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ARE STATED EXPECTATIONS ACTUAL BELIEFS?
NEW EVIDENCE FOR THE BELIEFS CHANNEL OF INVESTMENT DEMAND

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ABSTRACT

Despite growing interest in expectation surveys, critics argue that survey responses are not reliable measures of the expectations underlying financial decisions, and empirical work often finds only a weak correlation between investment and stated beliefs. In this paper, we document a systematic gap between an individual's own forecasted returns and the beliefs used in investment decisions. In particular, perceived past housing returns predict individual real estate investment decisions even conditional on flexible controls for an individual's forecasted distribution of future home-price growth. Many respondents acknowledge that they rely on past returns more than their survey-reported expected returns when making investment decisions, ruling out simple measurement-error explanations. To interpret these findings, we present evidence that investment decision-making induces cognitively uncertain investors to rely more on belief factors in which they are relatively confident, such as their estimation of recent local housing returns. Survey respondents that rely on past returns more than their surveyed forecasts frequently cite uncertainty about other belief factors as their rationale.

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"Prediction is hard, especially when it's about the future." -Yogi Berra

1 Introduction

A significant body of recent work in behavioral macroeconomics and finance seeks to understand both how people form expectations and how these subjective assessments of the likelihood of future states (i.e., beliefs) affect actions (e.g., investment decisions).[1] As a result, several new expectation surveys have been developed to study the link between stated expectations and subsequent behavior.[2] Critics of expectation surveys argue against their usefulness because respondents lack sufficient comprehension of the questions or because their answers do not correspond to decision-relevant expectations (Cochrane (2011, 2017)). As a response, survey designers have proposed several techniques to reduce measurement error, for example, by using multiple framings to ask the same question, designing instruments for self-reported expectations, and eliciting both point estimates and expected distributions (Glaser et al. (2007); Armona et al. (2018); Giglio et al. (2021)). However, even when researchers are able to both elicit beliefs and measure investment decisions for the same respondents, the empirical relationship between stated forecasts and actions is often weaker than predicted by theory.[3] Moreover, even though survey respondents are usually willing to answer numerical expectations questions, it is unclear whether the representation of subjective beliefs elicited by expectations surveys is an accurate characterization of the subjective probability function used in actual decision making.[4] Might the projection of beliefs onto survey forecasting exercises differ from the way actual beliefs are used in investment decision-making?

In this paper, we show that the role of home-price beliefs in explaining investment behavior, which we refer to as the beliefs channel, is stronger when subjective past home-price growth is used as an additional predictor of behavior even conditional on stated expectations. Traditionally, researchers treat stated beliefs as a sufficient statistic for forecast-relevant data

[1]See Manski (2004, 2018) for recent surveys.

[2]See, for example, Armantier et al. (2015); Armona et al. (2018); Bailey et al. (2018); D'Acunto et al. (2018, 2019c); Kosar et al. (2020); Liu et al. (2020); Giglio et al. (2021); D'Acunto et al. (2020). Hurd (2009) overviews the predictive power of surveyed subjective probabilities.

[3]For examples, see Vissing-Jorgensen (2003); Dominitz and Manski (2011); Amromin and Sharpe (2014); Drerup et al. (2017); Ameriks et al. (2020); Giglio et al. (2020); Liu and Sui (2020); Giglio et al. (2021). By contrast, Hendren (2013, 2017) finds that surveyed beliefs code some private information that predicts insurance demand even conditional on public observables.

[4]For example, Manski (2018) describes this open question as follows. "There has, nevertheless, been awareness that the willingness and ability of respondents to report probabilistic expectations does not imply that persons regularly think probabilistically and use subjective probability distributions to make decisions. It has long been known that survey respondents are willing and able to respond to questions seeking point predictions of uncertain events or verbal assessments of likelihood. Yet persons need not use point predictions or verbal assessments of likelihood to make decisions."

such as past price growth, implicitly assuming that past returns affect future investment only through the formation of the stated beliefs captured by survey. Such modeling of expectations and actions by first studying how expectations are formed and then how expectations affect actions permits a divide-and-conquer approach, where in the second step of modeling action prediction, the empiricist need not include any other variables in households' information set after controlling for their forecasts. In contrast, our results show that there is a direct empirical link from certain belief-formation factors to actions that bypasses stated beliefs.

To fix ideas, our findings can be illustrated mathematically as follows. In the classic Merton (1969) model of portfolio choice with a single risky asset with normally distributed future return r_{t+1}, the optimal share ϕ allocated to the risky asset is

$$\phi_t = \frac{E_t[r_{t+1}] - R_f}{\alpha \sigma_t^2}, \tag{1}$$

where $E_t[r_{t+1}]$ is the expected return from t to $t+1$ conditional on all information available at time t, σ_t^2 is the conditional variance of r_{t+1}, α is the constant absolute risk-aversion parameter, and R_f is the risk-free rate. The risky-asset share therefore depends on the distribution of returns used to form the expected return, and this expected return could depend on many factors. In a market with momentum, like the housing market, the prior period's return r_t could be one such factor used to predict $E_t[r_{t+1}]$. However, after conditioning on $E_t[r_{t+1}]$, σ_t^2 and α, past returns r_t would not *independently* enter this rational portfolio-choice rule. In contrast, our main empirical result can be summarized as finding that r_t affects ϕ_t even after flexibly controlling for $E_t[r_{t+1}]$, measures of α, and the forecasted distribution of r_{t+1}.[5]

Our analysis starts from the investment experiment of Armona et al. (2018) run in the New York Federal Reserve Survey of Consumer Expectations, wherein respondents were asked to allocate a $1,000 investment between a 2% risk-free savings account and a housing fund with returns tracking local home price appreciation (HPA). In the same survey, Armona et al. (2018) also collected respondents' estimation of past returns (a subjective measure potentially differing from actual realized home-price growth), their forecasted home-price growth, and a rich set of demographics. We show that in this experiment, perceived past returns better predict investment behavior than do stated forecasted returns.[6] Outside of this hypothetical experiment, perceived past home-price growth also improves the prediction

[5]While we offer the frictionless Merton model as an example of how portfolio decisions might be made, we are agnostic about the true form of investment demand and instead endeavor to establish that stated expectations are not a sufficient statistic for the beliefs channel of demand. See Giglio et al. (2021) for a discussion of how important real-world frictions affect the predictions of the Merton model.

[6]As we discuss below, this investment experiment allows us to abstract away from confounding demand shocks such as the effect of past returns on financial constraints.

of intention to purchase a non-primary residence even after controlling for stated forecasted returns and the forecasted distribution of returns. We further verify that our results are robust to controlling for individual-specific risk aversion and a rich set of demographics, addressing potential collinearity between forecasted returns and subjective past returns, instrumenting to account for measurement error in surveyed beliefs, and flexibly controlling for the forecasted distribution of returns to allow for any difference between risk-neutral and physical-risk beliefs.

Why do people rely on their memory of past returns when making investment decisions even conditional on how this memory affects their forecasts? We explore several explanations for our findings. We first address potential omitted variable bias from factors that are correlated with both beliefs and investment demand (e.g., risk aversion). Even after flexibly controlling for several such factors that could be correlated with both investment demand and past returns, perceived past home-price growth still improves investment-decision prediction. Next, to address whether measurement error in survey responses can explain our findings, we show that our results hold after instrumenting for elicited expected returns. Taken together, respondents' investment decision-making deviates from a fully rational framework wherein stated beliefs capture all decision-relevant information about future returns.

To motivate our preferred theoretical explanation for our findings, we collect additional data by asking respondents explicitly whether they rely more on past or expected returns when making decisions.[7] We rerun the investment experiment designed by Armona et al. (2018) in the 2020-2021 waves of the same survey, but before eliciting respondents' allocation of their $1,000 investments, we ask some respondents whether they consider the reported return forecasts they reported on the survey or their memory of past home-price growth more in their investment decisions.[8] A significant fraction (44%) of the population admits to relying more on their perceived past returns than their surveyed return forecasts. This confirms that our findings about the importance of memory even conditional on expected returns are not an artifact of survey noise or omitted variables for a meaningful fraction of respondents.

To interpret these empirical findings, we turn to a growing literature on limited attention and cognitive uncertainty (Gabaix (2014); Enke and Graeber (2021); Frydman and Jin (2019); Gabaix (2019); Khaw et al. (2020)). We show that a model where the complexity in financial decisions induces investors to rely on signals that they are more certain about is consistent with our evidence. Using an example similar to the one in Enke and Graeber

[7]This approach builds on a nascent survey literature in household finance which elicits both investors' decisions and asks them to self-examine the factors behind their investment choices (Chinco et al. (2020); Choi and Robertson (2020); Liu et al. (2020)).

[8]See Appendix B for detailed question framing.

(2021), when asked by a low-stakes survey question about past and expected home-price growth, a respondent might confidently reply 5% and 10%, respectively. However, when asked to make a more complex investment decision, she might start to question her certainty of her own return forecast (e.g., "Is my forecast really 10% as opposed to 7% or 13%?"). The respondent may therefore shrink her stated forecast towards something that she is more certain about, such as her own perception of last period's return, an object referred to as the "mental default" in Enke and Graeber (2021). For example, imagine an agent observes signals on past home-price growth and future rent growth. While the optimal combination of both of them comprises a more accurate forecast of future returns than using past returns alone, the agent perceives the future rent-growth signal to be less accurate. Accordingly, when making an actual decision with higher stakes and more complexity than a survey question about expected returns, the agent relies more heavily on past home-price growth instead of the combination of past returns and future rent growth.[9]

While other economic frameworks could also generate our empirical findings, we provide direct evidence for a cognitive uncertainty mechanism in Section 6.2. First, we show that certain factors play a large role in stated forecasts but are shrunk in actual investment decision-making. Second, we directly implement the Enke and Graeber (2021) test for cognitive uncertainty in the 2021 survey wave. After eliciting subjective confidence intervals, we find that investors who are less confident about their future forecasts relative to their recalled past returns drive the conditional reliance on past returns when making decisions. Finally, we analyze free-text responses about why some investors rely more on past returns than their surveyed expectations and find many answers consistent with cognitive uncertainty.

Prior Literature Our paper makes several contributions to the literature measuring the role of beliefs about returns on investment decisions (e.g., Glaser et al. (2007); Armona et al. (2018); Andonov and Rauh (2020); Giglio et al. (2021)), especially to findings emphasizing the empirically weak correlation between expected returns and investment (Vissing-Jorgensen (2003); Dominitz and Manski (2011); Amromin and Sharpe (2014); Drerup et al. (2017); Ameriks et al. (2020); Giglio et al. (2020); Liu and Sui (2020); Giglio et al. (2021)).[10] First, our results suggest that researchers could improve the measurement of the beliefs channel by directly controlling for factors that affect beliefs in addition to stated beliefs

[9] As demonstrated by Enke and Graeber (2021), cognitive uncertainty can also affect the expectation formation stage, itself a complicated process about which respondents may be uncertain. While complexity in the belief formation stage could help explain the wedge between stated beliefs and decision-making, the cross-sectional variance of stated beliefs does not decrease with subjective certainty about them, supporting our interpretation of the investment stage being a key source of cognitive uncertainty.

[10] See, too, work on inflation expectation formation and consumption decisions (e.g., Bachmann et al. (2015); D'Acunto et al. (2019c)).

themselves. At least in the housing market, such a factor appears to be perceived past returns, consistent with research emphasizing short-term price momentum in the housing market (Glaeser et al. (2014); Glaeser and Nathanson (2017); DeFusco et al. (2017); Armona et al. (2018); Guren (2018)).[11] Our findings also build on studies that uncover new sources and measures of belief heterogeneity by highlighting that belief factors may have direct effects at the decision stage (Binder (2017); Ben-David et al. (2018); Das et al. (2019); D'Acunto et al. (2019b,a)).[12] Moreover, our findings that *perceived* past returns matter more than objectively measured past returns suggest that belief surveys, perhaps especially of retail investors, would further benefit from asking respondents about their perceptions of past returns.[13]

We stress that our results do not argue against the usefulness of expectations surveys or reject the beliefs channel. Instead, we show that the magnitude of the beliefs channel could be larger than previously estimated, consistent with the prior literature recognizing the noisiness of stated forecasts (Glaser et al. (2007); Armona et al. (2018); Giglio et al. (2021)). Our contribution is to show that the gap between stated beliefs and the beliefs used in decision-making is not purely noise and instead has a systematic structure partially explainable by observable factors such as past returns experiences. Relatedly, we extend the extrapolative belief literature (e.g., Piazzesi and Schneider (2009); Greenwood and Shleifer (2014); Barberis et al. (2015); Glaeser and Nathanson (2017); Armona et al. (2018); Barrero (2020)) by showing that perceptions of past returns can directly influence behavior, finding evidence of implicit extrapolation even conditional on the explicit extrapolation that drives stated beliefs.[14]

Second, our paper is directly related to work on limited attention and cognitive uncertainty in decision-making (Gabaix (2014); Drerup et al. (2017); Enke and Graeber (2021); Frydman and Jin (2019); Gabaix (2019); Khaw et al. (2020)). For example, Drerup et al. (2017) allow investors' decision processes to deviate from a rational investment-return model and instead follow some intuitive rule of thumb, with such departures from rationality poten-

[11] Related work outside of real estate demonstrates extrapolation in the expectations of corporate managers (Barrero (2020)) and pension fund managers (Andonov and Rauh (2020)) and overreaction to recent memory (Bordalo et al. (2020b); Afrouzi et al. (2020)). For underreaction in analyst and manager forecasts, see Bouchaud et al. (2019) and Ma et al. (2020). Whether our findings generalize to beliefs and investment decisions in other asset markets that do not feature price momentum is a useful avenue for future research.

[12] For example, evidence from Finland in D'Acunto et al. (2019b) suggests that the wedge between beliefs and demand is particularly pronounced for low-IQ investors.

[13] See also Cookson and Niessner (2020), who find that a significant source of belief heterogeneity is heterogenous interpretations of public information.

[14] Similar to Andonov and Rauh (2020) and Andries et al. (2020), by considering investment decisions directly, we find a stronger role for extrapolative beliefs than would be appreciated from an examination of expectation formation alone. As we discuss below, this also helps reconcile large estimates of personal experience effects with somewhat smaller extrapolation effects in expectation formation.

tially depending on an investor's financial sophistication. Building on this literature, Enke and Graeber (2021) propose that investors are often aware of their own cognitive noise and shrink their choices towards "mental defaults," or example, an even 50-50 split between risky and risk-free assets. Our work extends this literature by showing that recalled past returns serve as a plausible individual-specific mental default, generating between-investor variation in mental defaults.[15] Moreover, by implementing the cognitive uncertainty elicitation proposed in Enke and Graeber (2021), we provide direct evidence that cognitive uncertainty is an important driver of our core findings.[16] Giglio et al. (2021) show that allowing for taxes, limited attention, and subjective uncertainty drives a wedge between stated beliefs and actions in the Merton (1969) model. By holding taxes and attention fixed, our setting isolates the role of subjective uncertainty by demonstrating that investors rely on belief factors about which they are more confident, similar to Andries et al. (2020). Furthermore, we find evidence that financial illiteracy is a potential driver of cognitive uncertainty, broadly consistent with the finding of Enke and Graeber (2021) that cognitive uncertainty is more acute in more complex environments.[17]

Our results are also consistent with the finding of Frydman and Jin (2019) that risk taking is more sensitive to more frequently occurring stimuli. In our context, subjective past experience is more salient to investors than their forecasts, which have yet to occur, a sentiment repeatedly born out in the free-text responses to a question about decision-making. In a similar spirit, Andries et al. (2020) find that investors extrapolate more in the absence of a signal in which they are confident, D'Acunto et al. (2019c) find that people rely most on the prices they personally observe most frequently to form expectations decisions, and Afrouzi et al. (2020) find that people overreact to their most recent memory. We also find that investors who are more informed are less likely to shrink their decisions towards past returns when making investment decisions. Taken together, our findings are consistent with the existence of cognitive uncertainty and suggest some of its important drivers. We further show that investors' uncertainty about the same object can vary across survey questions, plausibly covarying with their attention to a given factor. In particular, complexity and the financial risk associated with investment decisions could disproportionately increase subjective uncertainty for signals about which investors are relatively less certain by triggering a

[15]For practicality in their setting, Enke and Graeber (2021) use a common mental default for all agents (although they manipulate it experimentally in some treatments), adding that they "acknowledge that the mental default in general likely depends on a multitude of factors." One useful feature of our data is to allow us to model mental defaults varying cross-sectionally.

[16]See also work showing that individual-level measures of forecast confidence predict the level of forecast-investment correlation cross-sectionally (Bachmann et al. (2020); Giglio et al. (2021)).

[17]While risk-averse investors are more likely to display cognitive uncertainty in our data, risk aversion and cognitive uncertainty are two distinct behavioral traits (cf. Enke and Graeber (2021)).

stress response in respondents.

Third, our results offer a potential solution to reconcile the strong evidence of personal experience as a belief driver that strongly affects behavior (Kaustia and Knüpfer (2008); Chiang et al. (2011); Malmendier and Nagel (2011, 2016); Malmendier et al. (2019); Nagel and Xu (2019)) and the somewhat weak empirical link between self-reported expectations and behavior found in recent papers. This puzzle begins with the growing literature on the "experience effect," anchored by evidence in Malmendier and Nagel (2011) that investors with lifetime experience of low real stock-market returns simultaneously have low stock-return expectations and low equity shares. Although this evidence is consistent with the experience effect working through the beliefs channel, recent work matching individual-level expectations data with trading records often finds only a modest empirical relationship between stated beliefs and investment actions. For example, using administrative stock trading data with expectation surveys, Giglio et al. (2021) and Giglio et al. (2020) show that belief changes do not predict when trading occurs and explain the direction and magnitude of trades conditional on trading less than textbook models would imply. While Giglio et al. (2021) suggest that measurement error and inattention drive the empirical weakness of the beliefs channel, our paper shows that the somewhat weak empirical link between stated beliefs and behavior could be caused by a wedge between decision-relevant expectation and stated forecasts. Instead of using what they state they believe on surveys when they make investment decisions, investors could base their actions on their subjective past experience, which could help explain strong experience effects contrasted with the weak predictability of stated beliefs.

The reminder of the paper is organized as follows. Section 2 presents a theoretical model adapting notions of cognitive uncertainty to our setting and allowing for a role of risk aversion. Section 3 describes the survey data used in our study and presents summary statistics. Section 4 presents our empirical findings. Section 5 discusses various interpretations for our results, and Section 7 concludes.

2 Model

In this section, we provide a theoretical framework based on the nascent literature on cognitive imprecision (Gabaix (2014); Enke and Graeber (2021); Frydman and Jin (2019); Gabaix (2019); Khaw et al. (2020)) that can rationalize our empirical findings. While the stylized model presented here offers an intuitive framework to rationalize our empirical results, it is by no means the only model consistent with our findings.

As argued in Enke and Graeber (2021), people are often aware of their own cognitive limitations and shrink their posterior estimates of parameters towards a default value. Consider a GDP expectation survey as an example. Based on all available information, a respondent's best guess for next year's GDP growth could be 5%, termed the "signal" because it incorporates signals the respondent has received. However, because the respondent is uncertain about this answer, she might shrink it towards a "mental default." One possible mental default is the average GDP growth in the postwar period of approximately 3%. After shrinkage towards her default, the respondent might report 4% as her final answer.

In our context, we hypothesize that complexity and financial stakes in investment decisions trigger a stress response and induce investors to rely more on signals about which they are more certain. Because there is no personal wealth on the line when answering a survey question about forecasted returns, respondents perceive the survey question eliciting their expected returns as relatively simple and use all information available to them (e.g., 5% in the GDP example above). However, households find investment decisions to be complicated and stressful (e.g., Gennaioli et al. (2015)). Facing the complex real-world decision of buying an asset and having to consider other demand factors like risk aversion or other assets in their portfolios, cognitively uncertain investors upweight factors such as their perceived experiences as their lived experience feels more salient them than other information.[18]

Let r_{t+1} denote the future return respondents are asked to forecast and assume agents' prior belief $r_{t+1} \sim \mathcal{N}(\mu_d, \sigma^2)$, where μ_d stands for the mental default for r_{t+1}. Agents form their forecasts using two pieces of relevant data. The first is their perception of past home-price growth, denoted as r_t. The second is a home-price forecast based on forecasts for variables related to home prices, including, for example, forecasts of rent, inflation, GDP, and local unemployment. We call the second piece of information the signal, denoted s. Both r_t and s are noisy forecasts for r_{t+1}, which we write as

$$r_t = r_{t+1} + \varepsilon_p \tag{2}$$

$$s = r_{t+1} + \varepsilon_s \tag{3}$$

because each factor contains a random deviation from future returns ε. While the error in past returns as a forecast $\varepsilon_p \sim \mathcal{N}(0, \sigma_p^2)$, respondents act as if the distribution of the error in the signal ε_s depends on the context of the particular survey question being asked. We index parameters used in survey forecast questions with e for expected and parameters used in investment actions with a. When asked to forecast returns, respondents treat the distribution of ε_s as $\mathcal{N}(0, \sigma_{s,e}^2)$, and when asked about investment choices, some respondents act as if the

[18]See, e.g., Malmendier and Nagel (2011) for support for this personal-experience channel.

distribution of ε_s is $\mathcal{N}(0, \sigma_{s,a}^2)$ with $\sigma_{s,a} > \sigma_{s,e}$.[19] In a reduced-form way, the assumption $\sigma_{s,a} > \sigma_{s,e}$ captures that in forecasting returns, respondents focus on forming their beliefs and correctly measure the noisiness of s. By contrast, when making a complex investment decision with monetary incentives, some risk-averse respondents lacking confidence in their own forecasts need to shift their limited cognitive ability to other factors such as risk bearing capacity and therefore pay less attention to and perceive higher uncertainty in s.

This assumption is in part motivated by a finding of Enke and Graeber (2021) that investors display more cognitive uncertainty when facing more complex choices. This added complexity could affect the perceived uncertainty in s more than in r_t because past experience is salient to investors and relatively unaffected by question framing. Textual analysis of open-ended survey responses in Section 6.1 provide support for this mechanism; many investors explain that when it comes to investment decisions, past returns are observable and verifiable and therefore viewed as more reliable. Another rationalization that generates a disproportionate increase in perceived uncertainty in s relative to r_t is through the endogenous attention framework of Gabaix (2014), which would lead such respondents to have different loss functions in answering the expectation and the investment questions.[20] Whether driven by complexity, financial risk, or sparsity, the end result is that because of differential stakes when reporting forecasts versus making relatively complex and consequential financial decisions, agents may weight factors differently across domains.

To simplify the exposition, in this section we assume that σ_p stays constant from the expectation to the investment-decision stage, while σ_s increases. In Appendix A, we show that the sufficient and necessary condition to generate a positive coefficient on past returns even conditional on stated expected returns is that σ_s disproportionately increases relative to σ_p from the expectation to the decision question. Let $r_{e,t+1}$ and $r_{a,t+1}$ denote a respondent's stated return forecast and the decision-relevant forecast used in investment decisions, respectively. We have

$$r_{e,t+1} = E[r_{t+1}|r_t, s, (r_d, \sigma, \sigma_p, \sigma_{s,e})] = c_e + \beta_{1,e} r_t + \beta_{2,e} s \tag{4}$$

$$r_{a,t+1} = E[r_{t+1}|r_t, s, (r_d, \sigma, \sigma_p, \sigma_{s,d})] = c_i + \beta_{1,a} r_t + \beta_{2,a} s, \tag{5}$$

where by Bayesian updating,

[19] The true distribution of ε_s is allowed to be different from $\mathcal{N}(0, \sigma_{s,e}^2)$ and $\mathcal{N}(0, \sigma_{s,a}^2)$; our results are robust to any deviation between the perceived distribution of ε_s and the true distribution.

[20] Ambiguity-averse investors may also weight probabilities differently in the investment and belief formation stages (Dow and da Costa Werlang (1992); Fox and Tversky (1995); Ilut and Schneider (2014)). However, many respondents increase their reliance on past returns when investing even when past returns exceed their expected returns, at odds with the usual worst-case-weighting of ambiguity-averse investors.

$$\beta_{1,e} = \frac{\sigma^2_{s,e}(\mu^2_d + \sigma^2)}{(\sigma^2_{s,e} + \sigma^2_p)(\mu^2_d + \sigma^2) + \sigma^2_p\sigma^2_{s,e}}$$
$$\beta_{2,e} = \frac{\sigma^2_p(\mu^2_d + \sigma^2)}{(\sigma^2_{s,e} + \sigma^2_p)(\mu^2_d + \sigma^2) + \sigma^2_p\sigma^2_{s,e}}$$
$$\beta_{1,a} = \frac{\sigma^2_{s,a}(\mu^2_d + \sigma^2)}{(\sigma^2_{s,a} + \sigma^2_p)(\mu^2_d + \sigma^2) + \sigma^2_p\sigma^2_{s,a}}$$
$$\beta_{2,i} = \frac{\sigma^2_p(\mu^2_d + \sigma^2)}{(\sigma^2_{s,a} + \sigma^2_p)(\mu^2_d + \sigma^2) + \sigma^2_p\sigma^2_{s,a}}.$$

Because $\sigma_{s,a} > \sigma_{s,e}$, we have that $\beta_{1,e} < \beta_{1,a}$ and $\beta_{2,e} > \beta_{2,a}$. Intuitively, respondents who perceive their signal s to be noisier in the investment-decisions domain than the forecasting-returns domain will rely more on their past experience r_t and less on the signal s.

In our setting, our experiment asks respondents to allocate a fixed investment amount between a housing fund and a risk-free savings account. To map the investment-decision-relevant return forecast $r_{a,t+1}$ to the share invested in a housing fund, we again return to the standard Merton (1969) single risky asset model with constant absolute risk aversion used in the introduction, with the housing share ϕ_t given by

$$\phi_t = \frac{r_{a,t+1} - R_f}{\alpha\sigma^2_{a,t+1}},$$

where R_f is the risk-free rate, α is the absolute risk aversion parameter, and $\sigma^2_{a,t+1}$ is the conditional variance of $r_{a,t+1}$.[21] Taking a linear approximation of ϕ around the average value of r_a, α, and σ^2_a, and letting γ_α and γ_σ denote the partial derivatives of ϕ over α and σ^2_a, we have

$$\begin{aligned}
\phi_t &\approx \tilde{c} + r_{a,t+1} + \gamma_\alpha\alpha + \gamma_\sigma\sigma^2_{a,t+1} \\
&= c_1 + \beta_{1,a}r_t + \beta_{2,a}s + \gamma_\alpha\alpha + \gamma_\sigma\sigma^2_{a,t+1} \\
&= c_2 + \left(\beta_{1,a} - \beta_{1,e}\frac{\beta_{2,a}}{\beta_{2,e}}\right)r_t + \frac{\beta_{2,a}}{\beta_{2,e}}r_{e,t+1} + \gamma_\alpha\alpha + \gamma_\sigma\sigma^2_{a,t+1}. \qquad (6)
\end{aligned}$$

Equation (6) motivates the regression specifications we use in our empirical section below and provides a framework to think about what statistical role we might expect r_t to play in explaining decisions when agents have cognitive uncertainty.[22] In a standard model, condi-

[21]The variance $\sigma^2_{a,t+1}$ is conditional on all information available to an investor, including $r_{a,t+1}$ and s.

[22]We take a linear approximation in (6) instead of using a log-log specification to be able to include individuals in our estimation sample that choose $\phi = 0$ or report $r_{e,t+1} \leq R_f = 2\%$ or $r_t \leq 0$. Although

tional on expected returns $r_{e,t+1}$, there would be no role for r_t in (6) because r_t is simply a linear factor in $r_{e,t+1}$ with the same weight in (4) and (5) because $r_{e,t+1} = r_{a,t+1}$.[23] However, for investors with significant cognitive uncertainty, we have the result that $\beta_{1,e} < \beta_{1,a}$ and $\beta_{2,e} > \beta_{2,a}$ such that the coefficient on subjective past experience r_t in (6) is positive. Consistent with this prediction, our empirical findings below provide evidence that perceived past returns have independent predicting power for investment decisions even after conditional on stated forecasts.

3 Data and Summary Statistics

Our data come from 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. The survey elicits expectations about a variety of economic variables, such as inflation, stock market returns, GDP growth, and the unemployment rate. Respondents participate in the panel for up to twelve months, with a roughly equal number rotating in and out of the panel in each month. For a detailed overview of the SCE, see Armantier et al. (2017). The data that we use are mainly from the housing module of the SCE, an annual survey fielded in February every year since 2014 to the active panel members in the SCE that we will often refer to as the housing survey. The housing module has multiple blocks of questions, collecting perceived past home-price growth, housing choice and mortgage credit history, expectations of future home-price growth and credit conditions.

We use three samples throughout the paper. Our analysis starts with the 2015, 2020, and 2021 samples. One unique advantage of these three waves is that they all include an investment experiment designed by Armona et al. (2018), originally for the 2015 survey. Respondents are asked how they would allocate a \$1,000 investment between a 2% risk-free savings account and a housing fund that tracks home-price appreciation in their local zip code.[24] Usefully for our purposes, this experiment is not subject to any real-world constraints on housing-related behavior. For example, some borrowers might want to invest in housing

underpowered, our results are qualitatively robust to a log-log specification dropping these observations and controlling for an estimate of $\sigma^2_{e,t+1}$, as we show in the appendix.

[23] To relax the assumption that r_t enters $r_{e,t+1}$ linearly, many of our empirical specifications will control for flexible functions of $r_{e,t+1}$ and its forecasted distribution.

[24] To provide real-world stakes, a subset of respondents were promised a random chance of receiving the actual gross return of their investment. The survey instrument informed the randomly selected incentivized respondents that two out of 1,000 respondents would receive the gross return of their constructed derivative after one year. While belief survey research shows that incentivizing attentive responses improves elicitation accuracy (Carson et al. (2014)), a literature on survey responsiveness finds that people are often insensitive to the odds of receiving a reward and are more responsive to a small chance at a large reward rather than a certain small reward (Porter and Whitcomb (2003); Dohmen et al. (2011); March et al. (2016)).

but do not believe they qualify for a mortgage or have sufficient cash on hand. For other decisions, past returns could also be correlated with risk aversion, hedging demand, or beliefs at longer horizons. By abstracting away such demand factors, the hypothetical investment question offers a measure of investment choices unlikely to be affected by typical demand factors. We primarily use the housing share ϕ in the allocation of \$1,000 as our primary measure of investment behavior, but we also examine other housing-related behaviors, including the probability of buying a non-primary residence.

The second sample that we use is a combined sample based on the 2015-2021 housing surveys with seven years of data. Although the \$1,000 investment question was not asked from 2016-2019, we use data from these later years to show that our key results hold in other real-world outcomes, for example probability of buying investment properties. Our final sample is a subsample of the 2020-2021 housing survey waves. In addition to repeating the investment experiment of the 2015 data, we add to the 2020-2021 surveys the additional feature of asking some respondents whether they base their investment decisions more on past returns or expected returns and in 2021 an open-response question asking why.

3.1 Survey Questions

This section provides examples of how the the Survey of Consumer Expectations questions are framed. See Appendix B for a complete list of the relevant survey question text.

Respondents are asked about home price changes in their zip code over the last 12 months and how they expect home prices to change in their zip code over the next 12 months.[25] These questions are framed in three formats with each respondent randomly shown one of the three alternative framings.[26] In all multivariate specifications, we control for indicators of which format was used for a given respondent. For example, past one-year home-price percentage change perceptions are 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. Over the past 12 months, how has the value of such a home changed? (By value, we mean how much that typical home would approximately sell for.)* [increased/decreased] followed by *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.*

[25] The same past and expected returns questions are also asked about five-year horizons.

[26] The SCE wording is standard for belief surveys. Having multiple framings is motivated by Glaser et al. (2007), who find that framing affects how survey respondents report expected stock returns. See Armona et al. (2018) for further discussion.

A respondent's one-year expected returns in percentage points are elicited as follows:

> *You estimated that the current value of a typical home in your zip code to be* [X] *dollars. Now, we would like you to think about the future value of such a home. Over the next 12 months, what do you expect will happen to the value of such a home?* [increase/decrease] followed by what percent the respondent expects for the increase or decline.

The distribution of expected returns is elicited using questions such as:

> *You estimated that the current value of a typical home in your zip code to be* [X] *dollars. What do you think is the percent chance that the value of such a home, over the next 12 months (by February 2022), will...*
>
> *decrease by 5% or more:* ____ *percent chance*
>
> *decrease by 0% to 5%:* ____ *percent chance*
>
> *increase by 0% to 10%:* ____ *percent chance*
>
> *increase by 10% or more:* ____ *percent chance*

We provide the complete text of how investment decisions are elicited in Appendix B. As an example, the wording of the housing fund investment decision is illustrated in panel I of Figure 1. To cross-sectionally test whether cognitive uncertainty is related to a reliance on past over future returns, we follow the procedure of Enke and Graeber (2021) to allow respondents to express their uncertainty by choosing their own subjective confidence interval, as illustrated in panel II of Figure 1.See, too, other papers that elicit confidence in forecasted returns (e.g., Bachmann et al. (2020); Giglio et al. (2021)).

3.2 Summary Statistics

Table 1 reports summary statistics for our core variables. The average age in our sample is 51 years old. Homeowners comprise 76% of respondents, 29% have household income higher than $100,000, and 57% are college educated. Respondents were asked a series of five questions based on Lipkus et al. (2001) and Lusardi (2008) that provide an individual-specific measure of numeracy. We code the number of correct answers (ranging from 0 to 5) as a covariate. There is strong correlation between the numeracy score and education or income, consistent with Lusardi (2008). For example, 53% of the college graduates in our sample answered all 5 questions correctly, compared with 30% among respondents without a college degree. Similarly, 59% of households with income over $100,000 answered scored 5 out of 5, compared with 37% among other households. Later in the paper, we use the numeracy score, college education, and income as proxies for financial literacy to explore heterogeneity and potential drivers for cognitive uncertainty.

We note that, as an online survey, the SCE oversamples college-educated and high-income households. In general, we expect any bounded rationality identified in the SCE sample to be stronger in the overall population. Using a SCE-ACS weight to calculate nationally representative statistics, we verify that our results are largely unchanged or stronger after weighting the observations. For example, for the self-reflection question in 2020 and 2021, 46% of our weighted respondents report that they base their decisions on past returns, slightly higher than the 44% number before weighting.

On average, households perceive that local home-price growth over the past 12 months was around 4.7% and expect an average of 3.8% local home-price growth over the next 12 months. Both perceived past HPA and HPA forecasts show substantial heterogeneity, with standard deviations of 6.2% and 4.9%, respectively. There are also differences between perceived and objectively measured past experiences, which we term the perception gap. The average absolute perception gap is 4.9 percentage points, indicating that on average, people's perception of last year's local returns is five percentage points away from objectively measured average local returns. Both the actual experience and the perception gap affect investors' choices with similar coefficients after controlling for the forecasted distribution of future returns.

Our primary outcome variable is the average share of $1,000 invested in the housing fund and averages 57% with standard deviations over 34%. For other real-estate investment outcomes, the average self-reported probability of moving in the next three years is 30%. Among those who reported an over 5% moving probability, 67% expect to buy their next primary residence, in line with the 2019 U.S. homeownership rate of 65%. Around 10% of respondents expect to buy an investment property within the next 3 years.

Finally, Appendix Table A1 reports summary statistics on surveyed expectations about variables usually considered fundamental demand factors for housing: inflation, mortgage interest rates, residential rents, and economic conditions. The average survey respondent expects 3.6% inflation and 6.2% rent growth in the year following the survey, although there is considerable variation across respondents around these means. On average, respondents expect mortgage interest rates to rise only 35 basis points over the next year, and they expect year-ahead economic conditions to be roughly the same as the day they filled out the survey.

4 Home-Price Beliefs and Behavior

Before presenting our main results on how forecasted and perceived past home-price growth predict investment behavior, Table 2 investigates how stated beliefs are formed by estimating the relationship between a respondent's perceived past and her forecast of future local housing-price returns. Consistent with Armona et al. (2018) and Glaeser and Nathanson (2017), these results demonstrate that perceived past home-price growth is an important factor considered by investors in their stated beliefs, making it a plausible mental default for return forecast in investment decisions. Column 1 of Table 2 regresses the expected home-price growth on the perceived past home-price growth in a bivariate regression. Columns 2 to 4 add individual controls and forecasted fundamentals, both separately and together. Across all specifications, there is a strong relationship between the perceived past and the forecasted home home-price growth, showing that respondents incorporate past returns into their return forecasts. Every one percentage point higher perceived past home-price growth is associated with 24 basis points higher forecasted home-price growth, controlling for forecasted fundamentals and individual controls. We also note that the R^2 in column 4 is 0.26, suggesting that even with our detailed set of demographic covariates and controls for each individual's forecast of fundamentals, much of the variation in home-price beliefs is idiosyncratic and driven by unobservables.

To illustrate our core findings, we first present graphical evidence on the relationships between investment actions and forecasted and perceived past home-price growth. Figure 2 shows binned scatter plots of shares invested in the housing fund out of a $1,000 investment versus perceived past returns, both unconditionally (left-hand graph) and conditional on stated expected returns (right-hand graph). The unconditional graph on the left shows a strong relationship between past returns and investment, which we expect expected given momentum in housing returns, extrapolative beliefs, and the beliefs channel of investment demand. However, the right-hand graph shows that even conditional on stated forecasts, perceived past returns still have strong predictive power for investment. This statistically significant conditional relationship contrasts with the notion that an investor's forecasted return summarizes all past information relevant to expected returns used in her decision-making and suggests a wedge between survey-elicited expectations and investment demand. To relax the strong assumptions imposed in 2, including imposing a linear functional form and the independence of past returns and other factors that affect demand such as risk aversion and the distribution of expected returns, we next develop a multivariate regression framework for investment demand.

4.1 Perceived Past Home-Price Growth and Investment

To estimate the relationship between perceived returns, stated beliefs, and investment decisions, our main regression model is

$$Y_{i,t} = \alpha + \beta_1 \hat{r}_{i,t} + \beta_2 \hat{E}_t[r_{i,t+1}] + X'_{i,t}\phi + \varepsilon_{i,t}, \tag{7}$$

where $\hat{r}_{i,t}$ and $\hat{E}_t[r_{i,t+1}]$ are respondent i's perception of home-price appreciation (HPA) over the past 12 months and her stated expected HPA over the next 12 months, respectively, and Y_{it} is an investment outcome of interest.[27] In our baseline specifications, we consider the share of a \$1,000 investment allocated to a housing derivative tracking local home-price growth. Additional specifications consider the stated probability of buying a primary or a non-primary residence in the next three years. The vector X_{it} is a set of demographic controls relative to the prior literature on beliefs and contains binary indicators for owning a home, numeracy, ethnicity, gender, marital status, education, labor force status, census region, a quadratic in age, and logs of household income, home equity, liquid savings, and personal debt.

We begin with the housing fund share as the outcome variable. Table 3 examines whether perceived past home-price growth improves action prediction after controlling for an individual's forecasted home-price growth. Columns 1 to 3 regress the housing fund investment share ϕ_{it} on expected and perceived past returns, both separately and together. The bivariate regression results in columns 1 and 2 report coefficients for the past and future returns with similar magnitudes. In column 3, when we include both return variables in one specification, perceived past returns still have statistically significant predictive power for the housing investment allocation.

Whether these results demonstrate that stated beliefs are not a sufficient statistic for beliefs used in investing depends on whether perceived past returns are simply correlated with other non-belief factors that influence investment demand. As a first step to assess the potential role of omitted variables, columns 4-6 add the same demographic controls as in Armona et al. (2018). Of particular interest, these controls include a dummy for above-median self-reported risk aversion, helping us address potential endogeneity from high past returns causally increasing risk tolerance (Malmendier and Nagel (2011); Meeuwis (2019)), conceptually similar to a correlation between α and $\hat{r}_{i,t}$.[28] Being confident in one's assessment

[27]Estimating the Merton model (1) via a log-log specification and controlling for an estimate of $\sigma^2_{i,t+1}$ instead of (7) results in similar implied magnitudes; see Appendix Table A2 for regression results and Appendix C for details on the estimation of $\sigma^2_{i,t+1}$.

[28]While separating higher risk tolerance from higher expected returns with survey evidence is always challenging (cf. Malmendier and Nagel (2011)), Section 5.1 accounts for risk aversion in more flexible ways.

of past returns and having high risk tolerance are both strong predictors of risky-asset shares. The gender gap in the risky-asset share is also large; even when males and females have equal expected returns, males invest as if they expect 7 percentage point higher returns.

In column 6, which includes both expected and perceived-past HPA and the full set of demographic controls, perceived past HPA still has a statistically significant effect on investment decisions. We find that a one percentage point higher perceived past HPA is associated with 54 basis points higher share allocated to a local housing fund. Again, this finding contrasts with the traditional approach, which assumes that past returns affect decisions only through expectations and that belief factors can be omitted from action-prediction regressions conditional on stated beliefs.

Another consideration when interpreting Table 3 is the lack of controls for the expected distributions of returns. The role of other moments besides expected mean returns is captured in the σ^2_{t+1} term in the Merton model. For example, it could be that investors believe that past home-price growth is a strong predictor for *downside* risk even conditional on the expected mean. Without controlling for downside risk, the statistically significant coefficient on perceived past home-price growth could be driven by investors basing their decisions on downside risk (Armona et al. (2018); Adelino et al. (2018)). To address this, Table 4 includes a number of controls for the forecasted distribution of returns. Inspired by Engelberg et al. (2009), the SCF asks respondents about their belief probabilities of home prices going up by more than 10%, up between 0% and 10%, down by less than 5%, and down by more than 5%. In column 1, we add the probability of a decline in home prices to the specification in column 6 of Table 3. In column 2, we further add the other two self-reported probabilities. In column 3 and 4, we add a quadratic and cubic, respectively in each return-range probability. Across all these specifications, the relationship between perceived past home-price growth and investment remains statistically significant. Comparing column 3 with column 4, we also observe that adding incremental flexibility of a cubic in the forecasted distribution moments adds very little to the adjusted R^2 and almost does not change the coefficient on perceived past home-price growth, suggesting that our specification of the distribution of returns is sufficiently flexible. One might argue that we only measure the forecasted distribution of returns through four coarse bins, which limits our power. For example, we ask respondents about the probability of home prices going down by more than 5% but perhaps what affects their decision-making is their belief probabilities of home prices going down by more than 10%. While our sample sizes prevent us from being fully nonparametric about the expected distribution of returns and which moments are most important in demand, our results are also robust to restricting our sample to those who placed zero probability on a home-price decline larger than 5%.[29]

Collinearity between forecasted home-price growth and subjectively measured past home-price growth could also make it challenging to interpret the coefficients separately for these two return measures. However, *a priori*, such collinearity should bias us against finding evidence that past returns matter even conditional on stated forecasts. To address this, in columns 5 and 6 of Table 4, we include one return variable linearly in our specification while controlling for the other return variable flexibly through bin fixed effects. For example, in column 5, we first divide our observations into 50 equally sized bins according to their perceived past HPA. We then control for fixed effects for these bins and also control for the expected HPA linearly. Similarly, in column 6, we control for bin fixed effects for the expected HPA and report a linear coefficient for the perceived past HPA. Bin fixed effects allow us to control for one factor relatively nonparametrically and thereby absorb any correlation between perceived past returns and forecasted returns.[30] Column 6 shows that subjective past home-price growth remains an important predictor for investment behavior even after controlling for the forecasted home-price growth in a flexible way. Appendix Table A3 verifies that this result is robust to different numbers of bins for the returns variables.

We conduct several other robustness tests to probe the validity of our finding that while respondents incorporate past returns into their return forecasts, they increase their emphasis on past returns when actually making decisions. For example, our online survey oversamples high-income and educated households. To verify that our results hold in the general population, we weight observations using ACS-SCE sampling weights and show stronger effects of past experience in Appendix Table A4 for the nationally representative adult, as anticipated in Section 3.2. We also note that the hypothetical investment experiment studied in our main results is from the baseline stage in Armona et al. (2018), where respondents were not incentivized. In Appendix Table A5, we show that our results hold for the smaller subsample whose investment decisions were incentivized with the possibility of receiving the realized gross return of their composite housing and savings fund with their chosen weights (see Armona et al. (2018) for details). Further, Bordalo et al. (2020a) raise the possibility that past returns are correlated with beliefs about future fundamentals, a potentially important component of investment demand distinct from beliefs about future housing returns. We address this concern in Appendix Table A6, which shows that our results are also robust

[29]We also consider estimates of the Merton (1969) demand equation (1) directly using an estimate of σ^2_{t+1} implied by each individual's forecast distribution. See Appendix C and Appendix Table A2 for details.

[30]Note that because survey responses bunch around round number like "0%", "5%", or "10%", the actual number of bins tends to be smaller than the specified target number of equally sized bins. This is because, for example, 8.5% of the respondents answered "0%" as their forecasted home-price growth and these respondents are always put in the same bin, independent of the number of bins that specified. We report both the number of specified bins and actual bins.

to controlling for individual investor forecasts of fundamentals. Finally, Appendix Table A7 verifies that perceived past returns have added predictive power for investment decisions even conditional on actual past returns. In column 2, where both the perceived past and the actual past returns are included as controls, perceived past returns are still significant predictors of investment.

Taking stock, in all specifications, controlling for perceived past returns improve the prediction of investment decisions even conditional on stated beliefs. Moreover, this finding is robust to flexible specifications and explanations based on collinearity. This is consistent with the empirically weak predictive power of stated beliefs to explain investment actions relative to theoretical benchmarks (see Giglio et al. (2020); Liu and Sui (2020); Giglio et al. (2021)). Still, our main point of emphasis is not to reject the beliefs channel but to demonstrate that allowing belief factors to independently capture some of the gap between decision-relevant and stated expectations strengthens the empirical connection between beliefs and investment. In the remainder of this section, we test for cross-sectional heterogeneity in the emphasis of past returns in decision making and verify our results hold with other measures of housing investment.

4.2 Heterogeneity

We investigate heterogeneity across different subgroups in our sample to test potential explanations for our findings. We divide our sample into homeowners and renters, college graduates and not, those with household income above and below $75,000, ages above 50 and below 50, males and females, those with a high and low numeracy scores, and those who did and did not check a housing website in the past year.[31] Appendix Tables A8 and A9 report the results of estimating (7) for each subsample.

Across most subgroups, even after controlling for the forecasted distribution of future returns and demographics, perceived past home-price growth strongly predicts investment choices.[32] An important exception is renters, for whom the return-related variable with the highest statistical significance is the downside risk. One potential explanation is that renters are sensitive to downside risk in home prices and therefore avoid buying a home.

Another source of heterogeneity that we seek to explore with the heterogeneity results is

[31]Given that our surveys are answered by household heads, we note that male and female household heads could have different characteristics than average males and females in the general population. The question framing for recently checking a housing website is "Over the past 12 months, how often have you consulted websites or other sources that give you information on the estimated current value of your property or properties in your area?" with answers "Never", "1-2 times", "3-4 times", or "5 times or more".

[32]The results of Appendix Table A8 are further robust to controlling for a cubic in the probabilities that make up the forecasted distribution of returns.

financial literacy. As suggested by the framework in Section 2, it is possible that many investors lack the required expertise to make an informed home price forecast. Facing financial risk, they trust their subjective experience as a more reliable signal than their own stated forecasts for investment decisions. It could be that financially sophisticated investors can make a relatively informed forecast and use it as a basis for financial choices. We use several proxies for financial literacy, including income, education, age, numeracy score, and whether respondents checked housing websites or other sources for their homes' estimated values. We find evidence for the effect of financial sophistication. The combination of columns 3-6 of Appendix Table A8 and columns 1-2 and 5-8 of Appendix Table A9 suggests that our results are primarily driven by younger, low-numeracy, lower-income, non-college educated investors and those who do not actively follow the housing market.[33]

While our main focus is on the coefficients for the perceived past returns, we also note that the coefficients for the stated forecasts in columns 7 and 8 of Appendix Table A9 show that investors actively following the housing market display a much stronger reliance on their expected returns than do the other investors. This is consistent with the heterogeneity results in Giglio et al. (2021), who find a much stronger relationship between stated forecasts and actions for investors who pay more attention to their accounts, measured by frequency of logging in. Here, our contribution is that even the inattentive investors could also demonstrate a strong expectation effect if we properly measure their decision-relevant expected return by incorporating the perceived past returns. This supports the explanation that lack of knowledge about the housing market could induce investors to rely on their subjective past and shrink the role of stated forecasts, broadly consistent with the cognitive uncertainty framework in Section 2.

4.3 Other Housing-Related Behaviors

To examine robustness to alternative measures of investment beyond the investment experiment, we extend our analysis to include other measures of housing investment: the probability of buying a non-primary residence (including both investment and vacation homes) within the next three years, the probability of buying the next primary residence conditional on moving within the next three years, and viewing housing as a good investment. These variables are collected in all years between 2015 and 2021, and, unlike the housing-fund investment experiment, are subject to real-world constraints. For example, borrowers who would like to invest in housing might not nevertheless qualify for a mortgage or be interested in moving. Similarly, places with the highest past home-price growth tend to be high

[33]See also Agarwal et al. (2009), who find a higher incidence of financial mistakes among the young and old relative to the middle-aged.

cost areas, creating added challenge for households to become homeowners, even if they do believe home prices will continue to rise. Accordingly, we *a priori* expect the relationship between returns, forecasted or subjective historical and behavior to be weaker than in the investment experiment, similar to the findings of Armona et al. (2018).

Appendix Table A10 reports regression estimates using alternative investment action outcomes. Columns 1 and 2 show that there is a strong correlation between perceived past home-price growth and the probability of buying a non-primary home. For buying a primary residence, columns 3 and 4 show that we fail to have power to detect an effect of past returns on intention to buy an owner-occupied residence conditional on expected returns, although the coefficient magnitudes are similar to other columns. Still, this result could be in part due to constraints and confounds. Columns 5 and 6 show that both forecasted and subjective past home-price growth are strong predictors of viewing housing as a good investment. Taken together, controlling for past returns improves the ability of belief factors to predict real-world investment outcomes beyond in the investment experiment.

5 Robustness

In this section, we adjudicate among possible interpretations of the empirical findings in Section 4. First, we consider the possibility that our results are affected by omitted variable bias (Section 5.1) or measurement error in stated home-price expectations (Section 5.2). While there are surely omitted variables and measurement errors in stated beliefs, we show that they are unlikely to fully explain our results. Section 6 then provides direct evidence supporting cognitive uncertainty as a key reason why beliefs surveys may measure different projections of beliefs than the ones used in decision-making.

5.1 Omitted Variable Bias and Risk Aversion

The Merton (1969) framework for risky-asset demand in equation (1) above motivates our exploration of factors that should affect investment demand and that could be conditionally correlated with past returns r_t. Specifically, we check whether beliefs about the distribution of expected returns (σ_t^2), risk aversion (α), measurement error in surveyed expectations $\hat{E}_t[r_{t+1}]$, and multicollinearity between $\hat{E}_t[r_{t+1}]$ and r_t could be driving our results. Other potential omitted variables include demand shocks that depend on the outcome variable of interest. For example, when the dependent variable is the probability of buying a primary residence, omitted variables include preferences over home ownership, the relative quality of owner-occupied and rental housing in a respondent's local area, the likelihood of moving regions, mortgage-credit availability, etc. When the outcome variable is share invested in the housing fund, the environment is much simpler, motivating its use for our purposes. Presumably, an investor's decision about such a derivative investment is a function of only the forecasted distribution of the expected return distribution and risk aversion, especially when the initial investment capital is provided by the survey administrators.

For the forecasted distribution of home-price growth, we control for the subjective probabilities of future returns falling into four ranges—and polynomials of those bin probabilities—in Table 4. Such flexible controls help absorb any nonlinearities in the mapping from agents' physical risk to risk-neutral probabilities not captured by the Merton model.[34] As discussed in Section 4.1 above, flexible return-distribution controls add some explanatory power and reduce the magnitude of the coefficient on past returns in predicting investment. However, past returns are still a significant predictor of investment demand even conditional on the distribution of expected returns.

While Tables 2-4 include some risk-aversion controls, Table 5 further explores the role of risk aversion in explaining our results. Column 1 reports estimates from a bivariate regression of the housing investment share on a risk tolerance metric, measured using a 1-10 scale. The coefficient is both economically and statistically significant. Moving the risk tolerance from 1 to 10 increases the housing share by as much as 30 percentage points, suggesting that our risk tolerance variable is a particularly meaningful measure of risk appetites. In columns 2 and 3, respectively, we add the risk tolerance measure to our baseline specification linearly and by controlling for indicators of each potential value from 1 to 10. Conditional on this measure of risk tolerance, there is still a strong correlation between the perceived past home-price growth and the housing investment share, suggesting that our results cannot be fully explained by risk aversion as an omitted variable. We also note that the R^2 increases by only 0.011 from columns 2 to 3 as we move from a linear control for the risk tolerance score to more nonparametric indicators for each value of the risk tolerance score. This small marginal impact of additional flexibility suggests that finer measures of risk appetites are unlikely to reverse our main results.

Another alternative explanation based on risk aversion is through the wealth channel. Large past home-price growth increases households' net worth and could reduce their absolute risk aversion parameter, if for example we model households having constant relative risk aversion or decreasing relative risk aversion (see Chetty et al. (2017); Meeuwis (2019)). However, our risk-tolerance variable is measured contemporaneous with the investment decision, i.e., *after* any effect of past returns on current risk aversion has been realized. In

[34] See Adam et al. (2021) for related evidence that expectations survey respondents do not report risk-adjusted return forecasts.

Appendix Table A11, we interact past home-price growth with measures of the importance of home equity in an individual's portfolio. These measures include leverage in her primary residence, home value as a share of net assets, and home values divided by income. Intuitively, the wealth effect of past returns should be stronger for households with higher leverage or a more expensive home relative to their income. Across all specifications, the interaction terms have a statistically insignificant or negative coefficient, suggesting past returns lowering risk aversion is not an alternative explanation for our empirical findings.

5.2 Measurement Error in Home Price Expectations

Could our results in Section 4 stem from noise in survey responses? Such an explanation finds plausibility, for example, in the bunching of returns forecasts around 0%, 5%, 10%, etc. (Dominitz and Manski (1997); Manski and Molinari (2010); Binder (2017)). Similarly, the common finding across expectations surveys that different question framings on returns generate systematically different responses (Glaser et al. (2007); Armona et al. (2018); Glaser et al. (2019)) suggests a degree of instability and noise in stated beliefs. While such survey errors are likely present in both perceived past and forecasted returns, stated forecasts could be particularly noisy. For example, survey participants might more often round for forecasted returns than perceived past returns.[35] This could induce downward bias in the expected return coefficient and an upward bias in the past experience coefficient as the latter would be correlated with the signal in the former.

However, several pieces of evidence are inconsistent with a measurement-error interpretation. Foremost, as we discuss in Section 6.1, 44% of surveyed investors admit relying more on the past return over the expected return. We also analyze free-text responses to an open-ended question asking why respondents indicate they rely on past or expected returns. We find justifications consistent with cognitive uncertainty driving many people towards investment decision-making that significantly weights past returns. If an investor knows her expected return and the expected return is only imperfectly observed by the econometrician due to measurement error, we would still expect all investors to report that their decisions are based on their observable-to-them true expected returns. Instead, we find that a sizable fraction of the population is backward-looking and aware of it. Consistent with this qualitative evidence, our results that past returns matter even conditional on the expected returns are robust to instrumenting for the expected returns. To formalize the null hypothesis that

[35] To address this particular concern, we conduct a robustness test by restricting the sample to observations without rounding for perceived past or forecasted returns. Our results are actually stronger for these non-rounders, the opposite prediction of a measurement error alternative explanation based on rounding or even differential rounding.

measurement error explains our results and the bias correction instrumenting affords under the null, we first present an econometric framework and supporting simulation results, with the corresponding empirical results detailed in Appendix D.

To adjudicate the measurement error explanation of our results, we consider whether the following data generating process (DGP) could generate our results.

$$\begin{aligned} Y_{i,t} &= \beta_0 + \beta_1 E_t^*[r_{i,t+1}] + \varepsilon_{i,t} \\ E_t^*[r_{i,t+1}] &= \pi_0 + \pi_1 \hat{r}_{i,t} + Z_{i,t}'\pi_2 + v_{i,t} \\ \hat{E}_t[r_{i,t+1}] &= E_t^*[r_{i,t+1}] + \eta_{i,t}, \end{aligned} \tag{8}$$

where the outcome variable $Y_{i,t}$ is a linear function of the true forecast $E_t^*[r_{i,t+1}]$ plus some independent unobserved heterogeneity.[36] Consistent with classical assumptions about expectation formation, investors form expectations $E_t^*[r_{i,t+1}]$ as a function of perceived past returns $\hat{r}_{i,t}$ and other belief factors, including a systematic component $Z_{i,t}$ (expected economic conditions, expected rent growth, etc.) and a discretionary adjustment $v_{i,t}$.[37] In this data-generating process, investors base their decisions on their actual forecasts $E_t^*[r_{i,t+1}]$, but the econometrician observes only a noisy measure $\hat{E}_t[r_{i,t+1}]$ of true beliefs that contains measurement error $\eta_{i,t}$. The measurement error concern is that because forecasted returns are imprecisely reported, when we regress actions on $\hat{r}_{i,t}$ and $\hat{E}_t[r_{i,t+1}]$, we could still estimate a positive coefficient on $\hat{r}_{i,t}$ even if investors do follow a two-step procedure of first formulating $E_t^*[r_{i,t+1}]$ and then basing investment decisions on it.

Our alternative DGP is

$$\begin{aligned} Y_{i,t} &= \beta_0 + \beta_1 E_t^*[r_{i,t+1}] + \beta_2 \hat{r}_{i,t} + Z_{i,t}'\beta_3 + \varepsilon_{i,t} \\ &= \beta_0 + (\beta_1\pi_1 + \beta_2)\hat{r}_{i,t} + Z_{i,t}'(\beta_1\pi_2 + \beta_3) + \beta_1 v_{i,t} + \varepsilon_{i,t} \\ E_t^*[r_{i,t+1}] &= \pi_0 + \pi_1 \hat{r}_{i,t} + Z_{i,t}'\pi_2 + v_{i,t} \\ \hat{E}_t[r_{i,t+1}] &= E_t^*[r_{i,t+1}] + \eta_{i,t}, \end{aligned} \tag{9}$$

where we acknowledge measurement error η in stated beliefs but also allow the possibility that subjective past experience $\hat{r}_{i,t}$ and $Z_{i,t}$ have independent effects on actions, such that the null hypothesis in (8) corresponds to $\beta_2 = \beta_3 = 0$. Equivalently, an investor could weight factors differently in the action stage than in the forecast stage, for example, overweighting their own past experience in investment decisions relative to the forecast-stating domain.[38]

[36] To simplify the exposition, we abstract away from risk aversion in this version of the decision rule.

[37] Table 2 shows that forecasted fundamentals can explain a meaningful fraction of the variation in stated forecasts.

[38] As argued in Section 2, one motivation for overweighting and underweighting at the decision stage is

The following simulation illustrates that the DGP under the null hypothesis can generate a positive coefficient on $\hat{r}_{i,t}$ if we only control for $\hat{r}_{i,t}$ and $\hat{E}_t[r_{i,t+1}]$ together. We parameterize the model in 9 according to the null hypothesis of no independent effect of past returns on investment with $\beta_1 = \sqrt{2}$, $\beta_1 = \beta_2 = \beta_3 = \pi_0 = 0$, $\pi_1 = \pi_2 = 1$, and $\hat{r}_{i,t}$, $Z_{i,t}$, $\varepsilon_{i,t}$, and $v_{i,t}$ are independently, identically distributed $\mathcal{N}(0,1)$. We then vary the standard deviation σ_η of the measurement error $\eta_{i,t} \sim \mathcal{N}(0, \sigma_\eta^2)$ to test how measurement error affects the corresponding regression coefficients. Panel I of Figure 3 shows that the estimated coefficient on $\hat{r}_{i,t}$ increases in the variance of the measurement error. In other words, despite the data being generated under the null with the true coefficient β_2 on past returns being zero, measurement error in expected returns and the positive correlation between past returns and the signal in stated returns (from $\pi_1 > 0$) upward biases OLS estimates of the role of past returns in investment. This result highlights the potential for measurement error in stated returns to spuriously generate a non-zero estimated role for past returns in the second-stage statistical model of investment decisions.

As we detail further below, our survey responses to multiple-choice and open-ended questions about whether people rely on their surveyed stated beliefs when making investment decisions push back against the measurement error interpretation. While the derivations and simulations above show that measurement error could econometrically explain our findings of past returns mattering even conditional on stated returns, the high fraction of people that report relying more on past returns than their stated expected returns when making decisions provide strong evidence that our results are not driven spuriously by mismeasured forecasts.

We further show in Appendix D that if we instrument for $\hat{E}_t[r_{i,t+1}]$, this fixes the bias in the second-stage coefficient on $\hat{r}_{i,t}$. If past returns in fact have no effect on investment because they are fully incorporated into expectations, instrumental-variables estimates of β_2 should be statistically close to zero. To see this, consider the second-stage equation, where we regress investment decisions on predicted expected returns and perceived past returns

$$Y_{i,t} = \beta_0 + \beta_1 \widehat{E_t[r_{i,t+1}]} + \beta_2 \hat{r}_{i,t} + \varepsilon_{i,t}, \tag{10}$$

where the predicted values are a function of both the included ($\hat{r}$) and excluded (Z) exogenous variables $\widehat{E_t[r_{i,t+1}]} = \hat{\pi}_0 + \hat{\pi}_1 \hat{r}_{i,t} + Z'_{i,t}\hat{\pi}_2$ Under the null hypothesis, where both $\hat{r}_{i,t}$ and $Z_{i,t}$ only affect $Y_{i,t}$ through $E^*_t[r_{i,t+1}]$, instrumenting would provide an unbiased estimate of β_2 such that the expected 2SLS estimate of $\hat{\beta}_2$ would be 0. In Appendix D.1, we formally derive $E[\hat{\beta}_2] = 0$ under the null DGP. Panel II of Figure 3 illustrates this finding, showing

the investor's confidence in $\hat{r}_{i,t}$ relative to her confidence in $Z_{i,t}$. If an investor is more confident in $\hat{r}_{i,t}$ than in $Z_{i,t}$, she is likely to overweight $\hat{r}_{i,t}$.

that in simulations the estimated coefficient $\hat{\beta}_2$ on $\hat{r}_{i,t}$ is consistently close to 0 regardless of the size of the measurement error σ_η. This simulation result is also robust to adding measurement error in $Z_{i,t}$, alleviating potential concern that other factors considered in the stated forecasts being measured with noise could also affect the coefficient on $\hat{r}_{i,t}$. We then show that instrumenting for expected returns in our data does not drive the coefficient on past returns, allowing us to reject the measurement error explanation.

For instruments, we note that under the null, other belief factors $Z_{i,t}$ meet the requirements for a valid instrument for $\hat{E}_t[r_{i,t+1}]$ because under the null hypothesis, these factors are independent of the measurement error in expected returns and conditionally independent of the error term ε under the usual two-step model of expectation formation and investment decision-making.[39] We further develop an instrument based on the second moment of the mismeasured variable, a strategy based on Lewbel (1997), and detail the assumptions required for its validity. Appendix Tables A12 and A13 present results using these instruments that provide further econometric evidence allowing us to reject the null hypothesis that our findings are driven by noise in surveyed forecasts.

6 Evidence for Cognitive Uncertainty Mechanism

To understand the mechanism underlying the wedge between surveyed expectations and investment decisions, we ask half of the 2020 and all of the 2021 survey respondents whether they value subjective past returns more or return forecasts more in decision-making and report results in Section 6.1. Among other results, we find a substantial share of respondents reporting they don't use the forecasted returns they report on the survey but instead rely on past returns when investing. Categorizing free-text responses to an open-ended question in the 2021 survey that asked them why they do this, we find many responses conveying subjective uncertainty about their own forecast. We further show that lack of financial sophistication (proxied by non-college graduates) and risk aversion are both strong predictors for choosing perceived past HPA over forecasted HPA. Furthermore, the treatment group relies less its return forecasts than the control group does, consistent with an explanation based on cognitive uncertainty. In Section 6.2, we present direct evidence for inflation expectations and rent-growth expectations as "shrunk factors" (denoted s in equations (2) to (5)) in the cognitive-uncertainty framework of Section 2. Combined, the evidence points towards the complexity of the investment domain triggering cognitive uncertainty, which leads investors to rely relatively more on belief factors in which they have more confidence.

[39] We caveat that this particular IV strategy is invalid under richer models of measurement error being correlated with stated beliefs about fundamentals.

6.1 Direct Survey Measures of Decision Factors

For a more direct measure of decision-making factors, we first ask half of the 2020 and all of the 2021 survey respondents whether they rely more on their survey-reported returns forecasts or past home-price growth when making investment decisions.

Table 6 presents summary statistics for those who consider their stated expected returns (column 1) or past returns (column 2) as the more important consideration underlying their investment decisions. First, 44% of respondents report that they rely on past returns more than their survey-stated expectations in decision-making. This confirms our earlier empirical finding that, at least for a substantial share of our sample, realized returns do drive investors' decisions independent of their effect on expected returns.[40] Respondents relying on past or stated expected returns also have significantly different observable characteristics. Compared with those stating they rely on past returns, respondents who rely more on stated expected returns are more likely to be college graduates, have higher income and savings and are more risk seeking, contributing to their higher average housing investment in the housing derivative (62.4% versus 54.9%).[41] While both groups are more confident about past returns than forecasted returns, forward-looking respondents are relatively more confident about their forecasted returns than backward-looking respondents. Moreover, forward-looking respondents are more confident about both their estimate of past returns and their forecast of future returns. These summary statistics are broadly consistent with our preferred cognitive-uncertainty explanation that respondents weight past returns more heavily when they are more uncertain about other future signals.

Next we test whether people's reported reliance on future versus past returns is consistent with their actual investment decision rule. In other words, do those reporting that they rely on stated expected returns indeed base their investment decisions on their return forecast? Appendix Table 7 reports these results. Forward-looking respondents indeed rely more on their stated expected returns and less on their perceived past returns, consistent with their self-reported decision factors. We also note that the forward-looking group on average invests much more in the housing fund than does the backward-looking group.

[40] In the 2020 survey, we also elicited whether survey respondents are forward- or backward-looking if they were to invest in the stock market. Table 6 reports that 40% of survey respondents are backward-looking for the stock market. Among those that are forward-looking for the housing market, 77% are also forward-looking for the stock market. For the backward-looking group for the housing market, 64% of them are also backward-looking when investing in the stock market. While not our focus, these results suggest that our results for the housing market potentially apply to other asset markets.

[41] On average, Table 6 shows that 38% of respondents report relying more on past stock returns than expected stock returns when making stock-market investment decisions, consistent with Andries et al. (2020). Among respondents selecting stated expected return for the housing question, 80% of them also choose stated expected returns for the stock-market investment question.

We then directly test the cognitive uncertainty mechanism by studying how survey respondents' reliance on past returns changes as a function of their relative confidence in their forecasts. In other words, when investors are more confident about their forecasts than their perceived past HPA, do they rely more on their forecasts instead of the past returns? Table 8 reports the evidence consistent with this hypothesis. The main coefficients of interest are those for the interaction terms of forecasted returns or perceived past returns with the confidence gap in these two return variables. We can see that reliance on past return decreases as people become more confident about their forecasts relative to their perceived past returns.

In the 2021 survey, we pose an open-response question, asking respondents why they rely on either past or their stated expected returns more when making housing investment decisions. We code these responses into five categories for each of the two investor types.[42] For the group that relies more on their stated forecasted returns, we title the five categories fundamentals, expectations, past returns not guaranteed, last year different, and other. For the group that relies more on past returns in investment decision-making, the five categories are consistent trends, real data, uncertainty, conservative, and other. The definitions of each category are described in Appendix E, and the frequencies of these categories are plotted in Figure 4.

Overall, the answers for forward-looking investors resemble the rationale behind a textbook model of demand. Panel I of Figure 4 shows that most common response categories for this group are fundamentals and expectations, codes that reflect answers emphasizing beliefs about market fundamentals and the importance of expectations about the future in investing. The following illustrative example responses to why forward-looking investors rely more on forecasted returns are consistent with the classical approach to thinking about past returns insofar as they inform a forecast with investment demand ultimately depending on forecasted returns.

- "Because the question asked me to make a decision pertaining to the future, not the past. I used past price growth to project future growth in my assessment."
- "I'd be investing in future returns, while past returns are important information, future gains are what I'm more concerned with."
- "Because [my forecast] is a prediction about the future, not an observation about the past. I'm not investing 12 months ago."

However, the data also show forceful rationalizations by potential investors stating they make decisions by relying on past returns more than their own forecasts reported on the

[42] See Appendix B for the exact question wording and Appendix E for the procedure we follow in coding the open-ended text responses.

survey. Panel II of Figure 4 shows that the most common response categories for this group are consistent trends, real data, and uncertainty, codes that reflect answers emphasizing the consistency of the local housing market, the reliability of historical data, and uncertainty about stated expectations. In a textbook model of demand, consistent trends would simply be incorporated into expected returns. However, responses focusing on respondents' lack of confidence in their stated expectations relative to verifiable and observable past returns is entirely consistent with cognitive uncertainty affecting the weighting of belief factors differentially during the complex investment stage relative to expectations survey questions. For example, answering why they rely more on past returns than their stated expected returns, such respondents say things such as:

- "The future is always uncertain and many factors can change the outcome. The past performance is a certainty that has happened."
- "I rely on [past returns] more because it is what is documented in writing. My forecasting is only a best guess."
- "[Past returns] better indicator because based on facts not projections"
- "I rely more on past home price growth because it has happened already, but the forecast is uncertain."

Contrasting the pattern of responses by those that rely on past returns and those that rely on their forecasted returns offers strong evidence for heterogeneity in the degree to which surveyed expectations reflect the beliefs used in investment decision-making.

6.2 Reduced Form and Evidence for Shrunk Factors

The cognitive uncertainty model in Section 2 assumes existence of a signal s that an investor relies on when forming return forecasts but down-weights in investment decisions. Mathematically, this behavior would imply $\beta_{2,e} > \beta_{2,i}$ in equations (4) and (5) and $\frac{\beta_2}{\beta_3} > \frac{\pi_1}{\pi_2}$ in equation (9). In this section, we show that forecasted rent growth and inflation forecast are such factors.[43] Column 1 in Table 9 repeats column 5 of Table 2 for reference by regressing home-price growth forecast on perceived past home-price growth, forecasted rent growth, inflation forecast and demographic controls. Both forecasted rent growth and forecasted inflation are statistically significant factors considered in home-price growth even conditional on other factors. A one percentage point higher rent growth is associated with a 0.14 percentage point higher expected home-price growth, and a one percentage point higher inflation forecast is associated with a 0.12 percentage point higher expected home-price growth.

[43]See Kindermann et al. (2019) for evidence on the effect of rent growth on home-price forecasts.

Column 2 regresses the share invested in a housing fund on perceived past home-price growth, forecasted rent growth, forecasted inflation, and our usual individual controls. Despite rent growth's and inflation forecast's importance in home price forecast, they are ignored (if not down-weighted) in this reduced-form specification of the investment decision, inconsistent with their impacting investment only through beliefs. Column 3 reinforces this point by conditioning on flexibly specified return distribution forecasts that should capture the effect of beliefs on investment if stated beliefs are a sufficient statistic for the beliefs used in decision making. Instead, conditional on past beliefs, past returns are up-weighted and forecasted rent growth and forecasted inflation are down-weighted. While the negative coefficients on forecasted rent growth and inflation are statistically insignificant, their magnitudes are relatively large and insensitive to our controls for beliefs about the distribution of future returns.

The pattern of results in Table 9 are inconsistent with with stated beliefs fully capturing the beliefs channel of investment demand. They are, however, consistent with a model of decision making such as cognitive uncertainty wherein investors form different beliefs depending on the nature of the decision domain, relying more (less) on belief factors they are more (less) confident in when making financial decisions.

7 Conclusion

In this paper, we document that the subjective beliefs survey respondents state on expectations surveys are not sufficient statistics summarizing all decision-relevant information about expected returns used in decision-making. In the context of risky-asset investment demand, we find that belief factors can have independent effects at the decision stage even conditional on expected returns. We focus on a unique investment experiment where survey respondents allocated $1,000 between a risk-free asset and a derivative that earns what their zip code's local housing price index earns over the next year, although our results hold for other outcomes. While past returns are incorporated into expected returns, controlling for perceived past returns improves risky-asset investment prediction in the cross-section even after controlling for each individual's forecasted return distribution.

Our preferred explanation is that this extra extrapolation of relying on past returns even conditional on stated beliefs stems from cognitive uncertainty triggered by the complexity of the investment domain. We test this explanation by fielding new questions in the 2020 and 2021 waves of the Survey of Consumer Expectations. When asked whether they rely on their surveyed forecasted returns or past returns more in making investment decisions, 44% of respondents report using past returns to make investment choices. Respondents confident about their forecasted returns relative to their estimate of past returns are more likely to rely on them relative to past returns, and vice versa. Analyzing open-ended explanations for reliance on past or expected returns, respondents using past returns more frequently cite uncertainty and a lack of confidence in many of the speculative belief factors incorporated into their surveyed forecasts. We also test and reject several alternative explanations including omitted variables bias, multicollinearity, and measurement error in surveyed expectations.

These results have important empirical and theoretical implications. Empirically, our results suggest that researchers could improve the measurement of the beliefs channel of investment demand underlying investment choices by eliciting and controlling for perceptions of belief factors such as past returns. Correcting for the independent effect of belief factors even conditional on stated beliefs strengthens both the magnitude of the beliefs channel and the estimated degree of extrapolation in investment choices. Theoretically, our findings advance the growing literature of limited attention and cognitive uncertainty by providing novel supporting evidence about how cognitive noise affects investment decision-making.

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Figure 1: Investment and Subjective Confidence Survey Questions

I. Investment Question

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% interest per year.

What proportion of the $1,000 would you invest in:

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

The housing market fund	%
The savings account	%
	TOTAL: 0

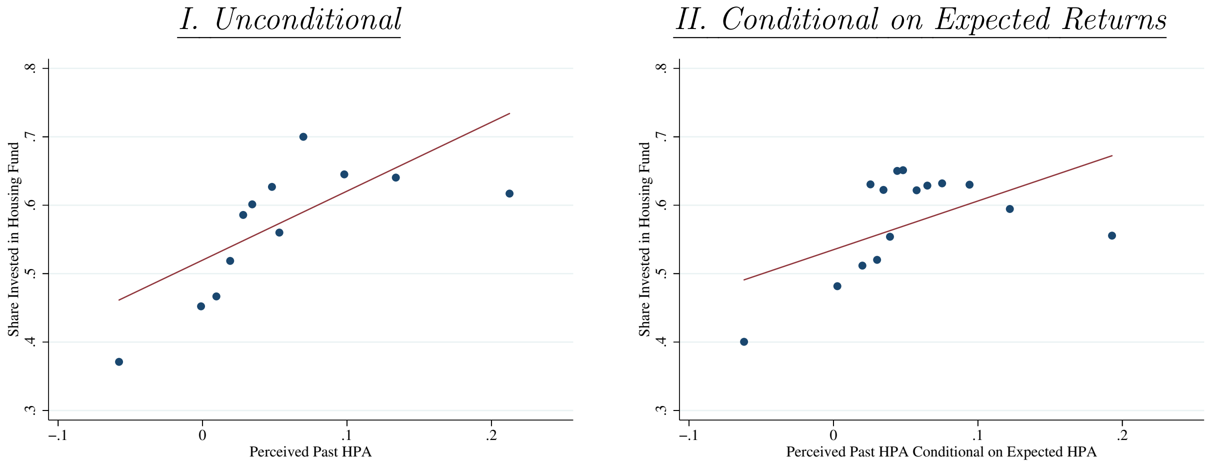
II. Subjective Uncertainty Question

You stated over the past 12 months, the value of a typical home in your zip code increased by 9%. How certain are you in your answer?

- (Completely certain) I am certain that the value of a typical home in my zip code increased by 9% over the past 12 months.
- (Very certain) I am certain that the value of a typical home in my zip code changed between an increase of 7.0% and an increase of 11.0% over the past 12 months.
- (Somewhat certain) I am certain that the value of a typical home in my zip code changed between an increase of 3.0% and an increase of 15.0% over the past 12 months.
- (Little certain) I am certain that the value of a typical home in my zip code changed between a decrease of 1.0% and an increase of 19.0% over the past 12 months.
- (Very uncertain) I am not at all certain that the value of a typical home in my zip code changed between a decrease of 1.0% and an increase of 19.0% over the past 12 months.

Notes: Figure shows the investment experiment question in the 2021 survey (panel I) and the subjective confidence elicitation question in the 2021 survey (panel II).

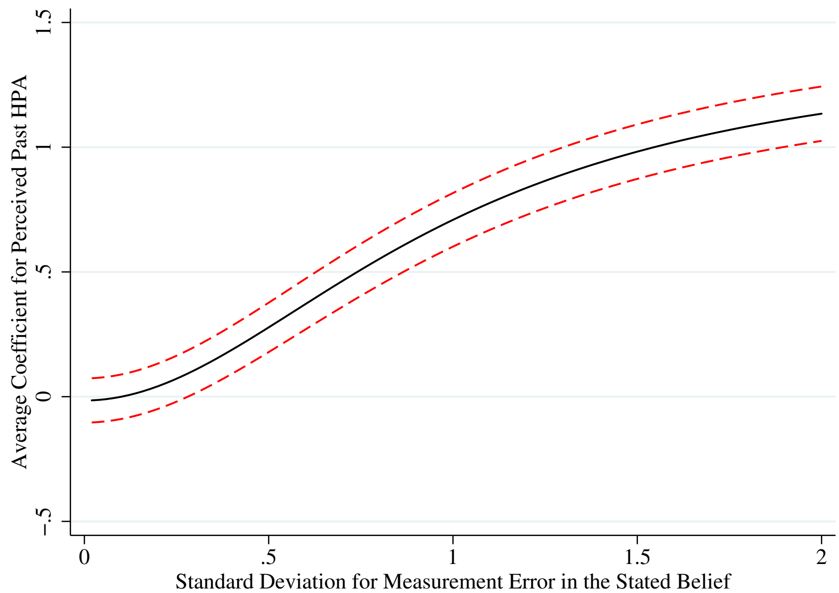
Figure 2: Risky Asset Shares and Perceived Past Returns



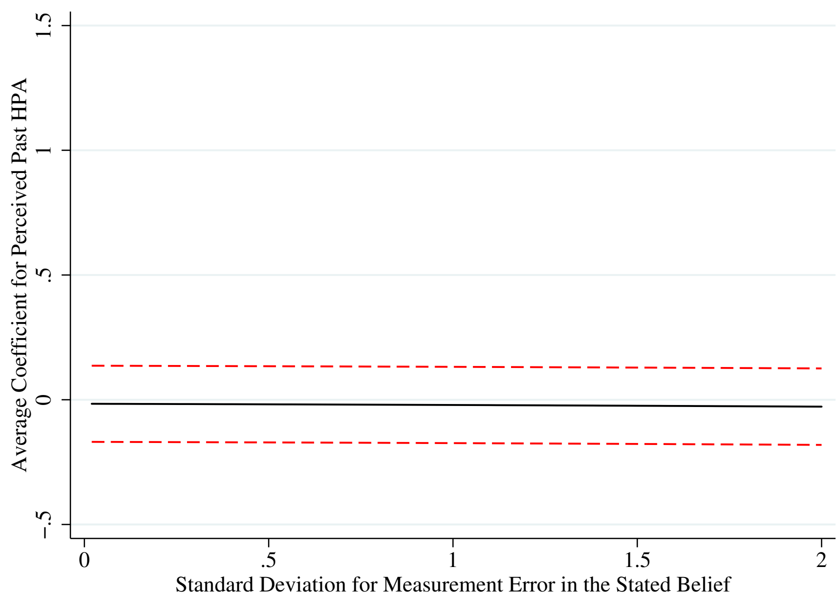
Notes: Figure presents binned scatter plots for the share of an \$1,000 investment in the housing fund versus the perceived past home-price growth unconditionally in panel I and after first partialling out individual-level forecasted home-price growth in panel II. N = 2,966.

Figure 3: Simulated Past Returns Coefficients Under Measurement Error

I. Simulated OLS Coefficient on Past Returns



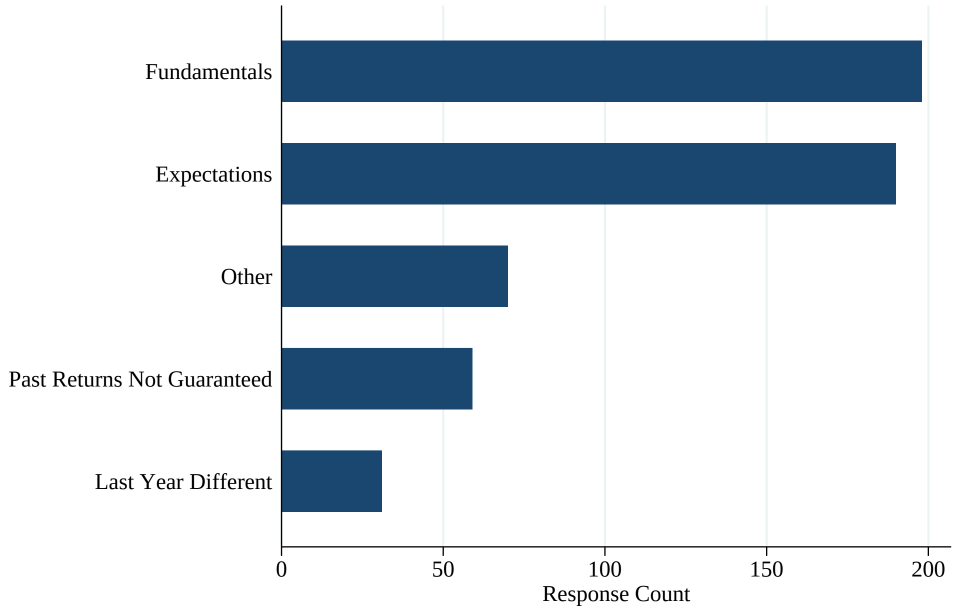
II. Simulated 2SLS Coefficient on Past Returns



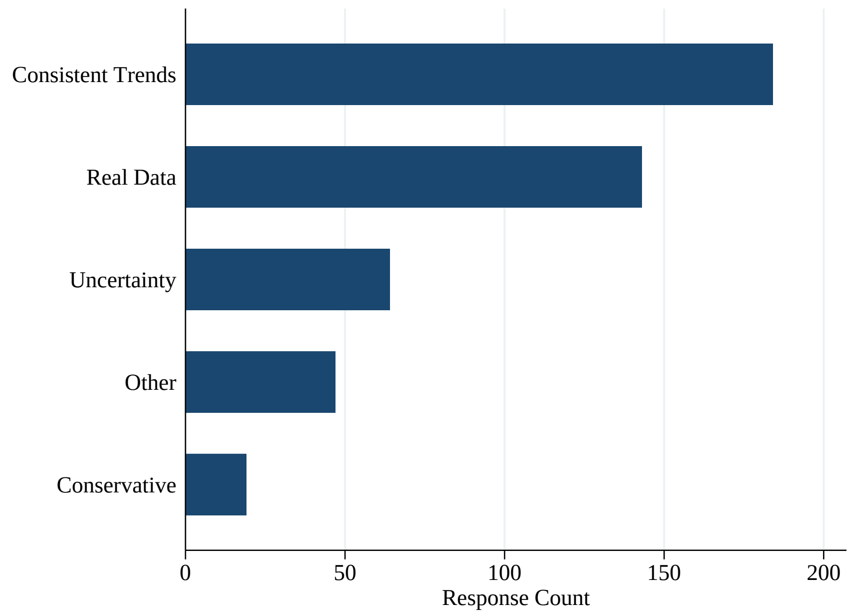
Notes: Panels I and II, respectively, plot average OLS and 2SLS coefficients on perceived past returns from a regression of simulated investment decisions on expected returns and past returns where expected returns are measured with error. The 2SLS estimator in panel II instruments for stated expected returns with expected rent growth. The data generating process is specified in (9) with $\beta_1 = \sqrt{2}$, $\pi_0 = \beta_2 = \beta_3 = 0$, $\pi_1 = \pi_2 = 1$, and $r_{i,t}, Z_{i,t+1}, \varepsilon_{i,t}, v_{i,t} \sim \mathcal{N}(0,1)$. The measurement error $\eta_{i,t}$ in the stated forecasts is normally distributed, with varying standard deviation shown in the horizontal axis. Black lines plot average coefficients from 100 simulations of 1,000 observations each. Dashed red lines plot average confidence intervals.

Figure 4: Coded Responses to Investment Decision Factor Rationale

I. Reasons for Relying on Expected Returns



II. Reasons for Relying on Past Returns



Notes: Figures plot the distribution of coded free-text answers to the 2021 survey question of why respondents state that they rely more on either their stated expected returns (panel I) or past returns (panel II) when making investment decisions. See Appendix B for question wording and Appendix E for details on the coding procedure. N = 548 for panel I and N = 457 for panel II.

Table 1: Summary Statistics: 2015-2020 Sample

	Response Count	Mean	Std. Dev.
I. Individual Characteristics			
Age (years)	7,065	51.22	19.04
Male Indicator	7,064	0.53	0.50
Minority Indicator	7,056	0.16	0.37
Married Indicator	7,066	0.65	0.48
Homeowner Indicator	7,025	0.76	0.43
College Graduate Indicator	7,064	0.57	0.50
1(Household Income $\geq$ \$100K)	6,998	0.29	0.45
1(Liquid Savings $\geq$ \$75K)	6,630	0.39	0.49
Numeracy Score (0-5)	7,065	4.05	1.05
Risk Tolerance (1-10)	7,066	4.45	2.24
II. Beliefs and Investment Actions			
Forecasted HPA in the Next 12 months (p.p.)	7,056	3.81	4.85
Perceived HPA in the Past 12 months (p.p.)	7,053	4.73	6.18
Confidence in Perceived Past Returns (1-5)	7,053	3.20	0.93
Confidence in Forecasted Return (1-5)	984	2.96	1.03
Actual HPA in the Past 12 months (p.p.)	6,711	5.38	3.98
|Perception Gap| (p.p.)	6,698	4.87	4.43
Share Invested in a Housing Fund (p.p)	3,015	57.26	34.26
Probability of Moving within 3 years	7,050	0.30	0.34
Probability of Buying a Primary Residence	4,999	0.67	0.33
Probability of Buying an Investment Property	7,049	0.10	0.18

Notes: Table reports means, standard deviations, and counts of individual responses used in the empirical analysis. Numeracy is coded between 1 and 5, based on the number of correct answers to 5 questions testing numerical literacy. Risk tolerance is coded from 1 (risk averse) to 10 (risk loving). Confidence level of past home-price growth estimate is coded from 1 (not all confident) to 5 (very confident). Perception Gap is the absolute value of the difference between a respondent's perception of last year's home-price growth in their zip code and zip-code-level returns estimated from CoreLogic's repeat-sales index. Share invested in a housing fund is asked in both 2015 and 2020 and represents the share of a hypothetical \$1,000 investment allocated by the respondent to an index of local housing market returns instead of a savings account with a 2% annual yield. Likelihood of buying a primary residence is asked to respondents who report an over-5% probability of moving within 3 years.

Table 2: The Effect of Perceived Past Returns on Belief Formation

Dependent Variable: Forecasted Returns				
	(1)	(2)	(3)	(4)
Perceived Past Returns	0.29***	0.28***	0.25***	0.24***
	(0.013)	(0.014)	(0.013)	(0.014)
Forecasted Rent Growth			0.15***	0.15***
			(0.011)	(0.011)
Forecasted Inflation			0.070***	0.065***
			(0.017)	(0.017)
Individual Controls		✓		✓
Fundamentals			✓	✓
Observations	6,993	6,993	6,993	6,993
R-squared	0.139	0.163	0.202	0.222

Notes: Dependent variable is surveyed expected house price appreciation over the next year. Perceived past returns are respondent's estimate of home-price appreciation in their zip code over the past year. One percentage point is denoted as 1. Individual controls include binary indicators for owning a home, numeracy, ethnicity, gender, marital status, education, labor force status, census region, age, age^2, and logs of household income, equity in home, liquid savings, personal debt, a dummy for consulting websites about home prices in the past 12 months, and a dummy for receiving questions in a percentage-change framing instead of a level framing, a 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), a dummy that equals 1 if respondent reports a 4 or less (on 1-10 scale) to a question about willingness to take risks in financial matters, where 10 is very willing. Fundamentals include measures of respondent expectations of general inflation, rent growth, mortgage-rate changes, future economic conditions, and future credit availability. The sample used is from survey years 2015-2021. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table 3: Effects of Forecasted and Past Returns on Investment

Dependent Variable: Housing Fund Share (on a 0-100 scale)						
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Returns	1.30***		0.88***	1.23***		0.93***
	(0.13)		(0.15)	(0.13)		(0.14)
Perceived Past Returns		1.01***	0.71***		0.85***	0.54***
		(0.10)	(0.11)		(0.10)	(0.11)
Confident in Past Returns				5.48***	5.44***	5.35***
				(1.29)	(1.30)	(1.29)
Above-median Risk Aversion				-9.63***	-9.45***	-9.38***
				(1.29)	(1.30)	(1.29)
Male				6.44***	6.68***	6.52***
				(1.27)	(1.26)	(1.26)
Homeowner				1.11	0.11	0.67
				(1.54)	(1.55)	(1.54)
Individual Controls				✓	✓	✓
Observations	2,963	2,963	2,963	2,963	2,963	2,963
R-squared	0.033	0.035	0.047	0.129	0.123	0.136

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). One percentage point is denoted as 1. Confident in past returns is a dummy that equals 1 if respondent reports being confident in their recall of past home price changes (i.e., answers 4 or more on a 1-5 scale, where 5 is very confident). Above-median risk aversion is a dummy that equals 1 if respondent reports a 4 or less (on 1-10 scale) to a question about willingness to take risks in financial matters, where 10 is very willing. Individual controls are controlled in columns 4 to 6. For definitions of these controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table 4: Robustness of Investment Effects to Distributional Controls

Dependent Variable: Housing Fund Share (on a 0-100 scale)						
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Returns	0.66***	0.59***	0.54***	0.55***	0.62***	
	(0.14)	(0.15)	(0.15)	(0.15)	(0.16)	
Perceived Past Returns	0.51***	0.49***	0.48***	0.49***		0.51***
	(0.11)	(0.11)	(0.11)	(0.11)		(0.11)
Pr(HPA next year $<$ 0%)	-0.14***	-0.14***	-0.15*	-0.0003	0.01	0.01
	(0.022)	(0.029)	(0.090)	(0.17)	(0.16)	(0.16)
Pr(HPA next year < -5%)		0.012	-0.14	-0.43	-0.41	-0.40
		(0.048)	(0.18)	(0.29)	(0.29)	(0.29)
Pr(HPA next year $>$ 10%)		0.057	0.34***	0.50***	0.44***	0.37**
		(0.038)	(0.086)	(0.17)	(0.17)	(0.17)
Confident in Past Returns	4.98***	4.99***	5.05***	5.09***	4.58***	4.79***
	(1.28)	(1.28)	(1.29)	(1.29)	(1.28)	(1.28)
Above-median Risk Aversion	-9.20***	-9.19***	-9.18***	-9.15***	-8.49***	-8.45***
	(1.28)	(1.28)	(1.27)	(1.27)	(1.27)	(1.27)
Individual Controls	✓	✓	✓	✓	✓	✓
Probabilities Squared			✓	✓	✓	✓
Probabilities Cubed				✓	✓	✓
Bin FEs for Past Returns					✓	
Bin FEs for Forecasted Returns						✓
Observations	2,963	2,963	2,963	2,963	2,963	2,963
R-squared	0.149	0.150	0.154	0.155	0.177	0.181

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). One percentage point is denoted as 1. Controls for the probability that next year's local housing returns fall within a given range are derived from answers to a question detailed in Section 3.1 about the distribution of returns; the omitted category is the probability that next year's returns are between 0 and 10%. For definitions of individual controls, see notes to Table 2. In column 5, we first divide our observations into 50 equally sized bins according to their perceived past HPA, and then control for fixed effects for these bins. In column 6, we control for bin fixed effects for expected HPA in a similar way. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table 5: The Role of Risk Aversion in Investment Decisions

Dependent Variable: Housing Fund Share			
	(1)	(2)	(3)
Risk Tolerance (1-10)	3.70***	2.74***	
	(0.28)	(0.29)	
Forecasted Returns		0.54***	0.54***
		(0.15)	(0.15)
Perceived Past Returns		0.48***	0.46***
		(0.11)	(0.11)
Confident in Past Returns		4.40***	4.56***
		(1.29)	(1.29)
Probabilities Cubic		✓	✓
Individual Controls		✓	✓
Risk Tolerance Score FEs × Year FEs			✓
Observations	2,963	2,963	2,963
R-squared	0.059	0.167	0.178

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). One percentage point is denoted as 1. Probabilities cubic is a vector of controls for a cubic polynomial for each respondent's stated probability that next year's returns fall in one of four ranges—see Section 3.1 for question framing. Risk tolerance score × year fixed effects are interactions of year fixed effects and risk tolerance score fixed effects. For definitions of individual controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table 6: Summary Statistics by Forward and Backward Looking

	Select $\hat{E}_t[r_{i,t+1}]$	Select $\hat{r}_{i,t}$	Equal Means (p-value)
	(1)	(2)	(3)
Number of Observations	772	613	
Share Invested in Housing Fund (p.p.)	62.40	54.90	0.00
Forecasted HPA in the Next 12 months (p.p.)	4.57	4.18	0.16
Perceived HPA in the Past 12 months (p.p.)	6.37	5.97	0.25
Actual HPA in the Past 12 months (p.p.)	7.04	7.25	0.43
|Perception Gap| (p.p.)	5.12	5.32	0.45
Confidence in Forecasted Returns (1-5)	3.06	2.86	0.00
Confidence in Perceived Past Returns (1-5)	3.21	3.05	0.00
Confidence in Forecast - Confidence in Past Returns	-0.11	-0.19	0.10
Age (years)	50.8	50.5	0.71
Homeowner Indicator	76.2	77.5	0.56
College Graduate Indicator	64.1	58.1	0.02
1(Household Income $\geq$ \$100K)	34.3	32.0	0.36
1(Liquid Savings $\geq$ \$75K)	32.1	27.2	0.05
Risk Tolerance (1-10)	4.89	4.49	0.00
Forward-Looking for Stocks	77.4	35.6	0.00

Notes: Table reports variable means for the 2020-2021 samples that were asked a question about whether they rely more on their stated expected housing returns (column 1) or their perceived past returns (column 2) when making housing investment decisions. Column 3 reports p-values for a t-test of whether the means in that row are equal across the two columns. Confidence in forecasted returns is only available for the 2021 sample. Forward-looking for stocks is an indicator for whether a respondent in the 2020 sample reported that she relies more on her own stated expected returns than past returns when making decisions about investing in the stock market. See notes to Table 1 for further details.

Table 7: Investment Decision Factors by Forward- and Backward-Looking

Dependent Variable: Housing Fund Share (on a 0-100 scale)			
	(1)	(2)	(3)
Forecasted Returns	1.41***	0.42	0.50
	(0.27)	(0.32)	(0.31)
Perceived Past Returns	0.19	1.16***	1.28***
	(0.22)	(0.25)	(0.24)
Forward-Looking			7.52***
			(2.70)
Forecasted Returns × Forward-Looking			0.91**
			(0.41)
Perceived Past Returns × Forward-Looking			-1.14***
			(0.32)
Individual Controls	✓	✓	✓
Sample	Forward-Looking	Backward-Looking	Full Sample
Observations	772	613	1,385
R-squared	0.175	0.234	0.185

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). The sample in column 3 is all respondents in the 2020-2021 surveys that were asked whether they rely more on their perceived past (column 2 sample) or their stated expected returns (column 1 sample) when making investment decisions. Forward-looking is an indicator for respondents that reported relying more on their stated expected returns. One percentage point is denoted as 1. For definitions of individual controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table 8: Effects of Cognitive Uncertainty on Investment Decision-making

Dependent Variable: Housing Fund Share (on a 0-100 scale)	(1)	(2)	(3)	(4)
Forecasted Returns	1.28***	0.87**	0.77**	0.20
	(0.24)	(0.34)	(0.33)	(0.35)
Perceived Past Returns	0.53***	0.78***	0.82***	0.79***
	(0.17)	(0.23)	(0.24)	(0.24)
Forecasted Returns	0.12	0.11	0.016	0.063
× (Conf Forecast - Conf Past)	(0.24)	(0.23)	(0.21)	(0.21)
Perceived Past Returns	-0.56***	-0.52***	-0.46***	-0.47***
× (Conf Forecast - Conf Past)	(0.17)	(0.17)	(0.17)	(0.16)
Confidence in Forecast Returns	3.39*	3.11*	5.08***	4.23**
- Confidence in Past Returns	(1.86)	(1.88)	(1.95)	(1.91)
Risk Tolerance (1-7)	6.58***	6.57***	5.11***	5.03***
	(0.72)	(0.72)	(0.78)	(0.77)
Forecasted Returns × Treated		0.89*	0.94**	0.88**
		(0.46)	(0.45)	(0.44)
Perceived Past Returns × Treated		-0.55	-0.74**	-0.71**
		(0.34)	(0.34)	(0.33)
Treated		1.62	2.05	3.01
		(3.35)	(3.37)	(3.26)
Individual Controls			✓	✓
Distribution of Forecasted Returns				✓
Observations	925	925	925	925
R-squared	0.161	0.165	0.233	0.257

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). One percentage point is denoted as 1. Treated is a dummy for the treatment group, who receives the nudging question before reporting their investment choices. Conf Forecast - Past is the difference between reported confidence in the respondent's 1-year HPA forecast and reported confidence in 1-year perceived past HPA. For definitions of individual controls, see notes to Table 2. Controls for the distribution of forecasted returns is a vector of linear controls for a respondent's stated probability of future returns falling into four ranges. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table 9: Evidence for Shrunk Belief Factors

Dependent Variable:	Forecasted Returns	Housing fund share	
	(1)	(2)	(3)
Forecasted Returns			0.53***
			(0.15)
Perceived Past Returns	0.29***	0.80***	0.49***
	(0.020)	(0.10)	(0.11)
Forecasted Rent Growth	0.14***	0.07	-0.09
	(0.016)	(0.11)	(0.11)
Forecasted Rate of Inflation	0.12***	-0.05	-0.17
	(0.026)	(0.15)	(0.15)
Individual Controls	✓	✓	✓
Probabilities Cubic			✓
Observations	2,963	2,963	2,963
R-squared	0.276	0.144	0.170

Notes: For definitions of individual controls, see notes to Table 2. Probabilities cubic is a vector of controls for a cubic polynomial for each respondent's stated probability that next year's returns fall in one of four ranges—see Section 3.1 for question framing. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Appendix

A Condition for Independent Effect of Past Experience

In this appendix, we derive the sufficient and necessary condition for an independent effect of past experience in the theoretical model of Section 2. We relax the assumption in Section 2 that σ_p is constant between the expectation to the investment decision stages. That is, we assume that $\sigma_{p,i} > \sigma_{p,e}$ and $\sigma_{s,i} > \sigma_{s,e}$. The model and coefficients are as follows

$$\begin{aligned}\phi &\approx \tilde{c} + r_i + \gamma_\alpha \alpha + \gamma_\sigma \sigma_i^2 \\ &= c_1 + \beta_{1,i} r_t + \beta_{2,i} s + \gamma_\alpha \alpha + \gamma_\sigma \sigma_i^2 \\ &= c_2 + \left(\beta_{1,i} - \beta_{1,e}\frac{\beta_{2,i}}{\beta_{2,e}}\right) r_t + \frac{\beta_{2,i}}{\beta_{2,e}} r_e + \gamma_\alpha \alpha + \gamma_\sigma \sigma_i^2. \end{aligned} \tag{11}$$

$$\beta_{1,e} = \frac{\sigma_{s,e}^2(\mu_d^2+\sigma^2)}{(\sigma_{s,e}^2+\sigma_{p,e}^2)(\mu_d^2+\sigma^2)+\sigma_{p,e}^2\sigma_{s,e}^2}$$

$$\beta_{2,e} = \frac{\sigma_{p,e}^2(\mu_d^2+\sigma^2)}{(\sigma_{s,e}^2+\sigma_{p,e}^2)(\mu_d^2+\sigma^2)+\sigma_{p,e}^2\sigma_{s,e}^2}$$

$$\beta_{1,i} = \frac{\sigma_{s,i}^2(\mu_d^2+\sigma^2)}{(\sigma_{s,i}^2+\sigma_{p,i}^2)(\mu_d^2+\sigma^2)+\sigma_{p,i}^2\sigma_{s,i}^2}$$

$$\beta_{2,i} = \frac{\sigma_{p,i}^2(\mu_d^2+\sigma^2)}{(\sigma_{s,i}^2+\sigma_{p,i}^2)(\mu_d^2+\sigma^2)+\sigma_{p,i}^2\sigma_{s,i}^2}$$

The coefficient for r_t in equation (11), $\beta_{1,i} - \beta_{1,e}\frac{\beta_{2,i}}{\beta_{2,e}}$, can be simplified as

$$\beta_{1,i} - \beta_{1,e}\frac{\beta_{2,i}}{\beta_{2,e}} = (\mu_d^2+\sigma^2)\frac{\sigma_{s,i}^2\sigma_{p,e}^2 - \sigma_{s,e}^2\sigma_{p,i}^2}{\sigma_{p,e}^2[(\sigma_{s,i}^2+\sigma_{p,i}^2)(\mu_d^2+\sigma^2)+\sigma_{p,i}^2\sigma_{s,i}^2]} \tag{12}$$

We derive a necessary and sufficient condition for $\beta_{1,i} - \beta_{1,e}\frac{\beta_{2,i}}{\beta_{2,e}}$ to be positive. The denominator and the factor $(\mu_d^2+\sigma^2)$ in equation (12) are both positive so it suffices to check the sign of $\sigma_{s,i}^2\sigma_{p,e}^2 - \sigma_{s,e}^2\sigma_{p,i}^2$. The positivity of $\sigma_{s,i}^2\sigma_{p,e}^2 - \sigma_{s,e}^2\sigma_{p,i}^2$ is equivalent to $\frac{\sigma_{s,i}^2}{\sigma_{s,e}^2} > \frac{\sigma_{p,i}^2}{\sigma_{p,e}^2}$. Thus, the coefficient for r_t in the investment stage is positive if and only if σ_s increases relatively more than σ_p between the expectation and investment decision stages.

B Survey Question Text

Framing of Perceived Past Home Price Returns

1. Questions framed in terms of the levels of house prices: "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?"

2. Questions framed in terms of percentage changes: "Now, think about how the value of such a home has changed over time. Over the past 12 months, how has the value of such a home changed? (By value, we mean how much that typical home would approximately sell for.) [increased/decreased]" followed by "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."

3. Questions framed in terms of changes of dollar amounts: "By about what dollar amount do you think the value of such a home has [increased/decreased] over the past 12 months? Please give your best guess."

4. Questions about confidence in past returns following the past home price return questions: "How confident are you in your answers?

   - 1 (Not at all confident)
   - 2
   - 3 (Somewhat confident)
   - 4
   - 5 (Very confident)"

5. Questions about confidence in past returns (2021 subjective confidence interval procedure): "You stated over the next 12 months, the value of a typical home in your zip code increased by 5%. How certain are you in your answer?

   - (Completely certain) I am certain that the value of a typical home in my zip code increased by 5% over the past 12 months.
   - (Very certain) I am certain that the value of a typical home in my zip code changed between an increase of 3.0% and an increase of 7.0% over the past 12 months.
   - (Somewhat certain) I am certain that the value of a typical home in my zip code changed between a decrease of 1.0% and an increase of 11.0% over the past 12 months.
   - (Little certain) I am certain that the value of a typical home in my zip code changed between a decrease of 5.0% and an increase of 15.0% over the past 12 months.
   - (Very uncertain) I am not at all certain that the value of a typical home in my zip code changed between a decrease of 5.0% and an increase of 15.0% over the past 12 months."

   The intervals for "Very certain", "Somewhat certain", "Little certain" and "Very uncertain" are the perceived past return $\pm 2\%$, $\pm 6\%$, $\pm 10\%$ and beyond $\pm 10\%$ respectively.

Framing of Expected Home Price Returns

1. Questions framed in terms of the level of house prices: "You estimated the current value of a typical home in your zip code to be [X] dollars. Now, we would like you to think about the future value of such a home. What do you think the value of such a home will be one year from today ____ dollars?"

2. Questions framed in terms of percentage changes: "You estimated the current value of a typical home in your zip code to be [X] dollars. Now, we would like you to think about the future value of such a home. Over the next 12 months, what do you expect will happen to

the value of such a home? Over the next 12 months, I expect the value of such a home to ... [increase/decrease]" followed by "By about what percent do you expect the value of such a home to [increase/decrease] over the past 12 months? Please give your best guess."

3. Questions framed in terms of changes of dollar amount: "'You estimated the current value of a typical home in your zip code to be [X] dollars. Now, we would like you to think about the future value of such a home. Over the next 12 months, what do you expect will happen to the value of such a home? Over the next 12 months, I expect the value of such a home to ... [increase/decrease]" followed by "By about what dollar amount do you expect the value of such a home to [increase/decrease]over the past 12 months? Please give your best guess."

4. Questions about the distribution of expected returns framed in terms of the level of house prices: "You estimated the current value of a typical home in your zip code to be [X] dollars.What do you think is the percent chance that the value of such a home one year from today

   - less than [95%*X] dollars: ____ percent chance
   - between [95%*X] and [100%*X] dollars: ____ percent chance
   - between [100%*X] and [110%*X] dollars: ____ percent chance
   - more than [110%*X] dollars: ____ percent chance"

5. Questions about the distribution of expected returns framed in terms of percentage changes: "What do you think is the percent chance that the value of such a home, over the next 12 months, will...

   - decrease by 5% or more: ____ percent chance
   - decrease by 0% to 5%: ____ percent chance
   - increase by 0% to 10%: ____ percent chance
   - increase by 10% or more: ____ percent chance"

6. Questions about confidence in expected returns (2021 subjective confidence interval procedure): "You stated over the next 12 months, the value of a typical home in your zip code will increase by 5%. How certain are you in your answer?

   - (Completely certain) I am certain that the value of a typical home in my zip code will increase by 5% over the next 12 months.
   - (Very certain) I am certain that the value of a typical home in my zip code will change between an increase of 3.0% and an increase of 7.0% over the next 12 months.
   - (Somewhat certain) I am certain that the value of a typical home in my zip code will change between a decrease of 1.0% and an increase of 11.0% over the next 12 months.
   - (Little certain) I am certain that the value of a typical home in my zip code will change between a decrease of 5.0% and an increase of 15.0% over the next 12 months.
   - (Very uncertain) I am not at all certain that the value of a typical home in my zip code will change between a decrease of 5.0% and an increase of 15.0% over the next 12 months."

   The intervals for "Very certain", "Somewhat certain", "Little certain" and "Very uncertain" are the return forecast ±2%, ±6%, ±10% and beyond ±10%, respectively.

Housing Investment Decisions

1. Investment in a housing fund: "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: The housing market fund? The savings account?"

2. Probability of buying a primary residence: "And if you were to move to a different primary residence over the next 3 years, what is the percent chance that you (or your spouse/partner) would buy (as opposed to rent) your new home?"

3. Probability of buying an investment property: "What is the percent chance that over the next 3 years you [or your spouse/partner] 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.)?"

4. Evaluating housing in their zip code as an investment: "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:" with options including "A very good investment," "A somewhat good investment," "Neither good nor bad as an investment," "A somewhat bad investment," *and* "A very bad investment."

Investment Decision-making

1. 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% interest per year. Which factor do you rely on more when making this investment decision? Please select only one.

   - Your forecast of home price growth in your local housing market over the next 12 months (You reported earlier that you expect 5% growth)
   - The realized growth in home prices in your local housing market over the past 12 months (You reported earlier 10%)

2. Why do you rely more on [the past OR your expected] home price growth?

C Density Estimation

For specifications estimating the Merton (1969) model in (1) directly, we require an estimate of the conditional variance of expected returns σ^2_{t+1}. To construct such an estimate, we follow the approach used by Armantier et al. (2017) to fit a parametric distribution for each respondent based on the probabilities the respondent reported for each possible density interval using a minimum distance procedure that minimizes the distance between the empirical and estimated parametric distribution. We assume the underlying distribution is a generalized beta distribution when the respondent assigns positive probability to three or more outcome intervals. We assume an isosceles triangular distribution when the respondent puts all probability mass in two intervals and a uniform distribution when the respondent puts all probability mass in one interval.

The generalized beta distribution is a flexible four parameter unimodal distribution that allows different values for its mean, median and mode and has the following functional form:

$$f(x) = \begin{cases} 0 & \text{if } x < \ell \\ (x-\ell)^{\alpha-1}(r-x)^{\beta-1}/B(\alpha,\beta)(r-\ell)^{\alpha+\beta-1} & \text{if } \ell \leq x \leq r \\ 0 & \text{if } x > r \end{cases}$$

where $B(\alpha, \beta) = \Gamma(\alpha)\Gamma(\beta)/\Gamma(\alpha+\beta)$ and $\Gamma(\cdot)$ is the gamma function.

The two parameters α and β describe the shape of the distribution and the parameters ℓ and r fix the support of the distribution. Fitting a unique beta distribution requires a respondent to have assigned positive probability mass to at least three (not necessarily adjacent) intervals. In the case one or more of the intervals are unbounded, the relevant ℓ and/or r are treated as unknown parameters that are estimated along with α and β.

The triangular distribution, for cases when a respondent assigns positive probability to exactly two adjacent bins, has the shape of an isosceles triangle whose base includes the interval with the greatest probability mass and a portion of the adjacent interval. Thus, the triangle is anchored at the outer bound of the interval with probability mass above 50 percent. Its density has the functional form:

$$f(x) = \begin{cases} \frac{4}{(r-l)^2}(x-\ell) & \text{if } \ell \leq x \leq \frac{\ell+r}{2} \\ \frac{4}{(r-\ell)^2}(r-x) & \text{if } \frac{\ell+r}{2} \leq x \leq r \\ 0 & \text{otherwise} \end{cases}$$

With the triangle being anchored at one of the other bounds, there is only one parameter (either ℓ or r) to fit, which fixes the center and height of the triangle. Note that an isosceles triangle is symmetric, so the mean, median, and mode are identical to each other. If one of the two bins is unbounded, the bounded bin is taken to be the one fully included in the support of the triangle. In other words, the triangle is anchored at the inner bound of the bounded interval and the outer leg's position is determined by how much mass is placed in the unbounded bin.

Respondents who respond with probability fully within one bin, the distribution is assumed to be uniform. The estimation for this is trivial, except in the case where the interval is unbounded. For when probabilities include a bin that is unbounded from below or above, bounds are imposed at -38 and 38 for bins that were unbounded below and above, respectively. These values are based on historical maximum and minimum changes and the outcomes of the distribution fitting are generally not sensitive to them.

Densities are not fitted for respondents who put positive probability in only two bins that are nonadjacent or for whom the probabilities do not sum to 100 percent."

D Addressing Measurement Error through Instrumental Variables

Motivated by the derivations and simulations in Section 5.2, we present results that instrument for $\hat{E}_t[r_{i,t+1}]$ with forecasted fundamentals $Z_{i,t}$. The logic behind these tests is that under the null hypothesis that measurement error is the reason for our statistically significant estimated effects of past returns on investment, we could address the resulting bias through instrumenting and the unbiased 2SLS estimate of β_2 would be 0. Under this null hypothesis of measurement error in stated beliefs and no independent role for belief factors, any forecasted fundamental would satisfy the exclusion restriction and be a valid instrument for stated beliefs. However, we demonstrate that our core findings are robust to instrumenting, leading us to reject the measurement-error hypothesis as the model generating our results.[44]

D.1 Instrumenting for expected returns removes bias in past returns coefficient

First, we formally derive $\hat{\beta}_2$ in (10) to demonstrate how instrumenting for expected returns removes the measurement error bias in the estimate of the coefficient on past returns. To simplify our derivations, we assume that the empirical variance-covariance matrix is the same as the population one. We have

$$\hat{\beta}_2 = \frac{Cov(\widetilde{r}_{i,t}, Y_{i,t})}{Var(\widetilde{r}_{i,t})}, \tag{13}$$

where $\widetilde{r}_{i,t}$ is the residual from regressing $\hat{r}_{i,t}$ on the other covariate, $\widehat{E_t[r_{i,t+1}]}$. For $\widehat{E_t[r_{i,t+1}]}$, by the assumption that the empirical variance-covariance matrix is the same as the population matrix, we have $\hat{\pi}_1 = \pi_1$ and $\hat{\pi}_2 = \pi_2$. Therefore

$$\widetilde{r}_{i,t} = \hat{r}_{i,t} - \psi(\pi_1 \hat{r}_{i,t} + \pi_2 Z_{i,t}), \tag{14}$$

where ψ is the coefficient from regressing $\widehat{E_t[r_{i,t+1}]}$ on $\hat{r}_{i,t}$, i.e.,

$$\begin{aligned}
\psi &= \frac{Cov(\widehat{E_t[r_{i,t+1}]}, \hat{r}_{i,t})}{Var(\widehat{E_t[r_{i,t+1}]})} \\
&= \frac{Cov(\pi_1 \hat{r}_{i,t} + \pi_2 Z_{i,t}, \hat{r}_{i,t})}{Var(\pi_1 \hat{r}_{i,t} + \pi_2 Z_{i,t})} \\
&= \frac{\pi_1 Var(\hat{r}_{i,t}) + \pi_2 Cov(\hat{r}_{i,t}, Z_{i,t})}{\pi_1^2 Var(\hat{r}_{i,t}) + 2\pi_1\pi_2 Cov(\hat{r}_{i,t}, Z_{i,t}) + \pi_2^2 Var(Z_{i,t})}
\end{aligned} \tag{15}$$

Plugging (14) and (15) into (13), we have

[44]We caveat that this instrumenting strategy applies to classical measurement error that is independent of stated beliefs and will not be unbiased if survey noise is correlated with elicited beliefs.

$$
\begin{aligned}
\hat{\beta}_2 &= \frac{Cov(\widetilde{r}_{i,t}, Y_{i,t})}{Var(\widetilde{r}_{i,t})} \\
&= \frac{\beta_1(\pi_1 Var(\hat{r}_{i,t}) + \pi_2 Cov(Z_{i,t}, \hat{r}_{i,t}))}{Var(\hat{r}_{i,t} - \psi(\pi_1 \hat{r}_{i,t} + \pi_2 Z_{i,t}))} - \frac{\beta_1(\pi_1 Var(\hat{r}_{i,t}) + \pi_2 Cov(\hat{r}_{i,t}, Z_{i,t}))}{Var(\hat{r}_{i,t} - \psi(\pi_1 \hat{r}_{i,t} + \pi_2 Z_{i,t}))} \\
&= 0.
\end{aligned}
$$

Thus, the second-stage 2SLS coefficient for $\hat{r}_{i,t}$ is 0 under the DGP in (8).

D.2 Instrumental Variables Results

Out of many potential belief factors that could be considered elements of $Z_{i,t}$, we focus on inflation forecasts and rent forecasts as instruments because belief-formation regressions suggests that survey respondents incorporate these views into their home price forecasts. Table 2 demonstrates that individual expectations of inflation and rent growth are incorporated into individual expected returns, satisfying the 2SLS relevance condition (see Appendix Table A12 for the exact first stage used in our 2SLS estimation). As an alternative to using forecasts of fundamentals as instruments for expected housing returns, we follow Lewbel (1997) and construct an additional instrument based on higher-order moments of the potentially mismeasured variable $(\hat{E}_t[r_{i,t+1}] - \overline{\hat{E}_t[r_{i,t+1}]})^2$. Appendix D.3 outlines the assumptions required by this approach, and Appendix Table A12 demonstrates the strong first stage for higher-order moments of stated returns.

Table A13 presents both OLS and IV estimates of (10) without and with individual-level controls in columns 1-3 and 4-6, respectively. Across all columns, $\hat{r}_{i,t}$ has statistically significant coefficients in both OLS specifications and when we instrument for $\hat{E}_t[r_{i,t+1}]$, inconsistent with the prediction of the null hypothesis that both $\hat{r}_{i,t}$ and $Z_{i,t}$ affect $Y_{i,t}$ only through stated forecasts $\hat{E}_t[r_{i,t+1}]$. At the same time, Table A13 offers additional evidence against the null hypothesis. Under the null hypothesis, forecasted fundamentals are excludable and valid instruments under the null hypothesis. However, instrumenting for stated returns does not reverse any measurement-error induced attenuation bias in Table A13. Contrary to what would be expected under the null hypothesis, instrumenting reduces the magnitude of expected returns. While inconsistent with the null hypothesis of no independent effect of belief factors on investment conditional on stated beliefs, we argue below that these results are consistent with expectations surveys eliciting beliefs that differ systematically from the beliefs used in decision making.

D.3 Justification of the Lewbel Instrument

For detailed derivations of the Lewbel instrument, we refer to Lewbel (1997). Conceptually, this strategy uses higher-order moments of a mismeasured variable as its instrument since it is correlated with the signal but conditionally uncorrelated with the noise. This section presents a concise summary of this approach. Consider the regression model similar to (8) regressing an outcome y on controls W and a noisy scalar measure x of x^*

$$
\begin{aligned}
Y_i &= \beta_0 + \beta_1 x_i + W_i' \beta_2 + \varepsilon_i \\
x_i &= x_i^* + \upsilon_i,
\end{aligned}
$$

where υ_i is the independent, mean-zero, and symmetrically distributed measurement error in x_i.

Note that while we present the case of a scalar mismeasured x for ease of exposition, the results generalize to multiple mismeasured variables X. Construct an instrument z for x as $z_i = (x_i - \overline{x})^2$. For z to be a valid instrument for x, we require four assumptions:

1. $E((1, W', x^*)'(1, W', x^*))$ exists and is nonsingular
2. $E(\varepsilon) = E(\upsilon) = 0$ and $E(\upsilon^3) = 0$
3. υ and ε are independent of each other and x^* and W
4. $E((x^* - \bar{x}^*)^2 \tilde{x}^*) \neq 0$ where $\tilde{x}^* = x^* - \gamma_0 - \gamma_1' W$ is the residual of regressing x^* on W

Assumption 1 requires that W and x^* are not collinear. Assumption 2 requires that the measurement error is symmetrically distributed such that its skewness is equal to 0. See Lewbel Lewbel (1997) for alternative instrument candidates that do not require this distributional assumption on the measurement error υ. Assumption 3 is akin to the classical measurement error assumption of independent measurement error and the exogeneity of x^* and the other covariates W. This independence condition is slightly stronger than (and implies) the condition required by Lewbel (1997) that

$$E((x^* - \bar{x}^*)^\psi \upsilon^\lambda \varepsilon^k) = E((x^* - \bar{x}^*)^\psi) E(\upsilon^\lambda) E(\varepsilon^k) \,\text{for}\, \psi, \lambda \in \{0, 1, 2\}, k \in \{0, 1\}.$$

Assumption 4 requires that, after conditioning on the included controls W, $(x^* - \bar{x}^*)^2$ is still correlated with x^*, as would be the case provided the moments of x^* are correlated with each other in a way not completely absorbed by W. Given the definition of $\tilde{x}^*$, assumption 3 also implies that

$$E((x^* - \bar{x}^*)\upsilon \tilde{x}^*) = E(x^* - \bar{x}^*) E(\upsilon) E(\tilde{x}^*)$$

and

$$E(\upsilon^2 \tilde{x}^*) = E(\upsilon^2) E(\tilde{x}^*).$$

Instrumenting for x using z will lead to an unbiased 2SLS estimate of β_1 and β_2 if $E(z\varepsilon) = 0$ and $E(z\upsilon) = 0$ (the exclusion restrictions) and $E(z\tilde{x}^*) \neq 0$ (the relevance condition).

By assumptions 2 and 3, the first exclusion restriction is

$$\begin{aligned}
E(z\varepsilon) &= E((x_i - \bar{x})^2 \varepsilon_i) \\
&= E((x_i^* - \bar{x}^* + v_i)^2 \varepsilon_i) \\
&= E((x_i^* - \bar{x}^*)^2 \varepsilon_i) + 2E((x_i^* - \bar{x}^*) v_i \varepsilon_i) + E(v_i^2 \varepsilon_i) \\
&= E((x_i^* - \bar{x}^*)^2) E(\varepsilon_i) + 2E(x_i^* - \bar{x}^*) E(v_i) E(\varepsilon_i) + E(v_i^2) E(\varepsilon_i) \\
&= 0.
\end{aligned}$$

By assumptions 2 and 3, the second exclusion restriction is

$$\begin{aligned}
E(zv) &= E((x_i - \bar{x})^2 v_i) \\
&= E((x_i^* - \bar{x}^*)^2 v_i) + 2E((x_i^* - \bar{x}^*) v_i^2) + E(v_i^3) \\
&= E((x_i^* - \bar{x}^*)^2) E(v_i) + 2E(x_i^* - \bar{x}^*) E(v_i^2) + E(v_i^3) \\
&= 0
\end{aligned}$$

given that $E(x_i^* - \bar{x}^*) = E(x_i^*) - E(x_i^*) = 0.$

Finally, using assumptions 3 and 4 and $E(\tilde{x}_i^*) = 0$, the relevance assumption is

$$\begin{aligned}
E(z\tilde{x}^*) &= E((x_i^* - \bar{x}^* + v_i)^2)\tilde{x}_i^*) \\
&= E((x_i^* - \bar{x}^*)^2\tilde{x}_i^*) + 2E((x_i^* - \bar{x}^*)v_i\tilde{x}_i^*) + E(v_i^2\tilde{x}_i^*) \\
&= E((x_i^* - \bar{x}^*)^2\tilde{x}_i^*) \\
&\neq 0
\end{aligned}$$

Given these results, the conditions required for 2SLS unbiasedness hold, and instrumenting using the Lewbel instrument—provided assumptions 1-4 hold—leads to estimates of β that are robust to measurement error in x.

E Open-ended Textual Response Coding Procedure

In this appendix, we explain how we code free text responses to the 2021 survey question "Why do you rely more on [the past OR your expected] home price growth?" For each group (relying on past or expected returns), we group them into four categories that capture the most frequently cited rationale for relying on past or expected returns in investment decision-making, with the remaining responses, including non-responses, assigned to an other category. When a response contains investment decision-making rationale that could fit into multiple categories, we assign it to the category that seemed the most prominent. See Figure 4 for the distribution of responses.

Coding for Respondents Relying More on Past Returns

1. Consistent Trends: We assign responses to this category when they emphasize that local house price returns have been stable or exhibit momentum or exhibit consistent trends. Similarly, when answers mention that a reliance on past returns because of a strong expectation that past returns and local market conditions will continue as in the past.

2. Real Data: We assign responses to this category when they emphasize that the past returns are based on "real" or "realized" or "actual" or "historical" or "observable" data.

3. Uncertainty: We assign responses to this category when they emphasize that the future is uncertain or unknown or that anything could happen in the future or that their stated forecasts are just a guess. We also assign responses to this category when answers emphasize that they are unfamiliar with house prices or the housing market or investing.

4. Conservative: We assign responses to this category when they emphasize that they chose to rely on past returns as the more conservative or safer approach given their forecast.

Coding for Respondents Relying More on Expected Returns

1. Expectations: We assign responses to this category when they emphasize anything about their own returns expectations. Many respondents in this category mention that what is relevant for an investment decision is their expectations about the future as opposed to the past. Other responses in this category emphasize that their expectations for future returns are informed or differ from what happened in the past or that they expect returns to be high enough to compensate them for the risk relative to the risk-free rate of 2%.

2. Fundamentals: We assign responses to this category when they cite a particular reason behind their price belief, such as local demand for housing being high, housing inventory being low, interest rates being low, high expected income growth, or an expectation of a strong post-pandemic economic recovery.

3. Last year different: We assign responses to this category if they specifically say they use their expected returns in investment decision-making instead of past returns because 2020 was a poor year to extrapolate from because it was different or unusual or dominated by the pandemic.

4. Past returns not guaranteed: We assign responses to this category when they state that there's no promise that past returns will continue. For example, multiple respondents in this category stated that "Past returns do not guarantee future growth."

Table A1: Summary Statistics: Fundamentals Forecasts

	Response Count	Mean	Std. Dev.
Expected Inflation (p.p.)	7,066	3.58	4.36
Expected Rent Growth (p.p.)	7,066	6.21	5.91
Expected Mortgage Rate Change (p.p.)	7,066	0.35	0.70
Expected Economic Conditions (1-5)	7,065	3.24	0.84

Notes: Table reports means, standard deviations, and counts of individual responses for one-year ahead forecasted fundamentals. Expected economic conditions is measured on a 1-5 scale with 1 being much worse, 3 being about the same, and 5 being much better than today.

Table A2: Log-log Specification of Effect of Expected and Past Returns on Investment

Dependent Variable: Log Housing Fund Share			
	(1)	(2)	(3)
Log(Forecasted Returns - 2%)	0.0054		-0.011
	(0.0132)		(0.015)
Log(1 + Perceived Past Returns)		0.0055**	0.0062**
		(0.0024)	(0.0027)
Log($\hat{\sigma}^2$)	-0.040***	-0.043***	-0.041***
	(0.014)	(0.014)	(0.014)
Log(Risk Aversion)	-0.195***	-0.193***	-0.192***
	(0.025)	(0.026)	(0.026)
Observations	1,605	1,605	1,605
R-squared	0.036	0.041	0.041

Notes: Table reports results from estimating the Merton model in (1) via a log-log specification. Dependent variable is the log share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). Log(Forecasted Returns - 2%) takes 2% as the risk free rate R_f in (1). Perceived past returns are transformed as Log(1 + Perceived Past Returns) to facilitate including responses that lagged returns were less than or equal to zero. The conditional variance of expected returns $\hat{\sigma}^2$ is estimated by fitting a generalized beta or triangular or uniform distribution to the respondents' expected probability of returns falling into four intervals, as described in Appendix C. Risk aversion is measured as (10 - Risk Tolerance), and Risk Tolerance is measured on a 1-10 scale from a question about willingness to take risks in financial matters, where 10 is very willing. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table A3: Addressing Collinearity Between Expected and Perceived Past HPA

Dependent Variable: Housing Fund Share (on a 0-100 scale)	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Returns	0.59***	0.61***	0.61***			
	(0.15)	(0.16)	(0.16)			
Perceived Past Returns				0.52***	0.52***	0.51***
				(0.11)	(0.11)	(0.11)
Bin FEs for Perceived HPA	✓	✓	✓			
Bin FEs for Expected HPA				✓	✓	✓
Number of Bins Specified	10	100	200	10	100	200
Number of Actual Bins	10	43	63	9	37	58
Probabilities Cubic	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Observations	2,963	2,963	2,963	2,963	2,963	2,963
R-squared	0.169	0.182	0.189	0.175	0.183	0.190

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). Columns 1-3 divide the sample into targets of 10, 100, and 200 equally sized bins according to their perceived past HPA and control for bin fixed effects. Columns 4-6 similarly control for bin fixed effects for forecasted returns. Probabilities cubic is a vector of controls for a cubic polynomial for each respondent's stated probability that next year's returns fall in one of four ranges—see Section 3.1 for question framing. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table A4: Investment Decision Factors Using Representative Weights

Dependent Variable: Housing Fund Share (on a 0-100 scale)						
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Returns	0.83***		0.36	0.79***		0.41*
	(0.23)		(0.23)	(0.20)		(0.22)
Perceived Past Returns		0.95***	0.83***		0.84***	0.72***
		(0.14)	(0.16)		(0.14)	(0.17)
Confident in Past Returns				4.12**	4.33**	4.24**
				(1.77)	(1.72)	(1.72)
Above-median Risk Aversion				-11.4***	-11.3***	-11.2***
				(1.81)	(1.76)	(1.77)
Male				4.96***	4.79***	4.90***
				(1.72)	(1.67)	(1.68)
Homeowner				0.48	-0.62	-0.34
				(2.08)	(2.06)	(2.08)
Individual Controls				✓	✓	✓
Observations	2,963	2,963	2,963	2,963	2,963	2,963
R-squared	0.015	0.035	0.038	0.131	0.144	0.147

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). Observations are weighted by SCE-ACS weights. One percentage point is denoted as 1. Individual controls are controlled in columns 4 to 6. For definitions of these controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table A5: Investment Decision Factors for Incentivized Subsample

Dependent Variable: Housing Fund Share (Incentivized Stage)			
	(1)	(2)	(3)
Forecasted Returns	0.15	0.28	0.12
	(0.60)	(0.60)	(0.59)
Perceived Past Returns	0.91**	0.91**	0.85**
	(0.38)	(0.39)	(0.39)
Objective Past Returns			0.78**
			(0.34)
Individual Controls	✓	✓	✓
Distribution of Forecasted Returns		✓	✓
Observations	330	330	330
R-squared	0.159	0.162	0.177

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). One percentage point is denoted as 1. Sample is 2015 respondents that were offered a chance at the gross proceeds of their investment decision but were not provided any objective information about past returns (the control group of Armona et al. (2018)). Controls for the distribution of forecasted returns is a vector of linear controls for a respondent's stated probability of future returns falling into four ranges. For definitions of individual controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table A6: Controlling for Forecasted Fundamentals

Dependent Variable: Housing Fund Share (on a 0-100 scale)	(1)	(2)
Forecasted Returns	0.87***	0.53***
	(0.14)	(0.15)
Perceived Past Returns	0.55***	0.49***
	(0.11)	(0.11)
Forecasted Fundamentals	✓	✓
Individual Controls	✓	✓
Probabilities Cubic		✓
Observations	2,963	2,963
R-squared	0.154	0.170

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). One percentage point is denoted as 1. Forecasted fundamentals include year-ahead forecasts of inflation, rent growth, mortgage rates, and economic conditions, along with indicators for non-responses and for whether an observation was trimmed at the 2nd or 98th percentile. For definitions of individual controls, see notes to Table 2. Robust standard errors in parentheses. Significant at $^*p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table A7: Actual versus Subjective Past Home Price Growth

Dependent Variable: Housing Fund Share		
	(1)	(2)
Forecasted Returns	0.78***	0.59***
	(0.15)	(0.16)
Actual Past Returns	0.54***	0.45***
	(0.17)	(0.17)
Perceived Past Returns		0.43***
		(0.12)
Confident in Past Returns	5.32***	5.26***
	(1.32)	(1.32)
Above-median Risk Aversion	-8.74***	-8.54***
	(1.32)	(1.32)
Probabilities Cubic	✓	✓
Individual Controls	✓	✓
Observations	2,766	2,766
R-squared	0.149	0.153

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). Variable units are in percentage points (one percentage point is denoted as 1). For definitions of individual controls, see notes to Table 2 Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table A8: Heterogeneity in Investment Decision-Making, Economic Characteristics

	Dependent Variable: Housing Fund Share (on a 0-100 scale)					
	Owner	Renter	College	Non-Coll	Inc>$75K	Inc≤$75K
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Returns	0.64***	0.46*	0.85***	0.32	0.91***	0.42**
	(0.19)	(0.24)	(0.23)	(0.20)	(0.29)	(0.18)
Perceived Past Returns	0.63***	0.17	0.45***	0.59***	0.40*	0.58***
	(0.14)	(0.21)	(0.17)	(0.15)	(0.21)	(0.14)
Pr(HPA< 0%)	-0.14***	-0.15**	-0.11***	-0.18***	-0.10**	-0.16***
	(0.033)	(0.063)	(0.039)	(0.042)	(0.045)	(0.038)
Pr(HPA< -5%)	0.0095	0.021	-0.038	0.057	-0.087	0.064
	(0.058)	(0.089)	(0.066)	(0.068)	(0.083)	(0.059)
Pr(HPA> 10%)	0.047	0.072	0.059	0.049	0.054	0.063
	(0.044)	(0.074)	(0.057)	(0.051)	(0.059)	(0.049)
Individual Controls	✓	✓	✓	✓	✓	✓
Observations	2,229	734	1,700	1,263	1,305	1,633
R-squared	0.166	0.134	0.163	0.155	0.172	0.134

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). For definitions of individual controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table A9: Heterogeneity in Investment Decision-Making, Other Characteristics

Dependent Variable: Housing Fund Share (on a 0-100 scale)	Age≥50	Age<50	Male	Female	High Numeracy	Low Numeracy	Checked Website	Didn't Check
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forecasted Ret.	0.74***	0.43*	0.79***	0.43**	0.85***	0.090	1.02***	-0.011
	(0.21)	(0.22)	(0.22)	(0.20)	(0.19)	(0.23)	(0.24)	(0.27)
Perceived Past Ret.	0.31*	0.65***	0.45***	0.52***	0.52***	0.54***	0.28	0.67***
	(0.16)	(0.16)	(0.17)	(0.15)	(0.14)	(0.18)	(0.18)	(0.20)
Pr(HPA$<0\%$)	-0.15***	-0.14***	-0.13***	-0.13***	-0.15***	-0.094*	-0.18***	-0.083
	(0.043)	(0.039)	(0.043)	(0.040)	(0.034)	(0.055)	(0.049)	(0.058)
Pr(HPA$<-5\%$)	0.072	-0.021	-0.044	0.059	0.0022	0.013	-0.014	0.0085
	(0.072)	(0.064)	(0.073)	(0.064)	(0.058)	(0.085)	(0.080)	(0.090)
Pr(HPA$>10\%$)	0.088	0.052	0.093*	0.025	0.031	0.12*	-0.0098	0.14*
	(0.057)	(0.050)	(0.054)	(0.053)	(0.047)	(0.062)	(0.056)	(0.080)
Individual Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,377	1,586	1,565	1,398	2,184	779	1,287	744
R-squared	0.185	0.140	0.148	0.135	0.162	0.158	0.174	0.137

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). For definitions of individual controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table A10: Other Housing-Related Behaviors: 2015-2020 Data

Dependent Variable:	Pr(Buy non-primary home)		Pr(Buy home)		Viewing Housing Good Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Returns	0.077	0.13*	-0.48***	-0.22**	0.18***	0.089*
	(0.048)	(0.061)	(0.081)	(0.074)	(0.039)	(0.039)
Perceived Past Returns	0.11**	0.064*	0.18	0.039	0.19***	0.13***
	(0.040)	(0.028)	(0.15)	(0.074)	(0.015)	(0.016)
Pr(HPA next year $<$ 0%)		0.0056		-0.034		-0.032***
		(0.0093)		(0.021)		(0.0051)
Pr(HPA next year $< -5\%$)		0.059***		-0.070**		-0.0086
		(0.011)		(0.021)		(0.014)
Pr(HPA next year $>$ 10%)		0.0052		-0.056		0.0042
		(0.013)		(0.034)		(0.0055)
Confident in past returns		2.03***		3.12**		1.74***
		(0.26)		(0.84)		(0.25)
Above-median Risk Aversion		-5.25***		-3.27***		-0.55
		(0.30)		(0.41)		(0.41)
Homeowner		1.89***		22.6***		0.19
		(0.51)		(0.62)		(0.35)
Individual Controls		✓		✓		✓
Observations	6,977	6,977	4,946	4,946	6,991	6,991
R-squared	0.002	0.083	0.004	0.259	0.031	0.085
Subsample	All	All	Pr(Move) $\geq$ 5%	Pr(Move) $\geq$ 5%	All	All

Notes: One percentage point is denoted as 1. Viewing housing good investment is a discrete variable for view of housing as an investment on a 10, 20, 30, 40, 50 scale, with 50 being a very good investment. For definitions of individual controls, see notes to Table 2. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table A11: The Effect of Housing Equity on Investment Decisions

Dependent Variable: Housing Fund Share (on a 0-100 scale)						
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Returns	0.66***	0.65***	0.64***	0.63***	0.61***	0.59***
	(0.20)	(0.20)	(0.20)	(0.19)	(0.20)	(0.19)
Perceived Past Returns	0.70***	0.68***	0.75***	0.74***	0.59***	0.56***
	(0.14)	(0.14)	(0.15)	(0.14)	(0.16)	(0.16)
Perceived Past Returns	-0.018	-0.022*				
× (Home Value/Equity)	(0.012)	(0.012)				
Perceived Past Returns			-3.07*	-3.77**		
× (Home Value/Net Assets)			(1.69)	(1.58)		
Perceived Past Returns					0.019	0.019
× (Home Value/Income)					(0.014)	(0.014)
Probabilities	✓	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓	✓
Risk Tolerance Score × Year FEs		✓		✓		✓
Observations	2,141	2,141	2,142	2,142	2,196	2,196
R-squared	0.165	0.194	0.165	0.194	0.166	0.195

Notes: Dependent variable is the share of a $1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). In columns 1 to 2, the sample is restricted to homeowners with a positive home equity. In columns 3 and 4, net assets is defined as home equity plus liquid assets and minus personal debt. The sample is restricted to households with positive assets. To reduce the effects of outliers, respondents with (Home Value/Equity), (Home Value/Net Assets), and (Home Value/Income) in the top and bottom 1% of the distribution for those variables are dropped. The results for the full sample including the outliers are similar to results for the trimmed sample. Robust standard errors in parentheses. Significant at *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table A12: First Stage Estimates of Expected Returns

Dependent Variable: 1-year HPA Expectation	(1)	(2)	(3)	(4)
Perceived Past Returns	0.31***	0.27***	0.29***	0.23***
	(0.02)	(0.02)	(0.02)	(0.02)
Forecasted Rent Growth	0.14***		0.14***	
	(0.02)		(0.02)	
Forecasted Inflation	0.00***		0.00***	
	(0.00)		(0.00)	
Lewbel Instrument		0.03***		0.03***
		(0.00)		(0.00)
Individual Controls			✓	✓
Partial F-statistic	43.40	98.23	49.37	108.98
Observations	2,966	2,966	2,966	2,966

Notes: The Lewbel instrument is $(\hat{E}_t[r_{i,t+1}] - \overline{\hat{E}_t[r_{i,t+1}]})^2$ as explained in Appendix D.3. For definitions of individual controls, see notes to Table A13. The partial F-statistic tests the hypothesis that the coefficients on the instruments are jointly equal to zero. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.

Table A13: Instrumental Variables Estimates of Investment Decisions

Dependent Variable: Housing Fund Share (on a 0-100 scale)			
	(1)	(2)	(3)
	OLS	2SLS	2SLS
Forecasted Returns	0.87***	0.23	-0.94**
	(0.14)	(0.65)	(0.43)
Perceived Past Returns	0.55***	0.73***	1.07***
	(0.11)	(0.23)	(0.17)
Individual Controls	✓	✓	✓
Instruments		E(Rent) E(Inflation)	Lewbel
First Stage F-stat		70.86	505.6
Observations	2,963	2,963	2,963

Notes: Table reports OLS and IV estimates of investment decisions on the predicted values of home price forecasts and the perceived past home price growth. Dependent variable is the share of a \$1,000 investment allocated by a respondent to an index of her local home-price appreciation (with the remainder allocated to a savings account earning 2%). The instruments in column 2 are forecasted rent growth and forecasted inflation. The Lewbel instrument used in column 3 is $(\hat{E}_t[r_{i,t+1}] - \overline{\hat{E}_t[r_{i,t+1}]})^2$, as explained in Appendix D.3. First-stage coefficients are reported in Appendix Table A12. Robust standard errors in parentheses. Significant at *p<0.10, **p<0.05, ***p<0.01.