Ownership, Learning, and Beliefs

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Abstract

We examine how owning a good affects learning and beliefs about its quality. We show that people have more extreme reactions to information about a good that they own compared to the same information about a non-owned good: ownership causes more optimistic beliefs after receiving a positive signal and more pessimistic beliefs after receiving a negative signal. Comparing learning to normative benchmarks reveals that people *over-extrapolate* from signals about goods that they own, which leads to an overreaction to information; in contrast, learning is close to Bayesian for non-owned goods. We provide direct evidence that this effect is driven by ownership channeling greater attention towards associated information, which leads people to overweight recent signals when forming beliefs. The relationship between ownership and beliefs has testable implications for trade and market expectations. In line with these predictions, we show that the endowment effect *doubles* in response to positive information and disappears with negative information, and demonstrate a significant relationship between ownership and over-extrapolation in survey data about stock market expectations.

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I. Introduction

Ownership is an intrinsic component of most economic settings. Goods are priced based on the beliefs and preferences of those who own them versus those who do not, and trade occurs when non-owners judge a good to be more valuable than owners. An implicit assumption of standard theory is that ownership *per se* does not affect people's preferences for a good or how they interpret information about it.[1] Prior behavioral work has shown that being endowed with a good changes one's valuation of it but has largely focused on the initial impact of endowment.[2] However, many important economic contexts involve periods of learning about both goods that are owned and those that are not, with people making decisions after receiving information and updating their beliefs accordingly. Since behavior is a function of both preferences and beliefs, showing that ownership can lead to differences in learning is important for both theory and empirical analysis.

This paper examines whether owning a good has a causal effect on how people respond to information about it. In a series of experimental studies, we show that ownership has a substantial impact on people's learning. When seeing the *same* information, people display more extreme reactions to signals about owned versus non-owned goods—owners become more optimistic after positive signals and more pessimistic after negative signals compared to non-owners. We then show that this difference in learning is driven by owners being more likely to over-extrapolate from recent signals. This leads to a *symmetric* overreaction relative to a Bayesian benchmark for owned goods in both the positive and negative domain, while belief updating is close to Bayesian for non-owned goods.

Employing techniques from cognitive psychology, we provide evidence that these results are due to ownership-driven attention. Using a change detection task, we show that ownership channels attention towards associated signals and this increased attention leads to greater over-extrapolation. Results from a signal recall experiment point to associative memory as a

[1]For example, the famous Coase theorem (Coase, 1960), which states that market exchange leads to efficient allocations of goods regardless of the initial allocation, holds only if ownership does not influence valuation or learning about the goods.

[2]In demonstrating the endowment effect, Kahneman et al. (1990) show that randomly assigning someone to own a good increases their valuation of it, generating a gap between the minimum owners are willing to accept to part with the good and the maximum non-owners are willing to pay for it. The large literature that followed has largely focused on preference-based explanations for this valuation gap (Ericson and Fuster, 2014).

potential mechanism for this relationship between attention and over-extrapolation.

We then demonstrate the implications of the observed ownership effect on beliefs in two distinct settings: product valuation with learning and the formation of stock market expectations. If owners become more pessimistic than non-owners after observing negative information and more optimistic after observing positive information, then the initial gap between non-owners' willingness to pay and owners' willingness to accept for a good—the endowment effect—will expand after good news and shrink after bad news. We show that this is indeed the case: the endowment effect *doubles* after owners and non-owners see the same good news about a product, and disappears after bad news. Finally, we replicate the relationship between ownership and over-extrapolation in a large field survey on stock market expectations.

To identify the causal effect of ownership on learning, we designed an experiment where ownership is as-if exogenously assigned, beliefs can be cleanly elicited, and a normative benchmark for learning can be reasonably established. People bought any three of six ex-ante identical goods and reported beliefs about their underlying quality. Participants knew that each good had a good-specific probability of a price increase in each period, which represents its fundamental quality. Specifically, in each period t a good i has a constant probability s^i of increasing in price and a probability $1 - s^i$ of decreasing in price. Because s^i does not change across periods, a price increase (decrease) is a positive (negative) signal about good i's quality. Participants observed 15 periods of price movements and were paid based on the final price of the goods they own. In each period t, we elicited beliefs $\hat{s}_t^i$ about the probability of a price increase s^i for each good i—both those that they own and those that they do not—with truthful reporting incentivized.

Since participants are not given information about the goods' qualities before making their allocation decisions, the choice of which goods to own is as-if random.[3] This ensures that ownership is exogenous to any omitted variable related to differences in preferences, skill or knowledge. Additionally, the setting represents a fairly simple learning environment since in each period the total number of price increases and decreases—which is easily inferred in every round—is a sufficient statistic for forming a Bayesian posterior.

[3] In a separate treatment, presented in the Internet Appendix, we show that our results do not depend on whether participants actively choose the goods or are randomly endowed with them.

We find that positive signals (price increases) lead to greater optimism (higher $\hat{s}^i$) about goods that are owned relative to those that are not. The opposite pattern emerges in response to negative signals (price decreases), which leads to greater pessimism about goods that are owned relative to those that are not. This ordering holds under any prior that does not condition on ownership and cannot be explained by fixed subject characteristics. Our setting also allows us to examine how ownership influences learning relative to a normative Bayesian benchmark. Using multiple methods to construct these benchmarks, we find near-Bayesian learning from information about goods that are not owned—belief errors are not significantly correlated with associated signals. In contrast, belief errors have a strong and positive correlation with signals about owned goods. This indicates that, relative to a Bayesian benchmark, individuals display a symmetric *overreaction* to information about owned goods.

We show that this overreaction is driven by people over-extrapolating from recent signals about owned goods, both relative to non-owned goods and the Bayesian benchmark. While Bayesian updating predicts that beliefs should be independent of signal ordering, we find that recent signals play a substantially larger role in explaining beliefs for owned goods than non-owned goods. The increased over-extrapolation for owned goods is robust to a host of normative benchmarks—including priors that vary with ownership and cumulative signals—as well as benchmarks that do not require distributional assumptions.

These results are not consistent with the fully rational model, which predicts that beliefs will not vary with ownership since signals are equally informative across both owned and non-owned goods. Models of rational inattention or heterogeneity in belief-updating based on fixed characteristics similarly predict no differences in learning.[4] The symmetric effect of ownership on over-extrapolation is also not consistent with models of motivated beliefs (Brunnermeier and Parker, 2005; Kunda, 1990) or misattribution (Bushong and Gagnon-Bartsch, 2019), which both predict asymmetric belief updating for owned goods.[5]

[4]Since beliefs are equally incentivized for owned and non-owned goods, there are no instrumental motives to pay more or less attention to one over the other (Martin, 2017; Caplin and Dean, 2015; Mackowiak et al., 2020). Heterogeneity in learning based on fixed characteristics such as IQ (D'Acunto et al., 2019), life experience (Malmendier and Nagel, 2015), or socioeconomic status (Das et al., 2020) also predicts no differences as these characteristics are balanced across ownership conditions.

[5]Models of motivated beliefs (e.g. Brunnermeier and Parker, 2005) predict that people should update more in response to positive signals than negative signals about goods that they own compared to goods that they do not. This is due to people deriving utility from holding more optimistic beliefs about the fundamental qualities of owned goods. The misattribution model of Bushong and Gagnon-Bartsch (2019) predicts an overreaction to signals about owned goods, but with a stronger effect for negative signals due to loss aversion.

A series of studies provide evidence that the differences in learning are due to an ownership-driven 'more-is-less' effect of attention. Research in psychology shows that attention is often channeled to value-relevant information, even when it is not instrumental (Smith and Krajbich, 2018, 2019).[6] In our setting, signals about owned goods are more value-relevant than those about non-owned goods since prices about the former translate directly into earnings; signals are equally instrumental for both sets of goods with respect to informing beliefs. While it is often assumed that more attention improves decision quality (see Gabaix, 2017, for review), theoretically this need not be the case. Notably, Dawes (1979) and Dawes et al. (1989) argue that greater attention impairs judgment if it is combined with an incorrect mental model of the decision environment.[7] However, to the best of our knowledge, this conjecture has yet to be tested in a learning context.

To identify attention as a mechanism in our setting, we sought to demonstrate that ownership channels attention to associated signals, that greater attention leads to over-extrapolation, and, as a result, overreaction. We explored the first link by using tools from cognitive psychology, incorporating a change detection task into the baseline experiment. This allowed us to look at whether ownership influences the allocation of attention and whether increased attention generates the predicted effect on beliefs. In this study, a randomly-selected price changed color in each round. Participants were then asked to correctly identify the corresponding good as quickly as possible.[8] We found that participants were more accurate when identifying price-color changes of owned goods, which is consistent with ownership channeling attention towards associated information. Moreover, greater attention—as measured by reaction time—was associated with more extreme belief-updating and overreaction.

To provide causal evidence for the attention channel, we designed a manipulation to exogenously shift attention to goods that were not owned. In this study, beliefs were elicited only for non-owned goods, allowing us to perform a comparative static exercise on how attention

This generates greater pessimism about owned versus non-owned goods.

[6]Here, value-relevance refers to information that affects a person's outcomes, e.g. the price of a stock she owns. This information may or may not be instrumental depending on whether it reduces decision-relevant uncertainty.

[7]The authors conjecture that more attention leads forecasters to overweight features of the decision problem relative to the normative benchmark. In a similar vein, Massey and Wu (2005) argue that an overreaction to signals in a belief-updating task may be driven by attention.

[8]Similar change detection tasks have been used to study the allocation of attention by measuring the accuracy of responses (Mrkva and Van Boven, 2017; Mrkva et al., 2019; Verghese, 2001).

impacts belief-updating. We found that exogenously manipulating attention led to a similar belief pattern for non-owned goods as for owned goods in the baseline condition.

Finally, we developed a signal recall paradigm to provide additional evidence for ownership-driven attention, as well as to explore a potential mechanism for the relationship between attention and over-extrapolation. Attention has been implicated as a key driver in what information is encoded into memory so that it can later be recalled (Mrkva et al., 2020; Chun and Turk-Browne, 2007; Oberauer et al., 2016; Schwartzstein, 2014). Associative recall—the increased tendency to recall information that is similar to the current cue (Kahana, 2012; Longuet-Higgins et al., 1970)—has been shown to generate over-extrapolation (Enke et al., 2019). Drawing on these findings, we designed an experiment where participants observed price signals about owned and non-owned goods, and were then asked to recall previous signals about each. After first verifying that attention improves recall accuracy in our paradigm, we show that people are more accurate when recalling signals about owned goods compared to non-owned goods. This provides further evidence for ownership-driven attention. We then show that this increased accuracy is driven by people being more likely to correctly recall signals that match the most recent one.

The Internet Appendix presents a formal framework of ownership-driven attention and memory. There, we demonstrate that our empirical results provide evidence for associative recall as a potential mechanism connecting ownership-driven attention and over-extrapolation. As discussed in Section VI.C, the findings also shed light on when ownership may lead to less versus more well-calibrated beliefs. It is important to note that while we believe that the causal relationship between ownership, attention, and over-extrapolation to be generalizable and well-identified in our studies, the evidence for the specific mechanism linking attention to over-extrapolation should be taken as suggestive.

We explore the implications of ownership's impact on learning in two settings. We first examine how ownership affects valuations when both owners and non-owners have the opportunity to learn about the quality of a good. Participants were assigned to own one of two goods and could learn about the quality of both from signals in the form of real Amazon ratings. Ratings were provided over the course of five rounds. We recorded participants' valuations of both the owned and non-owned goods in each round by eliciting their minimum willingness to accept (WTA) to part with the former and maximum willingness to pay (WTP) to obtain the latter. We document an initial endowment effect: before seeing any information about the products, the average WTA was significantly higher than WTP. Consistent with the predictions of ownership-driven over-extrapolation, seeing the same positive ratings for both owned and non-owned goods *doubled* this valuation gap. In contrast, negative ratings eliminated the endowment effect altogether. Finally, we used the Michigan Survey of Consumers to study whether asset ownership affects extrapolation from prior performance in asset markets (Greenwood and Shleifer, 2014). We find that those who owned assets extrapolated about *twice* as much from prior market returns as those who did not.

Our findings contribute to the literature on behavioral biases in belief formation. Prior research has shown that people tend to neglect base-rates (Kahneman and Tversky, 1973), underweight sample size (Kahneman and Tversky, 1972), display overconfidence (Moore and Healy, 2008), over-extrapolate from recent signals (Bordalo et al., 2018), and exhibit difficulty with contingent reasoning (Esponda and Vespa, 2014, 2019; Martínez-Marquina et al., 2019) when forming their beliefs (see Benjamin (2019) for a review).[9] Recent research has also studied the role of attention in belief formation. For example, people appear to not sufficiently account for correlations in the data generating process (Enke and Zimmermann, 2019), or the absence of information (Enke, 2020), and are inattentive when considering alternative causes, which leads to overly precise beliefs (Graeber, 2020). Moreover, recent work by Esponda et al. (2020) has shown that belief biases such as base rate neglect persist even with frequent feedback and ample learning opportunities.

While the empirical literature on this topic has largely focused on inattention as a source of biases in belief formation, theoretical work suggests that in some settings, more attention may generate less well-calibrated beliefs. Bordalo et al. (2012; 2013) and Kőszegi and Szeidl (2013) present models where attention may result in an overweighing of certain attributes, which leads to biases in consumer choice and decisions under risk. Dawes (1979) argues that greater attention can generate less well-calibrated beliefs if it is channeled through an incorrect mental model of the decision-problem.[10] We contribute to this literature in two ways: first,

[9]Moreover, research on over-extrapolation has demonstrated that biases in belief formation can have significant implications for the broader economy by affecting market expectations (Armona et al., 2019; Kuchler and Zafar, 2019; Da et al., 2020).

[10]In this spirit, Gagnon-Bartsch et al. (2018) formally demonstrate that incorrect mental models—termed

by demonstrating the relationship between ownership and a specific bias in belief-updating (i.e. over-extrapolation), and second, by providing some of the first empirical evidence that belief biases can be exacerbated through increased attention.

Another related line of work examines how trade and prior investment experiences affect beliefs and market behavior through their influence on emotions. Kuhnen and Knutson (2011) and Rudorf et al. (2016) show that beliefs are impacted by prior investment choices. Both studies document an asymmetric belief-updating pattern where participants respond more to news that is consistent with their prior choices: those who had previously selected an asset update more (less) in response to good (bad) news about it, and vice versa for the assets they did not select. The authors argue that this pattern is due to people's desire to maintain a positive emotional state. Using a similar experimental design, Kuhnen (2015) examines belief updating in response to the *same* information framed negatively versus positively. The paper finds that the emotional response generated by negative framing leads to more biased learning compared to the response generated by positive framing.[11] We add to this literature by exploring how ownership influences beliefs.[12]

Though investment decisions are often associated with ownership, most settings allow for trade which precludes the identification of how ownership causally impacts learning and beliefs. The ability to buy and sell goods as a function of beliefs means that ownership selects on people's reactions to signals. This creates a confound on the variable of interest: owners who have larger reactions to negative signals or smaller reactions to positive signals are most likely to sell and then be classified as non-owners. As a result, owners' reactions to positive (negative) signals will be overestimated (underestimated) compared to the underlying causal effect. This generates an association between ownership and *asymmetric* updating to positive versus negative signals—a pattern which could be misinterpreted as motivated reasoning.

To demonstrate how trade-based endogenous selection biases inference, Section VI.A

mistaken theories—will generate stable errors in learning even when agents have feedback about choice outcomes. Unless the mental model is corrected, greater attention is unlikely to mitigate biases and may exacerbate them if, for example, this leads a person to overweight certain attributes of the choice problem.

[11] Note that this is distinct from the environment studied in the current paper where the valence of signals is informative about the underlying state (fundamental quality). In our setting, a similar framing manipulation would likely exacerbate the errors that owners are already making in response to negative signals.

[12] While these studies elicit beliefs, they lack ownership as a feature and thus cannot be used to identify the effect we study. When describing their paradigm, Kuhnen and Knutson (2011) write that they do not examine situations where "individuals have ownership of certain assets." (p. 617). Because there is no scope for ownership to channel attention, it is not clear what predictions, if any, our framework makes in this setting.

presents an experiment that introduces the ability to trade into our basic paradigm. We observe an association between ownership and asymmetric belief updating, with owners displaying a more pronounced reaction to positive signals than negative ones. However, after controlling for the selection effect from trade, we recover the symmetric ownership-driven extrapolation pattern documented in our main studies.

Our results also have theoretical implications for settings which allow for learning before the opportunity for trade. A well-known puzzle in finance is that standard models predict only a small fraction of the trade volume observed in financial markets. Models of disagreement, where agents disagree about the value of an asset given the same information, are the dominant explanation for this puzzle (see Hong and Stein (2007) for a survey of this literature). The reason for *why* agents have different beliefs is not well understood. Our findings provide a potential microfoundation: if owning an asset systematically changes how people interpret information about it, then owners and non-owners will disagree about the same asset's value despite seeing the same signals. Moreover, our findings generate predictions for whether public news will result in higher or lower volume as a function of its valence (see Section VI.D).

The rest of the paper proceeds as follows. Section II describes the experimental paradigm used to explore the impact of ownership on learning and documents the basic effect. Section III presents results on learning relative to a normative benchmark and demonstrates ownership-driven over-extrapolation. Section IV explores the mechanism. Section V presents results on how differential learning influences the dynamics of the endowment effect and provides additional evidence from survey field data. Section VI discusses the implications of our findings and concludes.

II. The Effect of Ownership on Learning and Beliefs

A. Method

To examine the causal effect of ownership on learning and beliefs we sought to design a setting with the following features: 1) ownership was as-if exogenously assigned, 2) the relationship between signals and the underlying quality was simple to infer and transparent to facilitate learning, and 3) beliefs could be compared to a normative benchmark. We developed a paradigm that used an experimental asset market. Participants were recruited from Amazon's Mechanical Turk, a large crowdsourcing platform. The market featured six goods with equal starting prices of 100 experimental points per share. Participants were endowed with 2000 experimental points (500 points = 50 cents) and asked to spend the entire sum on shares of three of the six goods. The goods were ex-ante identical; as a result, ownership can be viewed to be as-if random in this setting.[13] Each participant then viewed a sequence of signals about the fundamental quality of goods that she owned and did not own. She then reported her beliefs about the fundamental quality of both owned and non-owned goods.

In our setting, for each round t, a good $i \in \{1, .., 6\}$ has a fixed probability of a price increase, s^i, which represents its fundamental quality. This good-specific quality remains constant throughout the experiment. In each round, the price level of the good (e.g. 106 per share) either increased or decreased by a constant amount; a price increase was always 6% and a price decrease was always 5%. The current and prior price levels for each good were provided to the participants in every round. Since a price increase is more likely to be observed if a good has a higher fundamental quality—a good with $s^i = 0.7$ has a higher probability of experiencing a price increase in any period t than a good with $s^i = 0.4$—price changes correspond to signals about a good's fundamentals.[14] Throughout the analyses, we use percent returns as our measure of prior cumulative signals since they are isomorphic to the net number of positive and negative signals in our setting.[15] Participants were incentivized based on the performance of their portfolio (see discussion of the payment mechanism below).

While participants were told that each good had a fixed s^i, they were not informed of the actual quality for any of the goods. Their task was to infer this quality from the signals. The key component of our study is the elicitation of beliefs about each good's fundamentals in each round. We refer to these elicited beliefs as $\hat{s}^i_t$. Participants observed price signals and reported their beliefs about each good's quality over the course of 15 rounds.[16]

[13]A separate experiment, presented in the Internet Appendix, replicates our findings when goods are randomly assigned rather than chosen. Participants are endowed with three goods while three other goods are impossible to own. This shows that our results are robust to whether the choice to own is active or not.

[14]Prior work has used an asset market with a similar structure to study the disposition effect in a controlled environment (Fischbacher et al., 2017).

[15]For example, a good that had an initial price of 100 and a current price of 112 has a return of 12%.

[16]Participants reported beliefs both for goods that are owned and not owned. This is an important feature of our experimental design as it allows us to test and identify specific mechanisms related to attention, which

We used two treatments for generating the fundamental qualities of the goods. In the first treatment, termed Discrete, participants were told that good-specific probabilities would be randomly selected, with replacement, from the set $s^i \in \{0.25, 0.3, 0.35, 0.45, 0.55, 0.65, 0.7, 0.75\}$. One concern with this method is that participants do not internalize the exogenously provided information as their prior belief.[17] As such, we ran a second treatment, termed Continuous, where participants were not provided with any information about the distribution of fundamental quality. Values of s^i ranged from 0.1 to 0.9 with a median of 0.43. The main findings are similar across both treatments and we collapse across them in the main text; separate results for each treatment are presented in the Appendix.

We follow convention in randomly generating the price paths before the experiment (e.g. Fischbacher et al., 2017). This facilitates between-subject analyses since it allows for comparisons of beliefs by ownership status conditional on seeing the same price paths. We drew six sets of price paths, two for the Continuous treatment and four for the Discrete treatment.[18]

Participants were also incentivized based on the accuracy of their forecasts, potentially receiving a bonus of \$1 if a randomly selected estimate was within plus or minus 5% of the true probability s^i. We chose to use this elicitation procedure as opposed to more complex mechanisms such as versions of the Binarized Scoring Rule (e.g. the quadratic scoring rule) due to recent evidence showing that the BSR can systematically bias truthful reporting. Danz et al. (2020) demonstrate that the BSR mechanism leads to conservatism in elicited beliefs, resulting in greater error rates relative to a simpler mechanism that offers little to no information about the specific incentives. The authors argue that simpler mechanisms that incentivize reporting of belief quantiles—such as the one used here—will result in more truthful reporting while imposing fewer cognitive burdens on participants.

In the Continuous treatment, participants were compensated for both the accuracy of their beliefs and the performance of their owned goods. In the Discrete treatment, it was randomly determined whether participants would be compensated based on either their belief accuracy or portfolio performance, and this was communicated to them ex-ante. This rules out hedging as a potential motive.[19] All participants were paid a base fee of \$1.20.

naturally requires data on both sets of goods.

[17] This is documented in recent work by Crosetto et al. (2020), discussed further below.

[18] Price paths for both treatments are presented in the Internet Appendix.

[19] We found no evidence for hedging since results in the Continuous treatment point in the opposite direction

This setting represents a simple learning environment for a Bayesian agent. Across both treatments, the number of prior increases u_t^i and decreases d_t^i—which is captured by the good's round-specific return—is a sufficient statistic for calculating the posterior. In the Discrete treatment, a rational prior belief is a probability of one eighth for each possible s^i. In each round, a rational agent would update their beliefs based on the signal using Bayes rule; posterior beliefs become the priors for the next round and the agent repeats the process for each new signal. We represent beliefs in the Continuous treatment using β distributions, which are distributions over probabilities, and as we demonstrate later on, are well-suited for approximating participants' priors. We conducted additional studies to elicit and estimate participants' priors. Results suggest that subjects entered the experiment with an average prior that can be well approximated using a $\beta\,(2.62, 2.62)$ distribution (both the method and estimation strategy are described in the Internet Appendix).[20] Beliefs are updated based on signals to generate a round t posterior mean of $(\frac{2.62+u_t^i}{2*2.62+u_t^i+d_t^i})$.

The process of selecting a prior for benchmarking highlights the advantages and disadvantages of each treatment. An advantage of the Discrete treatment is that the simple distribution of fundamental qualities provides a clear candidate for a prior belief. The disadvantage is that a participant's prior need not correspond to that of a rational Bayesian after reading the instructions, so this 'rational prior' may not be the prior that participants actually use. The Continuous treatment addresses this issue by using empirical estimates of the participants' priors. In this treatment, we use data from additional conditions where prior beliefs are elicited and judgments in the initial rounds of the experiment to calibrate the prior. Recent work by Crosetto et al. (2020) highlights the benefits of this approach. There, participants who were told that signals would be drawn from a uniform distribution reported single-peaked beliefs with more mass in the center and less in the tails, similar to the symmetric β distribution estimated in the Continuous treatment. We hope that demonstrating the robustness of our results to either method will increase confidence in the benchmarking exercise that follows.

of what would be predicted by hedging motives (i.e. greater pessimism after positive signals and greater optimism after negative signals about owned versus non-owned goods), and findings in the Continuous and the Discrete treatment are similar despite no motive for hedging in the latter.

[20]This distribution is centered at 50% with more mass in the middle, though it is relatively diffuse. In the Internet Appendix we demonstrate the robustness of our results to alternative benchmarks, with priors $\beta\,(2, 2)$, $\beta\,(2.5, 2.5)$, $\beta\,(3, 3)$, $\beta\,(3.5, 3.5)$, a simulation and ex-post forecast errors. The main patterns are robust to any of these specifications. Further supporting this parameterization, we find similar results in a treatment where participants were explicitly told that s^i was drawn from a $\beta\,(2.62, 2.62)$ distribution.

Because of the structure of the market, a price decrease is a negative signal about quality while a price increase is a positive signal. In order to restrict our sample to those who understood this structure, we include participants whose beliefs were positively correlated with prices and significant at the 10% level. The Discrete treatment also includes a set of questions that are separate from the main task but which feature an analogous updating problem—eliciting beliefs about fundamental quality in response to signals. In the Internet Appendix, we use these separate questions as an alternative comprehension check, demonstrating that our main results are robust to this exclusion restriction. Participants also answered control questions to assure they understood that the probabilities of each good going up or down in price were independent in each round, that their reported beliefs did not influence these prices, and that they would purchase and hold three of the six goods. This results in a final sample of 571 out of 840 subjects who completed the survey.[21]

B. Results

We begin by comparing the beliefs about owned and non-owned goods at different return levels in Figure 1. The red line shows the average beliefs $\hat{s}_t^i$ associated with goods that are owned for each return level. The blue line shows the average beliefs for goods that were not owned. The shaded areas indicate 95% confidence intervals. The red line has a steeper slope than the blue, consistent with a greater response to a cumulative signals for goods that are owned. For lower returns on the left of the graph, the red line is consistently below the blue line. This indicates that, for a given return level, participants are more pessimistic about goods they own—believing them to be worse than goods they do not own. For higher returns on the right side of the graph the general pattern is reversed. The red line is consistently above the blue line for such returns, indicating that participants are more optimistic about goods that they own compared to goods that they do not.

[21]Similar inclusion restrictions—which filter on whether participants are mostly updating in the same direction as the signal—are commonly used in belief-updating experiments (e.g. Mobius et al. (2011); Coutts (2019)). Because the restriction is applied equally to both ownership conditions (owned and not owned), it does not bias inference about the variables of interest. The number of participants excluded through the comprehension filter is within the range of prior belief-updating studies (e.g. 25% in Mobius et al. (2011), 49% in Enke and Graeber (2019)).

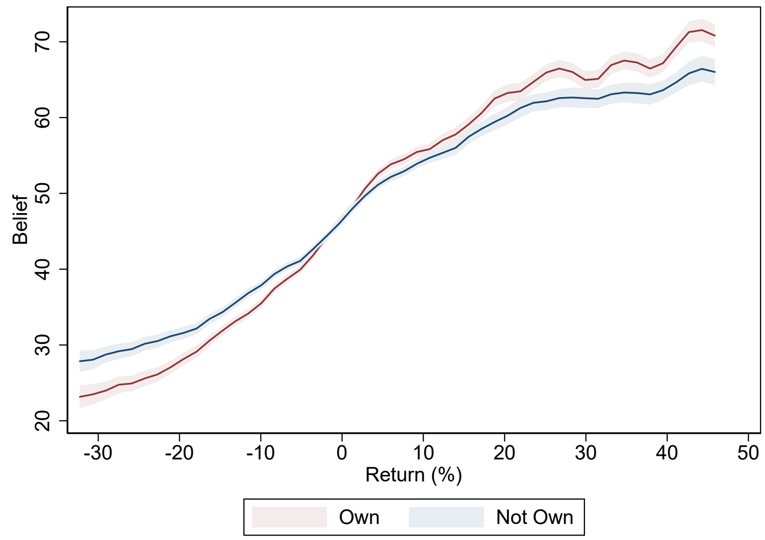

Figure 1. Beliefs as Function of Ownership and Returns. This graph shows a local linear plot of beliefs, $\hat{s}_t^i$, on returns separately for goods that are owned and not owned. Data include observations with returns from the 5th to the 95th percentile. The shaded area represents the 95% confidence interval.

Table I examines this pattern in greater detail. Beliefs are regressed on the good's *Return*, an *Own* dummy variable that is equal to one if the good is owned, and an interaction of the two variables. The coefficient on *Return* in Column 1 shows that there is a strong positive relationship between good i's performance and the respective belief $\hat{s}_t^i$ for non-owned goods, which is expected given the structure of the experiment. The coefficient of interest is on the interaction of *Own*Return,* which is positive and significant. This indicates that beliefs about goods that are owned are more responsive to cumulative signals than beliefs about goods that are not owned, consistent with the red line being steeper in Figure 1.

In our setting, a rational Bayesian would need to know only the return level and the round to form posterior beliefs. Thus in Column 2 we include return by round fixed effects. This column shows how beliefs about owned positions differ from those that are not owned given any Bayesian benchmark that does not condition on ownership.[22] This analysis also controls for any non-Bayesian benchmark that takes price paths as its input and does not condition on ownership when generating beliefs. If anything, the results here are slightly stronger.

People may update their beliefs differently depending on their individual characteristics,

[22]This is the same as fixed effects for the number of price increases and decreases, the main inputs for Bayesian posterior beliefs in our setting. See Section IV for further discussion.

such as differences in IQ (D'Acunto et al., 2019), differences in life experience (Malmendier and Nagel, 2015), or differences in socioeconomic status (Das et al., 2020). Column 3 adds participant fixed effects to account for such differences. Results are similar in this specification. After removing individual averages, the *same* person is more optimistic for owned goods after receiving positive signals and more pessimistic for owned goods after receiving negative signals, compared to receiving similar signals about goods she does not own.

We sought to test whether this pattern was robust to decreasing the number of goods that participants had to keep track of. To do so, we ran a version of the experiment where participants chose to own one of two ex-ante identical goods. Table IA.II in the Internet Appendix shows the same pattern as in the case with six goods.

These findings suggest a robust and significant difference in learning as a function of ownership. Participants display a more extreme reaction to the same information about goods that they own compared to those that they do not. Under any Bayesian prior that does not differ by ownership, they are more pessimistic about owned goods after seeing negative signals and more optimistic about owned goods after seeing positive signals.

III. Ownership, Belief Errors, and Extrapolation

The previous section demonstrated that the same information leads to differences in beliefs as a function of ownership. We now examine whether owners or non-owners are closer to normative Bayesian benchmarks when learning about a good. We find that belief errors—defined as reported beliefs minus the Bayesian benchmark—are more extreme for owned goods compared to non-owned goods in both the positive and negative domains. This implies that the greater response to information about owned goods represents an *overreaction* to information in our setting. We then show that this overreaction appears to be driven by people over-extrapolating from recent signals about owned goods.

A. Belief Errors

Figure 2 graphs the belief errors relative to the associated Bayesian benchmarks by return level. The blue line, representing goods that are not owned, is relatively flat. This implies that in our experiment, learning about non-owned goods is similar to the predictions of the

Bayesian model. On the other hand, the red line—which represents belief errors associated with goods that participants own—has a positive slope. This indicates that participants update more than a Bayesian agent for goods that they own, consistent with an overreaction to signals about owned goods.

Figure 2. Belief Error by Price. This graph shows the belief error relative to the Bayesian benchmark based on whether a good is owned as a function of its return. Data include observations with returns from the 5th to the 95th percentile. Shaded area represents the 95% confidence interval.

Table II repeats the regression analysis from the previous subsection using belief errors as the dependent variable. Column 1 shows the regression without controls. The coefficient on *Return,* which corresponds to belief-updating for non-owned goods, is roughly 0. This implies that we cannot reject that learning about non-owned goods is approximately Bayesian. In contrast, the coefficient on *Own*Return* is roughly 0.1 and significant at the 1% level. This implies that in response to a positive signal about an owned good, participants increase their beliefs by 20% more than both a Bayesian agent and in response to the same signal about a non-owned good.[23] Column 2 includes an individual fixed effect and shows similar results.[24]

Columns 3 to 6 repeat the analysis separately for the Discrete and Continuous treatments. Columns 3 and 4 examine only data from the Discrete treatment while columns 5 and 6

[23]In response to a positive signal (6% return) about a non-owned good, participants increase their stated quality by 3% (based on the coefficient on *Return* of 0.5), which is consistent with Bayesian updating. In contrast, the 0.1 coefficient on *Own*Return* implies that in response to the same positive signal, participants increase their beliefs about quality by 3.6% — 20% higher than a Bayesian observing the same information.

[24]We do not add a round by return fixed effect as this controls for any Bayesian prior and thus does not add information when explicitly including a benchmark.

examine data from the Continuous treatment. All four columns display a similar pattern. There is no statistically significant coefficient on the *Return* variable, indicating that belief updating about non-owned goods is indistinguishable from the Bayesian benchmark. On the other hand, the coefficient on $Own * Return$ is positive and significant in each specification.

These results indicate that irrespective of the method used (Continuous or Discrete), ownership leads to a more extreme reaction to information compared to the Bayesian benchmark, as well as relative to seeing the same information about a non-owned good. Thus, the observed pessimism after negative signals and optimism after positive signals about owned goods can be interpreted as an overreaction to the signals.

B. Extrapolation

Prior theoretical work has shown that over-extrapolation of recent signals can produce the type of symmetric overreaction documented in the previous section (Bordalo et al., 2018, 2020a). In this section, we demonstrate greater extrapolation of recent signals relative to Bayesian benchmarks for goods that are owned compared to those that are not owned. Moreover, while we show that people over-extrapolate from signals about owned goods, there is little evidence for over-extrapolation with respect to non-owned goods.

To look at differences in extrapolation, we regress beliefs on *Price Increase,* a dummy variable equal to one if there was a positive signal in round t and zero if there was a negative signal, the *Own* dummy variable, and an interaction between the two.[25] The coefficient on *Own*Price Increase* corresponds to how much more or less participants respond to a recent price increase for positions they own compared to positions they do not. The coefficient on *Own* represents how much more or less participants respond to a price decrease for positions they own compared to those they do not.

Table III Panel A shows that people appear to extrapolate more from both recent price increases and decreases for positions that they own. Column 1 examines raw beliefs without controls. The interaction of *Price Increase* with *Own* has a significant coefficient of 5.03, which indicates that people update their beliefs by 5% more after seeing a positive signal about an owned good compared to a non-owned good. The coefficient on *Own* is negative,

[25] We exclude the first round for the extrapolation tests since after receiving only one signal there is no difference between the most recent information and the total information.

which indicates there is also a larger negative reaction to price decreases for owned goods.

Without further controls it is unclear whether differences in updating are due to differences in extrapolation, or whether this simply reflects differential responses to a given information set. To identify extrapolation, and over-extrapolation in particular, we proceed to examine how belief updating deviates from a Bayesian benchmark that incorporates the dynamic nature of the process. In our simple learning setting, the ordering of signals does not matter for a Bayesian agent since the number of positive and negative signals is sufficient to calculate the posterior in a given round.

We use the following expression of the mean posterior belief $\hat{s}_t^i$ to represent the degree of extrapolation for good i in round t:

$$\hat{s}_t^i = \hat{s}_t^{Bayes_i} + \nu * Z_t^i \tag{1}$$

where $Z_t^i = 1$ if good i experienced a price increase and $Z_t^i =$ -1 if it experienced a price decrease in round t, and $\hat{s}_t^{Bayes_i}$ corresponds to the Bayesian posterior in that round. The parameter ν in the second term captures the extent of over- or under-extrapolation from the recent signal. A $\nu > 0$ corresponds to over-extrapolation while a $\nu < 0$ corresponds to under-extrapolation. The expression reduces to Bayesian updating when $\nu = 0$.[26]

To estimate ν, we measure belief errors relative to a Bayesian benchmark and use them as the dependent variable in the extrapolation regression. If an agent updates in accordance to Bayes rule, the difference between $\hat{s}_t^i$ and the Bayesian benchmark $\hat{s}_t^{Bayes_i}$ should not be influenced by recent price changes as the benchmark accounts for updating with respect to that information. If an agent over- or under-extrapolates from recent signals, then recent signals will have significant explanatory power for $\hat{s}_t^i$ even after controlling for the benchmark.

Column 2 presents belief errors that capture the degree of over- or under-extrapolation relative to a Bayesian agent.[27] The coefficient on *Price Increase* is -0.982 which indicates mild underreaction from price increases for non-owned positions. The point estimate on *Own*Price Increase* is 3.87 and the point estimate on *Own* is -2.28, both significant at the 1% level. This

[26]The goal of this exercise is to examine whether people's beliefs differ from the Bayesian benchmark as a function of prior signals. One could also consider whether belief *changes* differ from Bayesian predictions as a function of recent signals. We perform a version of this analysis as well by controlling for participants' priors in every round (it is presented in Table III, Column 4).

[27]Results split by Discrete or Continuous treatment are presented in the Internet Appendix.

suggests that the majority of the effect in Column 1 represents over-extrapolation from recent signals for owned positions.[28]

These results illustrate over-extrapolation relative to a prior that does not condition on ownership. However, the regressions may be capturing the general difference in beliefs for owned versus non-owned positions rather than differential extrapolation from the most recent signal. To test for such a possibility, we allow for benchmarks where the prior varies by ownership and by round. We do so in two ways.[29] First, we repeat the technique used to calibrate priors from participants' initial judgments (discussed in the Internet Appendix), but do so separately for owned and not owned positions. We refer to the belief relative to this benchmark as $\beta\,(Own)\ Error$. Second, since one round's posterior belief correspond to the following round's prior, we use participants' *own* reported average beliefs conditional on ownership status and recent price signals to calculate the implied prior for the next round.[30] Using this estimate, we can calculate the Bayesian posterior for an agent who observes the realized price signal that follows. We term this benchmark $\beta\,(Own\ Round)\ Error$.

Columns 3 and 4 present belief errors relative to these benchmarks and provide further evidence of over-extrapolation for owned goods. In Panel A, the coefficients on *Own*Price Increase* are positive and significant and the coefficient on *Own* is negative and significant. In some specifications the coefficients on non-owned goods are weakly positive, weakly negative, or insignificant suggesting there is not a strong pattern for non-owned goods. In contrast, across all specifications, the results indicate that even after allowing for different prior beliefs based on ownership and ownership interacted with price, participants exhibit greater over-extrapolation for owned goods.

As with any benchmark, there is a concern that it is misspecified. We attempt to further address this by presenting a series of results where we control for return levels and do not rely

[28]Equation 1 above imposes a uniform ν to price increases and decreases, which means the degree of extrapolation from positive signals and negative signals is uniform. The regression specification used in Panel A allows for differential extrapolation from positive and negative signals. The coefficient on *Own*Price Increase* can be interpreted as the ν in response to price increases and the coefficient on *Own* can be interpreted as the ν in response to price decreases. The analysis imposing a symmetric ν is conducted in the Internet Appendix. The results are materially similar.

[29]We calculate the benchmarks for the Discrete and Continuous treatment using the same method because priors that vary based on ownership need to be estimated in both treatments.

[30]We drop observations where an equal number of positive and negative signals have been observed. For such observations, a response of $\hat{s}_t^i = 50$ is consistent with any symmetric β prior, and hence any other response is inconsistent with any symmetric β prior.

on distributional assumptions. This non-parametric test is related to the concept of "divisible updating," which characterizes belief updating processes that are independent of how the individual chooses to partition information (Cripps, 2018). Bayesian updating satisfies this property as the order of signals should not matter for a Bayesian. In turn, showing that the order of signals matters, in that a recent signal is treated differently than the same signal received further in the past, points to a non-Bayesian process such as over-extrapolation and rules out other belief biases that could potentially generate the observed overreaction (Bohren and Hauser, 2019). Thus, if dummy variables for the direction of recent price movements are significant even after controlling for current return levels, this is evidence that participants are over-extrapolating from recent signals.

Column 1 of Panel B in Table III presents results with linear controls for returns. The coefficient on $Own * (Price\ Increase)$ indicates that participants extrapolate 3.53 more from a positive signal about owned goods than they do from the same signal about non-owned goods. The coefficient on Own indicates that participants extrapolate 2.32 more from negative signals about owned goods than they do from the same signals about non-owned goods. Linear controls may obfuscate interesting dynamics of the return response pattern, so in Column 2 we include dummy variables for levels of return in 10% increments. Including these controls yields similar results. It may also be the case that the extrapolation coefficients are capturing differential updating from return levels as a function of ownership rather than extrapolation. Column 3 includes a linear control for returns and also an interaction of return with Own to capture this differential reaction. Again, results are similar, suggesting a 2.20 greater extrapolation from positive signals and a -1.83 greater extrapolation from negative signals about owned goods. Column 4 includes dummy variables for returns along with an interaction of those dummy variables with ownership status. This flexibly controls for return levels separately for owned and non-owned goods. The pattern of results is unchanged.

Together, these findings imply significantly greater over-extrapolation from recent signals about owned goods, both relative to non-owned goods and a variety of normative benchmarks.

IV. Exploring the Mechanism

The previous two sections demonstrate differential learning as a function of ownership. People who own a good are more optimistic (pessimistic) about its quality after seeing positive (negative) signals about it compared to people who do not own it. Moreover, individuals overreact to information about owned goods compared to non-owned goods, and this difference in learning appears to be driven by over-extrapolation from recent signals. In this next section, we aim to provide evidence for a specific mechanism behind the effect.

The relationship between ownership and beliefs is not consistent with Bayesian learning, which predicts no differences by ownership status. The symmetric over-extrapolation and overreaction we observe is also not consistent with behavioral models of motivated beliefs (Brunnermeier and Parker, 2005; Kunda, 1990), which predict asymmetric updating and overall optimism, nor models of misattribution (Bushong and Gagnon-Bartsch, 2019), which also predict asymmetric updating but overall pessimism. Moreover, models of rational inattention cannot rationalize our findings because reported beliefs are incentivized in the same way for owned and non-owned goods. Finally, since our results are robust to the inclusion of subject fixed effects, the learning pattern cannot be explained by heterogeneity based on fixed participant characteristics.

We now consider a mechanism where ownership channels attention towards signals associated with owned goods. Under this mechanism, rather than affecting how information is interpreted (as models of motivated beliefs and misattribution predict), greater attention exacerbates over-extrapolation from recent signals. Work in cognitive psychology has shown that attention has an intimate relationship with value-relevant information (Smith and Krajbich, 2019, 2018; Enax et al., 2016); in turn, more attention is likely to be allocated towards signals associated with payoff-relevant assets, such as owned goods.

Why would greater attention lead to the observed over-extrapolation? Recent research has leveraged work from cognitive psychology (Kahana, 2012; Longuet-Higgins et al., 1970) to argue that over-extrapolation is at least partly driven by the associative nature of what 'comes to mind' through recall when making judgments (Enke et al., 2019; Gennaioli and Shleifer, 2010; Bordalo et al., 2020b). Enke et al. (2019) show that people over-extrapolate from information because they are more likely to recall similar prior information. For example, a person seeing an asset with positive returns is more likely to recall prior instances of price increases than decreases. In turn, judgments about future performance will over-extrapolate from the recent signals because the information set being used is more likely to include prior congruent signals than non-congruent signals. This process of associative memory implies that people behave as if they are over-weighting the most recent signal.

In order to recall a signal, it must first be encoded into memory. Work in economics and cognitive psychology posits that attention determines what information is encoded into memory, such that signals which are not attended to cannot later be recalled (Chun and Turk-Browne, 2007; Schwartzstein, 2014). Consistent with ownership-driven attention, Cunningham et al. (2008) show that people are better at correctly identifying owned goods than non-owned goods (see also Cunningham and Turk (2017)). If ownership increases the likelihood that signals are available for recall, then the associative process outlined above can lead to over-extrapolation. This generates testable hypotheses on comparative statics between ownership and beliefs: ownership is predicted to channel greater attention towards information about owned goods, which leads to a more extreme reaction to both negative and positive signals compared to the same signals about non-owned goods. Additionally, owners will be more likely to over-extrapolate than non-owners relative to a normative benchmark.

Importantly, in our setting there is no need for a Bayesian to recall prior information because the current round-specific price level contains a sufficient statistic for Bayesian updating.[31] However, research has shown that recall is spontaneous and *involuntary* (Mace, 2007) and that redundant information is not ignored (Eyster and Rabin, 2014). In both individual and social learning settings people have been shown to 'double count' redundant information (Eyster et al., 2015; Enke and Zimmermann, 2019; Alves and Mata, 2019). If prior signals are more likely to be encoded and recalled for owned goods, then this can lead to an overreaction and less well-calibrated beliefs about owned versus non-owned goods. Specifically, because the contemporaneous price level is sufficient for Bayesian updating, the involuntary associative recall of prior signals for owned goods is predicted to generate more belief errors and overreaction about those goods.[32] This 'more is less' hypothesis is in the spirit of Dawes (1979), who

[31]Such sufficient statistics are likely present in a variety of economically important settings, e.g. Grossman (1976) argues that prices serve this function in markets.

[32]Note that this hypothesis hinges on a greater propensity to involuntary recall signals about owned goods. Since participants in our baseline experiment saw the full history of price levels, an alternative explanation

conjectures that greater attention may lead forecasters to overweight features of the decision-problem relative to the normative benchmark. In our setting the mechanism corresponds to attention leading to the overweighting of recent signals due to associative recall.[33]

These hypotheses are derived formally in the Internet Appendix. Testing them requires evidence for the following conjectures: ownership channels attention towards signals about owned goods, increased attention leads to greater over-extrapolation, and ownership increases recall accuracy of congruent signals. Three experiments provide evidence for these conjectures.

The first employs a change detection paradigm from cognitive psychology to measure visual attention. We demonstrate that participants are more accurate when identifying changes associated with signals about owned goods than non-owned goods. This implies that more attention is channeled towards information about owned goods. Moreover, data on reaction times offers suggestive evidence that greater attention increases the ownership-driven effect on learning and overreaction.

The second study uses a comparative statics approach to exogenously manipulate attention towards non-owned goods. Here, we find that increasing attention towards non-owned goods produces a similar pattern as for owned goods in the baseline paradigm.

The third study incorporates a signal recall task into our basic paradigm: after observing a set of signals, participants are asked to recall prior signals about owned and non-owned goods. We first verify that attention increases recall accuracy in our setting. Consistent with the proposed associative recall mechanism we find a positive effect of ownership on recall accuracy and show that this increased accuracy is driven by people being more likely to correctly recall similar signals to the one they just saw. We stress, however, that associative recall is one potential mechanism for the relationship between attention and over-extrapolation in our setting.[34]

would be that owners pay greater attention to, and thus overweigh, *contemporaneously* provided prior price levels that are similar to the current one. To address the latter explanation, we ran a separate study where participants were randomly presented either with the full history of price levels or just the most recent one, depending on the round. The results, which are presented in the Internet Appendix, show that this did not affect learning in our setting: ownership led to more extreme reactions to information regardless of whether participants had access to the full history or not. This suggests that participants are not differentially attending to contemporaneous information about prior price levels as a function of ownership; in fact, they seem to not be attending to this information at all, which is not a mistake in our setting.

[33]Note that this hypothesis is less general than the hypotheses on comparative statics of ownership because it depends on the nature of updating about non-owned goods; we discuss this further in Section VI.C.

[34]Our results present direct evidence for ownership-driven attention exacerbating over-extrapolation, but provide only suggestive evidence for associative recall and do not rule out other mechanisms, e.g. attention

A. *Ownership-Driven Attention*

We incorporated a change detection task into our basic paradigm to examine whether ownership channels attention towards related signals. Participants (N=176) took part in the Discrete treatment, but were told that each round one of the six prices would randomly be highlighted in green. In addition to reporting their beliefs as in the baseline treatment, participants were tasked with correctly identifying which good the color change was associated with as fast as possible. As in the case of belief elicitation, we sought to incentivize accuracy and speed on the change detection task as transparently as possible. Participants were told that if the change detection task was chosen for payment, then conditional on being accurate, they had a better chance of earning a higher bonus if their reaction time was faster.[35] This change detection task is similar to those used in cognitive psychology, which examine the allocation of attention by measuring the speed and accuracy of responses (Mrkva and Van Boven, 2017; Mrkva et al., 2019; Verghese, 2001). Given the incentives for speed, ownership-driven attention predicts that participants will be more accurate when identifying color changes associated with owned goods.

Consistent with this prediction, participants are 11% more accurate when identifying information about owned versus non-owned goods ($t(2501) = 3.09, p = .002$). These results provide direct evidence that more attention is paid to signals about owned goods.

B. *Attention and Over-Extrapolation*

To investigate the relationship between attention, learning and over-extrapolation, we use reaction time data on the change detection task as a proxy for attention. Faster response times are a hallmark of greater attention paid to the task (Ninio and Kahneman, 1974). Indeed, we find that accurate answers on the change detection task were 9% more likely to have a below-mean response time ($t(2501) = 2.62, p = 0.010$). We classify a round as High Attention if the

increasing the salience of recent signals.

[35] Similar to the procedures outlined in Section II.A, we randomly chose one decision on the change detection task, belief elicitation task or performance of the goods to be paid out. To simultaneously incentivize accuracy and speed, conditional on the change detection task being selected for payment, participants who were correct and had below average reaction times would receive a bonus of $2 with a 70 percent chance and a bonus of $1 with 30 percent chance. If they were correct and had above average reaction times, the probabilities of receiving the higher versus lower bonus were flipped. They would not receive a bonus if the answer was incorrect.

response time is below the mean time. In Table IV, we see that high attention is associated with a stronger effect of ownership on learning and overreaction to information. We view this as suggestive evidence for the proposed relationship between attention and belief-updating.

In the next study, we sought to induce exogenous variation in attention by only eliciting beliefs for non-owned goods. If the effects in the main study are driven by ownership channeling attention to related signals, then belief updating about non-owned goods in this attentional paradigm should resemble those of owned goods in the baseline study. Table V compares belief-updating between the settings by adding the data from the exogenous attention paradigm to the data from the baseline analysis. The *Own* dummy is equal to one for goods owned by participants in the main study. *No Own Treat* is a dummy variable that is equal to one for observations in the attentional paradigm. Thus, the *Own* variables can be interpreted similarly to the prior regressions: the difference in updating from signals about an an owned good relative to a non-owned good in the baseline study. The *No Own Treat* coefficient represents the difference in beliefs about non-owned goods in the attentional paradigm compared to non-owned goods in the baseline study.

Table V shows that beliefs about non-owned goods in the attentional paradigm resemble beliefs about owned goods in the baseline study. For example, looking at Column 2 of Panel A which includes price fixed effects, the coefficient on *(No Own Treat)*Return* is 0.185 and is significant at the 1% level, which is similar to the point estimate in the baseline study. Examining extrapolation in Panel B we again see a positive and significant coefficient on the *(No Own Treat)*(Price Increase)* variable, consistent with over-extrapolation of recent signals in the attentional paradigm. Beliefs about goods in the attentional paradigm are generally closer to owned goods than to non-owned goods in the baseline study.

C. Ownership and Recall

As outlined above, ownership-driven attention is predicted to improve recall of signals linked to owned goods. To test this prediction, participants (N=298) completed a version of the baseline study with two assets rather than six, resulting in one asset that was owned and one asset that was not. Each was randomly assigned a round t and asked to recall whether the signal in the previous round $t-1$ was positive or negative. For example, after seeing a signal in round 5, the participant would be taken to a separate page and asked to recall the signal in round 4 for both the owned and non-owned goods.[36]

Table VI presents data on aggregate recall accuracy, as well as data split by whether the previous signal matched the most recent realization or not. Bordalo et al. (2013) argue that an attribute's departure from the average level draws attention to the good, so more extreme returns should channel greater attention to associated signals. In our setting, if attention facilitates memory encoding and subsequent recall, then signals about goods with more extreme returns should be recalled with greater accuracy than those associated with more moderate fluctuations. The first column tests our assumption on the relationship between attention and memory encoding by regressing recall accuracy on the absolute value of returns associated with the good. Consistent with greater attention facilitating memory encoding, the regression shows improved recall of signals about goods that have larger absolute returns. Column 2 shows that even after controlling for the absolute value of returns, participants are significantly more accurate when recalling signals about owned goods.[37] This provides further evidence for ownership-driven attention. Importantly, owners are significantly more accurate in recalling signals that match the most recent one: associative recall is nearly 50% larger than the aggregate recall effect. On the other hand, there is no difference between owners and non-owners when the prior signal did not match the current realization.

Together, these results provide evidence for associative memory as a potential driver of the relationship between ownership-driven attention and over-extrapolation.

V. Applications

In this section, we explore applications of the documented relationship between ownership and learning. First, we return to the classic endowment effect paradigm to demonstrate how differential learning affects valuations. We then replicate the ownership-driven extrapolation effect in field data on beliefs about aggregate stock market performance.

[36]We randomly chose to compensate participants based on the belief elicitation task or performance of the goods. The recall question was a surprise to participants.

[37]Columns 2-4 also include a variable controlling for the absolute deviation of a good's underlying quality from 0.5. Given the autocorrelation in signals, this control allows us to examine associative recall as distinct from a simple heuristic where owners are more likely to report the most recent signal realization. We thank an anonymous referee for this suggestion.

A. *The Effect of Ownership on Valuation*

In many contexts, owners and non-owners have opportunities to learn about the quality of a good before trading. Our results imply that after observing negative signals, owners will be more pessimistic and decrease their valuation of the good more than non-owners. In contrast, after observing positive signals, owners will be more optimistic and increase their valuation of the good more than non-owners. Prior work has documented an initial valuation gap between owners and non-owners, termed the endowment effect. Kahneman et al. (1990) showed that ownership increases people's minimum willingness to accept (WTA) to part with the good relative to non-owners' maximum willingness to pay (WTP) for the same good (see Ericson and Fuster (2014) for review). In this context, we predict that the valence of information will have an asymmetric effect on this initial WTA-WTP gap: the gap will shrink in response to negative signals, as owners become more pessimistic than non-owners about the good, and expand in reaction to positive signals, as owners become more optimistic than non-owners.[38]

A.1. *Experiment*

To test this, we endowed participants with power banks, which are auxiliary batteries for charging cell phones.[39] After being endowed with one of two power banks, each participant observed signals about the quality of the power bank they owned and the one that they did not own over the course of five rounds. Signals came in the form of ratings (1 to 5 star ratings) of the power banks taken from individual customer reviews on Amazon.[40]

After observing a rating, we elicited a WTA for the owned power bank and WTP for the non-owned power bank on a $0 to $100 scale in each round. To categorize positive and negative signals requires characterizing a neutral level of information. In this context, a reasonable "neutral" benchmark for quality is likely around 4 stars given a participant's experience on Amazon (Chen et al., 2008) and the average rating in our experiment (3.7 stars). Thus, we

[38] In exploring the mechanism for the endowment effect, Johnson et al. (2007) argue that the initial valuation gap can be explained by owners (non-owners) spontaneously generating reasons to own (not own) the product, before generating reasons to not own (own) it. This process leads owners to have more reasons to own the product than non-owners, translating to a valuation gap. This research is distinct from our own in that it does not look at learning from new information, or at how the endowment effect evolves in response to information.

[39] We chose power banks as they are generic products with substantial heterogeneity in quality. Thus, there is scope for significant learning about product quality from signals. They are also reasonably priced goods, making it practical to purchase a large number of them to give to participants.

[40] Participants saw a generic picture of the powerbank that could not easily be found online.

classify cumulative ratings below 3.5 as a negative signal, between 3.5 and 4.5 as a neutral signal, and above 4.5 as a positive signal (Bhatt et al., 2015). We drew multiple sets of ratings such that the cumulative signals were better for one power bank than the other in some sets, and vice versa in the other sets. Both endowment and the set of ratings drawn were counterbalanced. Details on the methods can be found in the Internet Appendix.

To ensure that our paradigm replicated the standard endowment effect without information, we ran a separate treatment without ratings where the WTA and WTP measures were elicited once. We found a sizable and significant endowment effect. Non-owners had an average WTP of \$28.93 while owners had an average WTA of \$34.47 ($p < .01$). Endowing participants with a good in our setting increased their valuation of it by 19%, which is well within the range of prior demonstrations of the effect (Ericson and Fuster, 2014).

A.2. Results

Figure 3 graphs the average valuation based on the cumulative signals in that round. Each bar represents the difference between the WTA for the good that is owned and the WTP for the good that is not owned. The red bar to the left and the dashed line represent the endowment effect in the absence of any information (\$5.54).

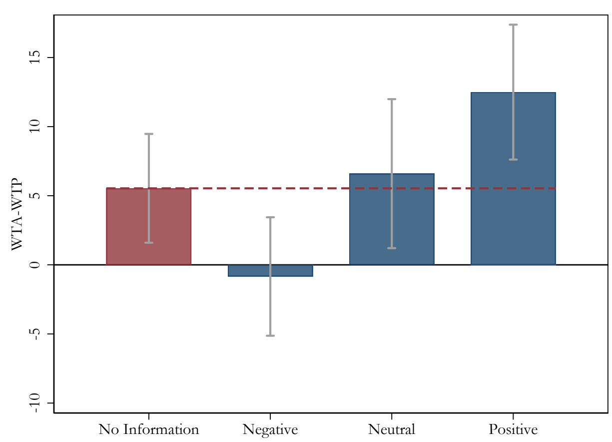

Figure 3. Valuation by Rating in Endowment Effect. The figure shows the difference between the willingness to accept for owned goods and willingness to pay for not owned goods based on its average cumulative signals. The dashed line represents the endowment effect without information. Gray bars represent the 95% confidence intervals.

The figures show that ownership influences valuations in line with the documented influence on learning and beliefs. In response to positive signals, the valuation gap increases. The Positive bar (above 4.5 stars) to the right of the figure indicates that when participants observed positive signals, the valuation gap increases substantially, roughly *doubling* in magnitude. On the other hand, the opposite pattern is observed for the Negative bar (below 3.5 stars): the gap between the valuations disappears, and even directionally reverses.[41]

Table VII examines the pattern more formally. It reports coefficients from the regression:

$$Value_{it} = \alpha + \beta_1 Own * Rating_{it} + \beta_2 Rating_{it} + \beta_3 Own_{it} \tag{2}$$

Rating is measured as the average rating in Panel A and the most recent rating in Panel B.[42]

The coefficient of interest is the interaction term, which we find to be robustly positive—consistent with a more extreme response to both negative and positive signals about owned goods. Columns 3 reports a coefficient on the interaction term of \$3.78 with no controls. This implies that a one-star decrease in the good's rating decreases the valuation gap by \$3.78. Columns 4-7 show that the significant interaction between ownership and ratings is robust to a variety of controls and fixed effects. Panel B repeats the analysis using the most recent rating and finds the interaction term is positive and significant across all specifications.

In addition to exploring valuation effects, this setting also demonstrates the conceptual robustness of the results in the baseline paradigm on learning and beliefs. While we attempted to make that experiment as transparent as possible, one may be concerned that participants were confused about the signal generating structure, reporting of probabilities, or the abstract nature of the setting. The endowment setting involves physical goods rather than abstract assets and participants reported valuations rather than probabilities. The setting has been utilized in so many experiments in part because it is viewed as intuitive and straightforward. Thus, the analogous results in a classic endowment effect setting should assuage concerns that

[41] The elimination of the valuation gap after negative signals is related to Lerner et al. (2004) who show that inducing negative emotions prior to trade eliminates the endowment effect. If the induced emotions spillover to valuations, as the authors argue, then they can be interpreted as generating a negative signal about the good. These results can be seen as a complimentary demonstration of the effect presented here.

[42] To make the coefficients easier to interpret, $Rating_{it}$ is normalized to 3 stars meaning a five-star rating has a value of $Rating_{it} = 2$ and a one-star rating to has a value of $Rating_{it} = -2$. Centering at 3-stars does not change the coefficients on $Own * Rating_{it}$ or $Rating_{it}$. Rather, it leads Own_{it} to represent the difference in value between owned and non-owned positions at a 3-star rating.

the findings documented in our main investigation were driven by experimental artifacts.

B. Stock Market Expectations and Ownership

To examine the generalizability of our laboratory findings, we explore the impact of ownership on learning and beliefs in field data. Studying this question requires information on signals and beliefs, and a setting where it is plausible that agents who hold and do not hold a given good are reasonably aware of the signals when forming beliefs. For this reason, we examine beliefs about aggregate stock market performance.

We study whether the belief response to recent market performance—the signal analogue to our experiment—is different depending on whether the individual owns stocks or not. The data comes from the University of Michigan Survey of Consumers. The survey asks whether a respondent owns stocks as well as how they think stocks will perform in the future. Specifically, respondents are asked: "What do you think is the percent chance that a one thousand dollar investment in a diversified stock mutual fund will increase in value in the year ahead, so that it is worth more than one thousand dollars one year from now?" We interpret stated beliefs about expectations for the stock market similarly to beliefs about the fundamentals $\hat{s}^i$ in our experiment. The data set contains the relevant data for 187 months, covering the years 2002 until 2019.

In this setting, investors select into owning stocks and may be differentially aware of information relating to those investments (unlike in our experiment where goods are identical ex-ante). These concerns are somewhat mitigated by examining aggregate market performance since recent market performance (i.e. the signals) is widely reported and discussed. In turn, it is likely that people are aware of this information regardless of whether they own stocks. Additionally, to the extent that owners and non-owners differ based on observable characteristics, we employ a rich data set to control for these factors. This being said, concerns about systematic differences based on non-observable factors remain. These results should be viewed as complimentary to the experimental findings where such issues are mitigated.

To begin, we examine how belief expectations vary with horizon of past market performance. Greenwood and Shleifer (2014) show that in six different surveys, investors extrapolate past market performance to form expectations about the future. To document a similar pattern in our sample, we examine two different left-hand side variables. The first is the percent ranking from 0 to 100 on whether the market will be higher. The second is whether a participant thinks the chance of a market increase is greater than 50%, a proxy of the bearish versus bullish measure used in Greenwood and Shleifer (2014). For past stock market returns we use the CRSP value weighted index over the prior quarter, six months, year and two years.[43] Market returns are from the period ending the month prior to when the survey was conducted. For example, if a participant took the survey in June of 2014, the lagged quarterly return would be the cumulative return from March 2014 through May of 2014.

B.1. Results

We explore how over-extrapolation varies with stock ownership. The Appendix shows that, consistent with Greenwood and Shleifer (2014), investors in our data generally over-extrapolate past market performance.[44] To examine whether such over-extrapolation varies with ownership we regress beliefs about future market performance on past performance and interactions of ownership and past market performance. Specifically we examine:

$$Probability\,Increase_{it} = Market_{[-m,-1]} + Market_{[-m,-1]} * Own_{it} + Own_{it} \tag{3}$$

where $Market_{[-m,-1]}$ is the previous market return during the relevant horizon and Own_{it} is equal to one if the participant states that they own the assets. Thus, the coefficient on $Market_{[-m,-1]}$ is the degree of extrapolation of past performance by participants who indicate that they do not own the assets. The coefficient on Own_{it} controls for the average difference in expectation between those who own and do not own the assets. The coefficient of interest is $Market_{t-1} * Own_{it}$. This corresponds to the difference in extrapolation between those who own and do not own the assets.

Table VIII shows that owners of stocks extrapolate significantly more than those who do not own stocks. Panel A examines the percent measure, while Panel B examines the expectations above 50% dummy variable. The first two columns in Panel A present the

[43] Hartzmark and Solomon (2020) argue that investors actually pay attention to market indices such as the S&P 500 or the Dow Jones. The Internet Appendix shows similar results using these measures.

[44] We also replicate the Greenwood and Shleifer (2014) finding that this is a mistake. The data illustrate an inverse relationship between recent past performance and future market performance, but respondents mistakenly over-extrapolate from past signals which leads to incorrect beliefs about the future.

probability of a market increase regressed on lagged quarterly market return. In Column 1, the *Own* dummy has a coefficient of 13.26 and is significant at the 1% level, indicating that asset owners are about 13% more optimistic than non-asset owners. This is consistent with more optimistic people selecting into owning stocks. The coefficient on lagged market returns is 14.22 and significant at the 1% level. This indicates that those who do not own assets extrapolate based on past market performance. Most important for our investigation, the coefficient on the interaction term with ownership is 17.85 and is significant at the 1% level. This indicates that those who own assets extrapolate from recent signals at roughly *twice* the level of those who do not.

The decision to own stocks is correlated with other demographic variables, so it could be that the ownership effects reported in Column 1 capture differences in demographic attributes. Column 2 presents the analysis including a large number of controls; specifically, dummy variables for sex, race, age, geographic region, education, and income. Interestingly, the coefficient on *Own* nearly halves, which indicates that a significant amount of the base level of optimism between owners and non-owners can be accounted for with demographic variables. That being said, the estimates of extrapolation are robust to demographic controls; if anything, the difference in extrapolation between owners and non-owners becomes larger upon their inclusion.[45] The coefficient for those who do not own the assets is 13.89 while the interaction term has a coefficient of 18.99 — both significant at the 1% level. Even after adjusting for differences in observables, asset owners extrapolate about twice as much as non-asset owners, consistent with the results we observed in the experiment.

Lastly, we explore a variety of different lags of market performance and find similar results across the board. In the 16 specifications using various lags of past market performance, two measures of future expectations, and with various demographic controls, we find that owners of assets extrapolate more than non-owners, with each specification significant at the 1% level.

[45] To further demonstrate robustness, the Internet Appendix repeats the analysis including interactions of the demographic controls with year by month fixed effects, thereby allowing for time varying effects of demographics on beliefs. Results are materially similar.

VI. Discussion and Conclusion

In this paper, we examine how owning a good affects learning and beliefs about its underlying quality. We find that upon receiving a negative signal about a good they own, people become systematically more pessimistic. They underestimate the good's quality both compared to receiving the same signal about a good they do not own and a normative benchmark. We observe the reverse pattern after observing positive signals: people overestimate the good's quality relative to seeing the same signals for goods they do not own and the normative benchmark. In exploring the mechanism, we demonstrate that ownership channels attention, leading to overreaction and over-extrapolation from recent signals for goods that are owned. This provides support for a "more-is-less" effect of attention, whereby more attention leads to less accurate judgments. Finally, we present evidence that the relationship between ownership and over-extrapolation may be due to the associative nature of memory. In what follows, we discuss the implications of our findings for settings with trade and endogenous information, and outline directions for future research.

A. *Ownership and Learning in Markets with Trade*

Our experimental setting did not allow participants to trade assets in order to identify the causal effect of ownership on learning and beliefs. As-if exogenous ownership is important in our setting for similar reasons as to why goods are randomly assigned to study the endowment effect: it ensures that observed differences are driven by ownership rather than ex-ante disparities in preferences or beliefs. In settings with trade, people select to hold assets that they believe are superior to the alternatives. This is nicely demonstrated in the experiments of Kuhnen and Knutson (2011) and Kuhnen (2015): participants are more likely to select a stock over a bond as their priors about the former increase. Since ownership is a function of beliefs, and not vice versa, differences in learning can be attributed to disparities in priors rather than ownership.[46]

We also precluded trade because the ability to buy and sell leads to self-selection precisely

[46] A large literature in psychology has shown that, depending on the context, people overweight or underweight information that conforms to their prior (Klayman and Ha (1989); see also Klayman (1995) and Nickerson (1998) for reviews). Controlling for prior beliefs would not solve this issue because it requires that changes in beliefs in response to signals are constant with respect to belief levels—an assumption that is unlikely to be satisfied, especially when beliefs are bounded (e.g. probabilities).

on the variable of interest—reactions to signals—which biases the data in favor of finding asymmetric updating. In a setting with trade, owners who have more extreme reactions to positive news are more likely to hold their position and remain owners, while owners who have more extreme reactions to negative news are more likely to sell and become non-owners. When estimating the influence of ownership on beliefs, this selection process leads to an overestimation of reactions to positive signals and an underestimation of reactions to negative signals. Despite a symmetric causal effect on beliefs, ownership will be associated with asymmetric belief updating in settings with trade, which may be misinterpreted as evidence for motivated reasoning or confirmation bias.[47]

To illustrate this, we ran a version of our experiment where participants could buy and sell assets every round. The design is otherwise identical to our Discrete treatment.[48] After allowing for trade, ownership appears to generate a different pattern in belief updating than the one documented in our main study. Figure 4 Panel A shows how participants who retained ownership reacted to negative signals (left figure) versus positive signals (right figure). Blue (red) bars represent the average change in belief upon seeing a signal about an owned (non-owned) good. We document what appears to be asymmetric updating, with owners updating more in response to positive signals than negative ones. Owners also respond more to positive signals than non-owners, while the response to negative signals is similar for both.

[47]For example, consider the case where ownership leads to greater over-extrapolation (as we document in this paper). After a negative signal, greater over-extrapolation by owners *increases* the probability of selling, with those who over-extrapolate most being the most likely to sell. In turn, beliefs among those who maintain ownership will be more positive than the estimate without trade. After a positive signal, greater over-extrapolation by owners *decreases* the probability of selling. This will lead to a positive bias in measured beliefs of owners because those who over-extrapolate the most are least likely to sell.

[48]Details on the methodology and analysis can be found in the Internet Appendix.

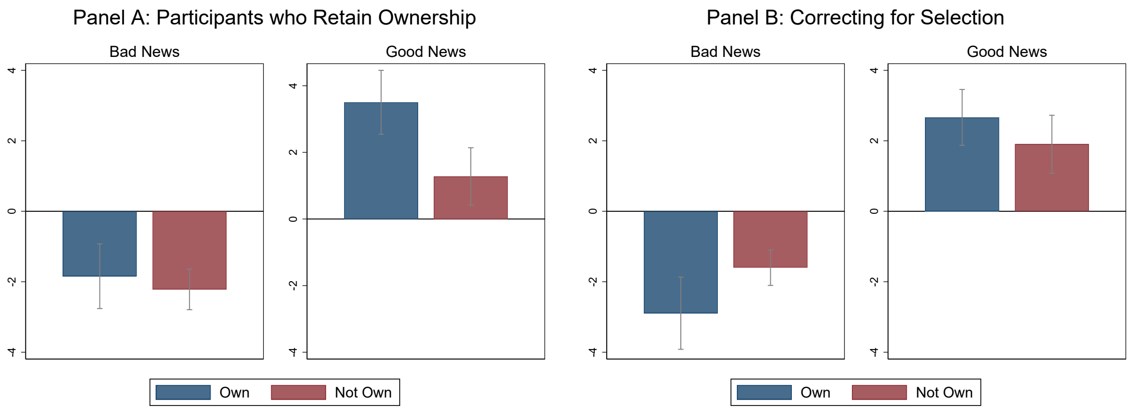

Figure 4. Belief Updating by Ownership in Trade Treatment. The figure shows the average change in belief in response to a price decrease (the left "Bad News" figure) and a price increase (the right "Good News" figure). In Panel A ownership is defined as holding the asset after the trade decision, when beliefs are elicited. Panel B includes the owners in Panel A as well as those who sold in response to the prior signal. Gray bars represent the 95% confidence intervals.

However, the figure is not an accurate depiction of belief updating as a function of ownership. The blue bars exclude people who responded to signals by selling and thus selecting out of ownership. Figure 4 Panel B shows that the pattern of belief-updating changes substantially when the sample of owners includes those who sold in response to the prior signal. After correcting for selection, we recover the symmetric effect documented in our baseline experiment: people update more in response to *both* positive and negative signals about owned goods compared to non-owned goods. The Internet Appendix presents these results in regressions.

Our results illustrate the importance of understanding the causal effect of ownership. Many economically important settings involve learning before there is an opportunity to trade, e.g. in the case of illiquid goods or situations where there are barriers to trade in place. Additionally, even in settings with trade, our results imply that previous owners will have systematically different beliefs than non-owners.

B. Ownership and Learning from Endogenous Information and Experience

Our experimental paradigm explored learning as a function of exogenously generated signals of quality. Prices conveyed information of the same valence to owners and non-owners—a price increase (decrease) corresponded to good (bad) news about quality for both. This design choice allowed us to study belief updating as a function of ownership while shutting down other channels that could interfere with inference. This section discusses the implications of our findings for learning from prices that are generated endogenously through the actions of market participants.

Prices that are endogenously generated, such as from trading decisions or auction mechanisms, may have different valences as a function of ownership, i.e. a realized price may be bad news for owners and good news for non-owners (and vice versa). This is because prices will reflect not only the quality of the underlying assets, but also differences in the preferences and beliefs of owners and non-owners. For example, if ownership generates an endowment effect where there is an initial WTA-WTP gap in valuations, then the transaction prices will likely fall between this WTA and WTP. This signal will be interpreted as "bad" news for the owners and "good" news for the non-owners. Our paper shows that both owners and non-owners update positively to good news and negatively to bad news—the documented effect is on the extent of updating rather than the direction. Thus, in response to viewing endogenous prices in the absence of new exogenous signals, the initial WTA-WTP gap should converge because the same signal is perceived with a different valence as a function ownership. This can account for why repeated exposure to endogenously generated prices mitigates the endowment effect.[49]

Documenting how ownership affects learning from exogenous information is important for several reasons. Though some market signals are endogenous to participants' preferences and beliefs, many common sources of value-relevant information—such as earnings announcements, patent applications, product launches, etc.—are exogenous. Additionally, large idiosyncratic price movements are typically in response to such information, and in these cases, the price signal will have the same valence for both owners and non-owners. The survey results in Section V.B provide suggestive evidence that owners and non-owners *do* respond differently to market prices in a manner consistent with ownership-driven over-extrapolation,

[49]e.g., Shogren et al. (2001) and Loomes et al. (2003) show that an initial endowment effect disappears after multiple rounds of auctions where participants view the endogenously determined price each round. More generally, while some studies have found that repeated market experience can eliminate behavioral biases (Smith et al., 1988), more recent work has shown that this disciplining effect is highly domain (Hussam et al., 2008) and context (Powell and Shestakova, 2016) specific. Evidence from the field similarly suggests that market experience has a limited disciplining effect, with both retail (Odean, 1998; Hartzmark, 2014; Harris et al., 2015) and institutional traders (Frazzini, 2006; Akepanidtaworn et al., 2019; Hartzmark and Solomon, 2019; Frydman et al., 2015) displaying significant behavioral biases.

and this has significant implications for investor sentiment and expectations.

C. Attention: More is Less versus More is More

Our documented "more-is-less" effect of attention is some of the first empirical evidence for the argument in Dawes (1979) that attention can degrade judgment and decision-making by leading people to place greater weight on normatively irrelevant information. The Internet Appendix formally derives a potential mechanism that can account for the empirical patterns in our paper. In the context of this model, our results suggest that attention exacerbates over-extrapolation by leading people to incorporate redundant information—prior signals—into the judgment process. This effect may be due to a mistaken theory of belief updating (Gagnon-Bartsch et al., 2018; Handel and Schwartzstein, 2018), where redundant signals are assumed to have informational content (Eyster and Rabin, 2014).

While we contribute to the literature by empirically demonstrating a "more-is-less" effect of attention, we emphasize that this does not imply that ownership always leads to less accurate beliefs. The more general conclusion is on a relative (i.e. comparative static) effect of ownership and attention. We predict that ownership-driven attention will lead to more extreme updating to information and increase over-extrapolation of recent signals, but this does not imply that inattentive inference will lead to better calibrated beliefs in all settings.

In some contexts, such as when individuals have access to sufficient statistics for Bayesian updating, inattentive inference may lead people to employ efficient updating heuristics (Anderson and Sunder, 1995; Green and Daniels, 2018) or a naïve use of Bayes rule (Barash et al., 2019).[50] This is likely to be the case in many economically important environments; for example, Grossman (1976) argues that market prices act as sufficient statistics for this purpose. In these environments owners are predicted to have less well-calibrated beliefs than non-owners and overreact to signals.

While our findings suggest that greater attention will exacerbate over-extrapolation (relative to the normative benchmark), it may lead to better calibrated beliefs (relative to the inattentive case) in environments where information aggregation requires recall. For example, take a decision that involves estimating electric-car mileage. Our recall experiment implies

[50] We are agnostic as to whether people are actually aware that information such as prices are sufficient statistics for judgment, or whether they use heuristics that lead them to act *as if* this were the case.

that Tesla owners will be paying more information to developments on this issue, commit relevant information to memory, and be more likely to recall it correctly than non-owners.[51] At the same time, owners will over-extrapolate from value-relevant information and thus be more optimistic or pessimistic than non-owners, depending on the valence of prior signals. Additionally, in settings where attention leads people to shift from heuristics towards more deliberative processing, such as when individuals have the correct mental models but cognitive costs lead them to form noisy expectations (Stanovich and West, 2008; Gabaix and Laibson, 2017; Imas et al., 2019), ownership will likely lead to learning closer to normative benchmarks.

D. Future Research

Our findings leave open a number of interesting questions regarding how the documented phenomenon interacts with contextual factors and orthogonal psychological mechanisms which could be related to ownership. Our evidence on the attentional mechanism suggests that the relationship between ownership and learning is perceptual. In settings where more deliberate cognitive factors like wishful thinking play a larger role, such as when ownership is linked to identity, a level-effect of overall greater optimism may indeed arise (e.g., Mobius et al. 2011). Conditional on this level-effect, however, we would still anticipate an interaction between ownership status and the valence of incoming signals.

In our studies, we largely followed the work in economics by using value-relevance as a sufficient condition for ownership (e.g. Kahneman et al. (1990); Ericson and Fuster (2014)). However, a rich literature across the social sciences suggests that value-relevance is not a necessary condition for *psychological* ownership (Jussila et al., 2015; Pierce and Jussila, 2010; Shu and Peck, 2011). Future research should explore the boundaries and moderators of the effects documented here as a function of psychological ownership. Additionally, the relationship between ownership and direct versus indirect experience is an interesting direction for future work.[52] Lastly, while we demonstrate an overreaction to information about owned goods, prior work has shown that people overreact to information in some settings (Bordalo et al., 2020a; Frydman and Nave, 2016) and underreact in others (Edwards, 1982; Barry and

[51] We thank an anonymous referee for providing this example.

[52] For example, Simonsohn et al. (2008) show that the behavior of players in a repeated prisoner's dilemma is influenced more by direct interactions with others compared to observing interactions as a third party.

Pitz, 1979). We discuss some potential factors that generate over- or under-reaction above, but predicting which effect will dominate in a given setting is beyond the scope of the current paper.

Our results have implications for the measurement of psychological frictions from data in settings that involve ownership. Economic analysis typically assumes that owners and non-owners form beliefs using the same process, explaining differences in behavior through preferences. Our findings suggest that ignoring the influence of ownership on the learning process can lead to erroneous conclusions. For example, one of the most well-documented behavioral anomalies is the disposition effect, where people are more prone to sell a good after a gain than a loss.[53] Our results imply that that this behavioral pattern cannot be driven by beliefs, suggesting that studies likely understate the psychological frictions stemming from preferences by ignoring the influence of ownership on beliefs.[54] More generally, ascribing a result to preferences rather than beliefs may lead to different conclusions about the underlying mechanism, which in turn can lead to different policy prescriptions.[55]

The results also have implications for the dynamics of trade volume in response to public signals. As demonstrated in our endowment effect experiment, the valuation gap between owners and non-owners shrinks in response to bad news and expands in response to good news. This should increase the potential for trade in the former case and decrease it in the latter. Future research should explore these dynamics in observational and experimental data.

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[53]Beginning with the initial discussion of the phenomenon (Shefrin and Statman, 1985) and empirical demonstration in Odean (1998) and Weber and Camerer (1998), the disposition effect has been replicated in a variety of settings (e.g. equity (Odean, 1998), housing (Genesove and Mayer, 2001) and gambling (Hartzmark and Solomon, 2012) markets) and with different types of market participants (e.g. retail and day traders) (Kaustia, 2010).

[54]A belief in mean reversion has been offered as a potential explanation for this effect: people hold on to losers and sell winners because they believe that the former will go back up and the latter will go back down. While many studies have proposed preference-based mechanisms such as realization utility for the disposition effect (Barberis and Xiong, 2012), belief in mean reversion has not been ruled out — largely due to a lack of data on beliefs in trading contexts (Barber and Odean, 2013).

[55]For example, Bohren et al. (2020) argue that wrongly ascribing discrimination to preferences rather than beliefs can lead to vastly different implications for policy.

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Table I

Beliefs by Returns and Ownership

This table shows how beliefs vary with ownership based on returns. *Own* is a dummy variable equal to one if the good was purchased by the subject. *Return* is the level of returns. Fixed effects are indicated below the regression results. Standard errors are clustered by subject, and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Own*Return	0.0763***	0.114***	0.0865***
	(3.68)	(6.00)	(5.39)
Return	0.510***		
	(26.27)		
Own	-0.619	-0.343	-0.296
	(-1.37)	(-0.82)	(-0.70)
Ret x Round FE	No	Yes	Yes
Subject FE	No	No	Yes
R^2	0.322	0.375	0.558
Observations	51390	51390	51390

Table II

Belief Errors by Returns and Ownership

This table shows how belief errors relative to a benchmark vary with ownership based on returns. Columns labeled *All* include all the baseline data relative to their benchmark. Those labeled *Discrete Treatment* include only data from the Discrete treatment, which uses the discrete initial prior provided in the instructions. Those labeled *Continuous Treatment* include only data from the Continuous treatment which uses an initial prior of $\beta(2.62)$. *Own* is a dummy variable equal to one if the good was purchased by the subject. *Return* is the level of returns. Fixed effects are indicated below the regression results. Standard errors are clustered by subject, and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All		Discrete Treatment		Continuous Treatment	
	(1)	(2)	(3)	(4)	(5)	(6)
Own*Return	0.105***	0.0780***	0.131***	0.0816**	0.0988***	0.0769***
	(5.67)	(5.00)	(3.40)	(2.42)	(4.68)	(4.34)
Return	-0.0174	-0.00799	-0.00579	0.0232	-0.0233	-0.0170
	(-0.95)	(-0.48)	(-0.16)	(0.71)	(-1.10)	(-0.87)
Own	-0.616	-0.546	-0.313	-0.389	-0.720	-0.631
	(-1.46)	(-1.29)	(-0.38)	(-0.47)	(-1.45)	(-1.27)
Subject FE	No	Yes	No	Yes	No	Yes
R^2	0.00724	0.296	0.0105	0.365	0.00631	0.266
Observations	51390	51390	14490	14490	36900	36900

Table III

Extrapolation of Signals and Ownership

This table shows how beliefs vary with recent price changes based on ownership. *Price Increase* is a dummy variable which is equal to one if the good experienced a price increase in the prior round. In Panel A, column 1 the dependent variable is the raw belief. In Column 2 it is the belief error relative to a Bayesian benchmark. In Column 3 it is the belief error relative to priors calibrated separately for owned and non-owned positions, indicated by $\beta\,(Own)\ Error$. Column 4 uses priors based on the average parameter from subjects from the prior round by price by ownership condition, indicated by $\beta\,(Round\,Own)\ Error$. Panel B examines raw belief as the dependent variable. *Ret* indicates a linear control for return. *Ret Dummy* indicates a dummy variable for intervals of 10% returns. Below are interactions for those variables with the *Own* dummy variable. Fixed effects are indicated in the bottom row. Standard errors are clustered by subject, and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Extrapolation Relative to Benchmarks

	Belief	Benchmark Error	β(Own) Error	β(Round Own) Error
	(1)	(2)	(3)	(4)
Own*(Price Increase)	5.029***	3.874***	2.460***	2.693***
	(8.02)	(7.54)	(4.85)	(4.86)
Price Increase	12.32***	-0.982**	-0.560	2.713***
	(22.70)	(-2.07)	(-1.18)	(5.37)
Own	-2.050***	-2.277***	-1.412***	-1.330**
	(-2.93)	(-4.58)	(-2.86)	(-2.48)
R^2	0.0937	0.00322	0.00135	0.0116
Observations	48930	48930	48930	42401

Panel B: Extrapolation Relative to Return Controls

	(1)	(2)	(3)	(4)
Own*(Price Increase)	3.525***	4.224***	2.203***	1.911***
	(6.48)	(7.96)	(5.59)	(4.91)
Price Increase	1.315***	-0.449	1.990***	0.694*
	(3.23)	(-1.09)	(5.60)	(1.92)
Own	-2.318***	-2.346***	-1.829***	-0.747
	(-4.39)	(-4.59)	(-3.56)	(-1.10)
Ret	Yes	No	Yes	No
Ret Dummy	No	Yes	No	Yes
Own x Ret	No	No	Yes	No
Own x Ret Dummy	No	No	No	Yes
R^2	0.332	0.357	0.333	0.359
Observations	48930	48930	48930	48930

Table IV

Level of Attention and Ownership

This table examines differences in beliefs and belief errors based on levels of attention. Attention is measured as High Attention, reaction time in the change detection task below the mean response time, in Panel A and Low Attention, reaction time in the change detection task above the mean response time, in Panel B. *Own* is a dummy variable equal to one if the good was purchased by the subject. *Return* is the level of returns. Standard errors are clustered by subject, and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: High Attention

	Belief			Belief Error	
	(1)	(2)	(3)	(4)	(5)
Own*Return	0.121**	0.100**	0.167***	0.111**	0.187***
	(2.34)	(2.01)	(3.13)	(2.14)	(3.29)
Return	0.541***			0.0370	0.0440
	(11.19)			(0.75)	(0.93)
Own	-0.381	-0.0243	0.0339	-0.504	-0.384
	(-0.32)	(-0.02)	(0.03)	(-0.44)	(-0.33)
Ret x Round FE	No	Yes	Yes	No	No
Subject FE	No	No	Yes	No	Yes
R^2	0.298	0.361	0.607	0.0133	0.401
Observations	4122	4122	4122	4122	4122

Panel A: Low Attention

	Belief			Belief Error	
	(1)	(2)	(3)	(4)	(5)
Own*Return	-0.00400	0.0143	0.0736	0.00372	0.106
	(-0.05)	(0.15)	(1.01)	(0.04)	(1.39)
Return	0.491***			-0.0513	-0.0468
	(7.26)			(-0.72)	(-0.73)
Own	0.855	0.911	1.022	0.941	1.112
	(0.77)	(0.73)	(0.82)	(0.83)	(0.91)
Ret x Round FE	No	Yes	Yes	No	No
Subject FE	No	No	Yes	No	Yes
R^2	0.144	0.227	0.607	0.00215	0.496
Observations	3102	3102	3102	3102	3102

Table V

Difference Across Attentional Study and the Main Study

This table shows how beliefs and extrapolation vary in the attentional study. Panel A explores beliefs and belief errors based on returns while Panel B explores the degree of extrapolation based on a positive price signal the prior period. Regressions include the main study and the data from the attentional study. *No Own Treat* is equal to one if the data is from the treatment condition. *Own* is equal to one if the good is owned and the observation is from the main study. Regressions also include *No Own Treat* and *Own* dummy variables. Columns labeled Belief examine raw beliefs while columns labeled Belief Error examine belief errors relative to a Bayesian. The attentional treatment uses the Continuous treatment, so only data from the Continuous treatment in the main study is used in this analysis. Fixed Effects are indicated in the bottom row. Standard errors are clustered by subject, and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Returns

	Belief		Belief Error
	(1)	(2)	(3)
(No Own Treat)*Return	0.170***	0.185***	0.178***
	(3.63)	(4.01)	(3.98)
Own*Return	0.0715***	0.116***	0.0986***
	(2.95)	(5.28)	(4.68)
Return	0.505***		-0.0230
	(22.23)		(-1.09)
Ret x Round FE	No	Yes	No
R^2	0.343	0.403	0.00905
Observations	40275	40275	40275

Panel B: Extrapolation

	Belief		Belief Error
	(1)	(2)	(3)
(No Own Treat)*(Price Increase)	3.570*	4.811***	4.707***
	(1.85)	(3.46)	(3.42)
Own*(Price Increase)	4.980***	4.208***	3.781***
	(6.41)	(6.37)	(6.02)
Price Increase	12.64***	-3.219***	-1.157**
	(18.82)	(-5.50)	(-1.99)
Ret x Round FE	No	Yes	No
R^2	0.0967	0.410	0.00356
Observations	37590	37590	37590

Table VI

Recall and Ownership

This table explores the relationship between recall, absolute value of returns and ownership. A dummy variable equals one if the direction of the signal is recalled correctly, is regressed on the absolute value of returns, the *Own* dummy variable in Columns 2 through 4. Columns 2 through 4 include a fixed effect for the absolute value of fundamental quality minus 0.5. Column 3 includes observations where the most recent signal realization and the previous signal match. Column 4 includes observations where they do not match. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All		Match	No Match
	(1)	(2)	(3)	(4)
Own		0.118*	0.161**	-0.00368
		(1.90)	(2.30)	(-0.04)
Absolute Value of Return	0.00536***	0.00353	0.00199	-0.0107
	(3.18)	(1.42)	(0.79)	(-1.46)
ABS Quality	No	Yes	Yes	Yes
Observations	268	268	149	119

Table VII

Endowment Effect Updating based on Ownership

This table shows how the value of a good varies with ownership based on its ratings. *Own* is a dummy variable equal to one if the subject was endowed with the good. *Rating* is the average star rating for a product in that round. *Last Rating* is the most recent rating. Fixed effects are indicated below the regression results. Regressions in the all studies column contain a fixed effect for the treatment. Standard errors are clustered by subject, and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative Rating

	(1)	(2)	(3)	(4)	(5)
Own*Rating	3.783***	1.405**	3.786***	3.771***	1.334*
	(3.39)	(2.03)	(3.39)	(3.37)	(1.95)
Rating	2.391***	3.591***	2.323***		
	(3.49)	(6.68)	(3.34)		
Own	3.620***	4.688***	3.607***	3.548***	4.640***
	(2.98)	(3.93)	(2.97)	(2.92)	(3.90)
Subject FE	No	Yes	No	No	Yes
Round FE	No	No	Yes	No	No
Review x Round FE	No	No	No	Yes	Yes
R^2	0.121	0.635	0.124	0.130	0.644
Observations	2650	2650	2650	2650	2650

Panel B: Last Rating

	(1)	(2)	(3)	(4)	(5)
Own*Last Rating	1.757***	0.890***	1.714***	1.723***	0.849***
	(5.41)	(3.96)	(5.28)	(5.31)	(3.88)
Last Rating	2.286***	2.723***	2.535***		
	(8.17)	(10.59)	(8.08)		
Own	3.525***	4.132***	3.569***	4.032***	4.644***
	(2.89)	(3.36)	(2.96)	(3.54)	(4.06)
Subject FE	No	Yes	No	No	Yes
Round FE	No	No	Yes	No	No
Review x Round FE	No	No	No	Yes	Yes
R^2	0.0837	0.611	0.0862	0.117	0.644
Observations	2650	2650	2650	2650	2650

Table VIII

Field Data Extrapolation by Ownership

This table shows how extrapolation of prior market performance varies with ownership. Panel A examines the probability of a stock market increase over the next 12 months and Panel B examines a dummy variable equal to one if this is greater than 50. Prior market return is from month -m to -1, with m indicated in each column. *Own* is a dummy variable equal to one if the subject owns stocks. Demographics indicate fixed effects for income, age, race, marital status and education. Standard errors are clustered by month, and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Probability of Increase

	3 Month=m		6 Month=m		1 Year=m		2 Year=m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own*Mkt[-m,-1]	17.85***	18.99***	18.22***	18.86***	14.16***	14.61***	8.427***	8.516***
	(4.28)	(4.41)	(8.49)	(8.90)	(8.47)	(8.89)	(7.63)	(7.65)
Mkt[-m,-1]	14.22***	13.89***	9.857***	9.775***	9.734***	9.217***	7.366***	7.140***
	(2.73)	(3.42)	(2.90)	(3.56)	(4.78)	(5.74)	(5.04)	(6.25)
Own	13.26***	8.074***	12.75***	7.562***	12.20***	7.010***	11.97***	6.833***
	(47.87)	(30.48)	(48.50)	(29.45)	(41.02)	(24.60)	(33.82)	(20.32)
Demographics	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.0514	0.112	0.0546	0.116	0.0591	0.120	0.0601	0.121
Observations	98828	92264	98828	92264	98828	92264	98828	92264

Panel B: Increase Probability >50

	3 Month=m		6 Month=m		1 Year=m		2 Year=m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own*Mkt[-m,-1]	0.240***	0.253***	0.243***	0.247***	0.182***	0.183***	0.105***	0.104***
	(3.98)	(4.01)	(7.29)	(7.16)	(6.69)	(6.80)	(5.68)	(5.64)
Mkt[-m,-1]	0.209**	0.204***	0.149***	0.151***	0.154***	0.151***	0.116***	0.114***
	(2.44)	(2.88)	(2.77)	(3.37)	(4.66)	(5.58)	(5.05)	(6.20)
Own	0.190***	0.108***	0.183***	0.101***	0.176***	0.0950***	0.174***	0.0931***
	(43.23)	(23.89)	(42.31)	(22.12)	(34.62)	(18.29)	(29.00)	(15.92)
Demographics	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.0395	0.0910	0.0419	0.0935	0.0454	0.0968	0.0462	0.0973
Observations	98828	92264	98828	92264	98828	92264	98828	92264