Heterogeneous Tastes and Social (Mis)Learning

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Abstract

We experimentally examine the degree to which people successfully engage in social learning in the presence of naturally occurring heterogeneous tastes. In this setting, properly extracting information from other people's actions requires an observer to account for how her predecessors' idiosyncratic tastes may have influenced those actions. We find support for social learning that obeys some basic comparative statics predicted by the rational model. However, we also find significant and systematic errors. Participants systematically over-infer or under-infer from others' behavior when that behavior is weakly or strongly predictive of the underlying state, respectively. This pattern of misinterpreting others' actions is consistent with participants overweighting the likelihood that others have tastes similar to their own. Information about others' taste does not eliminate these mistakes in inferences.

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1 Introduction

Economists have long understood that others' actions provide a valuable source of information. But there are exceptionally few instances where our choices do not in some way depend on our idiosyncratic preferences, and this poses a challenge for extracting information from others' actions. Proper inference requires us to account for how others' actions were driven by private information versus their particular tastes. Did your neighbor buy a new model of car because she had information that it performs well, or did she simply have a taste for that style or brand? Is the new restaurant really that good, or are many people just partial to that type of cuisine? We conduct an experiment to investigate how agents' heterogeneous tastes—and their perceptions of others' tastes—may impede information transmission.[1]

The following example illustrates the basic logic of our experiment. In particular, it highlights how the information conveyed by others' actions depends on an observer's perceptions of others' tastes, and how biased perceptions can distort social learning. Suppose a potential home-buyer observes another interested party back out of a purchase agreement. This observer must disentangle whether the other would-be buyer walked away because she received bad information about the house (e.g., a failed inspection) or if she simply disliked some feature after further reflection. If the observer over-estimates the likelihood that the person enjoys the look or style of the house, he will conclude that the potential buyer likely had some negative private information about the house—otherwise the deal would have gone through. Thus, the observer's beliefs over-react to the other person's action. In contrast, if the observer *under*-estimates the likelihood that the other person enjoys the house's aesthetics, his beliefs will under-react: he thinks most buyers would have walked away regardless of their private information. Clearly, one's perception of the distribution of tastes in the population dictates how they interpret others' actions.

In this paper, we examine the degree to which people successfully engage in social learning when there is naturally occurring heterogeneity in tastes.[2] To do so, we employed a three-stage field-in-the-lab experiment with sequential observational learning in which participants faced uncertainty about the nominal value of a gift card. In the first stage, we introduced participants to the

[1]Some models of social learning and herding (e.g., Banerjee, 1992; Bikhchandani et al., 1992) focus on idealized settings with common preferences to demonstrate how information may fail to aggregate even in the absence of realistic frictions such as heterogeneity in preferences. However, these frictions may be of first-order importance if they cause people to systematically misinterpret others' private information. Theoretical studies of social learning with heterogeneous tastes have examined both rational learning (e.g., Smith and Sørensen, 2000; Goeree et al., 2006) and biased learning that arises from improperly controlling for heterogeneity (e.g., Gagnon-Bartsch, 2016; Frick et al., 2020; Bohren and Hauser, 2021; Gagnon-Bartsch and Rosato, 2023). Relatedly, Gagnon-Bartsch et al. (2021) study misinference in open-outcry auctions when bidders have misspecified models of others' tastes.

[2]Prior experimental studies of social learning abstract from complications introduced by heterogeneous tastes by focusing on settings with induced common preferences (e.g., Anderson and Holt, 1997; Kübler and Weizsäcker, 2004; Çelen and Kariv, 2004; Goeree et al., 2007; Eyster et al., 2018).

seven American businesses—subsequently indexed by k—and asked a few simple survey questions about about their preferences and their perceptions of others' preferences. These surveyed tastes exhibited significant heterogeneity.

In the second stage, participants made a series of choices between a gift card and a cash bonus $x \in \{\$30, \$40, \$50\}$. We call the pair of cash bonus and business faced, (x, k), a "decision problem," and participants faced a variety of decision problems. In each, participants were uncertain about the value of the card—it contained either \$20 or \$100—and were given a private, binary, noisy signal of this underlying state. For each business, participants made choices after both possible signal realizations.

In the third "social-learning" stage of the experiment, participants observed others' privately-informed choices (either to accept the gift card or take the cash bonus) across a variety of decision problems, and we elicited their beliefs about which of the two signals the previous actor received. The fundamental challenge—which mirrors the home-buyer example above—is that these observers needed to consider, for instance, whether a given actor rejected a card because they received a bad signal or because they simply disliked that particular business. We also elicited what the second-movers would choose if they were facing the same decision problem as the actor they observed. They were not given a private signal themselves and thus had to rely on information gleaned from the observed action. As noted above, our exploration of the role of heterogeneous tastes on information transmission is built on the straightforward observation that inferences and choices in the second stage should depend on participants' beliefs about the tastes of the previous actor.

Our results offer four primary punchlines. First, despite the complexities of this learning environment, we find support for some social learning, and participants' inferences obey a few simple comparative statics predicted by the rational model. After observing another person choose the gift card rather than the bonus cash, participants (i) correctly infer that the other person likely received a positive signal about the value of the gift card, and (ii) make choices that largely align with what they would have done had they directly observed the signal themselves. Furthermore, participants' inferences are sensitive to the magnitude of the cash bonus—when this bonus is larger, observers become less confident that an actor who chose the cash over the gift card received a negative signal about the card. Finally, when armed with information about the actor's taste, observers correctly exhibit a form of sophisticated inference wherein they put less weight on the actor having received a positive signal the more the actor enjoys the business in question.

But our second conclusion is that, despite these successes, we find significant and systematic departures from rational social learning. Our evidence can be broadly categorized as *under-inference* from behavior that ought to provide a strong signal about the underlying state and *over-inference* from behavior that provides a weak signal. For example, although participants essentially only choose the gift card after getting a positive signal about the card's value, observers nearly universally fail to understand *how* informative the choice of taking the card is. In contrast, when a participant turns down the gift card in favor of the bonus cash, observers infer that the likelihood of the positive signal is too low. This is consistent with the patterns documented by Augenblick et al. (2023) in both the lab and field.[3] We provide a theoretical framework that highlights how an observer's (mis)perceptions of the distribution of preferences dictates the informativeness of others' actions, and we show theoretically how belief updating depends on these misperceptions. We provide multiple pieces of evidence—stemming from survey responses, elicited beliefs, and choices—suggesting that such misperceptions may drive inferences our experiment.

Our third conclusion is that the degree to which a person infers from others' behavior is closely related to their own taste. More specifically, participants in our experiment seem to exhibit an egocentric bias in their perceptions of others' tastes and subsequently infer as if others share their taste. A key feature of our experimental design—which allows us to shed light on this egocentric bias—is that the relatively complicated space of preferences can be reduced based on how an actor responds to their private information. As mentioned above, participants in the first stage of our experiment saw a binary signal about the value of the gift card and then made a choice whether to take the card or bonus cash. Furthermore, participants made privately-informed choices after both signal realizations. We can therefore characterize each person into one of three primary "strategic types": those who take the gift card regardless of their signal, those who take the gift card only after getting a positive signal, and those who do not take the gift card (favoring the bonus cash) regardless of their signal.[4] Critically, these same participants subsequently observed the actions of others and made predictions based on those actions. We can therefore analyze how participants' inferences from others in the second stage depended on their own strategic type in the first stage.

To highlight the degree to which inferences depend on participants' own tastes, we first show that participants' choices—and thus strategic types—vary across the businesses in the study. Aggregating over these businesses (and the varied bonus cash offerings), approximately half of participants took the gift card after a positive signal. In contrast, almost no participants took the card after a negative signal, meaning that choices were highly informative of the signal received and participants were primarily categorized into just two strategic types: those who followed their signal and those who always chose the bonus cash (see Table 2 for detail). We next show that these strategic types shaped inferences. Specifically, participants who themselves took the card after the positive signal inferred more from others' actions. Finally, we show that these type-based inferences are consistent with an egocentric bias in which people project their own type onto others—that is,

[3]See also Ba et al. (2022) and Fan et al. (2023) for recent papers that examine over- and under-inference.

[4]Note that the proportions of these three strategic types form a sufficient statistic for rational Bayesian updating in our setting. This allows us to simply calculate the fully-informed Bayesian benchmark in each decision problem in our experiment. We expand on this in Section 3.

participants infer as if others respond to the private signals in the same way they do. We interpret this pattern of data as stemming from an error in beliefs about others wherein observers (wrongly) believe that others share their taste more than they actually do.

Fourth and finally, we demonstrate that the errors in learning that we document persist even when observers have additional information about others. In a second experiment, we armed participants with highly informative signals about others' tastes. More specifically, for each decision problem, the observer saw the subjective rating of the business (ranging from "negative" to "strongly positive") from the person whom they were observing. Returning to the home-buyer example from above, this is akin to giving the observer some useful demographic information about the party who walked away. Despite this added information, inferences largely follow the patterns described above. We show that a few highly informative signals perhaps improve inferences, but on the whole, inferences are actually worse than in our first experiment.

Our experiment is a significant departure from prior experiments on sequential social learning in which agents either have common preferences or tastes induced by the experimenter.[5] By examining choices over gift cards, we introduce naturalistic variation in tastes; in this sense, our paper contributes to this literature by taking a field-in-the-lab approach to studying belief updating when agents have heterogeneous tastes. In an additional departure from most of this literature, we elicit observers' beliefs along with their actions in a social-learning setting.[6] As our results in Section 4.3 demonstrate, this is a critical step that allows us to disentangle the degree to which accurate or biased social learning occurs.

Given that we find people wrongly learn from others as if others share their tastes, we also contribute to a large body of research on "social projection bias" and the "false-consensus effect" showing that people often perceive their own tastes and attitudes as more common than they really are. The seminal study by Ross et al. (1977)—along with numerous studies that followed—find a positive correlation between subjects' own stated preferences and their estimates of others' preferences across many domains (e.g., art, sports, food, consumer products, politics, risk).[7] While this correlation may be rational when there is uncertainty about others' preferences (Dawes, 1989,

[5]Following Anderson and Holt (1997), many subsequent experiments studied modifications of the canonical observational-learning setup yet maintained common or induced preferences; see, e.g., Hung and Plott (2001); Nöth and Weber (2003); Kübler and Weizsäcker (2004); Çelen and Kariv (2004) and Goeree et al. (2007).

[6]Other experiments in this area that also elicit beliefs—or involve finer action spaces that more precisely reveal beliefs—include Çelen and Kariv (2004); Dominitz and Hung (2009) and De Filippis et al. (2022).

[7]Marks and Miller (1987) document the false-consensus effect in 45 studies published in the decade following Ross et al. (1977), and Mullen et al. (1985) find robust evidence of the effect in a large meta-study. More recently, Bursztyn and Yang (2022) find that correlations consistent with the false-consensus effect are widespread in a meta-analysis of economics field studies. Evidence on the false-consensus effect also spans a broad range of domains, including political preferences (e.g., Brown, 1982; Delavande and Manski, 2012), preferences over income redistribution (e.g., Cruces et al., 2013), risk preferences (e.g., Faro and Rottenstreich, 2006), and taste for effort (Bushong and Gagnon-Bartsch, 2023).

1990; Prelec, 2004), later studies suggest that these perceptions reflect a systematic bias, whereby subjects weight their own preference too heavily relative to information about others' preferences when making predictions about others (e.g., Krueger and Clement, 1994). In incentivized economics experiments, Engelmann and Strobel (2012) and Ambuehl et al. (2021) similarly find that a false-consensus bias remains if subjects must exert minimal effort to view information about others' choices. In a related vein, Bushong and Gagnon-Bartsch (2023) find that participants in a real-effort context project their current sense of fatigue onto others. While these and other papers show that people may mispredict others' tastes, our experiment examines how these mispredictions influence people's interpretation of others' actions and how those inferences shape subsequent choices.

Our experiment is also related to the theoretical literature on misspecified social learning. This literature considers several ways in which agents misunderstand how others' actions incorporate or reflect their private information. For instance, Eyster and Rabin (2010) and Bohren (2016), among others, examine how neglecting the redundancy of information in others' actions can lead society to grow convinced of a false state. Similar to our premise, Bohren and Hauser (2021) and Frick et al. (2020) analyze learning among agents who misperceive the distribution of types in the population they observe. And most closely related to our study, Gagnon-Bartsch (2016) and Gagnon-Bartsch and Rosato (2023) specifically examine social learning among agents who think others share their tastes. Gagnon-Bartsch and Rosato (2023) derives comparative statics that bear out in our data. Namely, when participants see a predecessor reject the gift card, those participants who enjoy that business more believe the predecessor is less likely to have received a positive signal about the card's value.

More broadly, our results suggest the importance of better understanding how people engage in social learning in the presence of heterogeneity, especially given that it arises in many familiar and important contexts across fields. Consider a canonical setting for social learning: the choice of whether and where to attend university. It is well-documented that these choices are shaped by both information about future returns and by idiosyncratic tastes. Although the focus of much effort has been on disseminating information about the future returns to education, students' idiosyncratic tastes (e.g., a preference for schools that have strong athletic programs) may provide a friction to information aggregation. This may help explain why students' beliefs vary widely regarding whether to attend school, where to attend school and, conditional on attending a particular school, the returns to a given major or degree program (Jensen, 2010; Wiswall and Zafar, 2015; Conlon, 2019; Delavande and Zafar, 2019). Beyond education, there are numerous domains where social learning plays a documented role in consumer choice despite differing tastes or motives, including investment products (Bursztyn et al., 2014), insurance plans (Sorensen, 2006), music (Hendricks et al., 2012), films (Moretti, 2011), and restaurants (Cai et al., 2009).

The paper proceeds as follows. In Section 2, we describe our experimental design. We then provide a theoretical framework in Section 3 and highlight some predictions of both rational and biased social learning. In Sections 4 and 5, we discuss the results from Experiments 1 and 2, respectively. We conclude and discuss some further applications of our results in Section 6.

2 Experimental Design

In this section, we present our experimental design. We conducted a pair of online experiments on Prolific with $n = 456$ total participants. In both experiments, participants made simple choices about gift cards to various common American businesses. Since the second experiment is a slight modification of the first, we begin by detailing our first experiment and then quickly describe the second by highlighting how it differs.

2.1 Experiment 1

Participants ($n = 229$) were recruited from the Prolific online panel and were restricted to those residing in the United States. Participants were required to have completed at least 100 previous tasks on Prolific to register for our study.

All participants in our experiments participated in two primary roles: an "actor" and an "observer." As we detail below, actors made a series of privately-informed decisions. Observers then saw choices made by actors, and we elicited the observers' updated beliefs about an unknown state of the world conditional on those observed choices.

Given that subjects participated in various roles, our experiment took place over several stages. There were three stages in total, and all participants completed each stage in the same order. In each stage, participants faced a series of decisions that involved gift cards. The gift cards were non-expiring cards to one of seven common American businesses: AMC Theatres, Amazon, Chick-fil-A, Home Depot, Old Navy, PetSmart, and Starbucks.

Stage 1: Basic Preference Information. In this stage, participants answered four survey questions about each of the seven businesses in our study. They first answered a simple yes/no to the following: "Have you or anyone in your household bought something from this business in the last five years?" They next provided a subjective rating of each shop by answering the following question: "Using the scale below [which took on four values ranging from 'negative' to 'strongly positive'], describe your attitudes toward this business and its product(s)." Third, participants guessed the distribution of subjective ratings amongst all participants in the experiment. Fourth, we elicited participants' valuation for a gift card for $100. We did not incentivize responses in this stage.

Stage 2: Actor Stage. In the Actor Stage, participants made a series choices between gift cards and bonus cash. In these decision problems, they additionally faced uncertainty over the nominal value of the gift card, which we denote by ω. The value ω varied independently across each decision trial, and it was either $\omega = \$100$ (which we call the "high-value state") or $\omega = \$20$ ("low-value state"). In every trial, the two states were ex-ante equally likely and this was communicated to participants. Prior to each choice, actors were also provided with a partially informative binary signal $s \in \{20, 100\}$ which accurately reflected the current state with probability $\phi = \frac{3}{4}$. That is, $\Pr(s = z|\omega = z) = \phi$ for each $z \in \{20, 100\}$. After receiving a signal, participants chose between the gift card and a cash bonus of a known amount. We label these actions "accept" (or $a = A$) and "reject" (or $a = R$), respectively. See the middle panel of Figure 1 for a visual representation of this choice.

As noted in the introduction, we varied the size of the cash bonus across the decision trials. In each trial, actors faced a choice between some amount of bonus cash $x \in \{30, 40, 50\}$ and the gift card. To limit the total number of questions in the experiment, each participant faced just two values of x, randomized at the shop level. That is, for a given business, participants faced either $x \in \{30, 40\}$ or $x \in \{40, 50\}$. Thus, all participants answered questions that involved $x = 40$.

By varying the size of the bonus across questions, we implicitly altered the share of participants who might choose the gift card over the bonus. For instance, suppose the bonus was \$50. Since a gift card is worth (weakly) less than its cash equivalent, it is immediately apparent that risk-neutral or risk-averse participants facing this scenario would not take the gift card if they were sufficiently confident that the card was in the low-value state.

Overall, participants faced many decision trials in the Actor Stage. For each of the seven businesses, they decided between the gift card and bonus cash upon receiving both the good signal ($s = 100$) and the bad signal ($s = 20$). And they repeated these decisions for two different amounts of bonus cash. Thus, each participant made 28 decisions in the Actor Stage (7 business $\times$ 2 signal realizations $\times$ 2 cash amounts). To incentivize these decisions, participants were told that one out of every twenty participants would have a choice implemented for real. If they were chosen, one of their decisions from the Actor Stage would be selected at random to determine their payoff from this stage (e.g., if they chose the gift card in that randomly-selected choice, then they would receive a gift card to that business for ω dollars.)

Stage 3: Observer Stage. In this stage, a participant saw choices that others made during the Actor Stage. For each observed choice, the participant guessed the probability that the actor received the high-value signal. More specifically, for each choice, the observer saw the amount of bonus money on offer and saw whether the actor took the gift card or the bonus money; the observer *did not* see the actor's private signal. The observer then used a slider to indicate their posterior belief that the actor received the high-value signal in that particular decision (see Figure 1). Each observer completed a series of such guesses, each time facing a randomly-drawn anonymous actor. Observers were paid according to the accuracy of their predictions using the binarized scoring rule.[8]

For each trial in this third stage, the observer also made a choice for themselves within the same decision problem faced by the actor in that trial. Since the observer did not receive a signal about the card, they had to use the information revealed from the actor's decision to inform their choice. For instance, if the observer saw that an actor chose between \$40 and a card to Starbucks, then the observer also chose between \$40 and that same gift card the actor faced.[9] This aspect of our design mirrors the second round of canonical experimental designs for sequential-action social learning. These choices were incentivized identically to the choices in the Actor Stage.

To summarize, the timeline within each trial of the observer stage is as follows: (i) the observer saw the decision problem faced by an actor and the actor's choice; (ii) the observer guessed the likelihood that this actor received the high-value signal; (iii) the observer stated what they would choose in the same decision problem.

While in most trials observers were told the identity of the shop prior to making a guess, in a small number of trials we masked the shop identity and replaced the salient logo in Figure 1 with a question mark (see Appendix for full experimental instructions). In this "unknown" case, observers were reminded that actors knew the shop identity when making decisions. Moreover, observers were (truthfully) told that the data revealed in unknown-shop trials was uninformative about the identity of the particular shop in any given trial.

In total, participants in the Observer Stage faced $28 + 6 = 34$ trials. 28 of these comprise each combination of business (7), amount for the cash bonus the actor faced (2), and actor choice (2). The six additional trials represent the "unknown shop" case for each combination of cash bonus ($x \in \{30, 40, 50\}$) and actor choice. The order of the trials were randomized.

As we emphasize below, the inferences that observers draw from actors' choices should depend on the distribution of others' preferences. Observers may naturally face uncertainty about this distribution. Thus, observing the choices of actors could, in theory, provide information about this distribution. For instance, if an observer was shown choice data in which many actors chose to accept the gift card over the cash bonus, the observer might reasonably infer that others quite enjoy the shops used in our study. To avoid influencing participants' beliefs in this manner, our experimental design took measures to limit this form of learning: the choice data we showed ob-

[8]Following the guidance of Danz et al. (2022), our experimental instructions first described the observer's objective in intuitive terms, and we relegated detailed information on the payment mechanism to a separate screen in the instructions. See the Online Appendix for the experimental instructions.

[9]The value on the card faced by the observer was known to be perfectly correlated with that on the card faced by the actor. So, if the actor had received a high-value signal about their card, then the card in the observer's decision problem also had a 75% chance of having the high value.

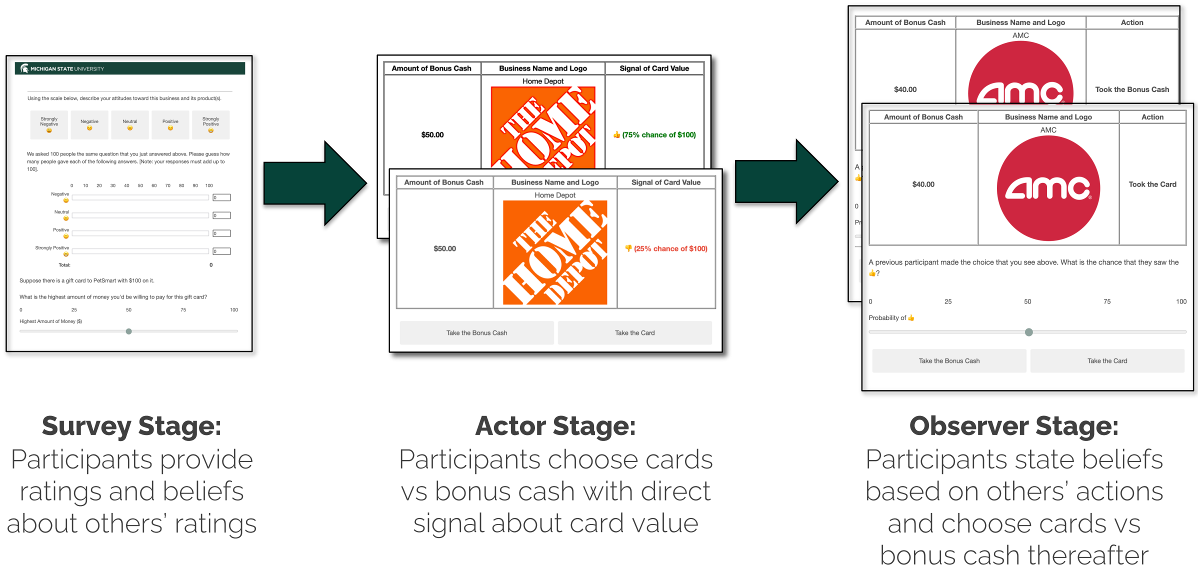

Figure 1: Overview of Experiments 1 and 2. *In the first stage, we elicited basic preference information from participants. Next, we asked participants if they would choose a gift card or cash after receiving a noisy signal about the value of the card. Finally, we asked participants about their inference from others' choices.*

servers during the belief-elicitation trials was chosen in a predetermined way so that it revealed no information about actors' preferences. We informed observers about this during the instructions, emphasizing that the data they would see was *not* a representative sample of actors' choice behavior.[10]

Finally, after the three stages described above, our experiment concluded with a short series of demographic and attention-check questions. Figure 1 provides a flow chart of the three main stages of the experiment.

Discussion. The purpose of the Actor Stage is threefold. First, it yields the privately-informed choices that uninformed observers learned from in the Observer Stage. Second, it provides us with a baseline measure of how participants responded to information. Choices in the Actor Stage reveal how people decided when they received direct signals about the gift-card's value, whereas the Observer Stage reveals how people decided when they received indirect information filtered through others' actions. Third, having all participants complete the Actor Stage means that participants in

[10]More specifically, the data that an observer encountered during the belief-elicitation trials was chosen such that for each shop k, the observer saw both possible actions for a given x. That is, they saw exactly one actor accept the card ($a = A$) and another reject it ($a = R$). This elicitation procedure is similar to the strategy method: we asked each observer for their updated beliefs conditional on each possible combination of the observables (i.e., shop identity, bonus cash, and actor choice). We described this procedure to observers prior to eliciting their beliefs, and thus they knew that they would see precisely 50% of actors accept the card and 50% reject it for each shop (including the "unknown" shop). Consequently, observers should not have used actors' choices to update their beliefs about the distribution of preferences.

the Observer Stage had already been in the role of an actor. Thus, they had first-hand familiarity with actors' choices and presumably understood how their decisions may have depended on their signals. An understanding of this mapping is crucial for drawing inference from others' actions.

The Observer Stage allows us to assess how observers form beliefs about the state based on others' actions. Moreover, the choice data from observers allows us to analyze the degree to which observers act on the information they glean from others' decisions.

2.2 Experiment 2

Experiment 2 was identical to Experiment 1 except that we varied the amount of information we provided participants ($n = 226$) in the Observer Stage prior to making their predictions about the actors' signals. For each trial in the Observer Stage of Experiment 2, we told the observer the subjective rating of the actor who made the decision they were observing. That is, in addition to seeing an actor's choice, observers also saw her subjective rating of the shop at hand. Furthermore, we restricted the bonus cash to $x = \$40$ in the Observer Stage of Experiment 2 to increase statistical power. Finally, to limit the number of questions, observers saw a random subset of all possible combinations of ratings, choices, and businesses.[11] In total, participants made 48 inferences. Stages 1 and 2 of Experiment 2—along with all other aspects of Stage 3—were the same as in Experiment 1.

3 Theoretical Framework

We now provide a simple model of observational learning within our setting and formalize various predictions. The baseline model considers rational learning, and we discuss how it simply extends to capture forms of biased learning. We use this model to guide our empirical analyses in the following sections.

3.1 Observational Learning with Heterogeneous Tastes

Following our experimental design, we consider an observational-learning context with binary actions and a binary payoff-relevant state. We primarily focus on just two players: a privately-informed "actor" (Player 1) takes an action, and an "observer" (Player 2) sees this action. We analyze the observer's updated belief about the state conditional on the actor's action.

[11] As in Experiment 1, our experimental instructions described how the observed data was selected. The combinations were drawn uniformly so that the observed data provided no information about the aggregate choice behavior and preferences in the population (similar to the procedure discussed in Footnote 10).

Actions, States, and Decision Problems. In each decision problem, an actor must decide between two options: (i) a gift card specific to a particular shop or (ii) a monetary bonus of $\$x$ that will be added to their experimental payment. We denote the actor's decision by $a \in \{A, R\}$, where A signifies accepting the gift card, and R represents taking the bonus payment (i.e., rejecting the gift card). The value of the gift card can be one of two amounts, $\omega \in \{h, l\}$, with $h > l$. Both states have an equal probability of occurring, and this is common knowledge.

We index the shops in our setting by k, and we label a *decision problem* by (x, k). Hence, (x, k) describes the monetary bonus and the particular gift card that the actor chooses between.

Preferences. We assume players have differing preferences over shops. Thus, even if the amount on a gift card were known, some may favor the gift card over the monetary bonus, while others may have the opposite preference. We denote the actor's valuation for the gift card to shop k in state ω as $v_k(\omega)$, with her value of the bonus being simply x. We can interpret $v_k(\omega)$ as the cash amount at which the player would be indifferent between a guaranteed payment of that amount and taking the gift card in state ω. We assume that preferences are monotonic in ω—$v_k(h) > v_k(l)$ for all k—and that gift cards are weakly less desirable than their face value in cash—$v_k(\omega) < \omega$ for all k and ω.

Actor's Private Information and Decision Rule. The actor receives a signal $s \in \{h, l\}$ correlated with the state. This signal is symmetric and has a precision of $\phi > 1/2$; in other words, $\Pr(s = h|\omega = h) = \Pr(s = l|\omega = l) = \phi$ and $\Pr(s = l|\omega = h) = \Pr(s = h|\omega = l) = 1 - \phi$. Let $\mu(s)$ represent the actor's belief in state $\omega = h$ given s. Under this structure, if the actor's beliefs adhere to Bayes' Rule, then $\mu(h) = \phi$ and $\mu(l) = 1 - \phi$. In our experimental design, we set $\phi = 3/4$.

We assume the actor's decision rule maximizes her expected utility: she opts for the card iff $\mu(s)v_k(h) + [1 - \mu(s)]v_k(l) > x$. Given our binary-signal environment, this condition implies that the actor's behavior in a given decision problem (x, k) is described by one of three "strategic types":

(i) *Always-Cash* types choose the cash bonus regardless of their signal;

(ii) *Signal-Dependent* types choose the card if and only if $s = h$;

(iii) *Always-Card* types choose the gift card regardless of their signal.[12]

Observer's Beliefs. The observer sees an anonymous actor's action, a, for each decision problem—that is, they see the action taken when facing shop k and cash bonus x. The observer then updates their belief about the likelihood that the actor received the signal $s = h$. We denote this updated belief by $\pi_{x,k}(a)$. Crucially, this belief relies on the observer's beliefs about the actor's preferences.

[12] An additional type is possible if we allow for irrational behavior: a *Mistaken* type chooses the card if and only if $s = l$. Our theoretical predictions will focus on the case where mistaken types are not present and players are aware of this.

Moreover, Bayesian updating in this environment depends solely on the likelihood the observer attaches to each of the "strategic types" mentioned above. Let $p_{x,k}$, $q_{x,k}$, and $1 - p_{x,k} - q_{x,k}$ represent the observer's assessed probability that the actor is an always-card type, a signal-dependent type, and an always-cash type, respectively, given shop k and cash bonus x. With these (potentially inaccurate) subjective probabilities, the observer's beliefs about the likelihood that the actor received $s = h$ after applying Bayes' Rule are:

$$\pi_{x,k}(A) = \frac{p_{x,k} + q_{x,k}}{2p_{x,k} + q_{x,k}} \quad \text{and} \quad \pi_{x,k}(R) = \frac{1 - p_{x,k} - q_{x,k}}{2(1 - p_{x,k}) - q_{x,k}}. \tag{1}$$

It's important to note that $p_{k,x}$ and $q_{k,x}$ are sufficient to capture the observer's beliefs: the observer need not separately consider risk attitudes or other aspects of taste (e.g., idiosyncratic preferences for the business or gift cards in general) beyond how they influence these proportions. Note further that by eliciting an observer's beliefs when they see someone accept the gift card in one trial and again in a separate trial when they see someone refuse it—i.e., by measuring both $\pi_{x,k}(A)$ and $\pi_{x,k}(R)$ while holding all other information constant—we can use the two equations in (1) to uncover the observer's subjective assessment of $p_{x,k}$ and $q_{x,k}$.

Finally, our variation in the value of the cash bonus across decision problems allows us to test a simple comparative static predicted by rational learning: an observer's belief $\pi_{x,k}(a)$ should increase in x. Intuitively, when x is larger, an actor becomes less willing to select the gift card. Thus, seeing the actor choose the card more strongly indicates that the actor received the good signal, which increases $\pi_{x,k}(A)$. By contrast, seeing them reject the card sends a weaker indication that the actor received the bad signal, which also increases $\pi_{x,k}(R)$. We examine this prediction in Section 4.3.

3.2 Beliefs About Others and Erroneous Inferences

In this section we allow for the possibility that people make mistakes when updating their beliefs and show how this may arise in our environment when people have distorted perceptions of others preferences. In our setting with a binary state, mistakes manifest as what appears like either over-reaction or under-reaction relative to the Bayesian benchmark. To measure these biases, we employ the framework from Grether (1980) as presented in Benjamin (2019). This involves examining whether the observer's updated beliefs, $\pi_{x,k}(A)$ and $\pi_{x,k}(R)$, deviate systematically from the beliefs that would be expected under Bayesian updating with complete information about the distribution of strategic types.

More formally, let $\bar{p}_{x,k}$ and $\bar{q}_{x,k}$ denote the true population frequencies of always-card and signal-dependent types, respectively. Writing updated beliefs in terms of log-odds, we can explore over-and under-reaction relative to the Bayesian benchmark with a set of two simple equations:

$$\ln\left(\frac{\pi_{x,k}(A)}{1-\pi_{x,k}(A)}\right) = c_A \cdot \ln\left(\frac{\bar{p}_{x,k}+\bar{q}_{x,k}}{\bar{p}_{x,k}}\right), \tag{2}$$

$$\ln\left(\frac{\pi_{x,k}(R)}{1-\pi_{x,k}(R)}\right) = c_R \cdot \ln\left(\frac{1-\bar{p}_{x,k}-\bar{q}_{x,k}}{1-\bar{p}_{x,k}}\right). \tag{3}$$

The left-hand side of Equations 2 and 3 is an observer's stated belief (in log-odds form) after observing an actor's choice, and the term on the right-hand side is the Bayesian belief scaled by c_A or c_R, which are constants measuring the degree of over- or under-reaction. After observing action $a \in \{A, R\}$, we say that an observer exhibits over-reaction ($c_a > 1$) when they place too much apparent weight on the new information, resulting in updated beliefs that are more extreme than warranted by the Bayesian benchmark. Conversely, under-reaction ($c_a < 1$) occurs when the observer does not update their beliefs enough based on the new information, leading to updated beliefs that are less extreme than the Bayesian benchmark would predict.

One reason we may see apparent deviations from the Bayesian benchmark is that people have the wrong beliefs about the relative prevalence of types in the population. We can see this more clearly by writing $\pi_{x,k}(A)$ and $\pi_{x,k}(R)$ in Equations 2 and 3 in terms of an observer's perceived frequencies of types, as in Equation 1:

$$\ln\left(\frac{p_{x,k}+q_{x,k}}{p_{x,k}}\right) = c_A \cdot \ln\left(\tfrac{\bar{p}_{x,k}+\bar{q}_{x,k}}{\bar{p}_{x,k}}\right), \tag{4}$$

$$\ln\left(\frac{1-p_{x,k}-q_{x,k}}{1-p_{x,k}}\right) = c_R \cdot \ln\left(\tfrac{1-\bar{p}_{x,k}-\bar{q}_{x,k}}{1-\bar{p}_{x,k}}\right). \tag{5}$$

The following proposition highlights how incorrect beliefs about the distribution of strategic types can lead to either over- or under-reaction in belief updating (relative to a fully-informed Bayesian):

Proposition 1. *Consider decision problem (x, k). Let $\bar{p}_{x,k}$ and $\bar{q}_{x,k}$ denote the true population proportions of always-card and signal-dependent types, respectively. Consider a Bayesian observer who believes these proportions are $p_{x,k}$ and $q_{x,k}$, respectively. This observer infers as follows:*

1. *When seeing action A, the observer will over-react if $\frac{q_{x,k}}{p_{x,k}} > \frac{\bar{q}_{x,k}}{\bar{p}_{x,k}}$, and will under-react if the inequality is reversed.*
2. *When seeing action R, the observer will over-react if $\frac{q_{x,k}}{1-p_{x,k}} > \frac{\bar{q}_{x,k}}{1-\bar{p}_{x,k}}$, and will under-react if the inequality is reversed.*

The proposition—which follows directly from Equations 4 and 5— illustrates how inaccurate beliefs about the proportions of strategic types in the population can lead to over- and under-reaction when inferring from the actions of others. Depending on how the observer's perceived proportions compare to the true values, various combinations of over- and under-reaction can emerge among observers following actions A and R.

One erroneous belief that participants may hold about the proportions of strategic types is an overestimation of $p_{x,k}$. The parameters of our experiment were chosen so that the expected monetary value of the card after $s = l$ is $(1-\phi)h + \phi l = 40$. This implies that, in theory, there should be few always-card types, especially when $x \geq 40$—that is, $\bar{p}_{x,k} \approx 0$. Given this feature of our design, the only way participants may misperceive $p_{x,k}$ is to overestimate it. Beyond this mechanical point, a number of concepts from both psychology and economics suggest such a misperception. For instance, people tend to overestimate small probabilities (see, e.g., Viscusi, 1985; Fischhoff and de Bruin, 1999; Enke and Graeber, 2023). Additionally, Frederick (2012) finds a widespread tendency for people to overestimate others' willingness to pay for goods. In our context this may manifest as overestimating the fraction of people willing to accept the card over the cash. Finally, participants may overestimate $p_{x,k}$ if they exaggerate the degree to which others are irrational (as in Kneeland, 2015). Proposition 1 reveals that overestimating $p_{x,k}$ would cause the observer's beliefs to under-react when the actor chooses A and over-react when he chooses R, even if the observer correctly perceived $\bar{q}_{x,k}$.

Another plausible error is that participants wrongly perceive others' preferences as more similar to their own, in line with the large literature on social projection bias and the false-consensus effect discussed in the introduction. To model the possibility that a participant's perception of the distribution of strategic types depends on her own type, let $\tau \in \{0, 1, 2\}$ denote a participant's strategic type in decision problem (x, k), where these values correspond to always cash, signal-dependent and always-card, respectively. We then let $p_{x,k}(\tau)$ and $q_{x,k}(\tau)$ denote a participant's perception of the type frequencies as a function of her own type.

To understand the implications of Proposition 1 under this form of "projection bias"—where people exaggerate their similarity to others—it is useful to consider what such a bias implies about people's perceptions of the distribution of types. First, it naturally suggests that participants overestimate the prevalence of their own type: $p_{x,k}(2) > \bar{p}_{x,k}$, $q_{x,k}(1) > \bar{q}_{x,k}$, and $p_{x,k}(0) + q_{x,k}(0) < \bar{p}_{x,k} + \bar{q}_{x,k}$. Second, it suggests that the perceived prevalence of a given type is systematically ordered across types. For instance, signal-dependent types perceive a greater proportion of signal-dependent types than do always-cash types—that is, $q_{x,k}(1) > q_{x,k}(0)$. And relative to signal-dependent types, always-cash types think there are fewer always-card types—that is, $p_{x,k}(1) > p_{x,k}(0)$.[13] Intuitively, since always-cash types do not enjoy the business under consideration, they

[13]The previous claims follow from the model of interpersonal projection bias developed in Gagnon-Bartsch et al. (2021) and Gagnon-Bartsch and Rosato (2023) when applied to the population distribution of valuations $v_k(\omega)$ in our environment. The model developed in those papers similarly predicts that, relative to a signal-dependent type, an always-card type believes that always-cash types are less prevalent.

underestimate how much others enjoy it by a greater degree than signal-dependent types (who tend to enjoy it themselves).

The pattern of misperceptions described above allows us to (in some cases) predict which types of observers will under- or over-react more than others in a given decision problem. Consider, for instance, the beliefs of observers who are signal-dependent types. Applying the insights from Proposition 1, we can see that if $\frac{q_{x,k}(1)}{p_{x,k}(1)} > \frac{q_{x,k}(0)}{p_{x,k}(0)}$, signal-dependent types over-react by a greater degree than always-cash types after observing action A. However, the aforementioned notion of projection bias does not make a crisp prediction about the ordering of these ratios of frequencies. By contrast, projection bias does yield an unambiguous prediction after observing action R. In that case, signal-dependent types overreact by a greater degree than always-cash types after observing action R if $\frac{q_{x,k}(1)}{1-p_{x,k}(1)} > \frac{q_{x,k}(0)}{1-p_{x,k}(0)}$. Notice that this inequality always holds under projection bias because, relative to always-cash types, signal-dependent types think both signal-dependent and always-card types are more prevalent.

Corollary 1. *Consider decision problem (x, k). Suppose that $q_{x,k}(1) > q_{x,k}(0)$ and $p_{x,k}(1) > p_{x,k}(0)$. Then, when seeing action R, signal-dependent types unambiguously over-react more than always-cash types.*

In light of Corollary 1, our empirical analyses will frequently compare beliefs across strategic types as a way of exploring whether participants in our experiment exhibit projection bias.

Observer's Beliefs with Rating Information. The updated beliefs described above are for the case where the observer only sees the actor's action, as in Experiment 1. In Experiment 2, we measure the observer's updated beliefs about the actor's information when they additionally see the actor's rating for the shop in question. In Stage 1 of our experiments, we elicited the actor's self-reported ratings for each business, denoted by $r \in \{1, 2, 3, 4\}$. A higher rating indicates a higher self-reported taste for shop, and thus it serves as a noisy signal of the actor's underlying preferences. Accordingly, we let $\pi_{x,k}(a|r)$ denote the observer's updated probability of $s = h$ conditional on the actor's action and rating for business k.

Rational learning yields a stark prediction in this case: for either action $a = A, R$, the observer's belief $\pi_{x,k}(a|r)$ is decreasing in r. For an intuition, suppose the actor chose action R. If the actor has a low rating for the business, this action is relatively uninformative since she likely would have turned down the card regardless of her signal. On the other hand, if the actor has a higher rating, the action more strongly indicates that the actor received the bad signal. Thus, the likelihood of $s = h$ is decreasing in r. If instead the actor chose A, this action is relatively uninformative when the actor has a high rating but is very informative when she has a low one—she would only take the card in this case if she received the good signal. Again, the likelihood of $s = h$ is decreasing in r. Our analyses of Experiment 2 tests these comparative statics.

4 Results, Experiment 1

We present our results as follows. First, we provide some simple descriptive information about the tastes of participants in our experiment.[14] We then explore the choice behavior of participants in Stage 2 of our experiment and show how they (i) make choices that accord with both their stated ratings towards shops and neutrality or aversion to risk; and (ii) utilize the information from their noisy signals. These form an important "first stage" in the sense that the choices made in Stage 2 are reasonable and (partially) convey participants' private information.

We then turn to our main analyses, which focus on inferences in Stage 3. We first show that inferences from observers follow some of the predicted features from the rational model. However, we show that these inferences also differ in significant ways and that observers systematically over- and under-infer from the actions they see. Moreover, we show that these differential responses depend on the observers' own taste as predicted by a model of projection bias and are not merely an artifact of cross-person heterogeneity or measurement error. We conclude by demonstrating that these inferences have a significant effect on the choices observers make after (mis)learning.

4.1 Survey Stage

Table 1 reports the average response to the survey questions from Stage 1 for each of the seven businesses. The variability in these responses reveal substantial heterogeneity in participants' personal experience with the businesses, attitudes toward the businesses, and their willingness to accept (WTA) a gift card. Hence, this setting appears well suited to study social learning under heterogeneous tastes. This heterogeneity is further explored in Panel (a) of Figure 2, which presents a histogram of participants' ratings of the shops on a 1-4 scale (ranging from "negative" to "strongly positive").

We also collected participants' guesses about how others would rate the shops. Panel (b) of Figure 2 highlights that people's perceptions of others' ratings were biased towards their own. For example, while "negative" ratings represented only 9% of the overall data, participants who themselves rated a shop negatively believed that approximately 30% of others would agree with them. These strong distortions in perceptions of ratings are observed across the spectrum of ratings. This is consistent with prior studies on the false-consensus effect noted in the introduction.

4.2 Actor Stage

We now turn to the aggregate choice data from Stage 2. In this stage, participants faced a series of choices over gift cards and bonus cash. Table 2 presents the aggregate choice data across all shops

[14] We relegate descriptive statistics about our participants (i.e., demographics) to the Online Appendix.

	$\mathbb{I}$(Personal Experience)	Self Rating	WTA
AMC	0.611	2.585	53.77
	(0.488)	(0.723)	(28.13)
Amazon	0.983	2.830	72.77
	(0.131)	(0.986)	(22.74)
ChickFilA	0.760	2.603	54.66
	(0.428)	(1.089)	(32.34)
HomeDepot	0.860	2.729	63.84
	(0.347)	(0.659)	(25.82)
OldNavy	0.559	2.476	54.13
	(0.497)	(0.710)	(26.39)
PetSmart	0.607	2.603	53.55
	(0.489)	(0.703)	(28.09)
Starbucks	0.865	2.533	57.14
	(0.342)	(0.933)	(27.47)

Table 1: Average Responses from the Survey Stage. *"Personal Experience" indicates the fraction of people who stated that their household purchased something from the business in the last five years. "Self Rating" was reported on a four-point increasing scale. Willingness to Accept ("WTA") was reported using a slider from \$0 to \$100. Standard deviations are in parentheses.*

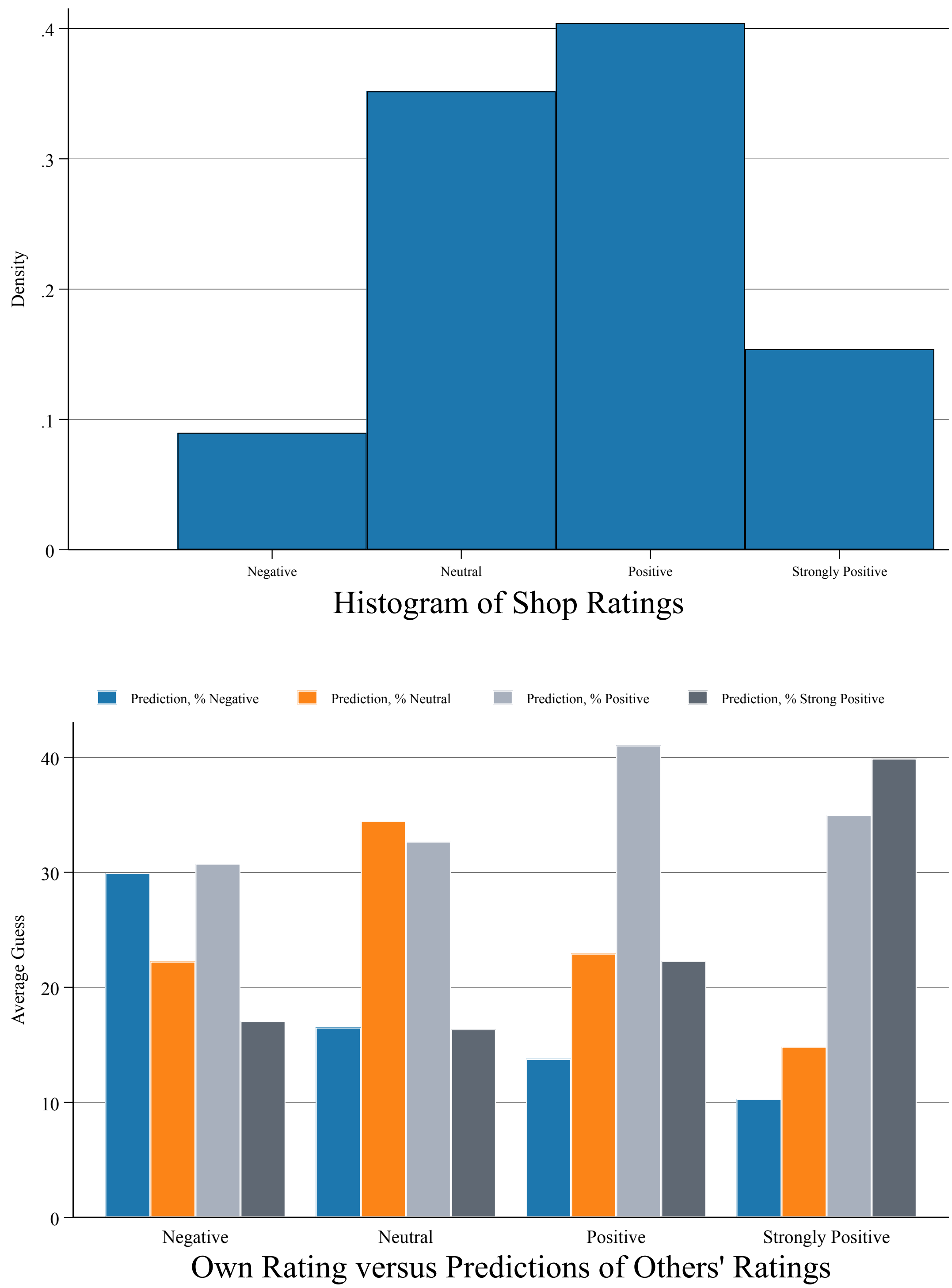

Figure 2: Ratings in the Survey Stage. *Panel (a) shows the distribution of ratings aggregated across businesses. While tastes varied across the shops in the experiment, the modal perception of them was positive. Panel (b) shows the distribution of perceived ratings conditional on one's own rating. Perceptions of others' tastes were heavily skewed towards a person's own stated preference.*

and participants, but disaggregated by the signal $s \in \{h, l\}$ the actor received and the cash bonus $x \in \{30, 40, 50\}$ they faced. After receiving the "good" signal (i.e., $s = h$), participants chose the gift card approximately 50% of the time across the various decision problems. In contrast, after receiving the "bad" signal (i.e., $s = l$), participants were very unlikely to choose the gift card. This is consistent with the idea that participants used the signals to guide their choices and that they were not very risk loving.

CHOICE AFTER SIGNAL $s = h$

	Cash Option			
	\$30	\$40	\$50	**Total**
$a = R$	331	789	489	**1609**
$a = A$	472	814	311	**1597**

CHOICE AFTER SIGNAL $s = l$

	Cash Option			
	\$30	\$40	\$50	**Total**
$a = R$	736	1573	793	**3102**
$a = A$	67	30	7	**104**

IMPLIED STRATEGIC TYPES

	Cash Option			
	\$30	\$40	\$50	**Total**
Always Cash	327	784	486	**1597**
Signal Dependent	409	789	307	**1505**
Always Card	63	25	4	**92**
Mistaken	4	5	3	**12**

Table 2: Choices and Implied Strategic Types from the Actor Stage of Experiment 1. *Participants ($n = 229$) made 14 choices for each signal realization across seven businesses.*

Furthermore—and as an important validation that our participants understood the choice environment—the percent of people who chose the gift card after the good signal decreased in the outside cash bonus, as demonstrated by moving across the columns in Table 2. For instance, rates of choosing the gift card after $s = h$ decrease from 59% to 51% to 39% when participants faced

$x = \$30, \$40,$ and $\$50$, respectively.

Our choice data allows us to classify participants according to the three strategic types discussed in Section 3. We do this as follows: for each shop k, each bonus amount x, and each participant, we observe their behavior after both signal realizations. If the person chose the card for both signal realizations for a given (x, k), we call them an "always card" type in that decision problem; if they didn't chose the card for either realization, we call them an "always cash" type; and if they chose the card only after receiving the good signal, we call them a "signal-dependent" type. A very small number of participants seemed to err by choosing the card only when they received the bad signal; we call them "mistaken" types. The lower half of Table 2 presents the frequencies of these types aggregated across businesses.

Following our theoretical setup from Section 3, we can further calculate $\bar{p}_{x,k}$ and $\bar{q}_{x,k}$, which denote the proportion of always-card and signal-dependent types in decision problem (x, k). We report these values in Table A2. As predicted, the proportion of always-card types, $\bar{p}_{x,k}$, is very low. We furthermore find that the proportion of signal-dependent types, $\bar{q}_{x,k}$, is decreasing in the outside option x. Averaging over all of the businesses in the study, we find $\bar{p}_{30} = 0.078, \bar{q}_{30} = 0.509$, $\bar{p}_{40} = 0.016, \bar{q}_{40} = 0.492$, and $\bar{p}_{50} = 0.005, \bar{q}_{50} = 0.384$. Put succinctly, for all three outside options, there are essentially no participants who always chose the gift cards.

Importantly, our analysis allows each participant to be different strategic types across shops or within a shop when facing different bonus amounts. We find that 21 (out of 229) participants never chose a gift card in any decision problem, while zero participants always chose the gift card in every problem. Therefore, the vast majority of people had experience with both choosing the gift card and turning it down.[15]

4.3 Observer Stage

Inferences Among Observers

We now analyze how observers formed inferences based on the choices they saw. We first demonstrate that observers did, in fact, infer from actors' choices by examining how their inferences depended on the action they saw. Recall that observers were asked to infer the likelihood that an actor received the good signal after observing that actor's choice. Table 3 shows the average of observers' updated beliefs, $\pi(a)$, after seeing each action $a \in \{A, R\}$. The top panel shows beliefs after the actor rejected the card ($a = R$), and the bottom panel shows beliefs after the actor accepted it ($a = A$). Column 1 of each panel shows the average belief for each value of bonus cash.

[15]Nine participants were signal-dependent types in every decision problem. Two participants chose seemingly at random (and very quickly); we exclude these two participants from our main analyses, though our findings do not change depending on whether we impose this exclusion or not.

Comparing the top and bottom panels reveals that the general direction of updating is reasonable: beliefs about the actor's signal move significantly below the 50-50 prior when the actor rejects the card and move significantly above when they accept it. We now turn to more specific aspects of belief updating.

The Effect of the Cash Option on Beliefs. We first examine how the cash on offer (x) shaped inferences. We find that observers account for x in a way consistent with the predictions of rational learning described in Section 3. Note that a rational observer in our setting would understand that, as x increases, the card becomes relatively less attractive. Therefore, when x is larger, there is more information revealed by action $a = A$, since it is more likely that the actor requires the good signal in order to choose the card over the cash. Beliefs following $a = A$ should thus move farther toward 1 as x increases. This is confirmed by comparing the rows of the bottom panel of Table 3 ($p < 0.001$, joint F-test for equality of rows in column 1). Similarly, less information is revealed by $a = R$ when x is larger, and beliefs should thus move closer to 0.5 following $a = R$ ($p = 0.002$, joint F-test for equality of rows in column 1). This is a key validation that observers in our experiment attended (at least partially) to actors' preferences and how those preferences might vary across decision problems.

The Responsiveness of Beliefs to Actions. While beliefs move in the rational direction, do they move by the rational amount? A Bayesian with complete knowledge would infer $\Pr[s = h|a = R] \approx 0.33$ on average if the actor choose R and $\Pr[s = h|a = A] \approx 0.95$ if the actor chose A.[16] The beliefs of participants in Table 3 generally depart from this benchmark in systematic ways. Most strikingly, observers wildly under-infer from the action $a = A$. Although the fully-informed Bayesian would become quite confident that the actor received the good signal following action A, we find significantly less confidence among our observers.

To more carefully examine the degree of over- or under-inference, we estimate Equations 2 and 3 with our data. We utilize the shop-by-shop proportions of always-cash and signal-dependent types for each cash level—$\bar{p}_{x,k}$ and $\bar{q}_{x,k}$, as presented in Table A2—to calculate the right-hand side of Equations 3 and 2. We then estimate the coefficients of over and under-reactions relative to the Bayesian benchmark using OLS. We present the results of those regressions in Tables 4 and 5.

[16]This average is taken across the seven businesses, similar to the data presented in Table 3. The Bayesian benchmark is calculated using the empirical frequencies of actors' choices conditional on their signals.

Inferences after observing $a = R$			
	All	Always Cash	Signal Dependent
BonusCash=30	29.18	31.09	28.55
	(1.36)	(1.63)	(1.92)
BonusCash=40	31.37	33.71	28.71
	(1.26)	(1.51)	(1.58)
BonusCash=50	33.53	34.57	31.83
	(1.51)	(1.70)	(2.15)
Observations (column total)	3,178	1,587	1,498

Inferences after observing $a = A$			
	All	Always Cash	Signal Dependent
BonusCash=30	77.45	75.69	78.72
	(0.97)	(1.52)	(1.12)
BonusCash=40	78.29	76.05	80.61
	(0.86)	(1.12)	(0.93)
BonusCash=50	81.41	80.57	83.17
	(1.04)	(1.28)	(1.30)
Observations (column total)	3,178	1,587	1,498

Standard errors (in parentheses) are clustered at the individual level. Joint tests for differences in columns (2) and (3) yield $p = .0409$ and $p = .0016$, after $a = R$ (top) and $a = A$ (bottom), respectively.

Table 3: Average inferences in Experiment 1. *Participants reported their belief about the likelihood that the actor received signal $s = h$—reported as a number out of 100. Column 1 shows the data for all participants; later columns stratify by the strategic type of the observer.*

In Table 4, we show that participants exhibited significant under-reaction across all businesses in the study after observing an actor accept the gift card ($p < .001$ for all businesses in rejecting test of $H_0 : c_A = 1$; Bonferroni adjusted for multiple hypothesis testing). We find some heterogeneity in reactions across shops, with the notable outlier of Amazon, where participants under-reacted the least (that is, were closest to the Bayesian benchmark). This shop-specific result reflects an ex-ante design feature: a gift card to Amazon is fundamentally different than a gift card to the other businesses, since it is essentially cash. Given this, we expected that (i) participants' valuations for an Amazon gift card would exhibit the least variation (since it is similar to cash; see Table 1), and (ii) participants were more likely to be signal-dependent types when facing Amazon gift cards relative to other businesses in the study (see Table A2). Our finding that participants reacted more when facing Amazon cards suggests that inferences may be closer to Bayesian when tastes are more homogeneous. We discuss the case of Amazon more below.

In Table 5, we show that after observing an actor reject the gift card, observers' beliefs tended to over-react. Table 5 shows that observers' beliefs over-reacted after seeing the actor reject the gift card for all shops except Amazon and Home Depot ($p < 0.001$ for other five businesses in rejecting test of $H_0 : c_A = 1$; Bonferroni adjusted). We also find evidence for under-reaction at Amazon ($p < 0.001$).

The Effect of a Person's Own Type on Their Inferences. Table 3 shows that an observers' inferences systematically varied depending on the observer's own choices. As described above, for each shop and bonus-cash amount, we can determine an observer's own strategic type based on her actions in Stage 2. We examine how an observer's own strategic type in a given decision problem influences the inference they draw from others' choices in that problem. For this exercise, we focus on the primary two types in our data—always-cash and signal-dependent types—since they make up 96.5% of the data. Splitting inferences by these strategic types reveals a striking truth: regardless of the observed action, signal dependent types infer *more* from the actions of others. We display this disaggregation in columns 2 and 3 of Table 3. After seeing actors choose $a = R$, signal-dependent observers state that the chances the actor saw the good signal are 4.1% lower than always-cash observers ($p = .037$; joint test across all bonus cash amounts). After $a = A$, signal-dependent observers state that these chances are 3.3% higher than always-cash observers ($p = .001$; joint test across all bonus cash amounts).

We further show that an observer's inferences depend on her strategic type by looking at the shop-by-shop reaction coefficients. In columns 2 and 3 of Tables 4 and 5, we present these coefficients separated by strategic type. As suggested by the aggregate result presented in Table 3, the shop-level coefficients show that signal-dependent observers under-inferred by less when facing $a = A$. When facing $a = R$, signal-dependent observers over-inferred more than their always-cash counterparts. This is consistent with Corollary 1.

Reaction coefficient after observing $a = A$			
	All	Always Cash	Signal Dependent
AMC	0.33	0.31	0.35
	(0.02)	(0.02)	(0.03)
Amazon	0.48	0.40	0.50
	(0.02)	(0.04)	(0.02)
ChickFilA	0.41	0.36	0.46
	(0.02)	(0.03)	(0.03)
HomeDepot	0.36	0.32	0.40
	(0.02)	(0.02)	(0.02)
OldNavy	0.44	0.43	0.46
	(0.02)	(0.03)	(0.04)
PetSmart	0.43	0.39	0.48
	(0.02)	(0.03)	(0.03)
Starbucks	0.37	0.35	0.38
	(0.02)	(0.03)	(0.02)
Observations (column total)	2329	1092	1152

Standard errors (in parentheses) are clustered at the individual level.

Table 4: Reactions Relative to the Bayesian Benchmark after $a = A$. *The table illustrates significant under-reaction both when aggregating across businesses in the study and at all businesses within the study. Signal-dependent types react more for all businesses ($p = 0.015$ for test of second versus third column equality).*

Reaction coefficient after observing $a = R$			
	All	Always Cash	Signal Dependent
AMC	1.69 (0.15)	1.59 (0.18)	1.83 (0.24)
Amazon	0.71 (0.05)	0.42 (0.10)	0.80 (0.06)
ChickFilA	1.53 (0.12)	1.46 (0.15)	1.61 (0.18)
HomeDepot	0.99 (0.09)	0.75 (0.13)	1.16 (0.11)
OldNavy	1.55 (0.15)	1.48 (0.17)	1.65 (0.26)
PetSmart	1.59 (0.13)	1.29 (0.17)	1.89 (0.19)
Starbucks	1.31 (0.12)	1.38 (0.15)	1.28 (0.18)
Observations (column total)	2956	1497	1374

Standard errors (in parentheses) are clustered at the individual level.

Table 5: Reactions Relative to the Bayesian Benchmark after $a = R$. *The table illustrates significant over-reaction after participants see a person reject the gift card except when updating about an Amazon or Home Depot gift card. Signal-dependent types tend to react more ($p = 0.030$ for test of second versus third column equality).*

Discussion of Results. Overall, the pattern of under- and over-inference that we observe accords with recent work by Augenblick et al. (2023) who find that experimental participants under-infer from weak signals but over-infer from strong signals. Recall that our observers under-infer after seeing an actor accept the gift card. In our setting, action $a = A$ is a very strong indication that the actor received good information since extremely few people take the card otherwise. Thus, we too find under-reaction to "strong signals"—that is, under-inference after seeing a highly informative action. Moreover, our observers also over-react after seeing an actor reject the gift card. The action $a = R$ is a much weaker indication of the actor's private information, since many actors reject the card even when they received a good signal. Thus, we also find over-reaction to "weak signals"—that is, over-inference after seeing a relatively uninformative action.

This pattern and interpretation also helps reconcile our findings with respect to Amazon. Given the features of tastes over Amazon gift cards discussed above, we would expect actions with respect to Amazon to be a relatively strong signal as compared to other shops when $a = R$ and relatively weak when $a = A$. This accords with our findings in Tables 4 and 5 and provides further evidence of the pattern noted above.

Our theoretical framework helps to highlight how our data is consistent with inaccurate beliefs about others' types (perhaps stemming from projection bias) that consequently shape the interpretation of others' actions. Specifically, the differential responses across observers that we document in Tables 3, 4 and 5 accords with the predictions in Corollary 1. It is worth noting that our results are consistent with a variety of mechanisms that may cause a person to overestimate the prevalence of their own tastes (e.g., projection bias, neglecting assortative matching based on tastes as in Frick et al., 2022, or limited information as in Dawes, 1989).

Finally, we push our data to its limit to calculate the implied beliefs about the prevalence of the strategic types within the population as a function of an observer's *own* type. We utilize our data on beliefs about actors' signals, $\pi_{x,k}(a)$, and the expressions in Equation 1 to solve for these implied beliefs about types.[17] We compute the implied beliefs for each observer and decision problem (utilizing both observed actions), and we average these results by the type of the observer. We find that always-cash types believe that their own type makes up 57% of the population, that signal-dependent types make up 28%, and that always card types—a tiny component of the true population—comprise the remaining 15%. In contrast, the inferences of signal-dependent types suggest that they believe always-cash types comprise 36% of the population, signal-dependent types (their own type) comprise 41%, and always-card types make up the remaining 23% .

Observers' Choices after Social Learning

We now analyze the choices that observers made as a function of the action they observed. This mirrors the typical analysis of behavior in social-learning environments. As shown in Table 6, we find that these choices reflect significant social learning: participants themselves chose $a = A$ much more frequently after observing that action versus when they observed $a = R$. In fact, comparing Tables 2 and 6 highlights that the aggregated choices of participants in the second-mover position (i.e., observers) closely mirror the aggregated choices of participants in the first-

[17] This exercise rests on the (rather heroic) assumption that participants' updated their beliefs according to Bayes' Rule.

mover position (i.e., actors).

CHOICE AFTER OBSERVING $a = A$

	Cash Option			
	\$30	\$40	\$50	**Total**
Take the Bonus Cash	349	763	443	**1555**
Take the Card	447	826	350	**1623**

CHOICE AFTER OBSERVING $a = R$

	Cash Option			
	\$30	\$40	\$50	**Total**
Take the Bonus Cash	724	1485	751	**2960**
Take the Card	72	104	42	**218**

Table 6: Counts of Choices for Observers, Experiment 1. *Observer's choices in aggregate look similar to their privately informed decisions.*

But the choice data above potentially obscures some key features of social (mis)learning. By looking at the beliefs of participants, we can examine the degree to which choices were driven by inferential learning to better understand why this pattern of choices arise. We first explore whether, controlling for the action observed, the elicited beliefs are predictive of subsequent actions. To model this, we employ a simple logit regression and control for both the action observed and the bonus cash offered (with $x = 50$ as our left-out group) in Column 1. Indeed, we find that the stated beliefs shape choices. As shown in the first two rows of Table 7, controlling for the action observed, stated beliefs have a significant effect on choices, as predicted by a rational model of social learning ($p < 0.001$ for both coefficients and all specifications). Those who infer relatively little when observing $a = R$—and therefore report a relatively higher belief—should be more likely to accept the card. By a similar logic, those who infer a lot when observing $a = A$ should also be more likely to accept the card. In subsequent columns of Table 7, we control for shop-level FEs and the tastes of the observer and find this result is preserved.

	Dependent variable: $\mathbb{I}$(Chose Gift Card)		
	(1)	(2)	(3)
Stated Belief $\pi(a = R)$	4.20***	4.14***	4.30***
	(0.50)	(0.49)	(0.50)
Stated Belief $\pi(a = A)$	1.63***	1.63***	1.69***
	(0.41)	(0.42)	(0.43)
Observed Action $a = R$	-4.75***	-3.91***	-4.67***
	(0.27)	(0.29)	(0.35)
Observed Action $a = A$	-1.59***	-0.63	-1.31**
	(0.35)	(0.38)	(0.46)
CashOption=30	0.63***	0.68***	0.73***
	(0.12)	(0.13)	(0.13)
CashOption=40	0.38***	0.41***	0.44***
	(0.08)	(0.08)	(0.09)
Rating = Negative		-1.99***	-1.86***
		(0.28)	(0.30)
Rating = Neutral		-1.40***	-1.06***
		(0.18)	(0.19)
Rating = Positive		-0.77***	-0.65***
		(0.16)	(0.16)
PersonalExperience			0.50**
			(0.16)
Shop-Level FEs	✗	✗	✓
Observations	6356	6356	6356

Logit estimation with standard errors (in parentheses) clustered at the individual level. All independent variables except stated beliefs are dummies. Ommitted categories are CashOption=50 and Rating = Strong Positive.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Modeling Observers' Choices in Experiment 1. *Using a logit model, we explore the determinants of choosing the gift card. Participants' choices reflect their own rating, the actions they observe, and their inferences in reasonable ways. However, the observed action has an outsize effect on subsequent choices.*

However, Table 7 offers a suggestion that, in addition to rational inference, observers' actions are driven by either erroneous social learning or social influence. Note that, when controlling for beliefs, there is a significant difference in the effect of observing $a = A$ versus $a = R$ ($p < 0.001$ for all specifications in Table 7). This is consistent with a form of herding wherein the observer follows the action of the actor above and beyond the inference they draw from it. This may lead to two different types of mistakes: observers may choose gift cards that they ought to reject, or may reject cards they ought to choose. We present suggestive evidence of both errors in in Table A4. Our evidence shows that approximately 20% of participants who did not take the gift card for either signal in the actor stage subsequently took the card in the observer stage after seeing the action $a = A$. We also note that a high proportion of signal-dependent types followed the actor's choice after $a = R$. Given that they over-infer from this action, this suggests some may have erroneously rejected the gift card due to this over-inference.

5 Results, Experiment 2

Our second experiment explores whether observers would improve their inferences when given a noisy signal about the actor's taste. This mirrors many real-world settings where people can easily observe characteristics or demographics of others when socially learning. To put this into practice, during the observer stage of the experiment, we gave participants the subjective rating about the business—$r \in \{$Negative, Neutral, Positive, Strongly Positive$\}$—of the person whose action they observed. We now investigate the subsequent inferences.[18]

We focus our analysis on the observer stage of Experiment 2. Table 8 shows the average of observers' beliefs, $\pi(a|r)$, for each action $a \in \{A, R\}$ conditional on the observed rating r. In addition to showing beliefs, we also provide as a benchmark what the fully informed Bayesian would respond for each rating. The left two columns show these when the actor rejected the card ($a = R$); the right two when the actor accepted it ($a = A$). Note that the rating data is highly informative in the case of $a = R$: those who like the business are much more likely to be signal-dependent types and hence their action is more revealing of the information they received. As in Experiment 1, the general direction of updating is reasonable: beliefs about the actor's signal moves up after $a = A$ and down when $a = R$ (relative to the prior belief of 50).

We also find evidence of a more subtle form of rational belief updating wherein after observing $a = R$, the higher an actor's rating was, the lower were observers' posterior beliefs ($p < 0.001$ comparing each observed rating against the next by row in Table 8). Thus, our evidence supports the rational comparative static discussed in Section 3.2. This requires some reasoning on the

[18]We first note that the results from the survey and actor stages of Experiment 2 very closely match those of Experiment 1. For the sake of brevity, we present the results from these two stages in an Online Appendix.

part of the observers, again suggesting that our participants (at least partially) consider an actor's preferences when inferring from them. However, this pattern does not bear out when $a = A$.

	After Observing $a = R$		After Observing $a = A$	
	Stated Beliefs	Benchmark	Stated Beliefs	Benchmark
Negative	41.98	40.44	76.44	100.00
	(1.26)	(.)	(1.60)	(.)
Neutral	38.39	40.52	75.23	97.17
	(1.19)	(.)	(1.06)	(.)
Positive	34.01	30.10	76.33	93.86
	(1.60)	(.)	(0.85)	(.)
Strongly Positive	27.76	20.61	75.54	94.39
	(1.80)	(.)	(1.08)	(.)
Observations (column total)	4003	-	3960	-

Standard errors (in parentheses); benchmarks calculated at the shop+observed rating level.

Table 8: Inferences in Experiment 2. *When facing $a = R$, participants utilized ratings information to form their inferences, but under-inferred from highly informative positive ratings (columns 1 and 2). Similar to our findings in Experiment 1, participants under-inferred for all ratings when facing $a = A$ as compared against a fully-informed Bayesian benchmark (columns 3 and 4).*

Intriguingly, we find that (much like in Experiment 1) observers under-infer from $a = A$ for all observed ratings (see columns 3 and 4 of Table 8). This provides a somewhat cautionary tale: if one thought that providing information would mitigate errors in social learning, our evidence suggests that it does not.

Moreover, although observers followed the qualitative pattern suggested by rational updating after observing $a = R$, their stated beliefs are under-responsive to the observed ratings relative to the fully-informed benchmark. Comparing rows 1 and 2 in Table 8 highlights how observers failed to fully account for the information they saw, especially when that information was highly informative. This again bears out the pattern from Experiment 1: participants under-inferred from strong, highly-informative actions.[19]

[19] In Appendix Table A6, we show that one reason for this may be because participants' own rating still weighs heavily on their inferences. In that analysis we show that, fixing the participants' own rating, they infer from others'

	Dependent variable: $\mathbb{I}$(Chose Gift Card)		
	(1)	(2)	(3)
Stated Belief $\pi(a = R)$	2.99***	2.85***	2.88***
	(0.39)	(0.39)	(0.40)
Stated Belief $\pi(a = A)$	1.69***	1.70***	1.69***
	(0.35)	(0.36)	(0.37)
Observed Action $a = R$	-4.09***	-3.36***	-4.07***
	(0.25)	(0.26)	(0.36)
Observed Action $a = R$	-1.50***	-0.72*	-1.38***
	(0.32)	(0.34)	(0.41)
Observed Rating (1-4)	0.07*	0.06*	0.07*
	(0.03)	(0.03)	(0.03)
Own Rating = Negative		-1.44***	-1.25***
		(0.25)	(0.25)
Own Rating = Neutral		-1.29***	-0.92***
		(0.20)	(0.22)
Own Rating = Positive		-0.47**	-0.31
		(0.17)	(0.17)
PersonalExperience			0.53**
			(0.18)
Shop-Level FEs	✗	✗	✓
Observations	7963	7963	7963

Logit estimation with standard errors (in parentheses) clustered at the individual level. All independent variables except stated beliefs and observed rating are dummies. Omitted category is Rating = Strong Positive.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Modeling Observers' Choices in Experiment 2. *Using a logit model, we explore the determinants of choosing the gift card.*

Observers' Choices after Social Learning. Finally, we reproduce our analysis from Experiment 1 wherein we examined the choices that observers made after seeing others' actions. Using a logit

ratings in the rational direction. However, those with particularly strong ratings themselves wildly under-infer from the rating information.

framework as before—presented in Table 9—we find that observers in Experiment 2 exhibit two puzzling behaviors. First, as in Experiment 1, the observed action holds sway for the observer's choice even when controlling for their inference. As before, we interpret this as evidence for erroneous social learning akin to herding. Second, we see that observing a higher rating is associated with a higher propensity to choose the card ($p = 0.036$ in column 3 specification). This could stem from observers learning about their own tastes for a business from others' ratings. However, given that we control for personal experience with the business in column 3 of Table 9, it seems reasonable to interpret this as a mistake stemming from either erroneous social learning or social influence rather than a result of optimal inference.

6 Conclusion

In this paper, we developed a field-in-the-lab experiment to explore social learning when agents have heterogenous tastes. We find that, while social learning does occur, there are systematic deviations from fully-rational learning. By eliciting beliefs in addition to actions in a social-learning paradigm, we are able to uncover previously undiscussed patterns in social learning. Participants under-infer from highly-informative actions and over-infer from weakly-informative ones. We show that these misinferences are consistent with biased beliefs about others' preferences, perhaps stemming from projection bias. Other misinferences are consistent with a non-common belief in rationality. Understanding the deeper underlying mechanisms for misunderstanding others remains an open challenge.

Applying our insights, we believe that our framework and results speak to social learning in settings where actors' objectives exhibit heterogeneity for reasons beyond simple differences in tastes, such as differing budget constraints or costs. For instance, imagine a novel medical treatment that requires traveling to a special facility. When learning about this treatment based on others' choices, we should account for the fact that some may opt for the status quo not because they have negative information about the novel treatment but rather because they simply can't afford it or live far from a treatment facility. Or in agricultural contexts, farmers often learn from their neighbors about the benefits of new technologies, like hybrid seeds and soil additives (Duflo et al., 2008; Conley and Udry, 2010). These products often work well for some soil types but not others, and farmers should therefore account for this variation when learning from their neighbors (Munshi, 2004).

Moreover, our findings could help inform the design of social networks that best facilitate the spread of (factual) information. Harnessing such networks is of growing interest beyond the tech sphere; for example, organizations have tried to promote the adoption of agricultural technologies by connecting farmers in social networks via SMS (Fabregas et al., 2019). However, if people do not adequately account for heterogeneity in such networks, then small homogeneous networks may outperform large diverse ones. Additionally, the results from our informational treatment in Experiment 2 suggest that any intervention intended to improve social learning must go beyond simply providing information about others. We believe that better understanding such barriers to information transmission is central to better designing policies or networks aiming to promote learning.

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Appendix

A Supplemental Analyses and Figures

In this Appendix, we present additional results that are supplemental to the main conclusions of the paper.

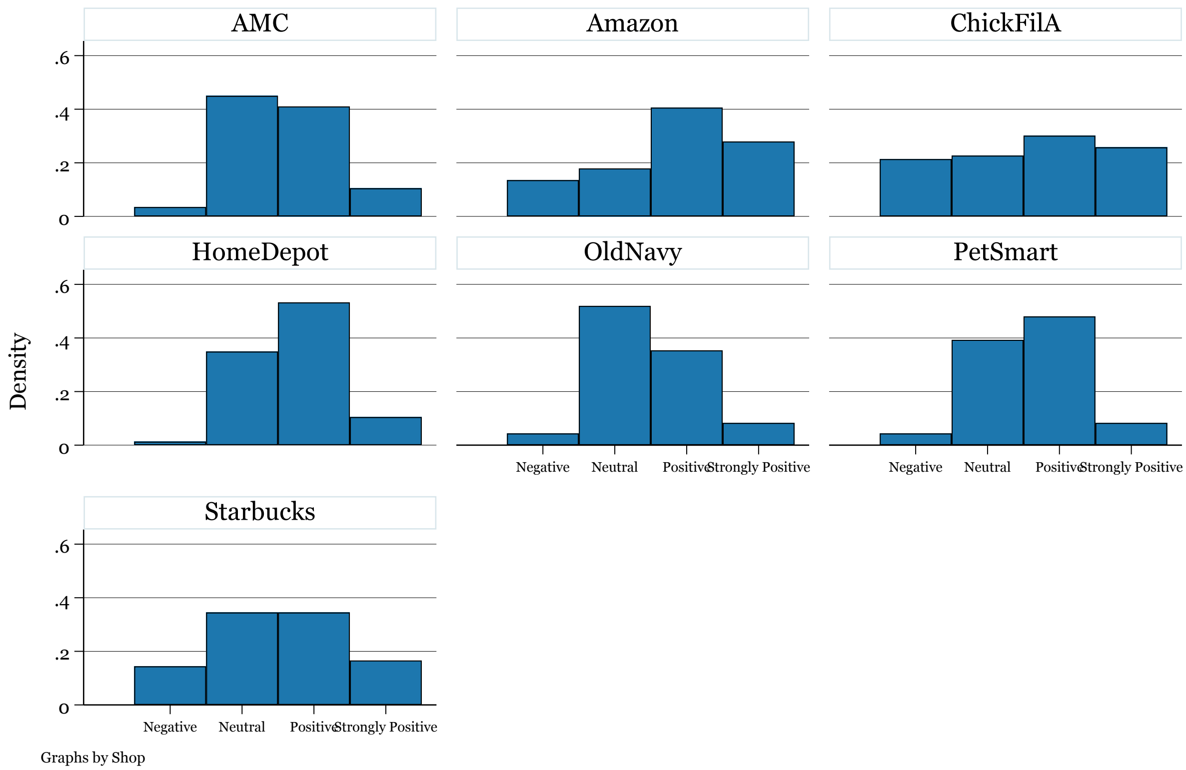
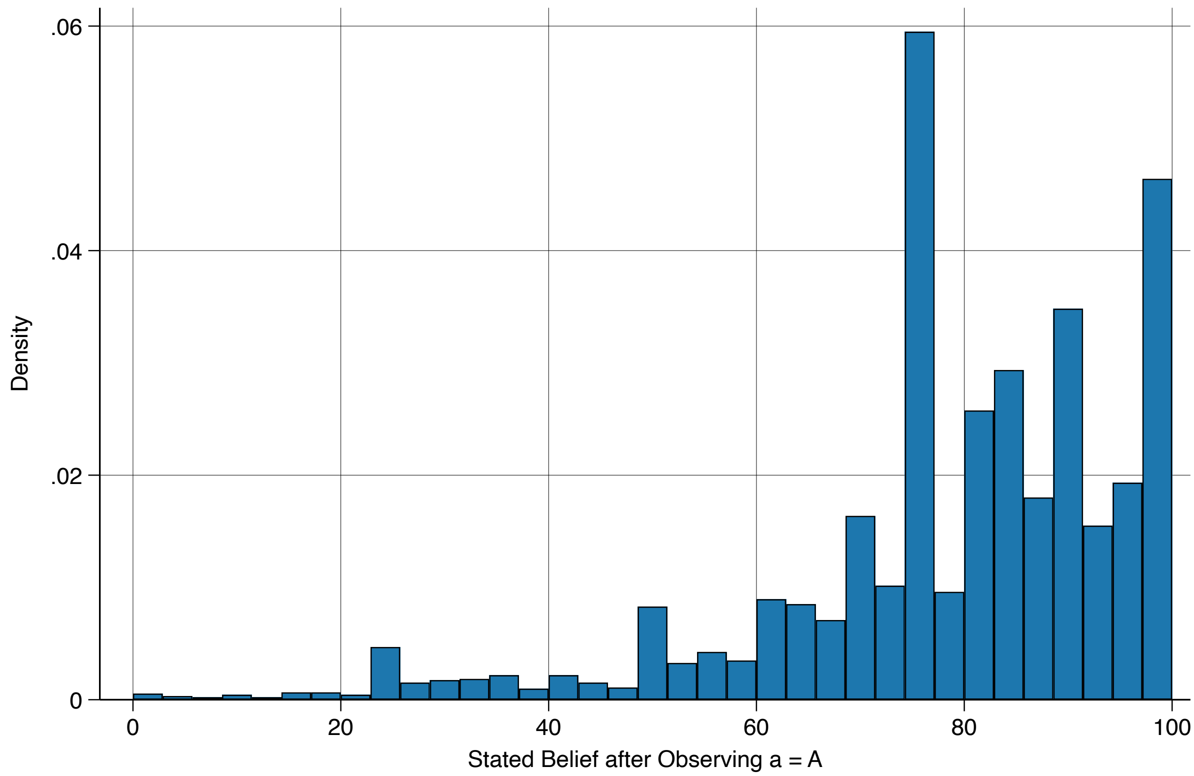
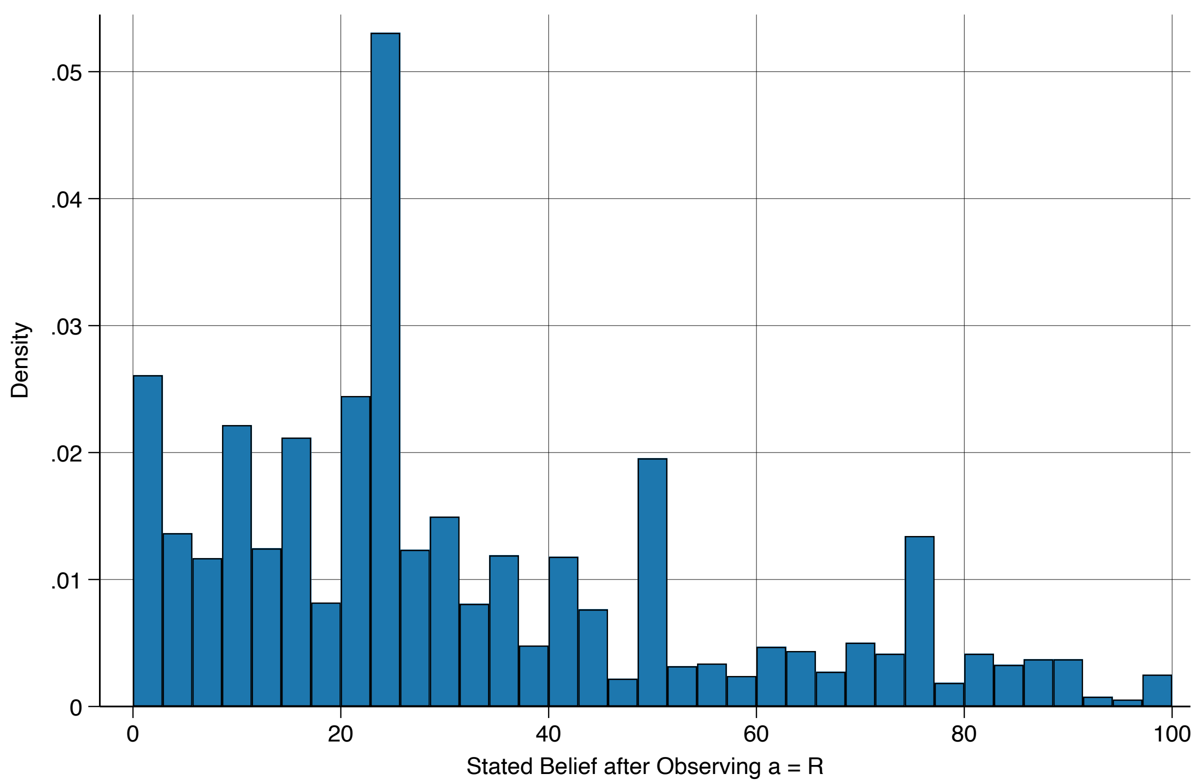


Figure A1: Histogram of Ratings by Shop, Experiment 1. *While ratings varied significantly across shops, all shops were generally viewed positively. For example, the lowest-rated shop (Old Navy; center row, center of figure) had an average rating of 2.48 out of 4.*


.06
.04
.02
0
Density
0
20
40
60
80
100
Stated Belief after Observing a = A


.05
.04
.03
.02
.01
0
Density
0
20
40
60
80
100
Stated Belief after Observing a = R

Dependent variable: $\mathbb{I}$(Take the Gift Card)	(1)	(2)	(3)
Bad Signal ($s = L$)	-3.94***	-3.19***	-4.99***
	(0.15)	(0.17)	(0.36)
Good Signal ($s = H$)	-0.50***	0.46**	-1.16***
	(0.09)	(0.16)	(0.35)
BonusCash=30	0.99***	1.11***	1.24***
	(0.11)	(0.12)	(0.12)
BonusCash=40	0.48***	0.54***	0.61***
	(0.07)	(0.07)	(0.08)
Rating = Negative		-2.14***	-1.62***
		(0.26)	(0.31)
Rating = Neutral		-1.57***	-0.89***
		(0.17)	(0.19)
Rating = Positive		-0.67***	-0.38*
		(0.15)	(0.16)
PersonalExperience			0.53**
			(0.18)
Shop-Level FEs?	✗	✓	✓
Observations	6412	6412	6412

Standard errors (in parentheses) are clustered at the individual level.
Estimated via logit. All independent variables are indicators.
Ommitted categories are CashOption=50 and Rating = Strong Positive.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1: Modeling Actors' Choices in Experiment 1. *Using a logit model, we explore the determinants of choosing the gift card. This simple approach shows that Actors' choices obey some basic desirable principles and that our self-rating data is informative about choices.*

	CashOption=30		CashOption=40		CashOption=50	
	$\bar{p}_{30}$	$\bar{q}_{30}$	$\bar{p}_{40}$	$\bar{q}_{40}$	$\bar{p}_{50}$	$\bar{q}_{50}$
AMC	0.05	0.42	0.00	0.39	0.00	0.31
Amazon	0.19	0.66	0.03	0.77	0.02	0.60
ChickFilA	0.06	0.50	0.01	0.44	0.00	0.37
HomeDepot	0.07	0.59	0.01	0.59	0.01	0.39
OldNavy	0.07	0.44	0.02	0.40	0.00	0.32
PetSmart	0.07	0.47	0.01	0.39	0.00	0.31
Starbucks	0.04	0.54	0.01	0.48	0.00	0.37

Table A2: Strategic Types in Experiment 1. *Each column represents the sample averages for always-card (p) and signal-dependent (q) types for the specified bonus-cash level and business.*

	CashOption=40	
	$\bar{p}_{40}$	$\bar{q}_{40}$
Rating = Negative	0.00	0.32
Rating = Neutral	0.00	0.32
Rating = Positive	0.03	0.55
Rating = Strongly Positive	0.04	0.71

Table A3: Relationship Between Ratings and Strategic Types in Experiment 2. *Entries show the proportions of always-card (p) and signal-dependent (q) types for $x = 40$, aggregated across businesses.*

Inferences after observing $a = R$		
	Second Choice: Take the Bonus Cash	Take the Card
Type in Actor Stage		
Always Cash	32.51 (1.37) $n = 1548$	69.90 (3.05) $n = 39$
Signal Dependent	26.07 (1.45) $n = 1346$	57.92 (3.74) $n = 142$

Inferences after observing $a = A$		
	Second Choice: Take the Bonus Cash	Take the Card
Type in Actor Stage		
Always Cash	77.25 (1.25) $n = 1243$	77.72 (1.66) $n = 344$
Signal Dependent	74.39 (1.86) $n = 302$	82.19 (0.87) $n = 1196$

Standard errors (in parentheses) are clustered at the individual level.

Table A4: *Average predictions about* $\Pr[s = h]$*—reported as a number out of 100—broken down by strategic type in the actor stage and subsequent choices (in the observer stage). Actions and inferences in the second stage are closely related, but a levels difference in inferences remains: signal-dependent types infer more for any observed action or own second choice.*

INFERENCES AFTER OBSERVING $a = A$ AND RATING

	All	Always Cash	Signal Dependent
Negative	76.44	77.27	76.07
	(1.60)	(1.88)	(2.13)
Neutral	75.23	74.69	76.18
	(1.06)	(1.25)	(1.40)
Positive	76.33	75.03	77.68
	(0.85)	(1.09)	(1.05)
Strongly Positive	75.54	74.01	77.25
	(1.08)	(1.26)	(1.47)
Observations (column total)	3960	1967	1897

INFERENCES AFTER OBSERVING $a = R$ AND RATING

	All	Always Cash	Signal Dependent
Negative	41.98	43.16	40.21
	(1.26)	(1.60)	(1.63)
Neutral	38.39	39.45	36.87
	(1.19)	(1.54)	(1.50)
Positive	34.01	33.10	34.16
	(1.60)	(1.81)	(2.24)
Strongly Positive	27.76	27.42	27.34
	(1.80)	(2.07)	(2.44)
Observations (column total)	4003	1989	1907

Standard errors (in parentheses) are clustered at the individual level.

Table A5: Inferences in Experiment 2. *Similar to our findings in Experiment 1, participants underinferred from $a = A$ (top panel). When facing $a = R$, participants utilized ratings information to form their inferences.*

	Own Rating			
	Negative	Neutral	Positive	Strong Positive
Observed Rating				
Negative	39.00	43.31	42.37	39.91
	(2.10)	(1.61)	(1.60)	(3.24)
Neutral	32.39	37.87	40.10	39.18
	(2.28)	(1.49)	(1.59)	(2.74)
Positive	24.10	32.70	36.69	35.54
	(2.95)	(1.87)	(1.92)	(3.70)
Strongly Positive	17.36	25.80	29.21	34.85
	(2.62)	(2.11)	(2.30)	(3.83)
Observations (column total)	406	1340	1650	607

Standard errors (in parentheses) are clustered at the individual level.

Table A6: Inferences in Experiment 2 after Observing $a = R$, by Observed and Own Rating. *After seeing someone reject the gift card, participants utilized the ratings information to form their inferences. But their own ratings shaped the degree to which they utilized information about others.*