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Abstract

Home price expectations are believed to play an important role in housing dynamics, yet we have limited understanding of how they are formed and how they affect behavior. Using a unique "information experiment" embedded in an online survey, this paper investigates how consumers' home price expectations respond to past home price growth and how they impact investment decisions. After eliciting respondents' initial beliefs about past and future local home price changes, we present a random subset of the respondents with factual information about past (one- or five-year) changes and then re-elicit expectations. This unique "panel" data allows us to identify causal effects of the information and provides insights on the expectation formation process. We find that, on average, year-ahead home price expectations are revised in a way consistent with short-term momentum in home price growth, though respondents tend to underpredict the strength of momentum. Revisions of longer-term expectations show that respondents do not expect the empirically occurring mean reversion in home price growth. These results are consistent with recent behavioral models of housing cycles. Finally, we present robust evidence of home price expectations impacting (actual and intended) housing-related behaviors, both in the cross section and within-individual.

Key words: housing, expectation formation, information, updating

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1 Introduction

Home price expectations play a prominent role in many accounts of the housing boom that occurred during the early- to mid-2000s, both in the US and globally (e.g. Shiller 2005, Foote et al. 2012, Glaeser et al. 2013, Kaplan et al. 2016). Beyond this particular episode, home prices display patterns such as strong momentum at a relatively short horizon (e.g. Case and Shiller 1989, Guren 2016) and mean reversion at a longer horizon (e.g. Cutler et al. 1991, Glaeser et al. 2014) that researchers in this area have found challenging to explain within a fully rational framework. As a consequence, in recent years there has been increasing interest in exploring theories of home price expectations that, to varying degrees, depart from full rationality and instead feature some form of extrapolation from recent growth.[1] However, so far there exists very little direct empirical evidence on home price expectations that such theories could be validated against.

In this paper, we present new evidence on how home price expectations are formed, and how they affect behavior. Specifically, we rely on a novel "information experiment" within an online household survey to test how respondents update their expectations about future home price growth in their local area when they are provided with objective information about recent home price growth. We furthermore embed an incentivized portfolio choice experiment in the survey that enables us to study the causal effect of expectations on a housing-related investment decision.

The survey has three main stages. In the first stage, respondents are asked about their perceptions of home price changes in their local area over the past one and five years, and about their expectations of future local home price changes over the next one and five years. Individuals also make a hypothetical decision on an investment with payoffs linked to future local home price changes— specifically, respondents are asked how they would allocate \$1,000 between a housing market fund with returns tied to local year-ahead house price growth and a risk-free savings account. In the intermediate stage, respondents are randomly exposed to either objective information about actual local home price changes over the past one year, or over the past five years, or no information (control group). In the final stage, future home price expectations are re-elicited, and respondents are again presented with the investment decision, which is now incentivized.

This empirical design allows us to study two main questions. First, we test *whether* and *how* respondents revise their expectations after being provided with information that may differ from

[1] Work in this vein includes Piazzesi and Schneider (2009), Adam et al. (2012), Burnside et al. (2016), Gao et al. (2015) Gelain and Lansing (2014), Guren (2016), Glaeser and Nathanson (2015), and Granziera and Kozicki (2015); see Glaeser and Nathanson (2014) for a review.

their priors about recent home price growth in their local area. For instance, if a respondent thought that prices had increased by 3% over the past year, and expects them to increase by 2% over the coming year before we provide her with the information, how does she react after learning that according to a house price index (HPI), prices had in fact increased by 6%? If she believes in momentum in house prices, we would expect her to adjust her future expectations upward, while a belief in mean reversion would lead her to revise her expectations of future growth downward. On the other hand, if she believes that home prices follow a random walk, there should be little systematic revisions in response to the provided information. Second, the investment decision allows us to investigate whether home price expectations are linked with (hypothetical and actual) behavior; the panel aspect of our design allows us to study this link both in the cross-section as well as within individual.

Our design has several advantages over alternative approaches. While the literature has documented correlations between past home price changes and subjective home price expectations (e.g. Case et al. 2012, Kuchler and Zafar 2015), by directly manipulating individuals' information sets, we can provide a causal interpretation to the relationship between past changes and expectations. Second, our design does not rely on any assumptions on either the respondents' information set or any belief-updating model, and does not suffer from confounds that would plague any cross-sectional analysis. Instead, we allow the updating patterns to inform us about the theories that best fit the empirical patterns. This is possible because our within-individual design, with rich data on priors and expectations over different horizons, generates quantitative evidence that models can be compared against. Relatedly, the heterogeneity in updating that we document sheds further light on different theories of belief-updating. Third, the panel on beliefs and choices, together with the exogenous information treatment, allows us to establish a causal link between expectations and behavior. To our knowledge, this is the first paper that brings direct evidence on the link between home price expectations and related behavior to the fore.

We find that, when provided with information about past year local home price growth, respondents on average update their year-ahead local home price expectations in an extrapolative manner: for each percentage point underestimation (overestimation) of past growth relative to the HPI, respondents adjust their expectations upward (downward) by 0.20 percentage points. In contrast, information about price growth over the previous five years has no significant effect on revision of year-ahead expectations (although directionally respondents also extrapolate).

A natural question to ask is how these findings compare with actual serial correlation in home price growth. Home price growth exhibits strong positive autocorrelation at the one-year horizon (Case and Shiller, 1989). The coefficient of a regression of local one-year home price growth on lagged one-year growth, averaged across the zip codes in our sample, is a precisely estimated 0.53; the coefficient in the case of one-year growth regressed on lagged five-year growth is 0.14 (and imprecisely estimated). Thus, over the short horizon, the average respondent directionally updates in a "rational" manner, that is, one that is consistent with data. However, the average respondent tends to *underreact* to past growth, given the strong short-term momentum in actual home prices.

A different picture emerges in the case of medium-term expectations (which we define as expectations for the two-to-five year horizon). Home prices tend to exhibit mean reversion over longer horizons. However, in our experiment, respondents tend to update their medium-term expectations in an extrapolative manner (though with smaller estimated effect sizes than at the one-year horizon). This evidence appears most consistent with "behavioral" models of housing market dynamics; for instance, the estimated effect sizes are close to the calibration in Glaeser and Nathanson (2015). From a broader perspective, these patterns support the view of extrapolation or an under-appreciation of mean reversion as a potentially important driver of fluctuations in financial markets (e.g. DeLong et al. 1990, Barberis et al. 1998, Barsky and DeLong 1993, Fuster et al. 2012, Barberis et al. 2015, Bordalo et al. 2016).

We also study heterogeneity in updating behavior. Treatment respondents (that is, those who receive the information) are more likely to update their expectations than a control group. Conditional on updating, treatment group respondents are much more likely to be "extrapolators" (revising their expectations in the direction of the gap between revealed HPI growth and their prior about past growth) than to be "mean reverters" (doing the opposite) for expectations at both horizons. We find mixed evidence for models of age-dependent updating (Malmendier and Nagel, 2016): younger respondents and those with shorter tenures in their locality are not more likely to update than their counterparts. However, conditional on updating, they are much more likely to be extrapolators. Perhaps our most intriguing result is that individuals residing in areas with inelastic housing supply (or with stronger long-term mean reversion in home prices) exhibit a higher propensity to extrapolate from past growth at both horizons we study. This is arguably rational behavior at the shorter horizon (since inelastic areas tend to have stronger momentum), but not for the longer horizon.

Turning to our second question of how expectations affect behavior, we find that expectations have an economically and statistically significant effect on respondents' investment allocation, both across respondents and within-respondent (meaning the change in the housing fund share between the hypothetical and incentivized rounds is related to the change in expectations following the information provision). Outside the stylized investment experiment, we also study the relation between respondents' baseline expectations and stated intentions of buying a non-primary (vacation or investment) home and the likelihood of buying (rather than renting) their next primary residence if they were to move over the next three years. In addition, for current owners, we elicit the likelihood of making investments in the home over the next year, as well as putting their home on the market over the next year. In each case, we find a (statistically and economically) significant correlation between expectations and intended behavior, controlling for an extensive set of observable respondent characteristics. These findings suggest that survey measures of house price expectations contain meaningful information to understand behavior, and are therefore important variables to track for policy makers and housing market analysts.

While the survey design is discussed in more detail later in the paper, we point out a few noteworthy features here. First, we randomize our respondents into different question "frames" when eliciting their perceptions and expectations to ensure that our results are not exclusive to a given frame. Specifically, half the respondents are asked for their perceptions and forecasts in terms of house price levels (from which we then calculate percent changes) while the others are directly asked about percent changes. Our main results hold within both frames. Second, the information provision (and re-elicitation of expectations) does not happen immediately after the respondents' priors are elicited, but only after they have gone through various other (unrelated) survey questions. This makes it unlikely that the effects of the information are driven by "demand effects" or a desire to give the "correct" answer. Our design also features a control group that is not provided with information, so that we can account for the effects on expectations that merely completing the survey may have. Third, we test whether the information provision has persistent effects on our respondents' beliefs by re-eliciting them in a separate follow-up survey two months after the initial one. We find that indeed, the average effect of the information on short-term expectations remains almost the same as within the main survey.

The empirical design in this paper is closest to that used in a recent literature that employs information experiments in surveys to understand expectation formation (Armantier et al. 2014, Cavallo et al. 2014, and Coibion et al. 2015). The actual dependence in home prices (and the regional variation in it) provides us with a natural benchmark against which we can evaluate the updating patterns of our respondents. These papers, in contrast, focus on inflation expectations, where there is no clear benchmark against which to compare observed updating patterns. The information experiment in our survey is also related to other experimental work in lab settings (e.g. Schmalensee 1976, Haruvy et al. 2007, Rötheli 2010, and Beshears et al. 2013).

Our work also relates directly to other survey-based studies on expectation formation. In the housing market, Case and Shiller (2003) and Case et al. (2012) measure expected future home price growth in a sample of recent homebuyers across four metropolitan areas, finding evidence consistent with extrapolation at one-year and ten-year forecast horizons. Niu and van Soest (2014) and Ma (2015) study home price expectations in the American Life Panel and the Michigan Survey of Consumers, respectively, while Bover (2015) conducts a similar exercise in Spanish data. Kuchler and Zafar (2015) study how experienced local home price growth (as measured by a HPI) affects expectations about future national home price growth.[2] Our approach is unique in that we directly measure respondents' perceptions of recent local home price growth (over the past one and five years) and test whether changing this perception through information provision affects future expectations. Other work has used surveys to study the properties of stock market expectations (e.g. Vissing-Jorgensen 2004, Amromin and Sharpe 2014, Greenwood and Shleifer 2014) and inflation expectations (e.g. Malmendier and Nagel 2016, Madeira and Zafar 2015). Gennaioli et al. (2016) present evidence that corporate CFOs' expectations of future earnings growth are extrapolative, and affect firm behavior.[3]

The remainder of the paper is organized as follows: the next section describes the design of the survey, how it was administered, and details about the respondent sample. In order to provide a benchmark for our experimental setting, Section 3 analyzes the dependence in actual home prices over different horizons. Section 4 characterizes respondents' perceptions and expectations at the baseline (prior to the information provision). Section 5 presents the experimental results of the effects of information on expected future home price growth. Section 6 studies the effect of expectations on behavior, and Section 7 offers a brief conclusion.

[2] Bailey et al. (2016) study how a qualitative survey measure of the attractiveness of housing as an investment is affected by the home price experiences of (out-of-town) friends, and also how these experiences affect housing-related behavior; we return to this study in the conclusion.

[3] There is a large literature in macroeconomics on the role that information frictions play in expectation formation (see e.g. the sticky/noisy information models of Mankiw and Reis 2002 or Sims 2003). In our setting we exogenously provide (differential) information to our respondents, thereby alleviating these frictions in information acquisition for them. Coibion and Gorodnichenko (2012, 2015) present a unifying framework to empirically test and distinguish between several sticky/noisy information models based on *aggregate* forecast data from surveys; these tests would not be applicable to our individual-level data.

2 Survey Design and Administration

Our data come from two original online surveys, both fielded as part of the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). The SCE is an internet-based survey of a rotating panel of approximately 1,200 household heads from across the US, with the goal of eliciting 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. Respondents are invited to participate in at least one survey each month.[4]

The first and main survey is a special module on housing, fielded in February 2015. Repeat panelists (that is, active panel members who had participated in a SCE monthly survey in the prior eleven months) were invited to participate in the housing module. Out of a total sample of 1,383 household heads on the panel that were invited, 1,205 participated, implying a response rate of 87%.

The housing module contains multiple blocks of questions, some differing between owners and renters. The respondents are asked, among other things, about their perceptions of past local home price changes and expectations for future local home price changes, (current and future) financing conditions, past housing-related behavior (such as buying a home, and housing debt), and the future likelihood of buying a home. Respondents also provide information about their zip code location, their household income, and many other demographic variables. The median survey time was 34 minutes, with owners having a median completion time 7 minutes higher than renters, since they answered many more questions. When appropriate, questions had built-in logical checks (for instance, percent chances of an exhaustive set of events had to sum to 100). Item non-response is extremely rare, and almost never exceeds one percent for any question.

The second survey is the regular monthly SCE survey, and was fielded during April 2015. Respondents of the housing module who still remained in the SCE rotating panel were invited to participate in a short follow-up module. Of the 978 household heads still in the panel, 856 did so, for a repeat response rate of 87.5%.

[4]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 www.newyorkfed.org/microeconomics/sce.html for additional information.

2.1 Survey Design

We next describe the relevant sections of the two surveys.

The experimental setup in the first survey consisted of three stages:

1. **Baseline Stage**: The first stage elicited respondents' perceptions about home price changes in their zip code over the past 12 months and the past 5 years. We also elicited respondents' expectations regarding home price changes in their zip code over the next 12 months, and the next 5 years (the precise questions will be discussed below).[5] In addition, respondents were presented with a hypothetical investment scenario where they were asked to allocate $1,000 between a fund indexed to year-ahead home price growth in their local area, and a 2% risk-free interest savings account.[6]

2. **Treatment Stage**: A block of other housing-related questions taking roughly 15 minutes separated the baseline and treatment stages. In the treatment stage, respondents were randomly assigned to one of three groups:

   - *1-year Treatment ("T1")*: Respondents were informed about the percentage change in home prices in their zip code over the 2014 calendar year. This information was based on the Zillow Home Value Index (ZHVI), which is freely available online.[7]
   - *5-year Treatment ("T5")*: Respondents were informed about the total percentage change in home prices in their zip code over the past 5 years, from the beginning of 2010 to the end of 2014.
   - *Control group*: Respondents in this group got no information on past home price changes.

[5]Furthermore, respondents were asked to rate the attractiveness of housing in their zip code as a financial investment on a 1-5 scale. We analyze this question in Appendix A.3.

[6]The exact question was: *"Consider a situation where you have to decide how to invest $1,000 for one year. You can choose between two possible investments. The first is a fund that invests in your local housing market, and pays an annual return equal to the growth in home prices in your area. The second is a savings account that pays 2% of interest per year. What proportion of the $1,000 would you invest in (1) the housing market fund, (2) the savings account?"*

[7]Respondents were shown the following: *"Zillow is one of the best-known sources of information about home prices. According to Zillow.com, home prices in your zip code during 2014 [increased/decreased] by [X]%."* (X, the respondent-specific local home price change, was shown with one decimal place.)

For more information on the construction of the ZHVI, see http://www.zillow.com/research/zhvi-methodology-6032/. The ZHVI estimates the market value of all homes in a geographic area, not just those that are actually sold, avoiding biases that may be associated with what type of homes are sold. We used the ZHVI as of January 2015, the month prior to the survey.

The coverage of ZHVI is incomplete at the zip code level, so if we do not have zip code level information, we use the state-level ZHVI change (respondents were told *"In cases where zip code level information is not available, we use the state-level change in home prices (or, in very few cases where no state-level information is available, the national change)."* 70.3% of our respondents' reported zip codes were covered by the ZHVI. In the very rare cases where we do not have state-level data (Maine and Kansas), we report national changes; 14 of our 1,205 (1.16%) respondents were in this category.

3. **Final Stage**: This stage followed right after the treatment stage. All survey respondents were re-asked their expectations of zip code level home price changes at the one- and five-year horizons—the same forecast horizons for which expectations were initially elicited at the baseline stage. The investment scenario that respondents had seen in the first stage was also presented again. It was identical to the initial scenario, except that the decision was now incentivized—respondents were informed that two people taking the survey would be paid in a year's time depending on the return of their investments.[8]

The follow-up questions were fielded to respondents in the April 2015 SCE monthly survey. Respondents were asked their expectations of zip code level home price changes at the one- and five-year horizons.

Some features of the study design merit further discussion. We include treatments that provide information on short- and longer-term home price changes since home price changes tend to exhibit momentum in the short term and mean reversion over a longer horizon, as will be discussed in the next section. The reason for including a control group was that 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). Since we are interested in revisions in expectations that are directly attributable to the information, we identify them from differences between the treatment and control groups' changes in expectations. The investment task allows us to investigate, in a direct fashion, whether home price change expectations impact both hypothetical and incentivized behavior, in the cross-section as well as at the individual level. Finally, the follow-up survey allows us to test whether the effect of the treatment, if any, persists beyond the initial survey horizon.

Home price perceptions (for the past one and five years) and expectations (for one and five years ahead) were elicited in two different formats. All respondents were first asked for the dollar value of a typical home in their zip code today. Each respondent was then randomly assigned to one of two "frames" which determined how the questions about the past and future were asked:[9]

[8] Paying only a randomly chosen subset of respondents is commonly done in large-scale economic experiments (e.g. Dohmen et al., 2011). Respondents were told: "*Note that you have a chance of earning extra money by answering this question. At the end of the month, we will randomly pick 2 survey participants. These 2 participants will be paid in Spring 2016 according to the investment choice they made (that is, the $1,000 and the return on their choices). If you are chosen, your payment will depend on how you had invested the money, so answer this question carefully.*

To determine the return on the housing market fund, we will use the Zillow home price index for your current zip code. In cases where zip code level information is not available, we use the state-level index (or, if that is not available, the national index)."

[9] This randomization was orthogonal to the randomization into treatment (T1, T5, or Control). Each respondent

- **(L)evel-frame**: The perception and expectation questions were asked in terms of house price *levels*. For example, past one year home price change perceptions were elicited as follows: *"You indicated that you estimate the current value of a typical home in your zip code to be [X] dollars. Now, think about how the value of such a home 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 one year ago (in February 2014)?"* We refer to this frame as the L-frame.

- **(C)hange-frame**: The perception and expectation questions were asked in terms of *percent changes*. For example, when eliciting past one year home price change perceptions, respondents were first asked if they thought home prices had increased or decreased over the past one year, and next asked for the percentage change: "*By about what percent do you think the value of such a home has [increased/decreased] over the past 12 months? Please give your best guess.*" We refer to this as the C-frame in the analysis.

These two approaches for eliciting perceptions and expectations were motivated by the finding of Glaser et al. (2007) that survey respondents' predictions of stock performance are influenced by whether they are asked to forecast future returns or future price levels. In the former case, expectations appear to be extrapolative, whereas when asked for levels, respondents appear to believe in mean reversion. We therefore want to study whether our findings are robust to the elicitation mode. In our analysis, we control for the frame assignment whenever the analysis is done on the full sample. For our main results on expectations, we also discuss how findings differ across frames.

Respondents, at the baseline stage, were also asked about their subjective distribution for both one- and five-year ahead home price growth. In the case of one-year ahead expectations, respondents were asked to assign probabilities to four intervals that future year-ahead home price changes may lie in (less than -5%; between -5% and 0%; between 0% and 10%; more than 10%). We use the responses to this question to measure respondents' beliefs of downside risk in home prices.

In order to reduce the importance of outliers and to screen out individuals who arguably did not take the survey seriously, the analysis in the paper removes respondents with extreme observations for our key variables: baseline perceptions of price changes over the last 12 months and past five years, and baseline as well as final stage home price expectations over the two horizons. Specifically, respondents who report answers in the top and bottom 2% of the response distribution

remained in the same frame throughout both surveys.

for those variables are dropped. In addition, we drop 12 respondents who provide a response of less than $10,000 for the value (today; in the past, or; in the future) of a typical home in their zip code. This leaves us with 1,020 individuals (from a total of 1,205 respondents who took the survey). Our results are qualitatively similar if we trim observations at 1% or 5%, or if we instead winsorize extreme responses.

2.2 Sample Characteristics

The first column of Table 1 displays the demographic characteristics of our sample. The sample aligns well with average demographic characteristics of the United States along most dimensions. For instance, the average age of our respondents is 50.4 years, and 52.9% of them report annual household income of less than $60,000, while the corresponding numbers among US household heads are 53.7 years and 54.5%.[10] 74.3% of respondents are homeowners, compared to a national homeownership rate in 2015:Q1 of 63.7% according to the Census. One notable divergence between our sample and the US population is in education. Our sample is significantly more educated than the overall population: 55% of our respondents have at least a Bachelors' degree, while only a third of the US household heads fall in this category. This may partly be a result of differential internet access and computer literacy across education groups in the US population.

The table also shows some other demographic variables, such as labor force status, tenure in the respondent's town or city, and numeracy.[11] Columns (2)-(4) of the table show that the demographic characteristics are not statistically different across the three treatment groups (the only exception being the proportion of males). This should not be surprising, since random assignment should have largely preserved balance between the three groups.

The last column of Table 1 shows the characteristics of the follow-up sample (excluding respondents who are removed based on being outliers in the initial survey). We also conduct pairwise tests for the equality of the means of characteristics for the follow-up sample (column 6) and the initial sample (column 1). We do not find any significant differences in observables across the two surveys, meaning there is no evidence for selection on observables into the follow-up survey.

[10] The statistics on the United States population come from the 2014 ACS 1-year sample of household heads.

[11] We ask respondents when they enter our survey panel to answer 5 questions that evaluate their numeracy. The questions are taken from Lipkus et al. (2001) and Lusardi (2009). Those who answer at least 4 of the 5 numeracy questions correctly are classified as having high numeracy.

3 Dependence in Actual Home Price Changes

Before turning to the empirical analysis, it is useful to investigate the actual dependence in home prices over different horizons. These patterns provide us with a benchmark of how individuals in the treatment groups *should* respond to objective information about home price changes in the last one or five years (at least if one is willing to assume that these past patterns will continue to hold going forward).

For this purpose, we estimate time series regressions of home price changes on lagged home price changes, over different time horizons. In particular, we test how strongly past one-year and five-year growth (the information we provide in the treatments) relate to future growth over the next one year or the next 2-5 years. These two horizons are chosen because they are the "short" and "medium" horizon that we will use in our analysis of respondents' expectations (revisions), as explained in Section 4.2.

Using CoreLogic Home Price Index data that covers the years 1976-2015, we estimate autoregressive coefficients at the zip code level (results are qualitatively similar at the county level) using the following specification:

$$\Delta_h \log(HPI_{g,t+h})/h = \alpha_g + \phi_g \Delta_l \log(HPI_{g,t})/l + \varepsilon_{g,t},$$

where $HPI_{g,t}$ is CoreLogic's Home Price Index in year t in zip code g, h is the horizon over which the change in the dependent variable is computed (i.e., one or 2-5 years), and l is the horizon over which the change in the independent variable is computed (one or five years). Dividing by h and l means that we annualize all home price changes. The parameter ϕ_g indicates persistence in home price growth for a given zip code g. We estimate the model using ordinary least squares (OLS) with Newey-West standard errors in order to account for the serial correlation in error terms due to overlapping observations.

Table 2 reports various statistics (mean; standard deviation; median) of the estimates across the zip codes, as well as proportion of the zip-code-level estimates that are statistically significantly positive or negative at $p < 0.05$. For example, for the regression of one-year home price changes on lagged one-year home price changes, the average estimate of ϕ_g across the zip codes of respondents in our sample is 0.53 (the median is 0.55, and the standard deviation across the zip code level estimates is 0.14). This means that on average, a one percentage point higher growth rate in year t is followed by about a 0.5 percentage point higher growth rate in year $t + 1$. The AR(1) coefficient is estimated to be significantly positive (at $p < 0.05$) for 91.2% of the zip codes in the sample. This indicates strong momentum in home price changes over short horizons, a pattern that has been well documented in the literature (e.g. Case and Shiller, 1989; Guren, 2016). On the other hand, the average estimate of a regression of one-year home price changes on lagged five-year changes is 0.14, but indistinguishable from zero for the vast majority—more than 80%— of the zip codes in the sample, and significantly positive for 15% of the the zip codes.

Turning to the regressions of medium-term home price growth (that is, over 2-5 years) on lagged changes, we first note that the average coefficient on lagged one-year changes is very close to zero. The estimate is significantly negative (positive) for only 8% (1.7%) of zip codes. Thus, the most recent growth alone has little predictive power for the longer horizon. In contrast, we see stronger evidence of mean reversion in the case of a regression of 2-5 year growth on lagged 5-year growth, where the average estimate is -0.38, and the estimate is statistically significantly negative for more than half of the zip codes. This longer-horizon mean reversion is again in line with patterns detected in earlier work (e.g. Cutler et al., 1991; Glaeser et al., 2014).

In sum, there is strong momentum in home price changes over short horizons, and mean reversion over longer horizons. Our qualitative conclusions are similar if we instead use the Zillow Home Value Index (which covers more zip codes than the CoreLogic index but starts only in 1996), or if we restrict to home price changes post-2000, with notably stronger mean reversion over the five-year horizon.

4 Analysis of Baseline Perceptions and Expectations

In this section, we analyze the properties of perceptions and expectations in the first (baseline) stage. These provide the "input" for our subsequent experimental analysis, but are also of interest by themselves.

4.1 Perceptions and Perception Gaps

Respondents were first asked for their perceptions of past home price changes in their zip code over the past twelve months and over the past five years. C-frame respondents directly report their beliefs in percentage point terms, but for L-frame respondents who report beliefs in levels, we compute percentage point changes. Summary statistics of respondents' perceptions of past home price changes are reported in Panel A of Table 3. Respondents, on average, perceive that home prices in their zip code increased by 3.8% over the past 12 months. The perceived average change over the past five years, annualized, is 1.5%. The large standard deviations, and the fact that average absolute perceptions are meaningfully larger than the average perceptions, indicate that there is substantial heterogeneity in perceived home price changes. The average perceptions are similar across the three groups (as indicated by the p-value in the fifth column of the table), which should not be surprising since assignment to groups is random. Columns (6) and (7) of the table show that the two question frames yield different responses, with the average perceived growth being significantly higher in the L-frame.[12]

A key ingredient in our analysis is a measure of respondents' ex-ante informedness about the treatment information. The measure we use to capture this is the difference between what the realized percentage point home price change over the past t years actually was in i's zip code according to the information source that we used (which we denote as $\pi_{i,t}$), and what respondent i believes the percentage point change in home prices was in her zip code (which we denote as $\hat{\pi}_{i,t}$). Note that the objective information (from Zillow) presented to the respondent is individual-specific and depends on her zip code. We refer to this difference as the "perception gap", $\alpha_{i,t} = \pi_{i,t} - \hat{\pi}_{i,t}$, with a positive (negative) gap reflecting an underestimation (overestimation) of past home price changes relative to the Zillow measure. For the five-year horizon, the perception gap is annualized.[13]

Panel B of Table 3 shows that the mean perception gap in our sample is 1.4 for the one-year horizon, and -0.5 for the (annualized) five-year horizon. That is, on average, respondents' perceptions of past home price growth are reasonably close to the Zillow HPI, with an underestimation at the one-year horizon and a slight overestimation at the five-year horizon. However, the corresponding standard deviations of 7.0 and 4.1, respectively, imply substantial heterogeneity in the perception "accuracy" among respondents; similarly, the average absolute perception gaps are quite large. This implies that on average, the information shown to respondents in treatments T1 and T5 is appreciably different from their priors.

We next investigate the correlates of these absolute perception gaps. Table 4 shows estimated coefficients from OLS regressions of the absolute perception gaps at the one- and five- year horizon

[12]The difference between the frames is larger (and more significant) at longer horizons for both perceptions (Panel A) and expectations (Panel C). This may be partly due to respondents failing to appreciate compounding; specifically, if a respondent thinks that house prices increased annually by x% on average over the past five years, they may report $5x$, rather than $100(1+\frac{x}{100})^5 - 100 > 5x$.

[13]We annualize the five-year perception gap as follows: $[1+(\pi_{i,5} - \hat{\pi}_{i,5})]^{1/5} - 1$. We continue to use the notation $\alpha_{i,5}$ to refer to the annualized five-year perception gap. The perception gap is annualized so that the analysis is comparable across the two horizons.

on a rich set of demographic controls. We see that college-educated, higher-income (those with household income $\geq \$75,000$), and high-numeracy respondents on average have smaller absolute gaps at both horizons (the estimates are however only significant at the one-year horizon). Respondents who report being more confident in their past perceptions,[14] and those who have checked housing websites over the past 12 months also tend to have smaller absolute gaps, as one might expect; however, the estimates are not significant at conventional levels. It is notable that tenure in one's town, being a homeowner, or planning to buy or sell a home soon are not associated with smaller gaps; the latter finding suggests that perceptions differing from objective measures are unlikely to be a result of rational inattention. Unsurprisingly, respondents residing in volatile housing markets (defined as areas with above-median volatility in home prices over the past five years) have significantly larger absolute perception gaps on average. Notably, the R-squared of these two regressions indicate that less than 7% of the variation in perceptions can be explained by these controls.[15] Thus, the extent to which respondents are "surprised" by the provided information is largely orthogonal to demographics.

4.2 Expectations of Future Home Price Growth

As mentioned above, we elicit respondents' home price expectations (at the zip code level) for the next one year and five years. We would expect a significant correlation between the five-year and year-ahead expectations simply because the five-year expectation is a combination of a respondent's expectations of year-ahead home price changes and 2-5 years ahead home price changes. We, therefore, separately analyze respondents' 2-5 year-ahead expectations. This is simply $y_{i,2-5} = \left[1 + \frac{(y_{i,5} - y_{i,1})}{(1+y_{i,1})}\right]^{1/4} - 1$, where $y_{i,h}$ is i's expectations about home price changes (in percent terms—with, for example, a percentage point change denoted as 0.01) at horizon h. We refer to these as "medium-term" expectations.

Panel C of Table 3 displays summary statistics of home price expectations at the baseline. We see that respondents, on average, expect a 3.5% increase in house prices in their zip code over the next 12 months, 11.0% over the next five years, and an annualized change of 1.7% at the 2-5 year horizon.

[14] After reporting their past perceptions, respondents were asked: *"How confident are you in your answers?"* on a five-point scale, where 1 meant "Not at all confident" and 5 meant "Very confident". Those reporting 4 or more are classified as being confident in their perceptions.

[15] When looking at individual demographic characteristics in a univariate framework, Appendix Table A-1 shows that males, higher-income respondents, college-educated individuals, high-numeracy respondents, married individuals, those who frequently check housing websites and other sources, and those confident in their recall have significantly smaller average absolute perception gaps at the one-year horizon. For the five-year horizon, homeowners, higher-income individuals, and C-frame respondents have smaller absolute gaps, on average.

The sizable standard deviations highlight the substantial heterogeneity in beliefs in the sample. As was the case for perceptions, the L-frame elicitation method yields higher means, particularly for the longer horizon. Finally, note that average expectations are similar to average past perceptions (reported in Panel A of the table), potentially the result of extrapolation from the (perceived) past to the future. We turn to this topic next.

4.3 Home Price Expectations and Past Perceptions

Table 5, using the cross-sectional variation in the sample, regresses home price expectations onto past perceptions, and documents a significant correlation between the two. Column (1), for example, shows that a one percentage point higher perceived past one-year local home price change is associated with a 0.26 percentage point higher year-ahead local home price expectation. Thus, respondents who report higher past home price growth also tend to report higher expected future growth, consistent with extrapolation. Interestingly, our estimate is very similar to that by Case et al. (2012), who find a coefficient of 0.23 in a regression of expected year-ahead MSA-level home price changes on lagged actual 12-month changes (for a sample of recent homebuyers in four MSAs over 2003-2012).[16] Controlling for expectations about various fundamentals in column (2) reduces the coefficient only slightly, even though the R-squared increases substantially.

Columns (3) and (4) show similar extrapolation from perceived longer-term past changes to year-ahead home price change expectations. The last four columns show that even medium-term home price change expectations are positively related to past perceptions, though the estimates are substantially smaller than those in the case of near-term expectations. This latter finding is somewhat different from Case et al. (2012), whose respondents report more extreme long-term (10-year) forecasts.

Note that these estimates cannot be given a causal interpretation due to various individual-specific as well as geographic confounds and potentially other omitted variables. For example, a respondent who is optimistic may report both higher past home price changes as well as future expectations. Furthermore, Table A-2 shows that the C-frame elicitation method yields a stronger correlation between year-ahead expectations and past one-year perceptions, as well as between medium-term expectations and past five-year perceptions. Thus, it appears difficult to reach convincing conclusions about the link between past (perceived) home price growth and expected future growth based on an analysis of cross-sectional variation alone. Our experimental framework,

[16]Our estimate is also qualitatively similar to that of Kuchler and Zafar (2015), who find a coefficient of 0.12 when regressing *national* home price change expectations on lagged actual 12-month MSA home price changes.

discussed next, allows us to get around these issues.

5 Experimental Analysis

5.1 Hypotheses on Updating Behavior

In general, we expect our information intervention to cause respondents to revise their home price expectations under two conditions. First, their expectations need to be influenced by their beliefs about the measures we use in our information treatments, i.e., past short- and long-term home price changes. This would not be the case, for instance, if respondents believed that home prices follow a random walk. Second, respondents are not already fully informed about the true values of these past changes (as we confirmed in Section 4.1).

If respondents' expectations evolved in a "data-consistent" way (that is, in line with actual movements in home prices, analyzed in Section 3), we would expect to see updating that is consistent with momentum in the T1 group for short-term expectations. That is, we would see an under- (over-) estimation of past one-year home price changes leading to an upward (downward) revision in year-ahead home price expectations. Recall that underestimations correspond to positive perception gaps. Therefore, in this case, year-ahead home price expectation revisions would be expected to be positively related to the one-year perception gap for T1 respondents. The relationship between medium-term expectation revisions and one-year perception gaps should be weaker. Turning to the T5 treatment, data-consistent updating would predict little systematic relationship between annualized five-year perception gaps and year-ahead expectation revisions (though directionally, the relationship in actual home price changes is positive). In contrast, respondents should realize that there tends to be a negative relationship between past five-year growth and future 2-5 year growth—so that, if they learn that home prices grew faster over the past five years than they had thought, they should revise their 2-5 year expectations downward.

Behavioral theories of expectation formation would typically predict extrapolation at both horizons, meaning that respondents would fail to perceive longer-term mean reversion. Models embedding such expectation formation in an equilibrium model of the housing market, such as Glaeser and Nathanson (2015), may also predict that individuals *underreact* to recent home price changes when forming their short-term expectations—that is, they extrapolate, but not enough. The reason for that is that the strong house price momentum would otherwise be "arbitraged away".

We will initially use the data from our information experiment to distinguish between these hypotheses based on average updating behavior. We will then explore heterogeneity in updating patterns in order to shed additional light on different theories of expectation formation. Specifically, we investigate differences in updating by respondents' past experiences to evaluate predictions of theories that emphasize such heterogeneity, such as Malmendier and Nagel (2016). We also further investigate the consistency of our respondents' updating behavior with actual home price patterns by studying heterogeneity across geographic areas with different patterns.

5.2 Non-Parametric Analysis

We first proceed with a non-parametric analysis of updating behavior. Panel D of Table 3 shows the revisions in home price expectations between the baseline and the final stage. The average revision in the sample is an increase of 0.3 percentage points at the one-year horizon, and a decrease of 0.12 percentage points for the 5-year forecast. While average revisions are similar across the three groups (the Control and two treatment groups), absolute revisions tend to be larger in the treatment groups. The final two rows show the fractions of respondents that change their expectations in the final stage (relative to the baseline stage). While even in the control group a majority of respondents update their expectations, this fraction is significantly higher in the treatment groups, suggesting that the information provision does affect respondent expectations.

Next, we provide graphical evidence on the relationship between perception gaps and home price expectation revisions. The first row of Figure 1 shows the mean year-ahead home price expectation revisions for each of the three groups, conditional on one-year perception gap decile bins. While the one-year perception gap can be constructed for each respondent (since past perceptions are elicited from all respondents), the one-year past home price change according to Zillow is only revealed to the T1 group. Hence, we expect to observe a systematic relationship between revisions and the perception gap for the T1 group but not the other groups. That is exactly what we see in the first row of Figure 1. In addition, there is a nearly monotonic relationship between year-ahead expectations and one-year perception gaps for the T1 group, with greater underestimation of past home price changes leading to a larger upward revision of year-ahead expectations. This pattern of updating is consistent with respondents perceiving momentum in the short-term, as observed in actual home price changes.

The second row of Figure 1 shows the average medium-term (that is, 2-5 years) home price expectation revisions, conditional on one-year perception gap decile bins. Here, for all three groups — T1, T5, and Control — we do not see a strong relationship between expectation revisions and perception gaps.

We next turn to the relationship between expectation revisions and (annualized) past five year perception gaps. The top row of Figure 2 shows a weak monotonic relationship between perception gap bins and average year-ahead revisions, for T1 and T5. That we observe a relationship for T1 respondents may be somewhat surprising since the five-year perception gap is never revealed to them. However, this is likely because of the high level of correlation between one- and five-year perception gaps within respondents (Spearman rank correlation of 0.377, significant at $p < 0.001$). The bottom row of the figure shows little systematic relationship in the case of medium-term expectation revisions. We certainly do not see a negative relationship for T5, as would have been the case if updating were consistent with mean reversion as observed in actual longer-term home price movements (see Section 3).

We next proceed with a more precise, regression-based evaluation.

5.3 Regression Analysis

Our main regression model for home price expectation updating is as follows:

$$\Delta y_{i,h} = \beta_0 + \beta_1 T_{1,i} + \beta_2 T_{5,i} + \beta_3 \alpha_{i,1} + \beta_4 \alpha_{i,5} + \beta_5 (T_{1,i} * \alpha_{i,1}) + \beta_6 (T_{5,i} * \alpha_{i,5}) + \beta_7 1_{\text{C-frame},i} + \varepsilon_{i,h}, \quad (5.1)$$

where $\Delta y_{i,h}$ is the revision in home price expectations, either for the one-year horizon ($h = 1$) or the 2-5 year horizon ($h =$2-5). $T_{1,i}$ ($T_{5,i}$) is an indicator that equals 1 if respondent i is assigned to treatment T1 (T5); $\alpha_{i,H}$ is i's perception gap for the past H years, where $H = \{1, 5\}$; and $1_{\text{C-frame},i}$ is an indicator that equals 1 if i's expectations were elicited using the C-frame. The βs are the parameters of interest.

The constant term, β_0, captures the average revision for the Control group. $\beta_0 + \beta_1$, for example, reflects the average revision for respondents in the T1 group with a perception gap of zero. β_3 and β_4 capture revisions related to the one-year and five-year perception gaps, respectively, for respondents that are not shown the relevant infomation. Ex ante, there is no reason to believe that these coefficients should be different from zero. β_7 allows for the possibility that revisions may depend on the elicitation method.

The main coefficients of interest are β_5 and β_6. β_5, for example, measures the sensitivity of home price expectations with respect to the one-year perception gap for the T1 group—it provides an estimate of the causal effect of the one-year past information on home price expectation revisions.

β_5 and β_6 will be different from zero if revisions are systematically driven by the difference between the revealed Zillow information and a respondent's prior. As discussed earlier, data-consistent updating would imply that β_5 would be positive when the dependent variable is $\Delta y_{i,1}$, and that β_6 would be negative when the dependent variable is $\Delta y_{i,2-5}$.

Equation (5.1) is estimated using ordinary least squares, with robust standard errors.[17] Columns (1) and (2) of Table 6 show the estimates for the short-term and medium-term expectation revision, respectively. In column (1), we see that the estimate of β_5 is positive and significant: the estimate of 0.20 implies that, for each percentage point underestimation (overestimation) of past one-year home price changes, T_1 respondents revise up (down) their year-ahead expectations by 0.20 percentage points. For comparison, the average AR(1) coefficient of home price growth in our respondents' zip codes is 0.53 (see Table 2). This implies that the average respondent, when forming her expectations, may undercorrect for momentum present in her local housing market. It is also notable that the estimate of β_3 is quite similar to the cross-sectional estimate of 0.26 in Table 5.

The estimate of β_6 is 0.07 but not statistically different from zero. This compares favorably with the average coefficient of 0.14 from regressing actual one-year growth in zip code home prices on lagged five year growth.

Looking at the other estimates in column (1), we see that β_1 and β_2—parameters that capture the average updating attributable to the treatment group that is not explained by the perception gap (on top of the average updating of the control group)—are indistinguishable from zero. This suggests that there is no effect of the treatments on home price expectation revisions (relative to control group responses), other than what is explained by the size of respondents' perception gaps. Likewise, both β_3 and β_4 are small in magnitude and not significantly different from zero, as one would have expected (since only those in the corresponding treatment groups received this information). The estimate of β_0 indicates that control respondents, on average, revise their expectations up by 0.11 percentage points, an (economically and statistically) insignificant revision. β_7 is also not statistically significant; that is, mean revisions for respondents in the C-frame are not different from those in the L-frame.[18]

[17] Demographics are not included in the specification because random assignment to treatment groups should ensure demographics are irrelevant to treatment effects. Indeed, when we control for demographics (not shown), there is no notable difference in estimates.

[18] In Appendix Table A-3, we estimate a version of equation (5.1) in which we add interactions of all variables with a C-frame dummy. This allows us to test if the impact of information differs systematically by whether expectations are elicited in levels or changes. The main interaction terms are not statistically significant (that is, the variables $T_{1,i} * \alpha_{i,1}$ and $T_{5,i} * \alpha_{i,5}$ interacted with the dummy), suggesting that the results are not being driven by a particular frame. This is in contrast to the findings for the cross-sectional relationship between perceptions and expectations (Table A-2), where the elicitation frame mattered.

Turning to column (2) in Table 6, we see a positive relationship between medium-term expectation revisions and perception gaps. Estimates of β_5 and β_6 imply that individuals revise up (down) their medium-term expectations by 0.04-0.05 percentage points per percentage point under- (over-) estimation of past home price changes. This apparent extrapolation is inconsistent with actual home price patterns. In particular, there is no evidence that, on average, our respondents view higher growth over the past five years as predictive of lower future medium-term growth, even though this is at least directionally the case in actual home prices.

5.3.1 Additional Specifications. We next consider variations of the regression model.

Asymmetric Updating. The main regression specification above imposes a linear relationship between perception gaps and revisions that is the same for positive and negative perception gaps. While we stay within this linear framework, columns (3) and (4) of Table 6 report estimates of a specification where we allow the effect of the perception gap on revisions to be asymmetric (that is, we estimate separate β_5 and β_6 coefficients for negative and positive perception gaps).[19] In neither column (3) nor (4) do we find strong evidence of asymmetric updating, though in both cases, the estimated reaction to negative one-year perception gaps (overestimation of past changes) is slightly stronger (though not significantly so).

Subjective Measure of Informativeness. As an additional piece of evidence that the expectation revisions of treated respondents are driven by the presented information, we turn to respondents' subjective assessment of how the provided information compared to their prior belief about past changes in local home prices.[20] Columns (5) and (6) of Table 6 report the estimates of a specification restricted to respondents in the treatment groups. Unlike in the other columns, where we estimate the sensitivity of expectations to (revealed) perception gaps of varying magnitudes, here we simply recover differences in mean revisions between groups delineated by their discrete response to the post-treatment subjective assessment of the provided information. The excluded group in the specification is the set of treatment respondents who reported their perceptions were close to the in-

[19] There is a fairly balanced distribution between positive and negative perception gaps among our respondents. 37% of T1 respondents have negative one-year perception gaps (overestimate past changes), while 54% of T5 have negative five-year perception gaps.

[20] Respondents assigned to T1 and T5 groups were asked immediately after the treatment how the displayed information compared to how they had thought home prices had changed in their zip code, and were then asked to select one of the following options (shown here for the case where home prices according to Zillow had increased): *(i) I had thought home prices had increased by more; (ii) This is about what I thought about how home prices had changed; (iii) I had thought home prices had increased by less (or that they had decreased).*

formation given (46.2% of treated respondents). Relative to them, we see that average revisions are in a direction consistent with extrapolation for all groups. For year-ahead home price expectations, the average revisions are statistically significant and sizable: overestimators decrease their year-ahead home price expectations by 1.3-1.8 percentage points (relative to those who responded that their past price perceptions were close to the information treatment) and underestimators increase their expectations by a similar magnitude. For 2-5 year expectations, average revisions are again consistent with extrapolation (thus showing no evidence of a belief in mean reversion), though estimates are smaller than those in column (5) and not always statistically different from zero.

Robustness Checks. Appendix A.1 reports and discusses a series of robustness checks. For example, we restrict the sample to only treatment respondents to rule out the possibility that idiosyncratic revisions in the Control group are driving our results. Similarly, to test the sensitivity of our results, we bring back "outlier" respondents who have been trimmed in the main analysis, and instead winsorize these observations at the 2% level. We also restrict the sample to those respondents who are able to recall their baseline perceptions accurately (as measured by the qualitative question about subjective informedness). Finally, we report results from a falsification exercise. The results are robust across these checks, and corroborate our main findings reported in Table 6.

5.4 Update Heterogeneity

Our within-subject design allows us to investigate heterogeneity in updating. There are at least two reasons for doing so. First, the previous analysis may mask substantial differences across individuals in how they update. While the average respondent seems to update in a way consistent with a belief in momentum, some respondents may not update their expectations at all, and others may update in a fashion consistent with mean reversion. Second, the underlying heterogeneity in updating (by either respondents' observable characteristics or geographic factors) can inform us about the theoretical models of belief formation that best fit the data. For example, models of age-dependent updating, as in Malmendier and Nagel (2016), would predict that younger respondents should be more responsive to our treatment. Likewise, data-consistent updating would predict that individuals residing in areas with inelastic housing supply (which tend to exhibit stronger momentum in the short term and stronger mean-reversion in the long term) should be more likely to update in a way consistent with momentum (mean reversion) when updating their short- (medium-) term expectations.

We denote the individual's updating type by $v_{i,h}$, where h denotes the horizon over which the respondent is forecasting (one year ahead, or five years ahead). That is, we allow the respondent to exhibit different behavior at different horizons (for example, extrapolation for short-term expectations, and mean reversion for long-term expectations).

The three update types are:

- **Non-Updater (NU)**: This type does not update following treatment:

$$v_{i,h} = \text{NU if } \Delta y_{i,h} = 0.$$

- **Extrapolator (E)**: This type updates in a way consistent with momentum in home prices. If the perception gap, α_i, is positive (negative) — that is, the respondent under-estimated (over-estimated) past home price changes relative to the Zillow index — she revises up (down) her home price expectations. Formally, the definition is:

$$v_{i,h} = \text{ E if } (\alpha_i > 0, \Delta y_{i,h} > 0) \text{ or } (\alpha_i < 0, \Delta y_{i,h} < 0).$$

- **Mean Reverter (MR)**: This type updates in a way consistent with mean reversion in home prices. For example, if she learns that prices in the past actually increased by more than previously thought (that is, $\alpha_i > 0$), she revises her future forecast downward. Formally:

$$v_{i,h} = \text{ MR if } (\alpha_i > 0, \Delta y_{i,h} < 0) \text{ or } (\alpha_i < 0, \Delta y_{i,h} > 0).$$

For this analysis, we focus on two quantities. One, the proportion of non-updaters in the two treatment groups pooled together, relative to the the proportion of non-updaters in the Control group. Second, conditional on updating, the odds of being an extrapolator versus a mean reverter; this quantity is defined for those in the treatment groups only (since it is based on the respondent's perception gaps as implied by the revealed information). The first metric can be viewed as a measure of updating on the extensive margin, while the latter is a measure on the intensive margin.[21]

The first row of Table 7 shows the updating types for the treatment sample, separately for the year-ahead and five-year ahead expectations. At both horizons, treatment respondents are about 0.8 times as likely as control respondents to not revise their expectations. Conditional on revising

[21] Dominitz and Manski (2011) use a similar approach of classifying heterogeneity in subjective expectations about stock market returns. Their approach relies on the cross-sectional variation in expectations.

their expectations, respondents are much more likely to update in an extrapolative manner at both horizons.

The remaining rows of the table show the updating patterns for various cuts of the sample. We also report the p-values to test the equality of proportions of non-updaters and updating types of the paired groups.

We do not see much difference in the propensity to update by treatment type for year-ahead expectations. However, the odds of extrapolation are significantly higher for T1 respondents. In the case of medium-term expectations, however, T5 information leads to a significantly larger impact on the extensive margin of updating, but no differential impact on the intensive margin.

Panel A of Table 7 shows cuts of the sample based on individual characteristics that allow us to test for experience-based updating. We see no evidence of a lower propensity to update by either age or tenure in one's locality. While these extensive margin patterns are not consistent with predictions of models of age-dependent updating, the intensive margin results for the one-year horizon conform with these models: conditional on updating, younger respondents and those with a shorter history in a location exhibit higher odds of extrapolating at both horizons.

Turning to individuals who have had negative experiences in the housing market (they are currently "underwater" on their mortgage, or went through a foreclosure or a short sale in the past), we see they are relatively more likely to update but have lower odds of extrapolating their short-term expectations; the differences are however not statistically significant, in part due to the small subsample of households with negative experiences. Over the medium-term horizon, perhaps wary of their past adverse experiences, such individuals are significantly less likely to be extrapolators in both relative and absolute terms—in fact, conditional on updating, they are more likely to update their medium-term expectations in a manner that is consistent with mean reversion (in stark contrast to the rest of the sample).

Panel B presents sample cuts based on housing-related factors in the respondent's location. The first cut we look at is by housing supply elasticity of the respondent's location. We use the Saiz (2010) MSA-level elasticity measure based on land topology factors. We study this cut because momentum in home prices in the short term and mean reversion in the long term is stronger in areas with relatively inelastic supply (see also Glaeser et al., 2008).[22] Treated respondents residing

[22]The average AR(1) estimate from a regression of one-year home price changes on lagged one-year home price changes for respondents in below-median elasticity zip codes is 0.57, versus 0.49 for above-median elasticity zip codes (difference statistically significant at $p < 0.01$). The average estimate from a regression of 2-5 years home price growth on lagged five year changes is -0.54 for below-median elastic zip codes, versus -0.21 for the above-median group (difference statistically significant at $p < 0.001$).

in below-median supply elasticity areas (that is, the more inelastic areas) are more likely to update their expectations at both horizons. For both horizons, conditional on updating, these respondents are also substantially more likely to extrapolate. While this is "data-consistent" at the short horizon, the opposite is true at the longer horizon: those respondents that should be more likely to perceive mean reversion are in fact less likely to do so.

The last two cuts of the table exploit variation in the serial dependence in respondents' local home prices in both the short and long term.[23] These cuts yield results that are similar to those based on supply elasticity, except that they utilize a larger sample since the Saiz elasticity measure is only available for a subset of locations. Individuals residing in areas with high short-term momentum "correctly" exhibit higher odds of extrapolating for one-year expectations, although the difference is not statistically significant. The last cut, by the strength of longer-term mean reversion, shows that conditional on updating, respondents residing in areas in above-median long-term mean reversion are twice as likely to be extrapolators than mean reverters, a pattern that is opposite to what "data-consistent" updating would predict.

This section restricts the heterogeneity analysis to cuts of the data that have direct implications for modeling of expectations. However, it is useful to explore differences in updating by other characteristics. This is discussed in Appendix A.2, where we conduct a multivariate analysis of updating.

5.5 Discussion: Implications for Modeling Home Price Expectations

Our results suggest that on average, respondents perceive momentum in home price changes over short horizons—they responds positively to the gap in their one-year past perceptions when revising their year-head expectations. While average revisions at the one-year horizon are thus directionally consistent with observed momentum in actual home price changes, the average respondent seems to *undercorrect* for the actual momentum: our estimate of perceived momentum is less than half of the coefficient of dependence in actual home price movements. On the other hand, we do not find evidence of the average respondent believing in mean reversion in medium-term home price changes relative to 5-year lagged growth rates (as is the case for actual dependence in home prices). If anything, the average respondent also appears to extrapolate when updating their medium-term expectations.

[23]For this purpose, in order to maximize coverage of our respondents' locations, we use county-level house price patterns; these are very similar to the zip-code-level ones shown in Table 2.

Thus, updating behavior, while directionally correct for short-term expectations, does not otherwise appear to be consistent with actual home price data. In contrast, it is at least qualitatively in line with behavioral models that assume extrapolation. In fact, a calibration in Glaeser and Nathanson (2015) implies a one-year updating coefficient of 0.2, exactly what we estimate. It may seem surprising that their non-rational agents extrapolate too *little* at the short horizon; however, if this were not the case, the strong short-term momentum in implied home prices would not persist in equilibrium. Other behavioral theories of expectation formation such as Fuster et al. (2012) would imply that while agents fail to correctly appreciate longer-term mean reversion (in line with our results), they correctly anticipate short-term momentum.

Our heterogeneity analysis indicates that updating patterns are partly consistent with models of age-dependent updating. The geographic heterogeneity patterns strengthen our findings of directionally data-consistent updating at the short horizon, but incorrect extrapolation at the longer horizon.

5.6 Persistence and Anchoring

A natural question to ask is whether the effects of the information provision persist beyond the relatively short time frame of the main survey. To investigate this, as described in Section 2.1, we re-elicited respondents' home price expectations in April 2015, about two months after the original survey.

We refer to the difference between the expectations elicited in the follow-up survey and the baseline stage in the main survey as "follow-up" revisions, opposed to the (within-survey) "initial" revisions in the main survey. The first two columns of Table 8 focus on revisions of year-ahead home price expectations. The dependent variable in the first column is the initial revision. That is, the column reports estimates of equation (5.1), restricting the sample to those respondents who also take the follow-up survey. The β_5 estimate for this subsample is 0.18, about the same magnitude and precision as the full sample. We next estimate the same specification as in equation (5.1), except that the dependent variable now is the follow-up revision. If the impact of the intervention is long-lasting, we expect the estimate of β_5 to be qualitatively similar. Estimates for this specification are presented in column (2) of Table 8. We see that β_5 is significant at the 5% level and positive. The point estimate declines in magnitude, but is not statistically different from the corresponding estimate in column (1). This indicates that the information intervention has persistent effects on our respondents' year-ahead expectations. The last two columns of the table show that the effect of information on medium-term expectations, which was much smaller in the main survey, is no longer statistically significant in the follow-up.

This analysis also directly addresses a potential concern with our design, namely that our information intervention may cause respondents to simply anchor their revised forecasts to the statistic presented to them in the treatment (Tversky and Kahneman, 1974), thereby explaining the correlation we find (at least for one-year information and expectations). Given that the information effect persists in the follow-up survey, two months after the time when the information was shown, it is unlikely that one can attribute the effect of information entirely to anchoring. Also, as noted earlier, the effects of information hold both in the C-frame and the L-frame, whereas one might expect anchoring to operate primarily in the C-frame (since the information is presented in terms of changes as well). Finally, anchoring alone should be equally strong for T1 and T5 and both expectation horizons, not consistent with the differences in treatment effects that we find.[24]

In principle, it is possible that when making their forecast in the follow-up survey, respondents anchor to their forecast in the final stage of the main survey, which would generate the persistence we observe (and be indistinguishable from genuine belief updating). While this is unlikely, given that it would require a strong focus of respondents on their revised forecast while ignoring many other anchors they may encounter in the two months between the surveys, we cannot rule this out entirely.

5.7 Ex-post Accuracy

Another interesting question is whether our intervention impacts the ex-post accuracy of respondents' expectations. For this purpose, we compute the absolute difference between the respondents' year-ahead home price expectations and the realized local home price change between February 2015 and February 2016 (according to the Zillow zip code level data). We refer to this absolute difference as the "ex-post forecast gap." This analysis is restricted to respondents for whom Zillow zip code level data are available (81.4% of the sample).[25] Caution is warranted in using an ex-post realized outcome as a benchmark for accuracy of ex-ante expectations, since (1) home price changes are uncertain, and (2) respondents' point forecasts may refer to various statistics (i.e. mean, median, mode, etc.) of their subjective probability distributions (Engelberg et al. 2009). Nevertheless, we

[24]In an analysis not reported here (but available upon request), we investigate the correlates of the tendency to give a forecast in the final stage (post-information) that is close to the number presented in the treatment—that is, the tendency to anchor to the presented statistic. We find no evidence of this tendency being less pronounced for individuals with higher numeracy or education, as one might have expected if respondents were naively anchoring their responses.

[25]The Zillow HPI coverage of our respondents' zip codes slightly increased between 2015 and 2016.

find such a comparison useful as suggestive evidence for whether information helps respondents form more accurate expectations.

Figure 3 shows the cumulative density plot of the ex-post forecast gap for the Control and Treatment respondents (combining the T1 and T5 groups). We see that the distribution for the control group is shifted to the right, indicative of our treatment moving respondents closer to the ex-post realized outcome; however, we cannot reject the equality of the two distributions at conventional levels of significance (p-value of 0.155 for a Kolmogorov-Smirnov test for equality of distributions). We find that 33% of treatment respondents are within 2 percentage points of the ultimately realized home price change, versus 26% for the control group. The average ex-post forecast gap is also smaller for the treatment group (4.36%, versus 4.88% for the control group; the p-value of a t-test for equality of means is 0.08). Thus, we find that the treatment seems to cause respondents' one-year forecasts to become marginally more accurate, based on the criterion above.

6 Expectations and Behavior

Our interest in home price expectations stems from the belief that they influence individuals' current and planned economic activity and economic outcomes. In this section, we investigate the link between home price expectations and actual as well as intended choices. While expectations play a key role in economic models of decision-making under uncertainty, there is surprisingly little *direct* empirical evidence on how subjective expectations impact financial decisions. This is largely a result of data limitations— establishing a direct link between expectations and behavior requires data on both from the same individuals, something generally not available.[26]

6.1 Investment in Housing Fund

As explained in Section 2.1, respondents were asked to allocate $1,000 for a year between a risk-free savings account (with a 2% annual return) and a housing fund that pays an annual return equal to the one-year growth in home prices in the respondent's area. This investment choice was

[26] Existing literature on financial decision-making that analyzes the role of expectations in choices usually has data on subjective expectations or actual choices, but not both. Thus, the literature either uses proxies for expectations or intended choices. See, for example, Malmendier and Nagel (2016), Bachmann et al. (2015), Crump et al. (2015), D'Acunto et al. (2015), and Bailey et al. (2016). On the other hand, Bover (2015) investigates the link between home price expectations and past purchases of durables. Also, these studies mostly exploit cross-sectional variation in expectations and cannot entirely rule out the role of confounds or the possibility of reverse causality. An exception is Armantier et al. (2015), who establish a link between inflation expectations and a financially incentivized investment decision where future inflation affects payoffs. In other contexts, such as education, the link between subjective expectations and actual choices is fairly well-established (Jensen 2010; Wiswall and Zafar 2015).

first elicited hypothetically (in the baseline stage) and then incentivized (in the final stage). While the scenario is clearly stylized, it offers a clean setting to test the link between expectations and behavior.

The dependent variable of interest is the share (on a 0-100 scale) that is allocated to the housing fund. Respondents, on average, allocate slightly more than half of their $1,000 endowment to the housing fund (54% in the baseline stage, 59% in the final stage). The standard deviation of the housing share is roughly 34% (in both stages), meaning there is substantial heterogeneity. We are interested in whether the housing share is systematically related to respondents' year-ahead home price expectations. We analyze this first cross-sectionally (in the baseline and final stage), and then test whether within-respondent, the change in the housing share between the two stages is related to the change in expectations.

Column (1) of Table 9 reports estimates from an OLS regression of the housing share onto year-ahead home price expectations reported in the baseline as well as an extensive set of controls.[27] We see that the housing share is significantly and positively related to home price expectations: the estimate indicates that a percentage point increase in year-ahead home price expectations is associated with a 0.82 percentage point higher investment in the housing fund. To put this estimate into context, a one standard deviation increase in baseline home price expectations is associated with a 3.1 percentage point increase in the housing share, while a one standard deviation increase in log household income is associated with a 4.7 percentage point increase in the housing share. Thus, the estimated effect size is economically meaningful. Coefficient estimates on other controls are also sensible: individuals who report being confident in their perception of past home prices, those who report having checked home prices in the past, and those with self-reported risk aversion below the median invest a higher share in the housing fund. Column (2) of the table reports estimates from the same specification as in column (1), except that we now also include respondents' perceived downside risk in year-ahead home price changes as an additional covariate.[28] Baseline home price expectations continue to be a significant correlate of the housing share (though the estimate declines to 0.52), and a higher perceived downside risk in home prices is associated with a lower share allocated to the housing fund.

Column (3) of Table 9 reports estimates from the same specification as in column (1), except that

[27] Because the dependent variable is not continuous but a fraction, we check the robustness of our results by estimating a fractional probit regression, following the methodology of Papke and Wooldridge (1996). The fractional probit specification yields estimates that are almost identical to the OLS model (results available from the authors upon request).

[28] Here, we sum the probabilities that the respondent assigns to year-ahead home price changes being less than -5%, and being between -5% and 0%.

we now use the revised housing share (from the final stage) as the dependent variable and revised year-ahead home price expectations as the explanatory variable of interest. The estimate is more than twice the corresponding estimate in column (1) of the table; the two estimates are statistically different (p-value = 0.011). The stronger link between expectations and behavior could be due to the fact that respondents answered several housing-related questions between the baseline and the post-information stage, prompting them to think harder about housing investments, or due to the post-treatment choice being incentivized. Column (4) supplements this specification by adding in controls for both the baseline housing share and an indicator for whether this share was a corner solution (that is, zero or 100). The coefficient on expected home price growth declines in magnitude, but remains highly statistically significant.

Columns (1)-(4) investigate the link between expectations and the housing share in the cross-section, controlling for an extensive set of demographic variables. However, one might be concerned about unobservable differences across individuals confounding the analysis. The within-survey panel on investment choices and home price expectations, generated as a result of our information experiment, allows us to investigate whether the relationship between home price expectations and behavior holds within-individual, and to give a causal interpretation to the relationship. Columns (5) and (6) of Table 9 report estimates of a regression of the within-individual change in the housing share onto changes in year-ahead home price expectations. Remarkably, the estimate is nearly identical to that in column (1): the estimate suggests that a percentage point increase in home price expectations leads to a 0.83 percentage point increase in the housing share.

The previous specification uses all variation in measured expectation revisions, but we can also isolate the effect of expectation revisions that happen due to our exogenous information treatment. The last two columns of Table 9 thus present estimates of an instrumental variable (IV) regression, where we instrument for the home price expectation revisions by the perception gap interacted with the corresponding treatment indicators. Column (7) shows that a one-percentage point predicted increase in home price expectations (due to the information intervention) leads to a 3.7 percentage point increase in the housing share. Note that while the first-stage relationship has a slightly low F-statistic of 9.7, the Kleibergen and Paap (2006) test comfortably rejects the hypothesis that the model is underidentified (p-value < 0.001).[29,30]

[29] In addition, we also estimate the model in column (7) with LIML (limited information maximum likelihood) instead of 2SLS. We get estimates and standard errors similar to those in column (7). This pattern, according to Angrist and Pischke (2008), suggests that even though the first-stage F-statistic is somewhat on the low side, our estimates are unlikely to be driven by a weak instrument problem.

[30] While the IV estimate is almost five times larger than the OLS one, the implied impact on the housing share is

Finally, we also investigate the direct impact of the information treatment on housing share revisions (the "reduced form" of the IV regression above). We use the same specification as in equation (5.1), except that the dependent variable is the change in the share allocated to the housing fund (and we now also include demographic controls). Column (1) of Table 10 shows that, for T1 respondents, a percentage point increase in the past one-year perception gap (that is, a 1 point underestimation of past one-year home price changes) leads to a 0.73 percentage point increase in the share assigned to the housing fund. T5 respondents exhibit an effect that is similar in magnitude for the five year perception gap. Controlling for the baseline housing share as well as for corner solutions at the baseline, in column (2), yields qualitatively similar estimates. The fraction of respondents who update their housing share in the final stage (relative to the baseline stage) is also significantly different across treatments (at $p < 0.01$): it is 38.4% in the Control but 46.1% in T1 and 47.5% in T5. Taken together, this is strong evidence that our information treatment not only impacts (certain) home price expectations, but also directly impacts housing-related behavior.

6.2 Other Housing-related Behaviors

While the investment choice provides us with a clean setting to investigate the role of home price expectations, its stylized setup arguably makes the role of home prices overly salient, relative to real-world choices. We next investigate how home price expectations are related to stated "real-world" behaviors. The trade-off, however, is that real-world choices may be impacted by several other constraints and confounds that we may be unable to fully control for.

Respondents were asked the probability of buying a non-primary home over the next 3 years (on a 0-100 scale).[31] The average response to this question is 9%, with a standard deviation of 18.5%. Column (1) of Table 11 shows that year-ahead home price expectations are positively and significantly related to the reported likelihood of buying a non-primary home, even after controlling for an array of demographics. The estimate indicates that a percentage point increase in year-ahead home prices is associated with a 0.41 percentage point higher reported likelihood of buying a non-primary home, a sizable impact on an average baseline likelihood of 9%. Other covariates, such as

qualitatively similar: a one standard deviation increase in the baseline one-year perception gap for T1 respondents leads to an increase of 1.43 percentage points in year-ahead home price expectations, which in turn results in a 5.2 percentage point increase in the housing share. This compares with an OLS-implied (column 5) impact of a 3.3 percentage point increase in the housing share for a standard deviation increase in home price expectation revisions. The larger IV impact may be due to the OLS estimate being attenuated due to "noise" in the measured expectation revisions.

[31]Specifically, respondents were asked *"What is the percent chance that over the next 3 years (February 2014 to February 2017) you will buy a home that you would NOT use as your primary residence (meaning you would use it as a vacation home, or as an investment property, etc.)?"*

risk preferences, income, and liquid savings, are meaningfully related to the choice. In column (2), we include medium-term home price expectations in addition to year-ahead expectations. While both coefficients are positive, only the one on year-ahead expectations is significant.

We next look at the reported likelihood of buying a home, conditional on moving over the next 3 years.[32] Columns (3)-(4) of Table 11 show that this choice is positively related to year-ahead home price expectations, though the estimate is not significant. Perceived downside risk in home prices is strongly negatively related with the reported likelihood of buying a home. A test of the significance of the expectations variables (one and two-to-five year expected home price changes, and the expected downside risk in year-ahead home price changes), reported lower in the table, rejects the null that these estimates are jointly zero.

We also ask respondents who currently own a home for the reported likelihood of selling their home over the next year.[33] The average reported likelihood is 14%. Column (5) of Table 11 shows there is no systematic relationship between short-term expectations and this likelihood. However, when we also include 2-5 year ahead home price expectations in column (6), we see a strong negative relationship between medium-term expectations and the likelihood of selling one's home within the next year. That is, respondents with less favorable longer-term expectations about their local home prices tend to report a higher likelihood of selling their home soon.

Finally, we asked homeowners the likelihood of making investments in their home over the next twelve months.[34] The average reported likelihood is 28%. Columns (7) and (8) regress this likelihood on both one-year expectations, and one and two-to-five year expectations jointly, respectively. We see that short-term expectations significantly impact the likelihood of making investments in one's home. Perceived downside risk in home prices is not significantly correlated with this likelihood.

Notably, the p-value of the joint test of the significance of expectations in the various columns in the table never exceeds 0.18, suggestive of housing expectations being a driver of intended behavior. In sum, the results in this section show that home price expectations impact actual and intended housing-related behavior, both in the cross-section as well as within-individual.

[32] Respondents are asked the probability they will move in the next three years; for those who respond that there is at least a 5% chance they will move, we ask this follow up question: "*And if you were to move to a different primary residence over the next 3 years, what is the percent chance that you would buy (as opposed to rent) your new home?*". The average reported probability is 65%.

[33] Respondents were asked: "*What is the percent chance that you will put your primary residence up for sale in the next 12 months?*"

[34] Respondents were asked: "*[W]hat do you think is the percent chance that, over the next 12 months (until February 2016), you will make any investments in your home costing more than $5,000 total?*"

7 Conclusion

Households' expectations are potentially a key driver of fluctuations in the housing market, one of the most important asset markets from a macro and household portfolio perspective. In this paper, we have made progress toward a better understanding of how households form their expectations, and how expectations affect behavior. Using a novel information experiment embedded in a survey, we have found that expectations about future home price growth react to information about past local home price growth, in a way not fully consistent with actual patterns in home prices. Specifically, on average respondents extrapolate from past information, but too little at a short (one-year) horizon, where actual momentum is strong, and too much at a longer (five-year) horizon, where home price growth tends to mean revert. We have also established a meaningful link between expectations and behavior, implying that our elicited expectations have information content and are not just "noise." One implication is that survey expectations are important for policy makers and housing market analysts to track.

Of course, expectations are not just affected by (perceived or actual) past local home price movements. They may be affected by personal experiences in the housing market, and also by social interactions. This latter channel is emphasized in recent work by Bailey et al. (2016) that is complementary to ours. In Appendix A.3, we offer a rough comparison of our estimates with theirs, and find similar effect sizes for the "individual" and "social" channels in affecting expectations. Measuring the importance of different drivers of expectations and the relative importance of own experiences (versus social channels) remains a priority for future research; survey-based information experiments, as implemented here, provide a powerful tool to do so.

Finally, our set-up exogenously exposes individuals to information about past home price changes. In the real world, however, individuals' decision to look up or to ignore certain information is endogenous. Information regarding past home prices is readily available, and so at least some of our respondents have made a choice to stay uninformed about these statistics. Understanding the process of information acquisition is another important avenue for future research.

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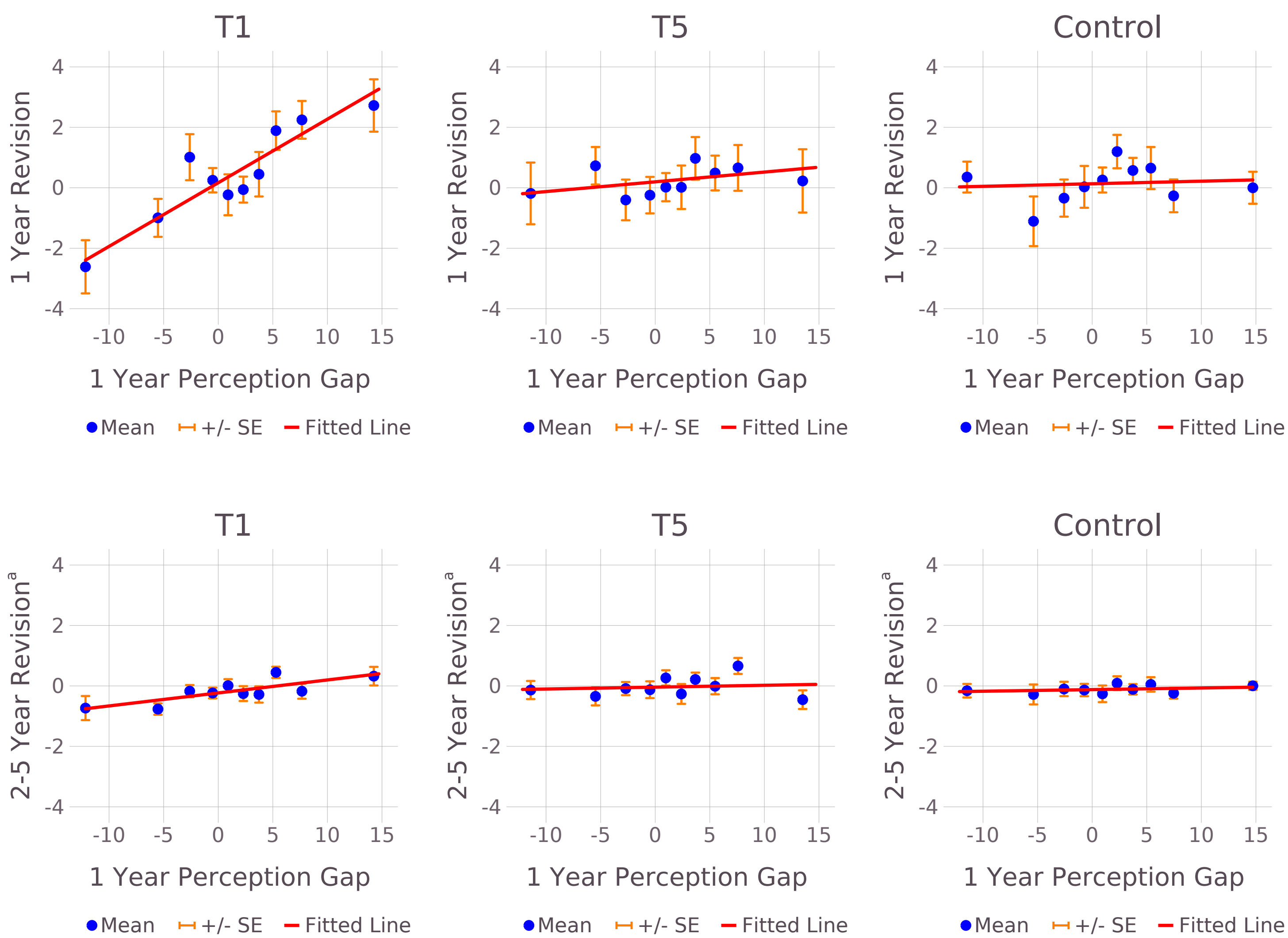
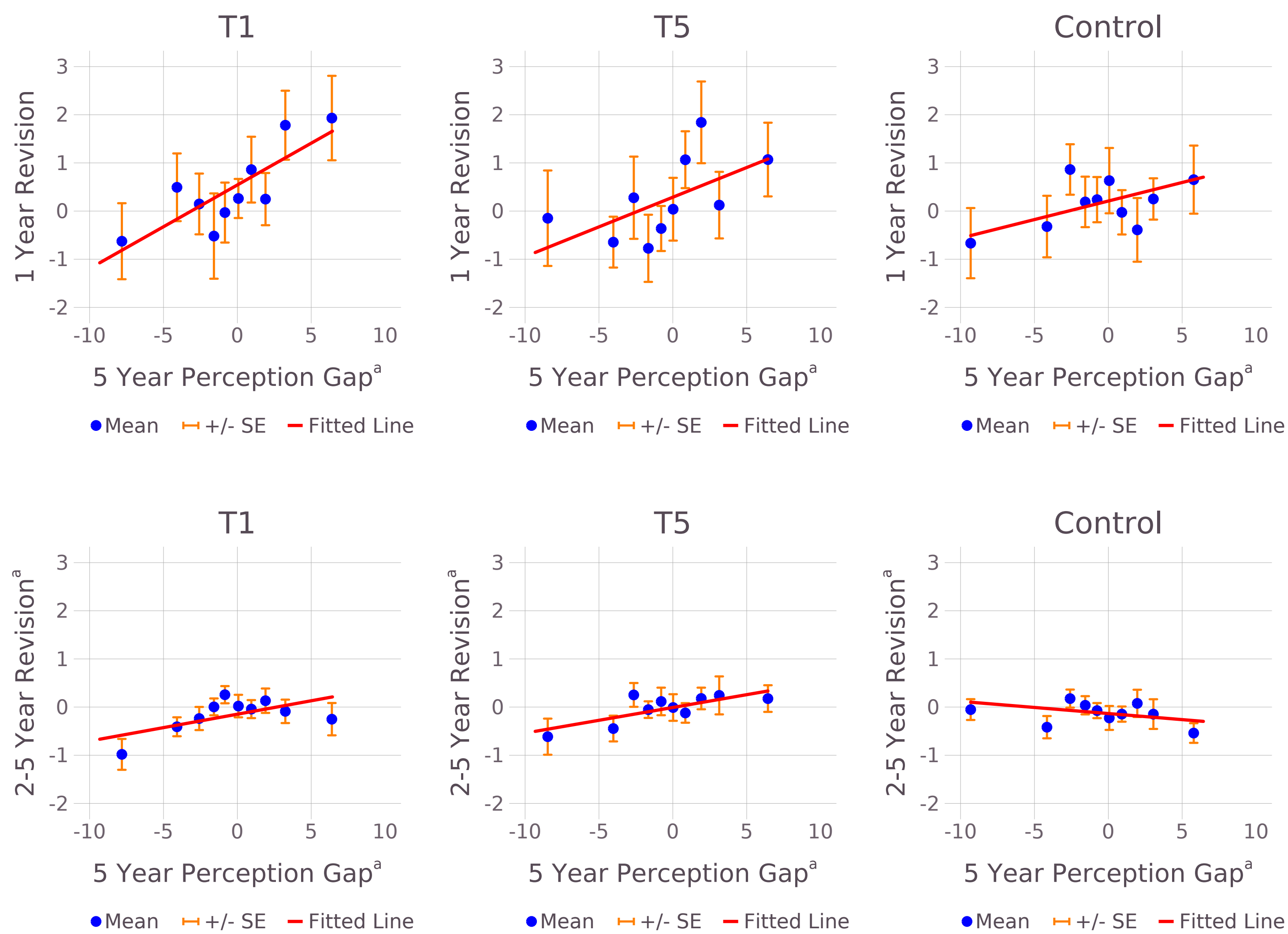
Figure 1. Average Revision in Home Price Expectations, conditional on 1-year Perception Gaps.



[a] Annualized

Figure 2. Average Revision in Home Price Expectations, conditional on 5-year Perception Gaps.



[a] Annualized

Figure 3. Cumulative Distribution Function of Realized Forecast Gap

Forecast gap = absolute value of (Final-stage 1-year expectation − Realization)

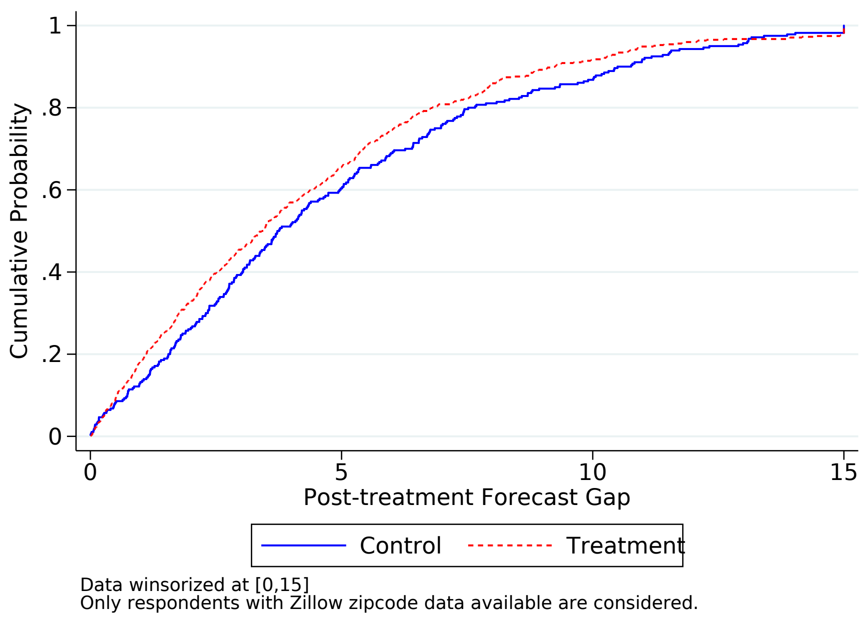


Table 1: Sample Characteristics

	Full Sample	Control	T1	T5	P-value[a]	Follow-up[b]
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	1020	336	345	339		729
Age (in years)	50.4	51.1	50.7	49.4	0.301	51.5
	(15.3)	(15.7)	(15.1)	(15.1)		(15.2)
Male	54.3%	57.4%	58.0%	47.5%	0.008	53.9%
White & Non-hispanic	78.8%	78.6%	79.7%	78.2%	0.887	80.1%
Married	67.8%	65.8%	69.9%	67.8%	0.523	66.3%
Homeowner	74.3%	75.0%	73.6%	74.3%	0.919	75.4%
Tenure in town/city (in yrs)	19.1	19.3	19.6	18.3	0.548	19.5
	(16.5)	(16.4)	(17.1)	(16.0)		(16.8)
Bachelor's Degree or More	55.3%	54.5%	54.2%	57.2%	0.680	55.0%
HH Income < \$60,000	52.9%	51.5%	53.0%	54.3%	0.768	51.9%
HH Income < \$30,000	20.0%	19.9%	20.3%	19.8%	0.985	20.2%
High Numeracy[c]	73.5%	75.9%	73.3%	71.4%	0.413	74.2%
Employed	66.5%	66.1%	66.4%	67.0%	0.970	65.6%
Unemployed	3.6%	4.8%	3.5%	2.7%	0.338	3.4%
Not in the Labor Force	28.9%	28.3%	30.1%	28.3%	0.828	30.2%
Census region location:						
Northeast	15.8%	14.0%	16.5%	16.8%	0.542	16.5%
Midwest	21.4%	22.3%	20.0%	21.8%	0.738	21.3%
South	38.4%	37.2%	40.3%	37.8%	0.677	37.4%
West	24.4%	26.5%	23.2%	23.6%	0.553	24.8%

Means of continuous variables reported. Standard deviations in parentheses for continuous variables.
[a] P-value of one-way ANOVA test of equality of each row variable across the three groups (Control, T1, T5).
[b] Follow-up is the sample that participates in the follow-up survey. Tests of equality of means or proportions between full sample (column 1) and follow-up sample fail to reject the null hypothesis of no differences (i.e. $p > 0.1$ for all variables.)
[c] High Numeracy indicates correctly answered four or more of five survey questions testing respondent's numeracy.

Table 2: Dependence in Actual Zip-code-level Home Price Changes (CoreLogic Data, 1976-2015)

	Survey Sample[a]			National Sample[b]		
	Estimates	Percent Positive[c]	Percent Negative[d]	Estimates	Percent Positive	Percent Negative
A. 1 year home price growth on lagged 1 year growth	0.53	91.2%	0.0%	0.53	89.7%	0.0%
	(0.14)			(0.14)		
	[0.55]			[0.56]		
B. 1 year home price growth on lagged 5 year growth	0.14	15.5%	2.3%	0.15	16.0%	1.2%
	(0.23)			(0.23)		
	[0.14]			[0.15]		
C. 2-5 year home price growth on lagged 1 year growth	0.03	8.1%	1.7%	0.03	8.8%	1.2%
	(0.12)			(0.12)		
	[0.02]			[0.02]		
D. 2-5 year home price growth on lagged 5 year growth	-0.38	3.2%	51.3%	-0.38	2.7%	49.9%
	(0.38)			(0.37)		
	[-0.40]			[-0.39]		

Table shows regression estimates of home price change dependence on previous changes. Mean coefficient across zip codes shown in first cell; standard deviation across zip codes shown in parentheses; median in square brackets.
Number of observations per zip code that these estimates are based on: A. 38 observations B. 34 observations C. 34 observations D. 30 observations.
[a] Consists of the sample of coefficients corresponding to each respondent's zip code, if covered by CoreLogic (N=753).
[b] Consists of the sample of all zip codes in the United States covered by CoreLogic. (N=7133).
[c] Indicates percent of local home price change coefficients statistically significantly positive at the 5% level, based on Newey-West standard errors (A: 1 lag; B: 5 lags; C: 5 lags; D: 10 lags).
[d] Indicates percent of local home price change coefficients statistically significantly negative at the 5% level, based on Newey-West standard errors (A: 1 lag; B: 5 lags; C: 5 lags; D: 10 lags).

Table 3: Home Price Perceptions and Expectations

	Full Sample	Control	T1	T5	P-value[a]	L-frame	C-frame	P-value[b]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Perceptions								
Past 1yr HP change	3.81	3.76	3.42	4.27	0.120	4.12	3.53	0.083
	(5.43)	(5.19)	(5.40)	(5.66)		(5.57)	(5.28)	
	[4.88]	[4.75]	[4.70]	[5.18]		[4.94]	[4.83]	
Past 5yr HP change	1.53	1.60	1.43	1.57	0.756	2.12	1.00	0.000
(annualized)	(3.04)	(2.85)	(3.10)	(3.18)		(3.44)	(2.52)	
	[2.71]	[2.58]	[2.70]	[2.84]		[3.37]	[2.10]	
Panel B: Perception Gaps (=Zillow HPA - Perceived HPA)								
1yr Perception Gap	1.38	1.42	1.43	1.28	0.954	1.13	1.60	0.287
	(7.02)	(7.17)	(7.13)	(6.77)		(7.31)	(6.74)	
	[5.44]	[5.57]	[5.43]	[5.33]		[5.58]	[5.32]	
5yr Perception Gap	-0.51	-0.80	-0.36	-0.39	0.286	-1.42	0.30	0.000
(annualized)	(4.07)	(3.93)	(4.09)	(4.19)		(4.39)	(3.57)	
	[3.00]	[2.81]	[3.07]	[3.10]		[3.39]	[2.64]	
Panel C: Expectations								
Baseline 1yr exp. HP change	3.51	3.39	3.41	3.73	0.427	3.64	3.39	0.297
	(3.83)	(3.72)	(3.79)	(3.96)		(4.02)	(3.64)	
	[3.79]	[3.69]	[3.70]	[3.98]		[3.84]	[3.75]	
Baseline 5yr exp. HP change	11.01	9.99	11.68	11.33	0.059	14.11	8.21	0.000
	(9.77)	(9.10)	(10.14)	(9.96)		(10.84)	(7.68)	
	[11.37]	[10.59]	[11.91]	[11.58]		[14.39]	[8.63]	
Baseline 2-5yr exp. HP change	1.70	1.51	1.88	1.72	0.022	2.36	1.11	0.000
(annualized)	(1.76)	(1.61)	(1.87)	(1.78)		(1.91)	(1.37)	
	[1.81]	[1.68]	[1.96]	[1.80]		[2.43]	[1.25]	
Panel D: Updates								
1yr forecast update	0.29	0.15	0.48	0.24	0.516	0.16	0.41	0.328
	(3.94)	(3.34)	(4.17)	(4.25)		(4.15)	(3.74)	
	[2.39]	[1.97]	[2.55]	[2.64]		[2.45]	[2.34]	
5yr forecast update	-0.12	-0.27	-0.25	0.18	0.715	-0.11	-0.12	0.981
	(8.01)	(6.25)	(8.37)	(9.12)		(9.26)	(6.69)	
	[4.80]	[3.78]	[4.85]	[5.78]		[5.64]	[4.06]	
2-5yr forecast update	-0.10	-0.11	-0.17	-0.03	0.484	-0.07	-0.14	0.438
(annualized)	(1.47)	(1.27)	(1.48)	(1.65)		(1.67)	(1.27)	
	[0.94]	[0.84]	[0.94]	[1.05]		[1.07]	[0.82]	
% update 1 year forecast	61.91%	56.89%	64.72%	64.01%	0.069	56.85%	66.48%	0.002
% update 5 year forecast	66.50%	60.48%	64.43%	74.56%	0.000	62.58%	70.04%	0.012

Perceptions, perception gaps, expectations, and updates all reported in percentage points. Mean reported in each cell. Standard deviation in parantheses. Mean absolute value in square brackets.
[a] P-value of one-way ANOVA test of equality of each row variable across the three groups (Control, T1, T5).
[b] P-value of one-way ANOVA test of equality of each row variable across the two framings (L-frame, C-frame).

Table 4: Correlates of Perception Gaps

	Abs. Perception Gap[a]	
	1yr	5yr annualized
	(1)	(2)
Male	-0.23	0.32*
	(0.31)	(0.17)
Lived in current town/city for 15+ years	0.01	0.04
	(0.33)	(0.18)
Checked housing websites[b]	-0.29	-0.06
	(0.33)	(0.19)
Confident in recalled price change[c]	-0.45	-0.17
	(0.31)	(0.18)
Likely to buy or sell home in future[d]	0.19	-0.10
	(0.40)	(0.22)
White	-0.13	-0.34
	(0.38)	(0.24)
Age $<$ 50	0.02	-0.10
	(0.33)	(0.20)
Income $\geq$ \$75,000	-0.63*	-0.20
	(0.33)	(0.20)
Bachelor's Degree or More	-0.56*	-0.17
	(0.33)	(0.19)
Homeowner	0.24	-0.35
	(0.35)	(0.22)
Married	-0.56	-0.11
	(0.35)	(0.21)
Employed	0.64*	0.38*
	(0.35)	(0.20)
High Numeracy[e]	-0.92**	-0.10
	(0.36)	(0.20)
T1	-0.16	0.28
	(0.36)	(0.21)
T5	-0.26	0.34
	(0.35)	(0.22)
C-frame	-0.38	-0.78***
	(0.29)	(0.18)
Volatile Local Home Market [f]	1.26***	0.78***
	(0.33)	(0.21)
Constant	6.61***	3.40***
	(0.76)	(0.46)
Observations	1018	1017
R-Squared	0.053	0.063
Joint sig of covariates[g]	0	0
Mean of dep. variable	5.44	3.00

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
[a] The gap between the perceived and actual zip code home price change in absolute magnitude. All gaps annualized.
[b] Dummy that equals 1 if respondent reports consulting websites about home prices in past twelve months.
[c] Dummy that equals 1 if respondent reports being confident in their recall of past home price changes (i.e. answers 4 or more on a 1-5 scale, where 5 is very confident).
[d] Dummy that equals 1 if probability of buying home in three years is $\geq$ 50% or probability of selling home in one year is $\geq$ 50%.
[e] Dummy that equals 1 if respondent correctly answered four or more of five questions measuring numeracy.
[f] Dummy that equals 1 if zipcode home price volatility over the past five years, as measured by Corelogic's HPI, is above the sample median.
[g] F-test on equality of all covariates to zero (excluding constant). P-value shown.

Table 5: Relationship between Home Price Expectations and Perceptions in Baseline Stage

	1 Year Expectations				2-5 Year Expectations [a]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past 1 Year Perceptions	0.262***	0.226***			0.058***	0.047***		
	(0.029)	(0.028)			(0.012)	(0.012)		
Past 5 Year Perceptions[a]			0.213***	0.202***			0.094***	0.080***
			(0.051)	(0.047)			(0.024)	(0.023)
Constant	2.563***	1.306	3.189***	3.208	2.120***	2.272***	2.161***	1.696**
	(0.222)	(1.143)	(0.210)	(2.449)	(0.097)	(0.469)	(0.103)	(0.755)
Observations	1020	1020	1019	1019	1020	1020	1019	1019
R-Squared	0.138	0.236	0.029	0.166	0.158	0.226	0.151	0.224
Control for Fundamentals[b]	No	Yes	No	Yes	No	Yes	No	Yes

OLS estimates reported. Regression also includes a C-frame dummy. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
[a] Annualized.
[b] Fundamentals include measures of respondent expectations of general inflation, mortgage rate changes, rent inflation, future economic conditions, and future credit availability.

Table 6: Home Price Expectation Revisions

	Home Price Expectation Revisions at horizon:					
	1 year	2-5 year	1 year	2-5 year	1 year	2-5 year
	(1)	(2)	(3)	(4)	(5)	(6)
T1 (β_1)	0.02	-0.12	0.19	0.03		
	(0.29)	(0.11)	(0.38)	(0.14)		
T5 (β_2)	0.10	0.10	0.07	0.13	-0.30	0.21
	(0.29)	(0.11)	(0.38)	(0.15)	(0.44)	(0.17)
1yr Perception Gap[a] (β_3)	0.00	0.00	0.00	0.00		
	(0.03)	(0.01)	(0.03)	(0.01)		
5yr Perception Gap (β_4)	0.05	0.00	0.05	0.00		
	(0.05)	(0.02)	(0.05)	(0.02)		
T1 * 1yr Perception Gap (β_5)	0.20***	0.04**				
	(0.04)	(0.02)				
T5 * 5yr Perception Gap (β_6)	0.07	0.05*				
	(0.08)	(0.03)				
T1*1yr Perc Gap*$\mathbb{1}$(Gap$\geq$0)			0.17**	0.02		
			(0.07)	(0.02)		
T1*1yr Perc Gap*$\mathbb{1}$(Gap$<$0)			0.23***	0.08**		
			(0.07)	(0.04)		
T5*5yr Perc Gap*$\mathbb{1}$(Gap$\geq$0)			0.08	0.04		
			(0.12)	(0.06)		
T5*5yr Perc Gap*$\mathbb{1}$(Gap$<$0)			0.06	0.06		
			(0.13)	(0.04)		
T1*$\mathbb{1}$(Perceptions below actual)					1.89***	0.61***
					(0.46)	(0.17)
T1*$\mathbb{1}$(Perceptions above actual)					-1.81***	-0.07
					(0.65)	(0.22)
T5*$\mathbb{1}$(Perceptions below actual)					1.79***	0.47**
					(0.51)	(0.20)
T5*$\mathbb{1}$(Perceptions above actual)					-1.26**	-0.17
					(0.57)	(0.23)
C-frame (β_7)	0.14	-0.11	0.15	-0.11	0.16	-0.05
	(0.25)	(0.10)	(0.26)	(0.10)	(0.31)	(0.12)
Constant (β_0)	0.11	-0.05	0.10	-0.05	0.21	-0.32**
	(0.24)	(0.10)	(0.24)	(0.10)	(0.32)	(0.13)
Observations	1015	1013	1015	1013	682	681
R-Squared	0.056	0.024	0.057	0.027	0.089	0.032
Joint sig of covariates[b]	0	.052	0	.104	0	.001
Mean of dep. variable	0.29	-0.10	0.29	-0.10	0.36	-0.10
SD of dep. variable	3.94	1.47	3.94	1.47	4.21	1.57
Sample	All	All	All	All	Treated	Treated

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
5 year perception gap and 2-5 year home price change expectations are annualized.

[a] Perception gap $\alpha_{i,t} = \pi_{i,t} - \widehat{\pi}_{i,t}$, the difference between Zillow information and respondent i's price change perceptions over the past t years.

[b] F-test on equality of all covariatesto zero (excluding constant). P-value shown.

Table 7: Heterogeneity in Updating at both Horizons

		1 year Home Price Expectations				5 year Home Price Expectations			
	Sample Size	Non Updater[a]	P-value[b]	Extrapolator/ Mean Revert	P-value[c]	Non Updater	P-value[b]	Extrapolator/ Mean Revert	P-value[c]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Full Sample (T1+T5)	684	0.83		1.68		0.77		1.72	
T1	345	0.82	0.847	2.03	0.062	0.90	0.004	1.86	0.446
T5	339	0.83		1.40		0.64		1.60	
Panel A: Individual Characteristics									
$<$ 40 years old	202	0.90	0.483	2.56	0.045	0.88	0.178	2.45	0.070
40-60 years old	272	0.72		1.50		0.86		1.43	
$\geq$ 60 years old	210	0.90		1.38		0.63		1.58	
Has Lived In Locality $<$ 15 years	332	0.87	0.563	1.90	0.247	0.78	0.869	1.77	0.736
Has Lived In Locality 15+ years	352	0.78		1.51		0.77		1.66	
No Negative Housing Market Experience	621	0.84	0.551	1.73	0.360	0.77	0.653	1.86	0.014
Foreclosure, Short Sale, or Underwater Mortgage	63	0.66		1.30		0.86		0.88	
Panel B: Location Characteristics									
Below-Median Supply Elasticity[d]	218	0.75	0.308	2.23	0.012	0.75	0.295	2.06	0.057
Above-Median Supply Elasticity	222	0.92		1.19		0.94		1.31	
Above-Median One-year Momentum [e]	315	0.93	0.341	1.84	0.464	0.74	0.457	1.76	0.422
Below-Median One-year Momentum	304	0.79		1.58		0.85		1.50	
Above-Median Long-term Mean Reversion[f]	310	0.83	0.673	1.90	0.319	0.78	0.913	2.15	0.007
Below-Median Long-term Mean Reversion	309	0.88		1.54		0.80		1.25	

[a] The proportion of respondents in the treatment group who do not update their home price expectations (relative to the control group).
[b] Significance test of differential effect of being treated between groups on the probability of updating. Uses a difference-in-difference approach by testing significance of regression coefficient for the interaction(s) of treatment indicator and group indicator(s).
[c] Significance test of difference in distribution of extrapolators and mean reverters among those who update, between groups. Reports p-value from Pearson χ_2 test.
[d] Housing supply elasticity measured at the MSA level according to Saiz (2010).
[e] Momentum measured by dependence of county-level 1 year home price appreciation on the previous year's home price appreciation.
[f] Mean reversion measured by dependence of county-level 2 to 5 year home price appreciation on the previous 5 year's home price appreciation. Above-median here means strong mean reversion (i.e., a relatively more negative regression coefficient).

Table 8: Persistence in Impact of Information

Dependent Variable: Revision in HP expectations				
	1 year		2-5 year	
	Final - Baseline	Followup - Baseline	Final - Baseline	Followup - Baseline
	(1)	(2)	(3)	(4)
T1 (β_1)	-0.26	-0.09	-0.11	-0.19
	(0.34)	(0.40)	(0.12)	(0.17)
T5 (β_2)	-0.38	-1.16***	0.11	-0.24
	(0.33)	(0.44)	(0.13)	(0.19)
1yr Perception Gap (β_3)	-0.01	-0.03	0.00	0.01
	(0.03)	(0.04)	(0.01)	(0.02)
5yr Perception Gap (β_4)	0.05	0.05	0.01	0.06**
	(0.06)	(0.06)	(0.02)	(0.03)
T1 * 1yr Perception Gap (β_5)	0.18***	0.13**	0.03**	0.01
	(0.05)	(0.07)	(0.02)	(0.03)
T5 * 5yr Perception Gap (β_6)	0.02	-0.09	0.04	-0.04
	(0.11)	(0.12)	(0.03)	(0.05)
C-frame (β_7)	0.32	0.29	-0.21**	-0.17
	(0.30)	(0.36)	(0.11)	(0.15)
Constant (β_0)	0.15	0.96***	0.05	0.38**
	(0.27)	(0.34)	(0.11)	(0.16)
Observations	691	691	681	681
R-Squared	0.048	0.028	0.026	0.022
Joint sig of covariates[a]	0	.033	.049	.173
Mean of dep. variable	0.16	0.71	-0.05	0.14

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01. Sample restricted for all columns to those who answered both the original and followup survey.
[a] F-test on equality of all covariates to zero (excluding constant). P-value shown.

Table 9: Investment in Housing Fund and Expectations

Dependent Variable: Housing fund share (on a 0-100 scale)	Baseline		Post-treatment (Final)		Revision (Final-Baseline)		Revision (IV Regression [i])	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline 1-year ΔHP Expectation	0.82***	0.52*						
	(0.29)	(0.29)						
Pr(Decrease in HP next year)[a]		-0.14***						
		(0.04)						
Final 1-year ΔHP Expectation			1.84***	1.19***				
			(0.28)	(0.21)				
(Final - Baseline) 1-yr ΔHP Exp. revision					0.83***	0.84***	3.67***	3.95***
					(0.23)	(0.21)	(1.42)	(1.39)
Baseline Share in Housing Fund				0.75***		-0.22***		-0.23***
				(0.04)		(0.04)		(0.04)
T1	2.54	2.99	2.57	0.75	0.22	0.95	-0.91	-0.17
	(2.56)	(2.56)	(2.55)	(1.72)	(1.84)	(1.72)	(2.06)	(1.98)
T5	1.50	1.86	0.44	-0.66	-0.70	-0.18	-1.05	-0.51
	(2.60)	(2.59)	(2.56)	(1.63)	(1.75)	(1.64)	(1.98)	(1.92)
Homeowner with zero equity [b]	-5.01	-4.82	-0.62	3.00	3.71	2.17	3.94	2.41
	(3.12)	(3.08)	(3.26)	(2.24)	(2.37)	(2.25)	(2.59)	(2.54)
Confident in recalled price change[c]	4.57*	3.82	1.48	-1.72	-2.75*	-1.38	-2.75	-1.48
	(2.37)	(2.36)	(2.31)	(1.53)	(1.67)	(1.54)	(1.81)	(1.73)
Above-median risk aversion[d]	-7.28***	-7.35***	-6.56***	-1.55	0.29	-1.68	0.88	-1.06
	(2.13)	(2.11)	(2.10)	(1.47)	(1.58)	(1.48)	(1.72)	(1.66)
Checked housing websites[e]	7.94***	8.08***	10.41***	4.76***	2.73	5.00***	2.74	5.15***
	(2.41)	(2.40)	(2.37)	(1.68)	(1.77)	(1.70)	(1.94)	(1.91)
C-frame	2.42	0.76	2.13	0.64	-0.05	0.39	-1.30	-0.68
	(2.10)	(2.16)	(2.06)	(1.43)	(1.56)	(1.45)	(1.74)	(1.65)
Constant	-29.07	-21.07	18.24	37.48**	47.79***	37.72**	49.59***	40.72**
	(19.68)	(20.38)	(19.28)	(14.56)	(15.96)	(14.90)	(17.67)	(17.05)
Demographics[f]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Corner Solutions Controlled For [g]	No	No	No	Yes	No	Yes	No	Yes
Observations	1018	1013	1013	1013	1013	1013	1012	1012
R-Squared	0.12	0.13	0.14	0.60	0.05	0.19		
Joint sig of covariates[h]	0	0	0	0	.016	0	.217	0
Mean of dep. variable	53.86	53.91	58.89	58.89	4.98	4.98	4.99	4.99
1st-stage F test statistic (IV only)							9.72	9.49

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
[a] The probability (on a 0-100 scale) that respondent assigns to year-ahead home prices decreasing.
[b] Because we also control for equity, which all homeowners have a value for, the interpretation of an isolated Homeowner variable is Homeowners with zero equity.
[c] Dummy that equals 1 if respondent reports being confident in their recall of past home price changes (i.e. answers 4 or more on a 1-5 scale, where 5 is very confident).
[d] Dummy that equals 1 if respondent reports a 4 or less (on 1-10 scale) to question about willingness to take risks in financial matters, where 10 is very willing.
[e] Dummy that equals 1 if respondent reports consulting websites about home prices in past 12 months.
[f] Includes binary indicators for owning a home, numeracy, ethnicity, gender, marital status, education, labor force status, and census region. Additionally, all regressions include controls for age, age^2, and logs of household income, equity in home, liquid savings, and personal debt.
[g] Includes Indicators for whether respondent assigned 0% or 100% to the housing fund in the baseline.
[h] F-test on equality of all covariates to zero (excluding constant). P-value shown.
[i] IV regression using treatment variables (perception gap times treatment indicators) as excluded instruments. First stage identical to column (1) of Table 6. As a result, uninteracted perception gaps are included as additional controls in columns (7) and (8).

Table 10: Impact of Information on Housing Fund Decision

Dependent Variable: Change in Share in Housing Fund (Final - Baseline)		
	(1)	(2)
T1 (β_1)	-0.62	-0.06
	(1.86)	(1.74)
T5 (β_2)	-0.27	0.43
	(1.73)	(1.63)
1yr Perception Gap(β_3)	0.12	0.02
	(0.14)	(0.13)
5yr Perception Gap (β_4)	0.14	0.01
	(0.24)	(0.23)
T1 * 1yr Perception Gap (β_5)	0.73***	0.79***
	(0.25)	(0.23)
T5 * 5yr Perception Gap (β_6)	0.88**	1.03***
	(0.38)	(0.36)
Baseline Share in Housing Fund		-0.21***
		(0.04)
C-frame (β_7)	-0.64	0.02
	(1.58)	(1.47)
Constant (β_0)	52.49***	41.01***
	(15.80)	(14.85)
Demographics[a]	Yes	Yes
Initial Corner Solutions Controlled For [b]	No	Yes
Observations	1017	1017
R-Squared	0.065	0.189
Joint sig of covariates[c]	0	0
Mean of dep. variable	4.99	4.99

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
[a] Includes binary indicators for owning a home, numeracy, ethnicity, gender, marital status, education, labor force status, and census region. Additionally, all regressions include controls for age, age^2, percent equity in home, and logs of household income, liquid savings, and personal debt.
[b] Includes indicators for whether respondent assigned 0% or 100% to the housing fund in baseline question.
[c] F-test on equality of all covariates to zero (excluding constant). P-value shown.

Table 11: Housing-related Behavior and Home Price Expectations

	Pr(Buy non-primary home)[a]		Pr(Buy home)[b]		Pr(Sell home)[c]		Pr(Invest in home next year)[d]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline 1 year HP Expectation	0.41***	0.39**	0.22	0.23	0.33	0.43	0.63*	0.54*
	(0.16)	(0.16)	(0.31)	(0.32)	(0.26)	(0.26)	(0.32)	(0.32)
Baseline 2-5 year HP Expectation [e]		0.26		-0.11		-1.31**		1.23
		(0.33)		(0.70)		(0.62)		(0.76)
Pr(Decrease in HP next year)[f]	0.03	0.03	-0.12**	-0.12**	0.06	0.06	0.03	0.03
	(0.02)	(0.02)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Above median risk aversion [g]	-4.66***	-4.60***	-2.98	-3.00	-3.32*	-3.52*	-5.67**	-5.48**
	(1.22)	(1.22)	(2.26)	(2.27)	(1.99)	(2.01)	(2.37)	(2.36)
Log(Household income in $)	3.74***	3.75***	2.55	2.56	1.99	1.83	6.76***	6.91***
	(0.96)	(0.96)	(2.20)	(2.21)	(1.60)	(1.60)	(2.20)	(2.20)
Log(Liquid Savings in $)	0.88***	0.88***	1.77***	1.78***	-0.37	-0.31	0.77	0.72
	(0.27)	(0.27)	(0.64)	(0.65)	(0.56)	(0.55)	(0.68)	(0.68)
Log(Non-housing debt in $)	-0.03	-0.03	0.36	0.36	0.32	0.34	0.11	0.08
	(0.33)	(0.33)	(0.62)	(0.63)	(0.47)	(0.47)	(0.61)	(0.61)
Equity in the home [h]	0.02	0.02	0.09**	0.09**	-0.01	-0.01	0.02	0.02
	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
C-frame	1.05	1.39	-2.75	-2.90	3.44*	2.08	1.47	2.75
	(1.16)	(1.28)	(2.31)	(2.47)	(1.92)	(2.08)	(2.32)	(2.44)
Demographics[i]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1008	1008	690	690	748	748	749	749
R-Squared	0.111	0.111	0.321	0.321	0.087	0.092	0.119	0.122
Joint sig of expectations[j]	.032	.067	.011	.029	.175	.033	.151	.107
Joint sig of all other controls[k]	0	0	0	0	0	0	0	0
Mean of dep. variable	8.98	8.98	64.90	64.90	14.38	14.38	27.93	27.93
Std. Dev. of dep. variable	18.49	18.49	34.53	34.53	25.04	25.04	31.89	31.89
Subsample	All	All	Pr(Move) $\geq 5\%$	Pr(Move) $\geq 5\%$	Owners	Owners	Owners	Owners

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
[a] Probability of buying a non-primary home in the next three years (on a 0-100 scale).
[b] Probability of buying a home conditional on moving in the next three years (on a 0-100 scale).
[c] Probability of putting home up for sale in the next twelve months (on a 0-100 scale).
[d] Probability of investing $5,000 in your home in next three years (on a 0-100 scale).
[e] Annualized expected home price change in zip code 2-5 years ahead.
[f] The probability that respondent assigns to year-ahead home prices decreasing (on a 0-100 scale).
[g] Dummy that equals 1 if respondent reports a 4 or less (on 1-10 scale) to question about willingness to take risks in financial matters, where 10 is very willing.
[h] Equity defined as $\frac{\text{Self-Appraised Home Worth} - \text{Mortgage Debt} - \text{HELOC Debt}}{\text{Self-Appraised Home Worth}}$.
[i] All regressions include binary indicators for owning a home, numeracy, ethnicity, gender, marital status, education, labor force status, age, age^2, and census region. Pr(Sell home) and Pr(Invest in home) also include home age and unit type as controls.
[j] F-test on equality of all expectations (1 year HP Expectation, 2-5 year HP Expectation, and Pr(Decrease in HP next year)) to zero. P-value shown.
[k] F-test on equality of all other covariates to zero (excluding constant). P-value shown.

Appendix

This appendix presents additional empirical results referred to in the main text. Tables A-1 to A-3 are described in the main text and should be self-explanatory. The remaining tables are described below.

A.1 Robustness Checks of Expectations Revisions Analysis

Table A-4 reports various robustness checks of our main analyis in Section 5.

Columns (1) and (2) of Table A-4 report estimates of the same specification as in columns (1) and (2) of Table 6, but restricting the sample to treatment respondents. The goal is to see if idiosyncratic updating patterns in the Control group are driving our results. The estimates of interest (the perception gap interacted with the treatment dummies) are qualitatively similar to those in the baseline.

Columns (3) and (4) show that the main results are similar if we winsorize the observations that are trimmed in the main analysis.

The next two columns of the table restrict the sample to control respondents and those treatment respondents who are able to consistently recall their perceptions of past home price changes. This is based on the qualitative question about subjective informedness, described in Section 5.3.1. Here we drop treatment respondents who reported that they thought past realized home price changes were lower than their perceptions, when in fact they had overestimated home price changes (and the converse). This drops 31 of the 345 respondents in the T1 block, and 38 of the 339 respondents in the T5 block. We see that the estimates, excluding these respondents, are qualitatively similar to those in the baseline specification.

Finally, we perform a falsification test of our specification by switching the interactions between perception gaps and treatment group assignment:

$$\Delta y_{i,t} = \beta_0 + \beta_1 T_{1,i} + \beta_2 T_{5,i} + \beta_3 \alpha_{i,1} + \beta_4 \alpha_{i,5} + \beta_5 (T_{1,i} * \alpha_{i,5}) + \beta_6 (T_{5,i} * \alpha_{i,1}) + \beta_7 1_{\text{C-frame},i} + \varepsilon_{i,t}.$$

The interactions terms, β_5 and β_6, should not be different from zero, since theoretically T5 respondents should have no information about their one year perception gap, and vice versa for T1 respondents. This is indeed what we see in columns (7) and (8) of Table A-4, where estimates of both interaction terms are indiscernible from zero. The uninteracted past one year perception gap coefficient (β_3) is now significant and positive because the original treatment effect on T1 respondents is embedded within this coefficient.

A.2 Multivariate Analysis of Heterogeneity

In this section, we provide an updating type analysis in a multivariate framework. Relative to the univariate cuts presented in Section 5.4, this analysis allows us to (1) test whether the main findings from Table 7 remain valid when we control for other observables; (2) investigate which other factors significantly correlate with a respondents' propensity to update and to extrapolate; and (3) control for the perception gap magnitude and sign. Restricting the sample to respondents in the treatment groups, we estimate a model where the respondent first decides whether to update her expectation, and then, conditional on updating, decides whether to extrapolate or not (that is, mean revert). We estimate the two equations jointly, allowing for a correlation between the two stages. This allows us to control for selection (on observables) into updating. We estimate both equations as bivariate probits.[35]

Table A-5 reports estimated marginal effects. Looking at updating patterns for the year-ahead revisions, reported in the first two columns, we see that lower-income, college-educated, and older respondents, and those less confident in their recall of past price changes are all more likely to update. Column (2) of the table shows that younger individuals, those with shorter local tenures, and those residing in high short-term momentum and high long-term mean reversion areas are substantially more likely to extrapolate (only the first estimate is statistically significant).[36]

Turning to medium-term expectations, demographics are not significant correlates of the propensity to update. However, several patterns of note stand out when investigating the conditional likelihood of extrapolating. Even after controlling for observables, individuals residing in areas with higher long-term mean reversion in home prices are more likely to extrapolate. Younger individuals and those with at least a bachelor's degree are also more likely to extrapolate, as are those who expect to be active in the housing market (that is, assign a probability of more than 50% to buying a home in the next 3 years). Individuals with negative experiences in the housing market are less likely to extrapolate at both horizons.

In sum, for the selective cuts presented in Table 7, the multivariate framework yields results that are qualitatively similar.

A.3 Comparison of Effect Sizes to Bailey et al. (2016)

Recent work by Bailey et al. (2016) studies how the local home price growth experiences of one's (out-of-town) friends affect the perceived attractiveness of housing as an investment in one's own zip code. This is done through a survey of individuals in Los Angeles, conducted on Facebook. Bailey et al. use a question from the SCE Housing module: "If someone had a large sum of money that they wanted to invest, would you say that relative to other possible financial investments, buying property in your zip code today is *(please select only one)*: (5) A very good investment; (4) A somewhat good investment; (3) Neither good nor bad as an investment; (2) A somewhat bad investment; (1) A very bad investment".

They find that individuals whose friends experienced stronger home price growth in their locations are more likely to give a higher rating to housing as an investment. Their estimated effect

[35] The model is equivalent to a Heckman selection model, where in the first stage we model selection into updating. Also note that the model is identified only by functional form.

[36] We do not separately include the Saiz supply elasticity measure, since it is quite strongly correlated with momentum and mean reversion, but only available for a smaller subset of respondents.

size is that a 5 percentage point increase (corresponding to about 2.5 standard deviations) in the average friend's 2-year house price growth increases the perceived attractiveness as elicited in the survey by about +0.2 points on the 1-5 scale, or +0.08 per one standard deviation increase in the right hand side.

We ask our respondents the same qualitative question as well, in the baseline and the final stages. Since our main focus is on quantitative measures of home price expectations, we do not discuss these questions in the main text; nevertheless it is useful to compare the estimated effects we get to those in Bailey et al. Table A-6 presents the results from a regression specification similar to the one in Table 6 in the main text. Here, the positive and significant coefficients on the interaction terms mean that being shown information about past growth that exceeded a respondent's prior makes the respondent view housing as an investment more favorably. This occurs both for one-year and five-year information, thus confirming that respondents appear to extrapolate (though with this qualitative question, it is not clear what future horizon they have in mind). In terms of effect size, a one standard deviation larger one-year perception gap (corresponding to 7 percentage points) increases the rating by about +0.1; a one standard deviation larger five-year annualized perception gap (4 percentage points) increases the rating by about +0.12. Thus, the magnitude of the effect is similar to the one in Bailey et al.

Table A-1: Average Perception Gaps, by Subgroups

	Abs. Perception Gap[a]	
	1yr	5yr annualized
Male	5.19*	3.1
Female	5.74	2.87
Has Lived In Locality 15+ years	5.52	3
Has Lived In Locality < 15 years	5.36	2.99
Checked housing websites[b]	5.2**	2.95
Did not check housing websites	5.83	3.07
Confident in recalled price change[c]	5.07*	2.88
Not confident in recalled price change	5.61	3.05
Likely to buy or sell home in future[d]	5.33	2.79
Unlikely to buy or sell home in future	5.46	3.04
White & Non-Hispanic	5.33	2.9*
Non-White	5.84	3.35
Age < 50	5.41	3.01
Age ≥50	5.47	2.98
Income ≥ $75,000	4.74***	2.87*
Income < $75,000	5.78	3.18
Bachelors Degree or More	5.01***	2.91
Less than Bachelors Degree	5.97	3.1
Homeowner	5.37	2.87**
Renter	5.65	3.36
Married	5.19**	2.94
Not Married	5.98	3.11
Employed	5.51	3.07*
Not Employed	5.28	2.76
High Numeracy[e]	5.11***	2.97
Low Numeracy	6.36	3.08
C-Frame	5.32	2.64***
L-Frame	5.58	3.39
Volatile Local Housing Market[f]	5.95**	3.45***
Non-volatile local housing market	5.14	2.72

Table shows mean absolute perception gap, by respondent characteristic. Asterisks in the first row of each sample split indicate significance level from a pairwise t-test conducted for equality of means of the absolute perception gap across subgroups. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.
[a] The absolute gap between the perceived and actual zip code home price change. All gaps annualized.
[b] Dummy that equals 1 if respondent reports consulting websites about home prices in past twelve months.
[c] Dummy that equals 1 if respondent reports being confident in their recall of past home price changes (i.e. answers 4 or more on a 1-5 scale, where 5 is very confident).
[d] Probability of buying home in three years is ≥ 50% or probability of selling home in one year is ≥ 50%.
[e] Dummy that equals 1 if respondent correctly answered four or more of five questions testing respondent's numeracy.
[f] Dummy that equals 1 if zipcode home price volatility over the past five years, as measured by Corelogic's HPI, is above the sample median.

Table A-2: Home Price Expectations and Perceptions, Interacted with Framing

	1 Year Expectations				2-5 Year Expectations [a]			
Past 1 Year Perceptions	0.169***	0.128***			0.054***	0.043***		
	(0.037)	(0.037)			(0.017)	(0.017)		
(1 Year Perceptions) * C-frame	0.185***	0.194***			0.008	0.008		
	(0.058)	(0.053)			(0.024)	(0.023)		
Past 5 Year Perceptions[a]			0.227***	0.195***			0.056*	0.042
			(0.064)	(0.059)			(0.033)	(0.031)
(5 Year Perceptions[a]) * C-frame			-0.039	0.018			0.102**	0.104**
			(0.106)	(0.094)			(0.048)	(0.047)
C-frame	-0.804**	-0.946***	0.049	-0.125	-1.247***	-1.292***	-1.288***	-1.343***
	(0.312)	(0.287)	(0.295)	(0.265)	(0.129)	(0.126)	(0.127)	(0.122)
Constant	2.944***	1.706	3.159***	3.259	2.137***	2.293***	2.242***	1.797**
	(0.239)	(1.125)	(0.226)	(2.457)	(0.106)	(0.476)	(0.112)	(0.766)
Observations	1020	1020	1019	1019	1020	1020	1019	1019
R-Squared	0.155	0.254	0.029	0.166	0.158	0.226	0.158	0.231
Control for Fundamentals[b]	No	Yes	No	Yes	No	Yes	No	Yes

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
[a] Annualized.
[b] Fundamentals indicate controls for expectations of general inflation, mortgage rate inflation, rent inflation, future economic conditions, and future personal credit difficulty.

Table A-3: Home Price Expectation Revisions and Perception Gaps, by Frame

Dep. Variable: Home Price Expectation revisions at horizon:	1 year	2-5 year
	(1)	(2)
T1	0.21	-0.27
	(0.44)	(0.17)
T1 * C-frame	-0.37	0.30
	(0.58)	(0.22)
T5	-0.20	0.07
	(0.48)	(0.21)
T5 * C-frame	0.34	0.07
	(0.62)	(0.24)
1yr Perception Gap	-0.04	-0.01
	(0.03)	(0.01)
(1yr Perception Gap)*C-frame	0.09*	0.02
	(0.05)	(0.02)
5yr Perception Gap	0.10	-0.00
	(0.06)	(0.03)
(5yr Perception Gap)*C-frame	-0.10	0.02
	(0.09)	(0.04)
T1 * 1yr Perception Gap	0.19***	0.07***
	(0.06)	(0.02)
(T1 * 1yr Perception Gap)*C-frame	0.01	-0.05
	(0.09)	(0.03)
T5 * 5yr Perception Gap	-0.06	0.05
	(0.10)	(0.04)
(T5 * 5yr Perception Gap)*C-frame	0.26	0.00
	(0.17)	(0.06)
C-frame	0.00	-0.24
	(0.40)	(0.16)
Constant	0.21	0.00
	(0.30)	(0.13)
Observations	1015	1013
R-Squared	0.067	0.030
Joint sig of covariates[a]	0	.035
Mean of dep. variable	0.29	-0.10

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
5 year perception gap and 2-5 year home price change expectations are annualized.
[a] F-test on equality of all covariates to zero (excluding constant). P-value shown.

Table A-4: Home Price Expectation Revisions (Robustness Checks)

	Home Price Expectation Revisions at horizon:							
	Treated[c]		Winsorized[d]		Consistent Recall[e]		Falsification[f]	
	1 year	2-5 year	1 year	2-5 year	1 year	2-5 year	1 year	2-5 year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1 (β_1)			-0.08	-0.06	0.03	-0.10	0.32	-0.05
			(0.37)	(0.13)	(0.28)	(0.11)	(0.28)	(0.11)
T5 (β_2)	0.08	0.21*	-0.15	0.16	-0.09	0.12	0.17	0.10
	(0.32)	(0.13)	(0.37)	(0.14)	(0.30)	(0.12)	(0.30)	(0.12)
1yr Perception Gap[a] (β_3)	0.01	-0.01	0.02	-0.01	0.02	0.00	0.09***	0.02**
	(0.04)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
5yr Perception Gap (β_4)	0.03	0.03	-0.00	0.04**	0.04	0.00	0.06	0.01
	(0.06)	(0.03)	(0.06)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)
T1 * 1yr Perception Gap (β_5)	0.20***	0.04*	0.16***	0.03*	0.17***	0.05**		
	(0.06)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)		
T5 * 5yr Perception Gap (β_6)	0.09	0.03	0.10	0.00	0.11	0.05*		
	(0.09)	(0.04)	(0.09)	(0.03)	(0.08)	(0.03)		
T1 * 5yr Perception gap							0.05	0.03
							(0.08)	(0.03)
T5 * 1yr Perception gap							-0.07	-0.01
							(0.05)	(0.02)
C-frame (β_7)	0.12	-0.08	0.34	-0.24**	0.12	-0.11	0.11	-0.12
	(0.33)	(0.12)	(0.31)	(0.12)	(0.25)	(0.10)	(0.26)	(0.10)
Constant (β_0)	0.13	-0.17	-0.10	0.08	0.09	-0.05	0.02	-0.06
	(0.29)	(0.11)	(0.33)	(0.12)	(0.24)	(0.10)	(0.25)	(0.10)
Observations	681	680	1187	1184	948	946	1015	1013
R-Squared	0.071	0.034	0.033	0.020	0.060	0.031	0.034	0.017
Joint sig of covariates[b]	0	.042	.005	.042	0	.019	.001	.195
Mean of dep. variable	0.36	-0.10	0.07	-0.04	0.21	-0.09	0.29	-0.10

OLS estimates reported. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
5 year perception gap and 2-5 year home price change expectations are annualized.
[a] Perception gap $\alpha_{i,t} = \pi_{i,t} - \widehat{\pi}_{i,t}$, the difference between Zillow information and respondent i's price change perceptions over the past t years.
[b] F-test on equality of all covariates to zero (excluding constant). P-value shown.
[c] Sample restricted to treated respondents only.
[d] Outlier responses are winsorized at top/bottom 2% instead of trimmed.
[e] Excludes treated respondents who reported that the provided Zillow information was higher (lower) than their prior perception, but in fact had a negative (positive) perception gap.
[f] A placebo where we assume T1 (T5) respondents are revealed the past 5 year (1 year) information instead of the information actually revealed to them.

Table A-5: 2-stage Model for Updating Type

	1 year exp. HP change		5 year exp. HP change	
	Pr(Update)	Pr(Extrapolate | Update)	Pr(Update)	Pr(Extrapolate | Update)
	(1)	(2)	(3)	(4)
T1	-1.53	5.90	-11.76***	7.10**
	(3.96)	(4.65)	(3.51)	(3.29)
Age < 40	-9.18**	12.94**	0.60	8.06*
	(4.46)	(5.09)	(4.30)	(4.15)
Lived in current town/city for 15+ years	3.89	-2.50	-3.49	1.90
	(3.97)	(4.53)	(3.78)	(3.59)
Income $\geq$ \$75,000	-8.71**	-5.74	-4.61	-0.13
	(3.93)	(6.69)	(3.98)	(3.92)
Male	-4.42	2.30	-3.15	-2.84
	(3.63)	(4.16)	(3.57)	(3.40)
Homeowner	-5.56	-3.09	-0.71	-2.13
	(6.12)	(7.07)	(5.83)	(5.49)
Bachelor's Degree or More	8.75**	5.99	-1.67	9.64***
	(3.88)	(6.83)	(3.72)	(3.52)
Pr(Sell Home in 1 Yr) > 0%	-0.26	1.43	-1.41	-1.49
	(4.96)	(5.72)	(4.73)	(4.41)
Pr(Buy | Move in 3 Yrs) > 50%	-5.16	6.27	-5.00	10.41**
	(4.80)	(5.24)	(4.68)	(4.35)
Negative Housing Market Experience [a]	9.12	-7.95	2.07	-10.86*
	(6.48)	(6.72)	(6.31)	(5.66)
Confident in recalled price change[b]	-10.13***	6.64	-1.55	1.11
	(3.81)	(4.73)	(3.90)	(3.74)
Negative Perception Gap	-5.58	-5.06	-4.56	2.23
	(3.63)	(5.57)	(3.55)	(3.39)
High Short-Term Momentum [c]	-3.39	5.26	3.34	0.32
	(3.92)	(4.41)	(3.77)	(3.70)
High Mean Reversion [d]	-2.02	4.24	0.13	9.19**
	(3.86)	(4.44)	(3.75)	(3.69)
Perception Gap Magnitude	0.75*	0.74	0.12	0.06
	(0.41)	(0.67)	(0.14)	(0.13)
Observations	679	679	678	678
Mean of dep. variable	64.36	40.35	69.32	43.81

Table reports average marginal effects in percentage points from a two stage probit selection model, modeling respondents to first choose whether to update and then whether or not to extrapolate. Delta method standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.
[a] Has experienced a foreclosure or a short sale, or is currently underwater on mortgage.
[b] Dummy that equals 1 if respondent reports being confident in their recall of past home price changes (i.e. answers 4 or more on a 1-5 scale, where 5 is very confident).
[c] Respondent's County is above the median value of regression coefficients of 1yr on 1yr home price changes.
[d] Respondent's County is below the median value of regression coefficients of 2-5yr on 5yr home price changes.

Table A-6: Impact of Information on Qualitative Assessment of Housing as a Good Investment

Dependent Variable: Change in Qualitative Assessment of Housing as a Good Investment (Final - Baseline)		
	(1)	(2)
T1 (β_1)	-0.001	-0.007
	(0.044)	(0.043)
T5 (β_2)	-0.019	-0.047
	(0.045)	(0.044)
1yr Perception Gap[a] (β_3)	0.000	-0.002
	(0.004)	(0.003)
5yr Perception Gap (β_4)	0.005	0.006
	(0.006)	(0.005)
T1 * 1yr Perception Gap (β_5)	0.014***	0.015***
	(0.005)	(0.005)
T5 * 5yr Perception Gap (β_6)	0.032***	0.028***
	(0.011)	(0.011)
C-frame (β_7)	-0.026	-0.030
	(0.038)	(0.037)
Constant (β_0)	0.006	0.069**
	(0.034)	(0.034)
Initial Corner Solutions Controlled For [a]	No	Yes
Observations	1019	1019
R-Squared	0.035	0.098
Joint sig of covariates[b]	0	0
Mean of dep. variable	-0.014	-0.014
SD of dep. variable	0.61	0.61

OLS estimates of a regression of change in qualitative question on housing as a good investment (on a 1-5 scale, where a higher value means a more positive assessment of housing as an investment; see text for exact survey question). Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

[a] Includes indicators for whether respondent assigned maximum or minimum value to the baseline qualitative question on whether buying property in your zip code is a good investment.

[b] F-test on equality of all covariates to zero (excluding constant). P-value shown.