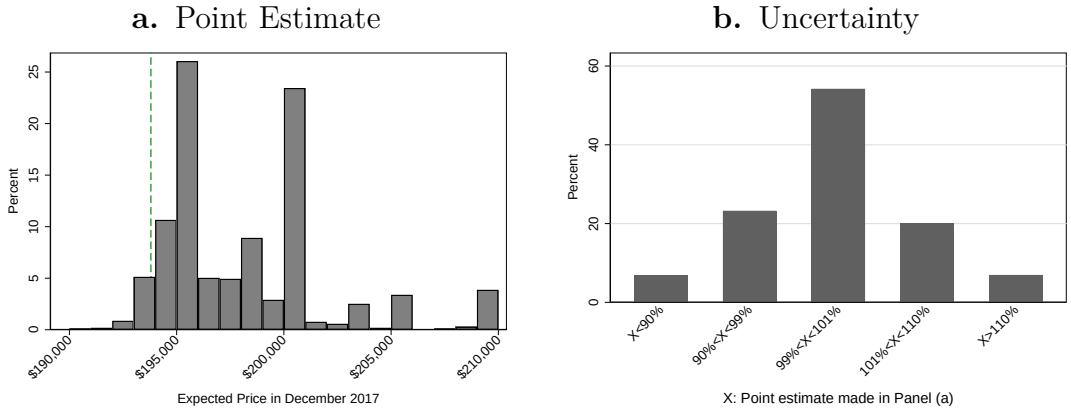
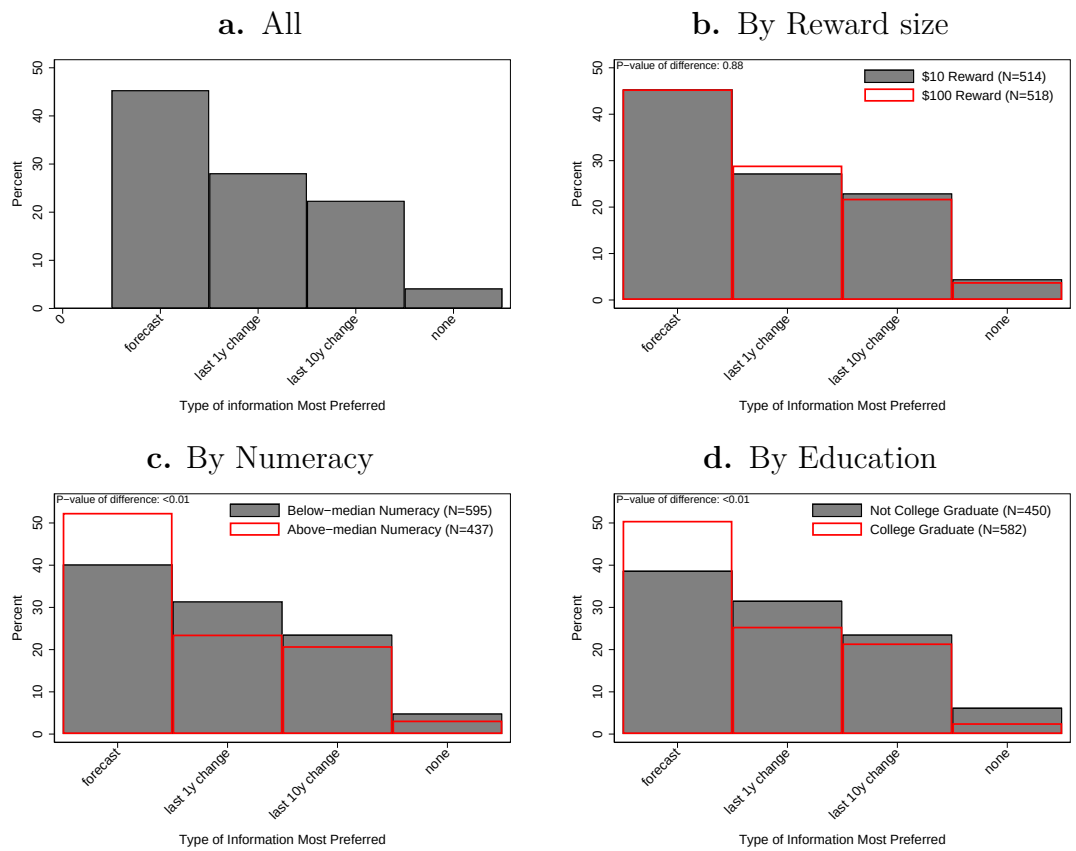
Figure 1: Prior Beliefs: Expectations about Median House Price



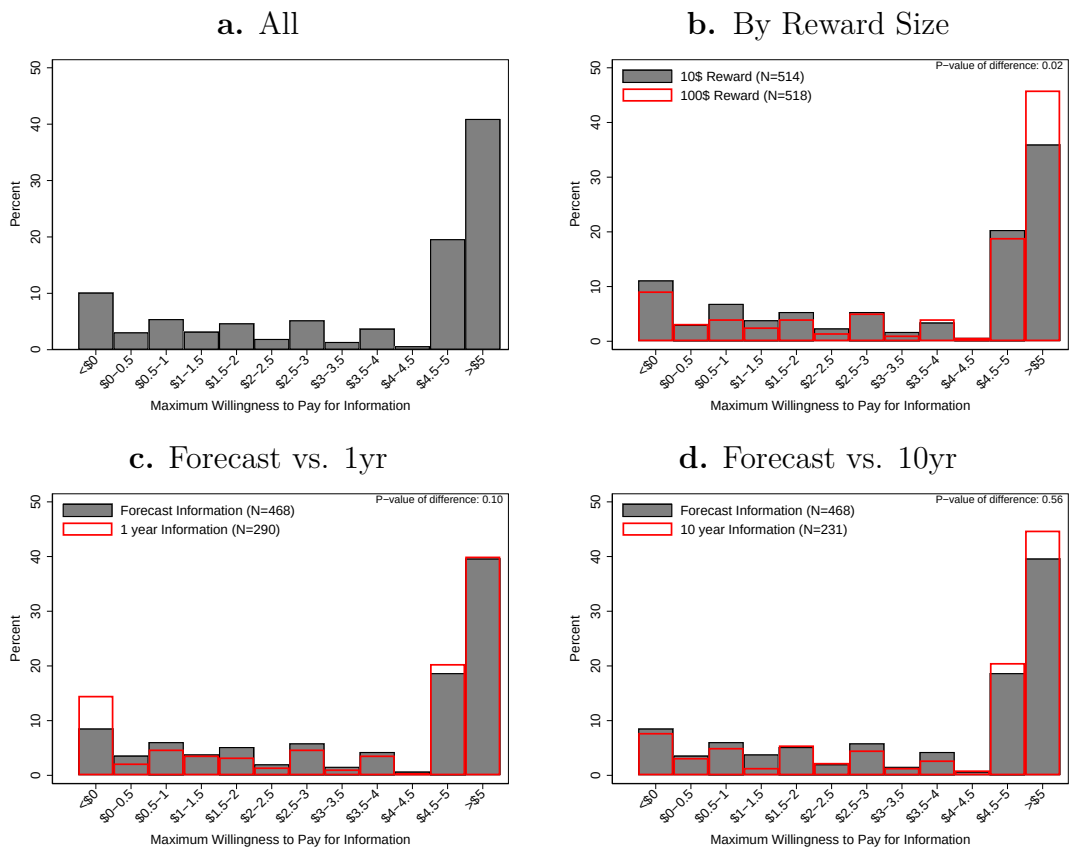
Notes: Panel (a) shows the distribution of the expected value of the typical home in the U.S. 1 year forward (i.e., from December 2016 to December 2017). The green line corresponds to the median house value in U.S. in December 2006. The histogram is censored at $190,000 and $210,000. Panel (b) corresponds to the distribution of the confidence about the forecast made in Panel (a) by individuals.

Figure 2: Type of Information Most Preferred



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

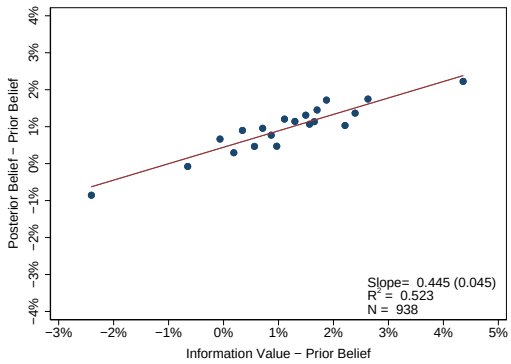
Figure 3: Willingness to Pay for Favorite Information



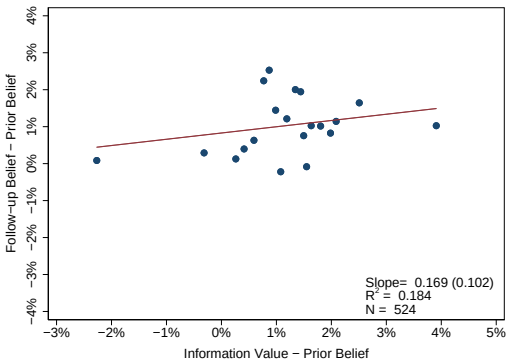
Notes: Panel (a) shows the distribution of maximum willingness to pay for favorite information in the whole sample. Panel (b) shows the distribution of maximum willingness to pay for information according the size of the reward. Panel (c) compares the distribution of MWP between individuals who preferred forecasts information and individuals who preferred information over the last one year. Panel (d) compares the distribution of MWP between individuals who preferred forecasts information and individuals who preferred information over the last ten years. P-value of difference refers to the Epps-Singleton characteristic function that tests the equality of two distributions.

Figure 4: Short and Medium-Term Learning Rates

a. Short Term



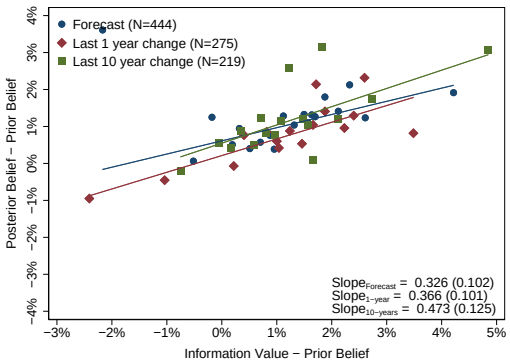
b. Medium-Term



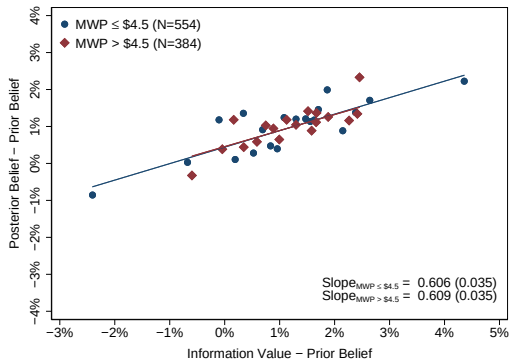
Notes: Learning rates are estimated using equation (4) from section 3.3. The graphs show a binned-scatter plot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., posterior belief minus the prior belief) on the signal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

Figure 5: Learning from Feedback

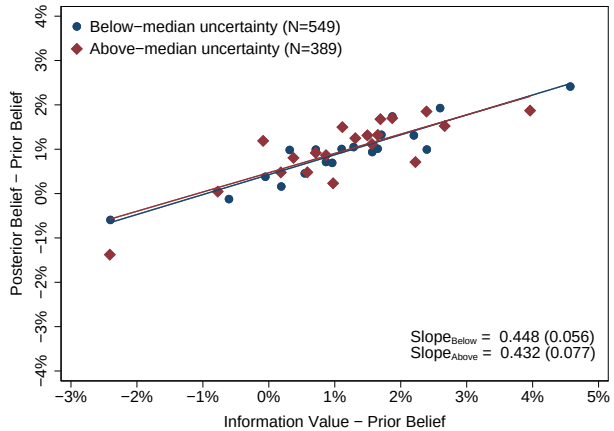
a. By Info Chosen



b. By WTP



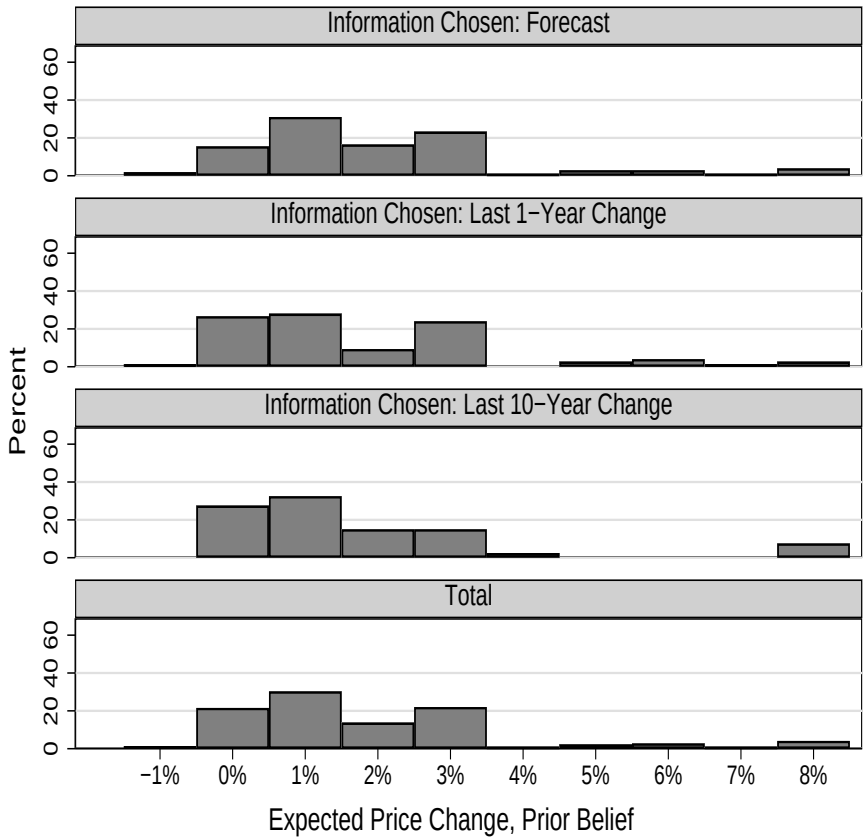
c. By Uncertainty in Priors



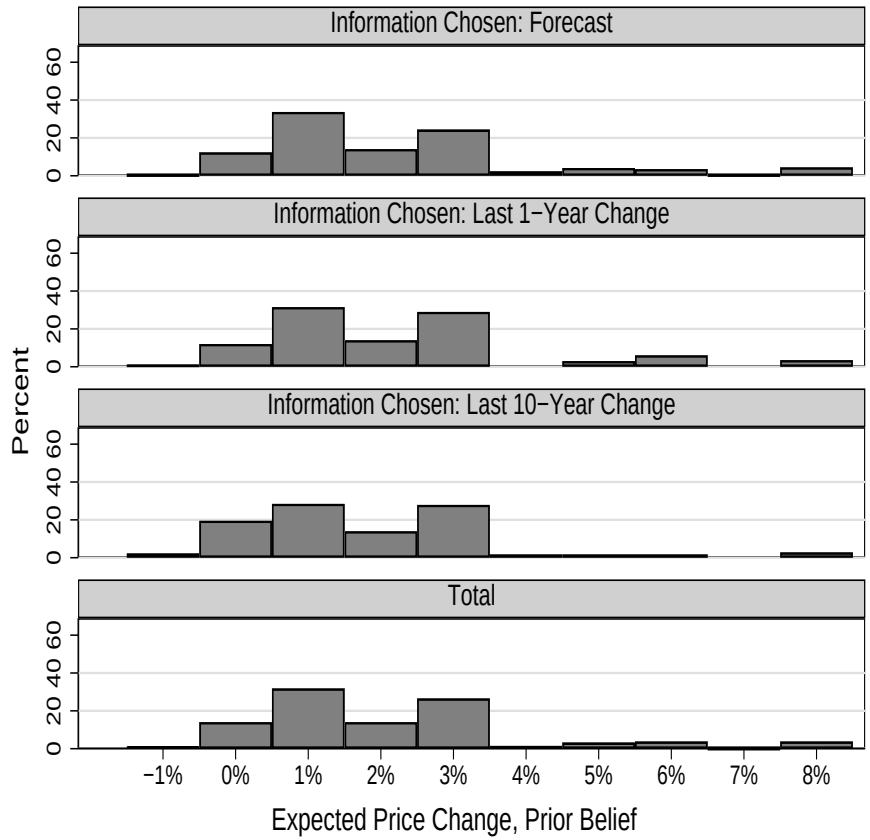
Notes: Learning rates are estimated using equation (4) from section 3.3. The graphs show a binned-scatter plot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., the dependent variable is the belief update during the baseline survey) on the signal gap (i.e., signal value minus the prior belief) interacted by a dummy that takes the value 1 if the individual was shown the signal. The regressions control for the signal gap (i.e., without the interaction) and dummies for maximum willingness to pay. Panel a. presents the results according info chosen (i.e., forecast, last 1-year change, and last 10-year change). Panel b. presents results according WTP (i.e., above and below the median WTP). Finally, panel c. presents the results according the uncertainty (i.e., above and below the median uncertainty).

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

a. Information not to be Shown

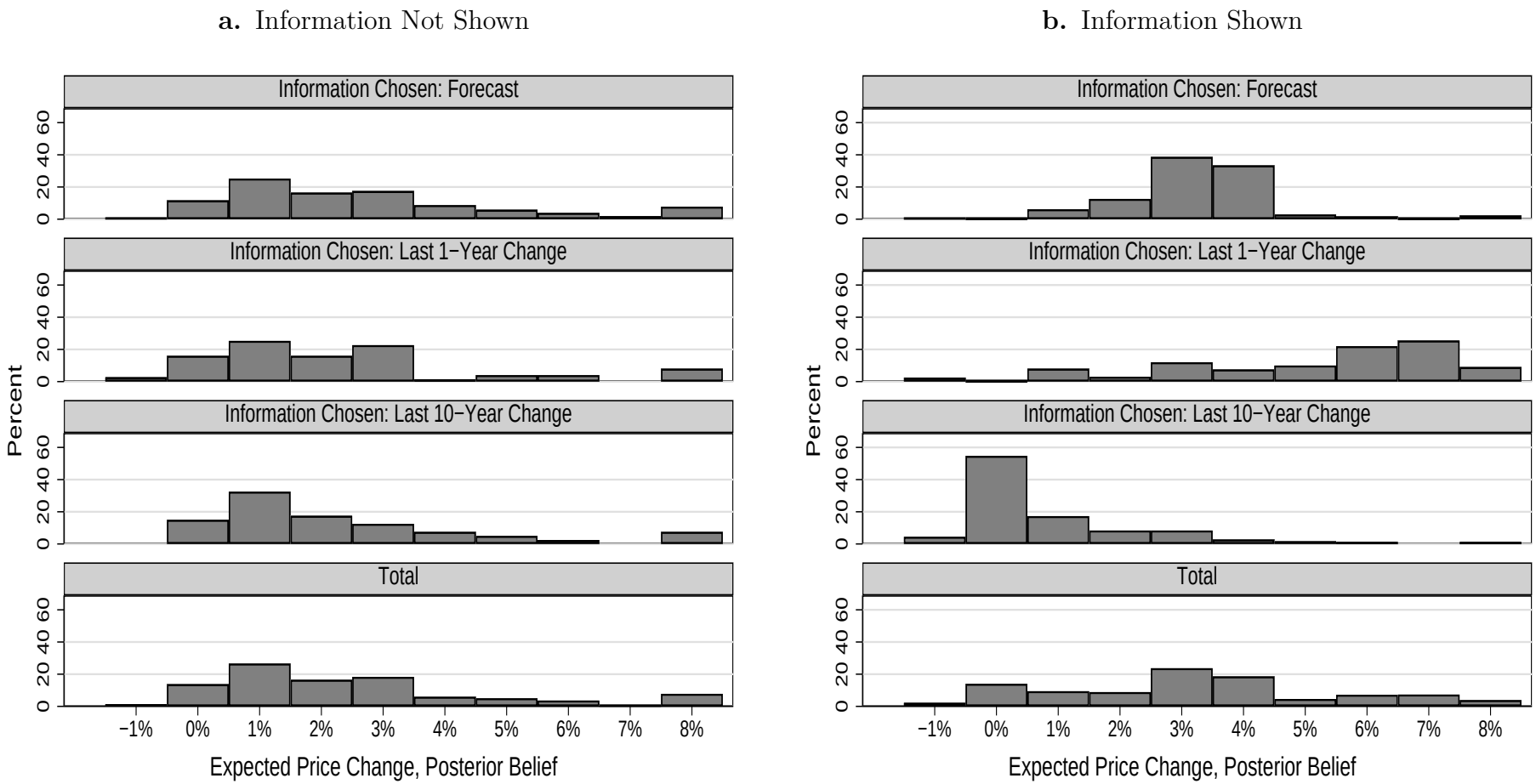


b. Information to be Shown



Notes: The distribution of the prior beliefs according the type of information most preferred. 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



Notes: The distribution of the posterior beliefs according the type of information most preferred. 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)
Prior Belief ($1,000s)	197.8	197.9	197.7	0.408
	(0.121)	(0.172)	(0.170)	
Prior Belief (% change)	0.0210	0.0210	0.0200	0.408
	(0.001)	(0.001)	(0.001)	
Income > $60,000	0.570	0.593	0.546	0.127
	(0.015)	(0.022)	(0.022)	
College Graduate	0.564	0.566	0.562	0.888
	(0.015)	(0.022)	(0.022)	
Age	50.82	51.09	50.55	0.578
	(0.485)	(0.694)	(0.677)	
Female	0.467	0.459	0.475	0.612
	(0.016)	(0.022)	(0.022)	
Married	0.640	0.660	0.620	0.183
	(0.015)	(0.021)	(0.021)	
White	0.819	0.788	0.849	0.010
	(0.012)	(0.018)	(0.016)	
Own Residency	0.746	0.751	0.741	0.722
	(0.014)	(0.019)	(0.019)	
Responded to follow-up survey	0.555	0.554	0.556	0.961
	(0.015)	(0.022)	(0.022)	
Observations	1,032	514	518	

Notes: Individual characteristics obtained from baseline survey. Column (1) corresponds to all respondents, columns (2) and (3) correspond to each of the treatment of the size of reward. Column (4) present p-value for the test of the null hypothesis that the mean characteristic is equal across all treatment groups. All variables constructed from the survey data.

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

		Invited to Follow-Up			Responded Follow-Up invitation		
	All	No	Yes	P-value	No	Yes	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prior Belief ($1,000s)	197.8	198.0	197.7	0.284	197.7	197.7	0.932
	(0.121)	(0.213)	(0.147)		(0.378)	(0.159)	
Prior Belief (% change)	0.0210	0.0220	0.0200	0.284	0.0200	0.0200	0.932
	(0.001)	(0.001)	(0.001)		(0.002)	(0.001)	
Income > $60,000	0.570	0.546	0.582	0.276	0.654	0.569	0.097
	(0.015)	(0.026)	(0.019)		(0.047)	(0.021)	
College Graduate	0.564	0.555	0.569	0.673	0.615	0.560	0.290
	(0.015)	(0.026)	(0.019)		(0.048)	(0.021)	
Age	50.82	51.52	50.45	0.302	48.60	50.78	0.146
	(0.485)	(0.861)	(0.585)		(1.363)	(0.645)	
Female	0.467	0.499	0.451	0.142	0.529	0.436	0.083
	(0.016)	(0.027)	(0.019)		(0.049)	(0.021)	
Married	0.640	0.639	0.640	0.996	0.606	0.646	0.442
	(0.015)	(0.026)	(0.018)		(0.048)	(0.020)	
White	0.819	0.820	0.818	0.956	0.837	0.815	0.589
	(0.012)	(0.020)	(0.015)		(0.036)	(0.016)	
Own Residency	0.746	0.755	0.742	0.636	0.750	0.740	0.829
	(0.014)	(0.023)	(0.017)		(0.043)	(0.018)	
Observations	1,032	355	677		104	573	

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

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

	Univariate regressions				Multivariate regressions			
	Indicator: chose...				Indicator: chose...			
	Forecast (1)	1-yr (2)	10yr (3)	MWP (4)	Forecast (5)	1-yr (6)	10-yrs (7)	MWP (8)
Female	0.022	-0.012	-0.010	-0.293	0.033	-0.015	-0.019	-0.171
	(0.032)	(0.029)	(0.027)	(0.243)	(0.033)	(0.030)	(0.028)	(0.251)
College Graduate	0.106***	-0.075**	-0.031	0.079	0.073**	-0.050	-0.023	0.016
	(0.032)	(0.030)	(0.027)	(0.250)	(0.033)	(0.031)	(0.029)	(0.257)
High Numeracy	0.119***	-0.087***	-0.032	-0.050	0.112***	-0.083***	-0.030	-0.295
	(0.032)	(0.029)	(0.027)	(0.240)	(0.034)	(0.030)	(0.029)	(0.254)
Looked for Outside Info during survey	0.150***	-0.122***	-0.028	0.048	0.123***	-0.102***	-0.021	-0.065
	(0.044)	(0.036)	(0.037)	(0.335)	(0.046)	(0.038)	(0.038)	(0.340)
Uncertainty in Prior Belief (Std)	0.005	-0.004	-0.000	-0.291**	0.005	-0.002	-0.002	-0.262**
	(0.016)	(0.015)	(0.013)	(0.123)	(0.016)	(0.015)	(0.013)	(0.124)
Median House Value in State (Std)	0.029*	-0.021	-0.008	0.216*	0.021	-0.011	-0.010	0.173
	(0.016)	(0.014)	(0.013)	(0.125)	(0.016)	(0.014)	(0.014)	(0.132)
House Value Volatility in State (Std)	0.005	-0.014	0.009	0.305***	-0.007	-0.007	0.014	0.258**
	(0.016)	(0.014)	(0.014)	(0.118)	(0.017)	(0.014)	(0.015)	(0.121)
Dummy Looked for Info in Past	-0.005	0.015	-0.010	0.589**	-0.031	0.031	-0.000	0.445*
	(0.032)	(0.029)	(0.027)	(0.246)	(0.033)	(0.030)	(0.029)	(0.263)
Dummy Own House	-0.082**	0.091***	-0.010	0.658**	-0.071*	0.084**	-0.013	0.538*
	(0.037)	(0.032)	(0.031)	(0.279)	(0.039)	(0.033)	(0.032)	(0.291)
Conf. in past Recall	-0.027*	0.026*	0.001	0.258**	-0.013	0.014	-0.001	0.125
	(0.016)	(0.015)	(0.014)	(0.126)	(0.016)	(0.015)	(0.014)	(0.134)
Mean	0.47	0.29	0.23	4.41	0.47	0.29	0.23	4.41
Observations	989	989	989	938	989	989	989	938
R^2					0.039	0.031	0.004	

Notes: Heteroskedasticity-robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. An interval regression is estimated in columns (4) and (8) using maximum willingness to pay as the dependent variable. In columns (1), (2), (3), (5), (6) and (7) an OLS regression is estimated using a dummy variable (=1) if the individual preferred the forecast information, 1 year information, or 10 years information as the dependent variable. Column (1) to (4) present the coefficients from the univariate regression between the dependent variable and each independent variable. Columns (5) to (8) present the coefficients from the multivariate regression.

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

	Max. Willingness to Pay			Dummy Chose Forecast		
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy High Reward	0.729***	0.695***	0.409	0.00449	0.00314	-0.00957
	(0.240)	(0.241)	(0.401)	(0.0326)	(0.0325)	(0.0497)
High Reward*College			0.547			0.0263
			(0.497)			(0.0657)
High Reward*Std. Numeracy		0.552**			0.0201	
		(0.259)			(0.0330)	
Constant	4.051***	4.059***	4.155***	0.471***	0.469***	0.418***
	(0.166)	(0.167)	(0.278)	(0.0231)	(0.0231)	(0.0355)

Notes: (N=938) Heteroskedasticity-robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Columns (1) through (3) report results for interval regressions with maximum willingness to pay as the dependent variable. Columns (4) through (6) report OLS regressions where the dependent variable is a dummy indicating if the individual preferred the forecast information. The variable *Dummy Less than College* equals 1 if the level of the education of the individual is less than a Bachelor degree. The variable *Std. Numeracy Score* indicates the level of ability in numeracy, with higher values indicating higher numeracy and normalized to have a mean of 0 and a standard deviation of 1.

Table 5: Cost of Information and Dispersion of Expectations

		Low Price	**High Price**	P-value Diff
		(1)	(2)	(3)
Prior	Mean	2.05 (0.088)	2.08 (0.099)	0.78
	SD	1.95 (0.062)	2.08 (0.070)	0.16
	Uncertainity	3.85 (0.129)	3.62 (0.131)	0.37
Posterior	Mean	3.15 (0.103)	2.84 (0.107)	0.04
	SD	2.30 (0.073)	2.26 (0.076)	0.70
	Uncertainity	2.78 (0.111)	2.90 (0.121)	0.59
Observations		495	443	

Notes: The average level, the dispersion and uncertainty is presented for the prior and posterior belief. The prior belief refers to the expected change for home prices to the end of the year before the information, that may help with forecasting, was presented to individuals. Posterior belief refers to the expected change after the information was shown to individuals. Both in the prior and posterior belief the survey elicited the respondent's subjective belief distribution about home prices. To measure uncertainty at the individual level, we fit these binned responses to a normal distribution for each individual, and use the estimated standard deviation of the fitted distribution as a measure of individual-level uncertainty, with higher values denoting higher uncertainty. Columns (1) and (2) present the information for individuals who were randomly assigned to the Low and High Price respectively. Column (3) presents p-value for the test of the null hypothesis that the mean characteristic is equal across (1) and (2). Numbers in parentheses in each cell are standard errors.

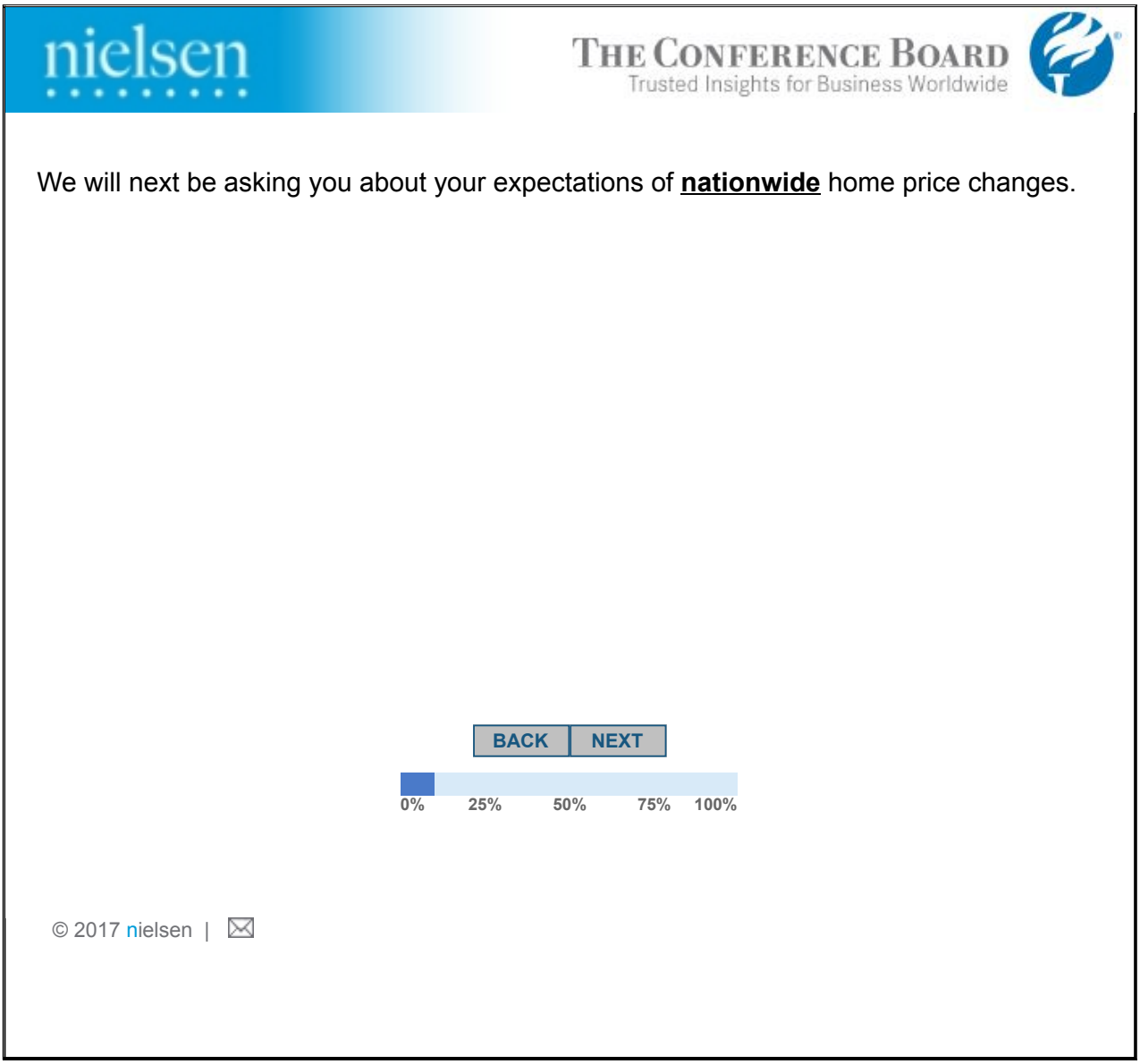
Table 6: Effect of Information-Acquisition on the Distribution of Expectations

		Baseline Sample		Follow-Up Sample
		Prior	Posterior	Follow-Up
		(1)	(2)	(3)
Information Shown				
All	Mean	2.12 (0.073)	3.15 (0.084)	3.08 (0.127)
N=747 (419)	S.D.	2.01 (0.052)	2.29 (0.059)	2.60 (0.090)
	Uncertainty	3.76 (0.105)	2.72 (0.090)	3.10 (0.141)
Forecast	Mean	2.19 (0.110)	3.26 (0.073)	3.35 (0.186)
N=354 (189)	S.D.	2.07 (0.078)	1.36 (0.051)	2.56 (0.132)
	Uncertainty	3.73 (0.148)	2.75 (0.130)	3.26 (0.221)
1 Year Change	Mean	2.23 (0.139)	5.01 (0.161)	3.57 (0.254)
N=209 (124)	S.D.	2.01 (0.099)	2.32 (0.114)	2.83 (0.181)
	Uncertainty	3.55 (0.208)	3.10 (0.186)	3.54 (0.282)
10 Year Change	Mean	1.86 (0.138)	0.85 (0.113)	2.02 (0.200)
N=184 (106)	S.D.	1.87 (0.098)	1.53 (0.080)	2.06 (0.143)
	Uncertainty	4.04 (0.213)	2.22 (0.158)	2.30 (0.213)
Information Not Shown				
All	Mean	1.93 (0.135)	2.48 (0.149)	2.79 (0.224)
N=242 (134)	S.D.	2.10 (0.096)	2.32 (0.106)	2.60 (0.160)
	Uncertainty	3.84 (0.178)	3.44 (0.181)	3.54 (0.286)
Forecast	Mean	2.05 (0.192)	2.75 (0.217)	2.77 (0.309)
N=114 (69)	S.D.	2.05 (0.137)	2.32 (0.155)	2.56 (0.221)
	Uncertainty	4.07 (0.273)	3.36 (0.260)	2.97 (0.360)
1 Year Change	Mean	1.77 (0.222)	2.27 (0.251)	3.03 (0.430)
N=81 (41)	S.D.	2.00 (0.159)	2.26 (0.179)	2.76 (0.312)
	Uncertainty	4.16 (0.321)	3.77 (0.331)	5.03 (0.665)
10 Year Change	Mean	1.90 (0.349)	2.17 (0.348)	2.42 (0.505)
N=47 (24)	S.D.	2.39 (0.252)	2.39 (0.251)	2.47 (0.373)
	Uncertainty	2.73 (0.317)	3.08 (0.401)	2.65 (0.426)
Observations		989		553

Notes: The average level, the dispersion and uncertainty is presented for the prior, posterior, and follow-up belief conditional on seeing the information and the most-preferred information source. The prior belief refers to the expected change for home prices to the end of the year before the information, that may help with forecasting, was presented to individuals. Posterior belief refers to the expected change after the information was shown to individuals, and follow-up belief refers to the expected change for home prices between the follow-up survey (4 months after the baseline survey) and the end of the year. Both in the prior, posterior, and follow-up belief the survey elicited the respondent's subjective belief distribution about home prices. To measure uncertainty at the individual level, we fit these binned responses to a normal distribution for each individual, and use the estimated standard deviation of the fitted distribution as a measure of individual-level uncertainty, with higher values denoting higher uncertainty. The first number in N corresponds to the number observations in the baseline survey. The number in parentheses corresponds to the number of observations in the Follow-Up survey. In columns (1) and (2) we present the results for the Baseline Sample. In columns (3), the sample includes individuals who were invited and responded the Follow-up survey. Numbers in parentheses in each cell are standard errors.

Online Appendix: For Online Publication Only

A Survey Instrument



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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

BACK NEXT

0% 25% 50% 75% 100%

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

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

Please enter a number in the box below.

[ ] dollars

BACK NEXT

0% 25% 50% 75% 100%

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

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

Please enter a number in the box below.

194000 dollars

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

If not, please change your answer.

BACK NEXT

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	

BACK NEXT

0% 25% 50% 75% 100%

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

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

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

BACK NEXT

0% 25% 50% 75% 100%

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

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

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

BACK NEXT

0% 25% 50% 75% 100%

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

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

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

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

BACK NEXT

0% 25% 50% 75% 100%

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

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

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

- (●) see information
- ( ) receive $0.01

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

- (●) see information
- ( ) receive $0.50

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

- (●) see information
- ( ) receive $1

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

- (●) see information
- ( ) receive $1.50

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

- (●) see information
- ( ) receive $2

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

- (●) see information
- ( ) receive $2.50

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

- (●) see information
- ( ) receive $3

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

- (●) see information
- ( ) receive $3.50

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

- (●) see information
- ( ) receive $4

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

- (●) see information
- ( ) receive $4.50

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

- (●) see information
- ( ) receive $5

BACK NEXT

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%

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Scenario 1 was picked at random for you.

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

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

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

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

NEXT

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.

[ ] 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%

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

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

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

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

BACK NEXT

0% 25% 50% 75% 100%

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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%

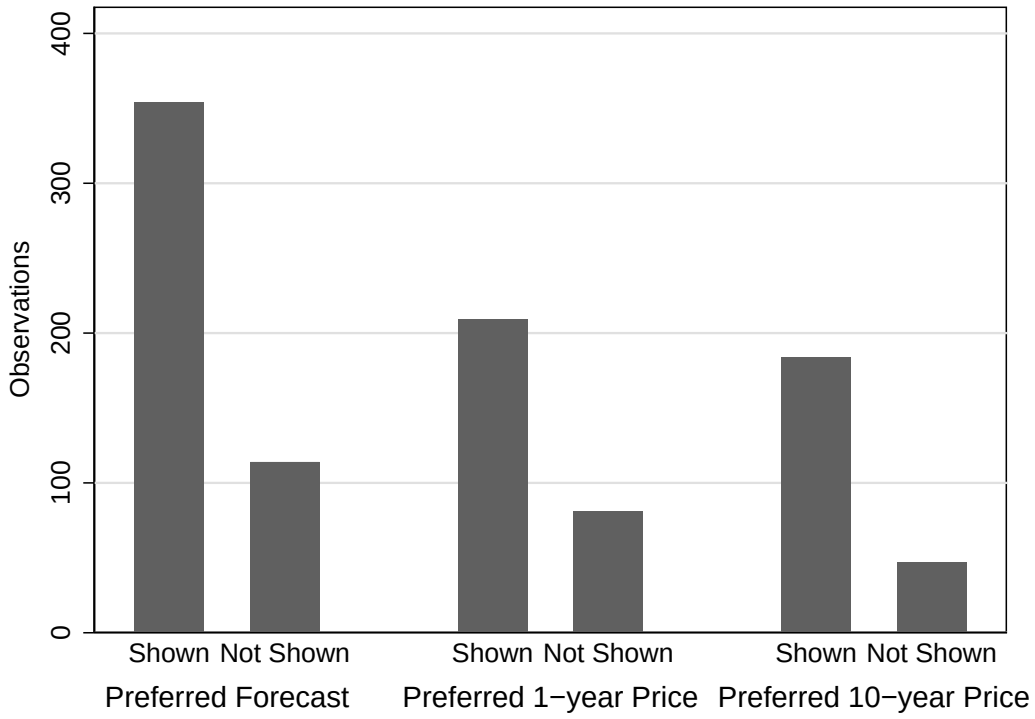
B Additional Results

B.1 Decomposition of learning rates

In this section, we give more details about the identification of the learning rates. Figure B.3.a shows how the beliefs evolved after the information was provided. The y-axis indicates the revision in national home price beliefs, i.e., posterior belief *minus* prior belief. The x-axis shows the "gap" between the signal and the prior belief. For instance, if the respondent had a prior belief of 1% and was shown the forecast of experts (which was 3.6%), the x-axis would take the value of 2.6%. Intuitively, the x-axis shows how much potential for revision there is, and the y-axis shows the actual revision. If individuals fully reacted to the signal shown, we would expect all dots to lie on the 45-degree line. If individuals did not react to the information, we would expect the dots to lie in a horizontal line. The slope of the line is 0.616, 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).

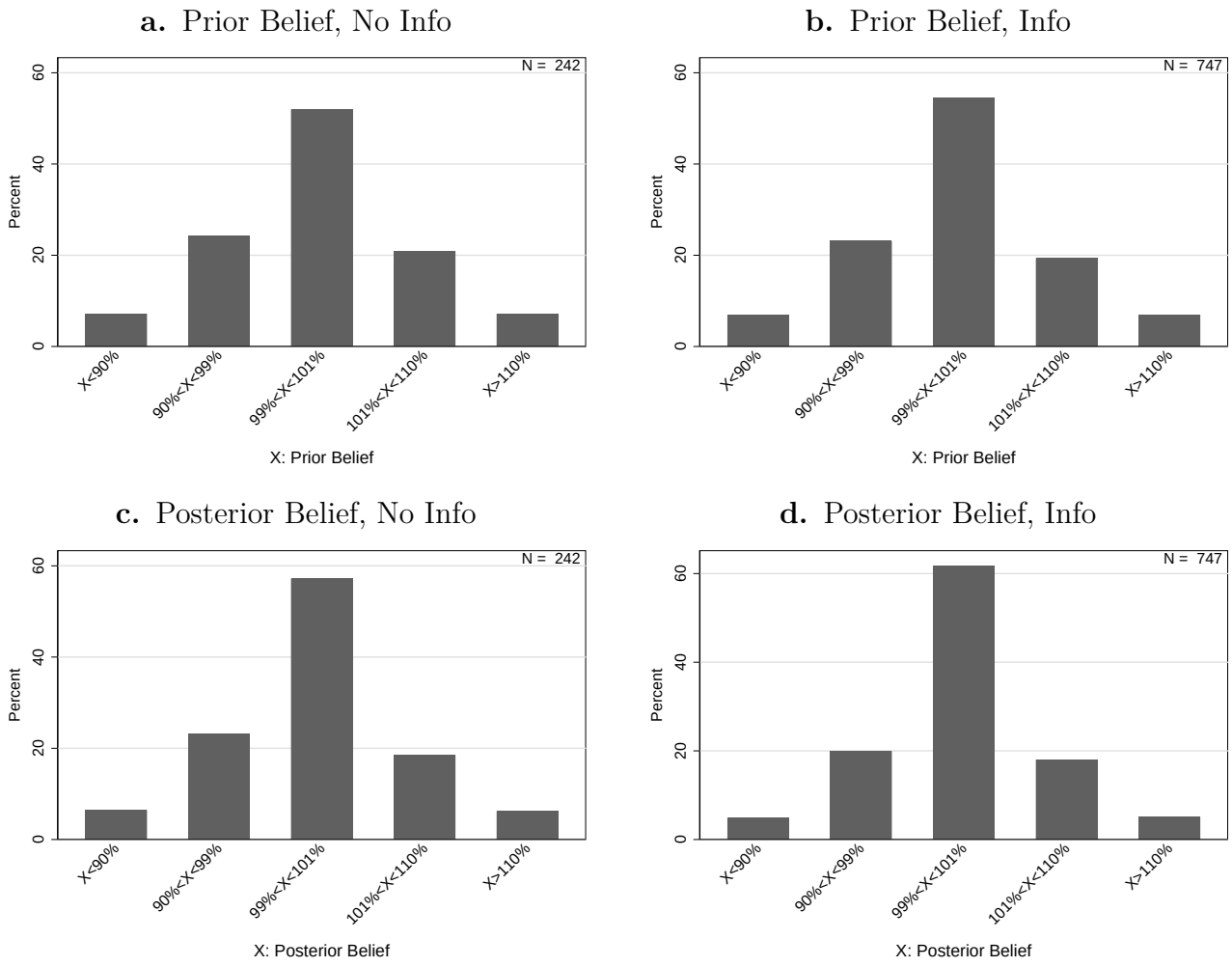
Figure B.3.b is identical to Figure B.3.a, except that instead of corresponding to individuals who were shown the signal, it corresponds to individuals who were not shown the signal. Consistent with the typos and/or information search, there is reversion to the signal when the signal was not shown. However, the magnitude of this reversion to the signal is substantially lower than the corresponding magnitude of the reversion when information is actually shown (0.132 versus 0.616). Figure 4.a presents the estimated learning rates (estimates of α), which roughly correspond to the difference between the slopes in Figure B.3.a and B.3.b (i.e., the incremental convergence towards the signal due to the signal provision).

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



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

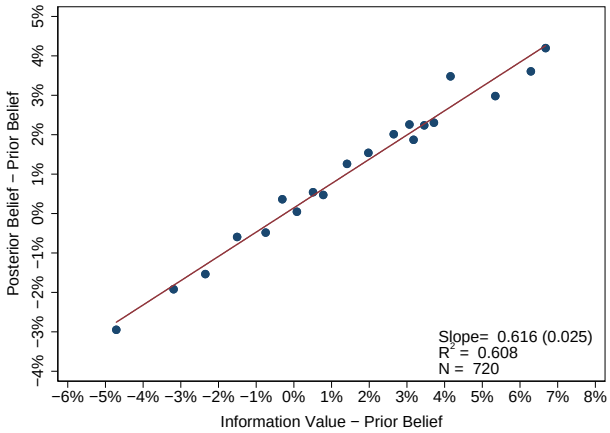
Figure B.2: Certainty in Prior and Posterior Beliefs, By Information Provision



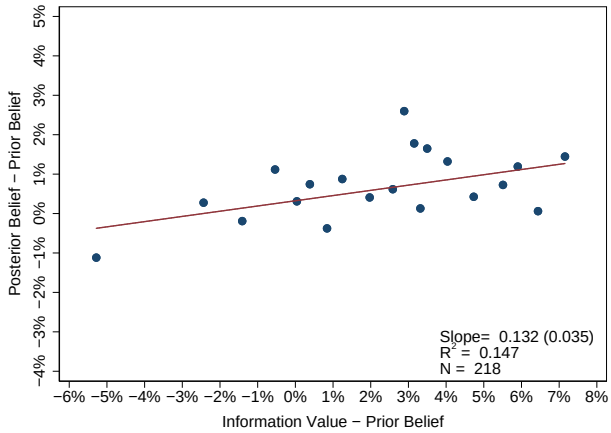
Notes: Certainty in Prior and Posterior Beliefs according information provision. It measures how confident are individuals in their beliefs. The x-axis presents the range of possible variations in the estimation. And the y-axis presents the estimation of the percent chance of the possible variations.

Figure B.3: Changes from Prior to Posterior Beliefs

a. Revisions if Signal Shown

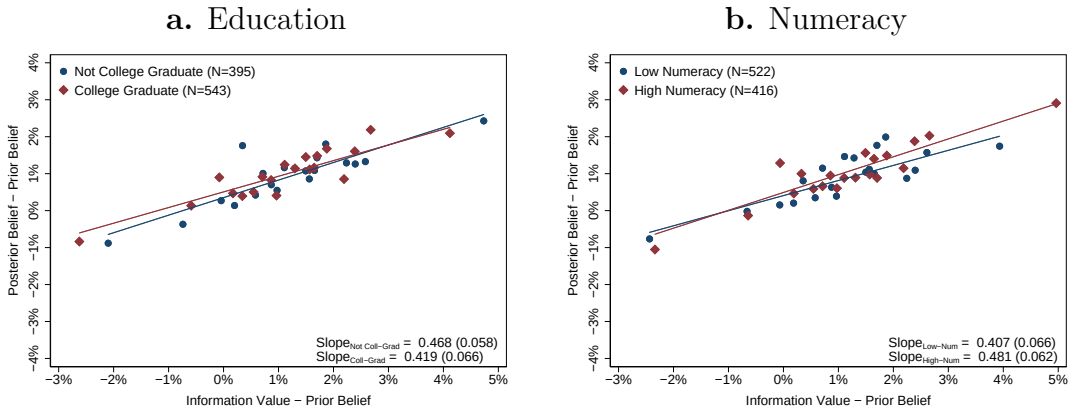


b. Revisions if Signal not Shown



Notes: The figures measure how individuals revise their estimations of the expected value of a typical home 1 year forward according to the information shown. 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.

Figure B.4: Learning Rates according Education and Numeracy



Notes: Learning rates are estimated using equation (4) from section 3.3. The graphs show a binned-scatter plot based on 20 bins. Slopes, robust standard errors (in parentheses) and R^2 are based on a linear regression of the belief update (i.e., the dependent variable is the belief update during the baseline survey) on the signal gap (i.e., signal value minus the prior belief) interacted by a dummy that takes the value 1 if the individual was shown the signal. The regressions control for the signal gap (i.e., without the interaction) and dummies for maximum willingness to pay. Panel a. presents the results according education (i.e., individuals who graduate from college or not) and panel b. presents the results according numeracy (i.e., individuals who have high or low numeracy).

Table B.1: Randomization Balance by Scenario Assigned

	All	1	2	3	4	5	6	7	8	9	10	11	F-test P-value
Prior Belief ($1,000s)	197.8	197.7	197.3	198.1	198.1	197.8	197.3	197.9	197.5	198.6	199.5	196.3	0.118
	(0.125)	(0.311)	(0.301)	(0.367)	(0.354)	(0.368)	(0.397)	(0.441)	(0.469)	(0.552)	(0.960)	(0.726)	
Prior Belief (% change)	0.0210	0.0200	0.0180	0.0220	0.0220	0.0210	0.0180	0.0210	0.0190	0.0250	0.0290	0.0130	0.118
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.004)	
Income > $60,000	0.579	0.547	0.581	0.619	0.633	0.593	0.521	0.607	0.562	0.562	0.440	0.556	0.749
	(0.016)	(0.043)	(0.044)	(0.043)	(0.043)	(0.045)	(0.051)	(0.054)	(0.058)	(0.062)	(0.101)	(0.176)	
College Graduate	0.573	0.577	0.605	0.571	0.594	0.542	0.500	0.583	0.630	0.547	0.560	0.667	0.902
	(0.016)	(0.042)	(0.043)	(0.044)	(0.044)	(0.046)	(0.051)	(0.054)	(0.057)	(0.063)	(0.101)	(0.167)	
Age	50.72	50.37	49.88	50.93	51.57	51.18	52.12	48.13	49.33	53.19	52.52	45	0.546
	(0.496)	(1.359)	(1.370)	(1.508)	(1.345)	(1.464)	(1.432)	(1.669)	(1.850)	(1.919)	(3.159)	(4.308)	
Female	0.465	0.453	0.434	0.389	0.508	0.492	0.521	0.500	0.425	0.516	0.360	0.556	0.526
	(0.016)	(0.043)	(0.044)	(0.044)	(0.044)	(0.046)	(0.051)	(0.055)	(0.058)	(0.063)	(0.098)	(0.176)	
Married	0.643	0.657	0.667	0.579	0.648	0.661	0.604	0.679	0.603	0.719	0.720	0.333	0.390
	(0.015)	(0.041)	(0.042)	(0.044)	(0.042)	(0.044)	(0.050)	(0.051)	(0.058)	(0.057)	(0.092)	(0.167)	
White	0.820	0.730	0.814	0.841	0.852	0.831	0.885	0.845	0.808	0.812	0.720	0.889	0.236
	(0.012)	(0.038)	(0.034)	(0.033)	(0.032)	(0.035)	(0.033)	(0.040)	(0.046)	(0.049)	(0.092)	(0.111)	
Own Residency	0.749	0.672	0.798	0.714	0.836	0.737	0.760	0.714	0.699	0.812	0.800	0.667	0.082
	(0.014)	(0.040)	(0.035)	(0.040)	(0.033)	(0.041)	(0.044)	(0.050)	(0.054)	(0.049)	(0.082)	(0.167)	
Responded to follow-up survey	0.559	0.518	0.558	0.563	0.578	0.576	0.594	0.655	0.521	0.406	0.600	0.667	0.269
	(0.016)	(0.043)	(0.044)	(0.044)	(0.044)	(0.046)	(0.050)	(0.052)	(0.059)	(0.062)	(0.100)	(0.167)	
Observations	989	137	129	126	128	118	96	84	73	64	25	9	

Notes: Individual characteristics obtained from baseline survey. Column (1) corresponds to all respondents, columns (2) and (12) correspond to each of the treatment of the scenario selected. Column (13) presents p-value for the test of the null hypothesis that the mean characteristic is equal across all treatment groups. All variables constructed from the survey data.

Table B.2: Effect of Information-Acquisition on the Distribution of Expectations

		Baseline Sample		Follow-Up Sample		
		Prior	Posterior	Prior	Posterior	Follow-Up
		(1)	(2)	(3)	(4)	(5)
Information Shown						
All	Mean	2.12 (0.073)	3.15 (0.084)	2.15 (0.101)	3.22 (0.114)	3.08 (0.127)
N=747 (419)	S.D.	2.01 (0.052)	2.29 (0.059)	2.07 (0.072)	2.33 (0.081)	2.60 (0.090)
	Uncertainty	3.76 (0.105)	2.72 (0.090)	3.57 (0.136)	2.69 (0.120)	3.10 (0.141)
Forecast	Mean	2.19 (0.110)	3.26 (0.073)	2.16 (0.154)	3.21 (0.101)	3.35 (0.186)
N=354 (189)	S.D.	2.07 (0.078)	1.36 (0.051)	2.12 (0.110)	1.39 (0.072)	2.56 (0.132)
	Uncertainty	3.73 (0.148)	2.75 (0.130)	3.54 (0.191)	2.70 (0.174)	3.26 (0.221)
1 Year Change	Mean	2.23 (0.139)	5.01 (0.161)	2.36 (0.182)	5.17 (0.200)	3.57 (0.254)
N=209 (124)	S.D.	2.01 (0.099)	2.32 (0.114)	2.03 (0.130)	2.22 (0.142)	2.83 (0.181)
	Uncertainty	3.55 (0.208)	3.10 (0.186)	3.38 (0.274)	3.15 (0.255)	3.54 (0.282)
10 Year Change	Mean	1.86 (0.138)	0.85 (0.113)	1.87 (0.193)	0.95 (0.161)	2.02 (0.200)
N=184 (106)	S.D.	1.87 (0.098)	1.53 (0.080)	1.99 (0.138)	1.66 (0.115)	2.06 (0.143)
	Uncertainty	4.04 (0.213)	2.22 (0.158)	3.83 (0.271)	2.12 (0.199)	2.30 (0.213)
Information Not Shown						
All	Mean	1.93 (0.135)	2.48 (0.149)	1.66 (0.144)	2.43 (0.184)	2.79 (0.224)
N=242 (134)	S.D.	2.10 (0.096)	2.32 (0.106)	1.67 (0.103)	2.13 (0.131)	2.60 (0.160)
	Uncertainty	3.84 (0.178)	3.44 (0.181)	3.80 (0.237)	3.38 (0.235)	3.54 (0.286)
Forecast	Mean	2.05 (0.192)	2.75 (0.217)	1.72 (0.195)	2.45 (0.237)	2.77 (0.309)
N=114 (69)	S.D.	2.05 (0.137)	2.32 (0.155)	1.62 (0.140)	1.97 (0.170)	2.56 (0.221)
	Uncertainty	4.07 (0.273)	3.36 (0.260)	4.00 (0.344)	3.03 (0.290)	2.97 (0.360)
1 Year Change	Mean	1.77 (0.222)	2.27 (0.251)	1.81 (0.285)	2.50 (0.347)	3.03 (0.430)
N=81 (41)	S.D.	2.00 (0.159)	2.26 (0.179)	1.83 (0.207)	2.22 (0.252)	2.76 (0.312)
	Uncertainty	4.16 (0.321)	3.77 (0.331)	4.24 (0.469)	4.27 (0.526)	5.03 (0.665)
10 Year Change	Mean	1.90 (0.349)	2.17 (0.348)	1.20 (0.309)	2.23 (0.506)	2.42 (0.505)
N=47 (24)	S.D.	2.39 (0.252)	2.39 (0.251)	1.52 (0.229)	2.48 (0.374)	2.47 (0.373)
	Uncertainty	2.73 (0.317)	3.08 (0.401)	2.50 (0.398)	2.88 (0.506)	2.65 (0.426)
Observations		989		553		

Notes: The average level, the dispersion and uncertainty is presented for the prior, posterior, and follow-up belief conditional on seeing the information and the most-preferred information source. The prior belief refers to the expected change for home prices to the end of the year before the information, that may help with forecasting, was presented to individuals. Posterior belief referes to the expected change after the information was shown to individuals, and follow-up belief referes to the expected change for home prices between the follow-up survey (4 months after the baseline survey) and the end of the year. Both in the prior, posterior, and follow-up belief the survey elicitated the respondent's subjectivie belief distribution about home prices. To measure uncertainty at the individual level, we fit these binned responses to a normal distribution for each individual, and use the estimated standard deviation of the fitted distribution as a measure of individual-level uncertainty, with higher values denoting higher uncertainty. The first number in N corresponds to the number observations in the baseline survey. The number in parentheses corresponds to the number of observations in the Follow-Up survey. In columns (1) and (2) we present the results for the Baseline Sample. In columns (3), (4) and (5) the sample includes individuals who were invited and responded the Follow-up survey.