Failing to Learn from Others*

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Abstract

We provide evidence of a powerful barrier to social learning: people are much less sensitive to information others discover compared to equally-relevant information they discover themselves. In a series of incentivized lab experiments, we ask participants to guess the color composition of balls in an urn after drawing balls with replacement. Participants' guesses are substantially less sensitive to draws made by another player compared to draws made themselves. This result holds when others' signals must be learned through discussion, when they are perfectly communicated by the experimenter, and even when participants see their teammate drawing balls from the urn with their own eyes. We find a crucial role for taking some action to generate one's 'own' information, and rule out distrust, confusion, errors in probabilistic thinking, up-front inattention and imperfect recall as channels.

Keywords: information aggregation, learning, social learning, experience effects

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1 Introduction

We learn new information in two main ways: through our own personal efforts and experiences or by acquiring information from others. For example, we may try out a new restaurant, experiment with a novel technology, or track the performance of our own investments. But we also have access to a vast trove of data that can be accessed through conversations with others, observing their outcomes, or reading about their experiences. Efficient learning requires us to correctly aggregate information from these different sources.

This paper tests the standard assumption in economics that equivalent pieces of information are weighed equally regardless of their source. Our three pre-registered experiments each involve a simple statistical learning task, in which participants make incentivized guesses of the fraction of red balls in an urn. To inform their guesses, they have access to noisy, independent signals. The signals are drawn either themselves or by another participant, with both opportunity and incentives to learn others' signals. If social learning is frictionless, we would expect participants' guesses to be equally sensitive to signals they generate themselves and signals drawn by their partners.

In the first experiment, we recruit 500 adults at the Behavioral Development Lab in Chennai, India. Participants play five rounds of the task with different treatments in randomized order. In a control condition, participants generate all signals themselves, i.e. they draw balls from the urn with replacement by themselves. In the treatment conditions, some of the signals are drawn by the participant themselves, while others are drawn by a randomly-matched partner. The participant then has a chance to learn their partner's draws in different ways. In some treatments, participants can learn the signals via discussion with their partner, who has an incentive to share information.[1] In other treatments, the experimenter directly informs participants about their partner's signals, thus shutting down any communication frictions between participants.

Our three empirical approaches—non-parametric, reduced-form, structural—impose different assumptions but yield similar results. We focus here on the reduced-form approach, which simply asks how much the average guess changes in response to an additional red (as opposed to white) draw—we call this the "sensitivity" to information or, alternatively, the "weight" placed on signals.

[1] In these discussion rounds, participants were also asked to make a joint guess, such that in addition to learning each other's signals, participants could also jointly deliberate.

Participants' guesses are substantially less sensitive to their partner's draws compared to their own draws. When participants have a chance to learn their partner's draws through a face-to-face discussion, subsequent guesses are 54% less sensitive to their partner's signals than to their own ($p < 0.01$).[2] The lower sensitivity to others' information is not driven by a lack of communication: when participants are additionally perfectly informed of their partner's draws by the experimenter—ensuring the relevant information is shared—they discount the information by a nearly identical 46% ($p = 0.02$). When informed of the partner's draws by the experimenter but without the aid of joint deliberation, the results are even starker: participants are 87% ($p < 0.01$) less sensitive to their partner's information. Consequently, signals that participants' partners gather are worth between 37% and 85% less—in terms of payoffs from more accurate guessing—than signals they gather themselves.

In a second experiment with 292 adults in the same setting, we test additional treatment variations to evaluate mechanisms. Our most striking finding is that participants underweight their partner's information by 41% relative to their own even when they sit beside their partner and can observe them drawing balls from the urn with their own eyes ($p = 0.04$). This result narrows the list of potential mechanisms. Specifically, it eliminates or diminishes any role for (i) distrust of the information communicated by the partner and/or experimenter, since the information is directly observed with one's own eyes; and (ii) the mode of presentation of the information, including both its visual salience and whether the information is learned draw-by-draw or communicated in summary form. Moreover, randomly increasing incentives for accuracy by 50% does not increase sensitivity to others' information.

The third experiment evaluates the external validity of our findings in a higher-literacy population while further exploring mechanisms. In a simpler between-subjects experiment with 4,489 participants from the UK and US on the Prolific platform, we randomize the order of learning one's own signals versus a partner's signals. Again, participants are less sensitive to others' compared to their own information, by 17% ($p < 0.01$), despite it being perfectly communicated to them.[3] Presenting own and

[2] This comparison is not confounded by the order in which participants learn their own versus others' information, as described in detail in Section 4.

[3] The magnitude of discounting of others' information is significantly lower in the online experiment than in the lab experiments. This difference could be because the online experiment generates less of a sense of playing with another person or of truly drawing the signals oneself. Indeed, participants are often less sensitive to treatments in online experiments (Gupta et al., 2021). Differences in the study populations between India and the US/UK may also contribute to the difference.

others' signals using visually identical animations does not reduce underweighting, nor does increasing the stakes of the experiment or reducing any sense of competition by barring the partner from making any guess.

What determines whether people treat information as 'theirs' and therefore more influential? In our third experiment, we find a critical role for taking some action to generate one's own information. When participants have to click a button to generate each of their own draws, they are less sensitive to their partner's information than to their own. In contrast, when they passively observe draws appearing on the screen with a label identifying them as 'Yours' or 'Your partner's', this under-sensitivity is significantly reduced (and, in some specifications, disappears completely). This suggests that being actively engaged or exerting some effort to uncover information oneself—as one might when trying out something oneself—makes it more influential than equivalent information perfectly received from others.

A debriefing survey at the end of the third experiment sheds further light on the psychological mechanisms. First, underweighting of others' information does not appear to be driven by imperfect up-front attention or later recall: underweighting of others' information is statistically significant and quantitatively similar even among participants who perfectly recall their partner's draws after making their guess. Second, participants are largely unaware of their bias against information coming from others. 77% of participants reported that they treated their own and their partner's information the same. Yet these same participants are just as insensitive to their partner's information.

Taken together, our experiments establish a tendency for people to underweight information uncovered by others even when there is no reason to do so. The experimental design rules out order effects, distrust, difficulties in probabilistic reasoning, overconfidence, or competitiveness as explanations. Whether people discount others' information also does not depend on how people learn others' information, e.g. by discussion with the person themselves, reported by a third party, or seen with one's own eyes, and communicated in summary form or in a piece-meal way. Instead, our results suggest a bias in favor of information generated oneself, which people treat as more precise or relevant.

The main contribution of this paper is to the literature on social learning. Our results further our understanding of how agents aggregate the information that reaches them through others (see Mobius and Rosenblat 2014 for a review). Existing research finds that people fail to fully account for the correlation structure of the information that reaches them (Eyster et al., 2015; Enke and Zimmermann, 2019) and instead naively average their social neighbors' views or information (Chandrasekhar et al., 2020). In field settings, people sometimes also react very differently to information depending on the source, e.g. they may react more to information coming from celebrities (Alatas et al., 2020) or from people who are socially or economically similar to them or who are of a particular gender (BenYishay and Mobarak, 2019; BenYishay et al., 2020).[4] We provide evidence for a different, potentially far-reaching bias in information aggregation which may hinder social learning whenever people have to aggregate their own and others' information. This phenomenon may underlie other documented cases of incomplete social learning, whether in agricultural technology adoption in the field (Foster and Rosenzweig, 1995; Conley and Udry, 2010) or observational learning in the lab (Weizsäcker, 2010). It could also play a role in explaining the often modest effects of interventions providing people with information regarding the experiences or outcomes of others (Haaland et al., 2022).

Our paper also relates to the literature in psychology and economics on learning from experience. In the field, this literature has shown that people's beliefs and economic decisions are powerfully shaped by their personal experiences, even when much more complete data are easily available (Malmendier and Nagel, 2016; D'Acunto et al., 2021). In the lab, closest to to our study, Simonsohn et al. (2008) show that when people play repeated strategic games with rematching, their actions in each round are more sensitive to their experiences with their recent partners than to information they are provided on other players.[5] Our findings have a similar flavor, but with a simpler setup without dynamics and without any notion of receiving feedback or earning utility from one's past actions. Instead, we show that information uncovered through one's own actions is weighed more than information uncovered by others even prior to making any choice or receiving feedback.

An open question is how this bias plays out in the field and whether under-sensitivity to others' information is a reasonable heuristic. In some situations, for example when returns to an action are idiosyncratic, information that comes from others is truly less

[4]This finding could be consistent with Bayesian learning if the information from particular sources is considered to be less precise or relevant to the receiver.

[5]Another related paper is Miller and Maniadis (2012), which shows using a balls-and-urns task that a personally-experienced event affects subsequent choices more than an equally-informative observed event which did not directly affect the player.

relevant to one's own decisions. Or information received from others may be untrustworthy or correlated and thus one should react less to it than to one's own independent signals. However, in many cases, people have limited information from their own experiences while information from others is far more informative and reliable, so discounting others' information is costly. More research is required to understand the prevalence and strength of the effect we document in natural settings.

The remainder of this paper is organized as follows. Section 2 presents the broad aspects of the design shared by the different experiments. Sections 3 presents the empirical framework. Sections 4, 5 and 6 present the detailed designs and results of the three experiments. Section 7 discusses confounds and alternative interpretations. Section 8 discusses open questions and concludes.

2 Overview of Design

In all three experiments, participants play multiple rounds of the same basic statistical learning exercise: a balls-and-urns task based on a large literature studying individual learning (Benjamin, 2019). Here, we describe the task and features of our design common to all experiments. We defer discussion of treatment variations and details specific to each experiment to the corresponding sections below.

The goal in the experimental task is to guess the number of red balls in an urn containing 20 balls. Participants are informed that the number of red balls in the urn is drawn uniformly from 4 to 16 in each round, as explained with help of the illustration in Appendix Figure A.I(a) in the in-person experiments.[6] In the online experiment, we explain that "the computer will randomly choose the exact number of red marbles [in the urn], where every number between 4 and 16 was equally likely to be chosen."

In each round, participants receive independent, noisy signals about the composition of the urn, by privately drawing a number of balls from the urn with replacement.[7] The number of draws in each 'signal' is randomized—either 1, 5 or 9 draws—creating

[6] We avoided more extreme distributions—fewer than 4 or over 16 red balls out of 20—as these were more likely to generate signals with complete agreement between the two partners.

[7] In Experiments 1 and 2, participants physically drew balls from an urn in our lab, while in Experiment 3 (the online experiment) the drawing was simulated using an animation of an urn. In each case, participants were informed that both partners were drawing from the same urn. In Experiments 1 and 2, at least one participant was always present with the urn, eliminating any concern that the urn might be switched out between players.

variation in how informed each participant is.[8]

Depending on the treatment condition, participants either play the game entirely on their own—the *Individual* treatment—drawing two sets of balls themselves, or else draw one set of balls themselves and have access to another set of balls that a partner (another participant in the experiment) drew. The different treatments vary how the information obtained by one's partner can be learned: via open-ended discussion, directly communicated by the experimenter, observed with one's own eyes, etc. Guesses are made after making each set of draws (or potentially learning them via their partner). We test for frictions in social learning by comparing the sensitivity of guesses to draws across conditions.

2.1 Incentives to pool information and make accurate guesses

Participants have incentives to pool information and make accurate guesses. The incentives provided were chosen to be easy for participants to understand: a penalty per ball away from the truth. Formally, each guess is incentivized by a piece-wise linear loss function.[9] For example, in Experiment 1, a perfectly accurate guess earns each member of the pair Rs. 105 and the payment decreases by Rs. 15 per ball the guess deviates from the truth. This incentive scheme was explained to participants in Experiments 1 and 2 using the illustration shown in Appendix Figure A.I(b). These incentives are sizable. Rs. 105 is about \$1.50 and Rs. 15 is about \$0.20, while average daily earnings in our Chennai sample are about Rs. 350 (\$5). Further, as we will show below, randomizing higher stakes for half the rounds in Experiments 2 and 3 does not change our findings.

Participants make multiple guesses throughout the experiment, and we randomly select one guess to score and pay participants for its accuracy. In Experiments 1 and 2, we select one guess among all the guesses that either partner made (including intermediate guesses). We then divide the payoff equally between the two participants irrespective of who made the guess. Each participant receives their half in a separate envelope at the end of the experiment. Each person thus has an incentive to make every

[8] To be precise, we randomly choose the number of draws in the two sets of draws received in each round with uniform probability from $\{(1,1),(1,5),(5,1),(5,5),(1,9),(9,1)\}$. This excludes cases with more than 10 draws total.

[9] On top of their participation fee, each person receives a payment equal to $\max\{(A - B \times |g - r|), 0\}$, where g is the guess, r the true number of red balls for the randomly-selected guess, and A and B are constants.

guess from their pair as accurate as possible. Neglecting to ask your partner for information, withholding information from them, or ignoring their information thus reduces your own expected payoff. In Experiment 3, the online experiment, participants never need to (and, indeed, cannot) communicate, and information is shared by design. Each participant is rewarded for a randomly selected one of their own guesses, i.e., we do not split incentives between partners.

2.2 Complexity and comprehension

We designed the experimental task to balance two goals. First, given relatively low education and numeracy levels in the samples for Experiments 1 and 2, it was meant to be easy to understand and feasible for most participants. We therefore avoided eliciting probabilistic beliefs or employing difficult-to-explain scoring rules. Similarly, we used uniform priors as they are easy for participants to understand. We also provided training in the task to the participants of Experiments 1 and 2 before the first round. Participants individually played two unincentivized practice rounds with two guesses in each, and during these rounds received two 'tips' on making good guesses.[10] The vast majority understood the tasks, as measured by excellent performance on comprehension checks (Table A.I).

The simple setup of our experiment does not require participants to use others' actions to make (potentially complex) inferences about their information. Nor must they attempt to correct for any redundancy in the information that reaches them through multiple sources. Instead, participants in our experiment can directly learn their partner's independent signal itself. This is in contrast to studies where participants observe other participants' decisions, sometimes in complex real-world networks, and must both infer the underlying signals as best they can and then make decisions based on those inferences (Goeree et al., 2007; Reshidi, 2020; Chandrasekhar et al., 2020).

The second goal was to design a task that is sufficiently complex—as in many learning problems in the field—to create some ambiguity and wiggle room for biases and

[10]The first tip explains that it makes sense to guess there are more red than white balls if you draw more red than white, and vice-versa. The second tip is that "the more balls you draw, the more confident you can be in your guess". We note a possible caveat that some participants might have construed these tips to imply their 'own' information was more valuable than someone else's. However, the tips were given in the context of a practice round where all balls were drawn oneself, so there was no implication of discounting others' information. Nonetheless, these tips were not provided in Experiment 3.

heuristics to enter participants' decision-making. Making the optimal guess sufficiently easy to compute—e.g. with very few states or possible signals—might have potentially eliminated all biases since the correct action would become obvious to everyone.

A caveat resulting from the above design choices is that we do not, strictly speaking, measure participants' beliefs about the color composition of the urn. Doing so would involve eliciting their full probabilistic belief distribution, or at least attempting to elicit the mean (or median or mode) of their belief distribution by employing a proper scoring rule (Palfrey and Wang, 2009). The incentives we employ do *not* constitute a proper scoring rule, and the optimal guess of a participant is not generally their mean or modal belief.[11] Guesses should therefore be thought of as actions which participants have an incentive to tailor to the signals they receive. Our empirical tests examine whether these guesses are equally sensitive to one's own and others' signals. However, as a benchmark, we also compute what a risk-neutral Bayesian seeking to maximize expected payoffs would guess given the signals and our incentive structure. In addition, our structural model accounts for the incentive structure faced by participants.

3 Empirical Framework

Our goal is to test whether individuals' guesses are equally sensitive to signals drawn by themselves versus by others. We further examine how this depends upon the precise mode of social learning, such as whether the partner's information must be learned through a discussion, is communicated by a third party (the experimenter), is directly observed, etc. We present three types of empirical analyses—non-parametric, reduced form, and structural—to answer these questions. These three approaches impose different assumptions and have different strengths, but ultimately lead to similar conclusions.

[11] Practically speaking, our goal was for participants to broadly understand that they face an incentive to pay attention to information, think about it, and try to make accurate guesses. We avoided using more complex scoring rules such as quadratic or binarized scoring due to the difficulty of explaining them even to higher-education populations (Danz et al., 2022). A simpler alternative would be to pay a reward if a participant guessed the truth exactly, while paying zero otherwise. This has the attractive feature of giving the participant incentives to report the mode of their belief while still easy to understand. We did not pursue this route since we felt it would be unfair to participants, and could cause disappointment or ill will, making future recruitment harder. That said, our incentive scheme is close to a proper scoring rule for the median of the Bayesian posterior under risk neutrality, due to its absolute value form. The exception is following rare extreme draws (mostly red or mostly white) where the truncation of the loss function at zero incentivizes shading the guess towards 50% red.

3.1 Non-parametric approach

In the non-parametric approach, we present the results with minimal assumptions, by simply plotting average guesses in each treatment against the signals drawn. For simplicity, we summarize each signal by the net number of red draws (i.e., number of red minus number of white draws). That is, if a participant saw 4 red draws and 1 white draw, we would classify the signal as being 3 net red draws.[12] To enable a transparent comparison of the sensitivity of guesses to own versus others' signals, we plot the guesses separately against the signals drawn oneself versus the signals drawn by one's partner.

3.2 Reduced-form approach

Next, we impose a linear relationship between signals and the resulting guesses and test for differences in this relationship across treatments. We estimate the following equation by OLS, separately by treatment:

$$Guess_i = \alpha + \beta_1 \cdot \mathit{Own\ Info}_i + \beta_2^p \cdot \mathit{Partner's\ Info}_i + \epsilon_i \tag{1}$$

where $Guess_i$ is i's guess of the number of red balls (after having a chance to learn both signals), and $\mathit{Own\ Info}_i$ and $\mathit{Partner's\ Info}_i$ are the net number of red draws (i.e., red minus white draws) drawn oneself and by one's partner, respectively. β_1 and β_2^p capture the sensitivity of participants' guesses to signals drawn themselves and by others, respectively. If participants learn their partner's signals and treat them the same as their own signals, it should be that $\beta_1 = \beta_2^p$. If instead $\beta_2^p < \beta_1$, participants in that treatment are less sensitive to their partner's draws than to their own.

There are two ways in which we modify our tests to deal with order effects in the experiments. First, in all three experiments, participants play the game multiple times in randomized order. Although they receive no feedback after each round, and thus the scope for learning is limited, we control for order effects by including dummies for round number interacted with $\mathit{Own\ Info}_i$ and $\mathit{Partner's\ Info}_i$.[13]

[12] This simplification loses some information, e.g. it does not capture the total number of draws. A signal with 1 net red could come from a single draw of a red ball or from 9 draws with 5 red and 4 blue. A Bayesian should react differently to these two signals. The structural model does not share this weakness.

[13] We stack the regression for all treatment conditions in a given experiment and estimate them

Second, the order in which one receives information may affect the weight placed on it. For a Bayesian, the order of receiving information should not matter, and this should not introduce a bias to our analysis. Nonetheless, ex ante we might worry that participants put more weight on signals they saw first ('first impressions matter') or on signals they saw last ('recency effects'). We therefore designed our experiments to avoid order effects or to be able to control for them. In Experiment 3, the order of learning one's own and one's partner's signals is randomized with equal probabilities, and thus Equation 1 is unbiased. In Experiment 1, instead, participants learn their partner's signals only after they have received their own signals. Therefore, Experiment 1 includes a control condition (the *Individual* condition) in which both signals are drawn oneself. For a clean comparison, we therefore compare the sensitivity of guesses to one's partner's draws versus one's own *second* set of draws from the *Individual* condition. That is, we compare β_2^p from equation 1 with the corresponding coefficient on participants' second set of draws in the *Individual* condition.[14] In practice, we find that participants tend to put more weight on the signals they receive *second*, so treatments that provide partners' information last would tend to bias us *against* finding under-sensitivity to others' information.

3.3 Structural approach

In our third empirical approach, we estimate a simple model of quasi-Bayesian updating. This approach has a number of strengths relative to the reduced-form analysis. First, it exploits the full information content of the signals, including the number of draws, rather than the simplified 'net red draws' employed in the reduced form. Second, it accounts for the incentive structure faced by participants, modeling them as risk-neutral agents trying to maximize expected payoffs given their beliefs. Third, by taking the form of a standard learning model, it allows us to estimate interpretable weights placed on one's own and others' signals, with a clear Bayesian benchmark. Finally, it also accounts for noisy choice together with censoring in guesses at 4 and 16, which might otherwise cause guesses to appear less sensitive than those of a risk-neutral Bayesian. On the other hand, the structural model makes more assumptions than the non-parametric

jointly in one regression, allowing all coefficients to vary by treatment.

[14] Experiment 2 has aspects of the design of both Experiment 1 and Experiment 3. Some comparisons involve a randomized order of receiving information, as in Experiment 3. Others are similar to Experiment 1 in that one's partner's information is received after one's own information.

and reduced-form analysis, including imposing risk-neutrality.

Let d_1 be the participant's own signal and let d_2 be her partner's signal, e.g., d_1 might equal $\{\text{Red}, \text{Red}, \text{White}, \text{Red}, \text{White}\}$ and d_2 might equal $\{\text{Red}\}$. We then assume that the participant updates her beliefs about the state of the world s (the number of red balls in the urn) according to a modified version of Bayes' Rule:

$$Posterior(s|d_1, d_2) \propto Prior(s) * P(d_1|s)^{\omega_{1rt}} * P(d_2|s)^{\omega_{2rt}} \tag{2}$$

where $Prior(s)$ is the participant's prior about the probability of state s, and $P(d_i|s)$ is the (objective) probability of observing a set of draws d_i conditional on state s. Recall that participants are told each state is equally likely, and there are 13 possible states $s \in \{4, 5, ..., 16\}$, so $Prior(s) = \frac{1}{13}$. Next, ω_{1rt} and ω_{2rt} are the weights that the participant puts, respectively, on her own and her partner's signals in treatment t when that round occurs in chronological order r. For $\omega_{1rt} = \omega_{rt2} = 1$, equation (2) reduces to Bayes' rule.

We allow ω_{1rt} and ω_{2rt} to differ from the Bayesian benchmark depending on both the treatment condition and the chronological order of the round. In particular, we assume the following functional form to mirror the reduced-form analysis described above:

$$\omega_{1rt} = \beta_{1t} + \mu_{1r}$$
$$\omega_{2rt} = \beta^p_{2t} + \mu_{2r}$$

where β_{1t} and β^p_{2t} are, respectively, the weight the participant puts on her own and her partner's signal in treatment t, and μ_{1r} and μ_{2r} are the additional weight she puts on each signal when that treatment occurs in chronological order r.

Just as with the reduced-form analysis, we control for the order in which information arrives in one of two ways. In Experiment 1, the partner's information is always conveyed second, so we use a control condition (the *Individual* treatment) where both signals are drawn by the participant herself. We then estimate a version of β^p_{2t} using participants' second set of signals in this *Individual* round. Comparing this estimate to β^p_{2t} in other treatments, we can identify the effect of drawing information yourself, net of any order effects. In Experiment 3, we randomize whether participants' own information or their partner's information comes first, so ω_{1rt} and ω_{2rt} will not be biased by differential treatment of earlier or later signals.

In addition to systematically biased updating, we allow for noisy choice. Doing so allows us to account for heterogeneity in guesses conditional on signals (i.e., not everyone with the same signals makes the same guess). We assume that agents are risk-neutral but calculate the expected payoff of each possible guess with noise. In particular, we can define $Earnings(g, s)$ to be the earnings that a participant would earn if they made guess g and the true state was s. Given the experimental incentives, this implies $Earnings(g, s) = \max\{0, 105 - 15 * |g - s|\}$. We assume that the agent calculates the expected payoff of each guess g using the (potentially biased) updating rule given by equation 2 plus a random additive error term. That is, we assume the perceived expected payoff from making guess g given draws d_1 and d_2 is given by

$$EP(g|d_1, d_2) = \sum_{s=4}^{16} Posterior(s|d_1, d_2)Earnings(g, s) + \alpha\epsilon_{i,g}. \quad (3)$$

The agent then chooses the guess that maximizes this perceived expected payoff. For simplicity, we assume $\epsilon_{i,g}$ is iid Type 1 extreme value. The parameter α then governs the extent of noisy choice.[15] We estimate the model by maximum likelihood.[16]

4 Experiment 1: Establishing the Main Results

4.1 Recruitment and Sample

Experiment 1 was conducted in person at the Behavioral Development Lab in Chennai, India, between July and December 2019. Participants were recruited on a rolling basis, with about 4 to 10 individuals completing the experiment on a given day. We recruited individuals—not pairs—residing in low- to middle-income neighborhoods within a reasonable travel time of the lab. Surveyors went door-to-door to advertise an academic

[15]See Goeree et al. (2007) for an example of a similar model of noisy discrete choice in a balls-and-urns decision problem.

[16]In particular, given the assumptions above, the probability that an agent with signals d_1 and d_2 will choose guess g is $P(i \text{ guesses } g|d_1, d_2) \propto \exp\left(\frac{1}{\alpha}\left[\sum_{s=4}^{16} Posterior(s|d_1, d_2)Earnings(g, s)\right]\right)$. We then choose parameters that maximize the joint likelihood of observing all the choices in our data. We calculate standard errors by bootstrapping the data, drawing pairs with replacement from the data. Throughout, we report bootstrapped standard errors for legibility but denote significance using bootstrapped confidence intervals (e.g., an estimate is significant at the 5% level if the center 95% of bootstrapped estimates do not include zero).

study on 'your choices and how you aggregate information' which would 'help us understand how you make decisions'. No more specific study details were provided at this stage. Potential participants were informed that they would spend 2 to 3 hours at the study office and could expect to earn Rs. 150 to 280 ($2 to 3.90) per person, plus a payment of Rs. 100 ($1.40) to cover travel expenses. Recruitment stopped when we reached our pre-specified target of 500 individuals. Participants were randomly assigned to pairs within an experimental session.[17]

Column 1 of Table 1 reports characteristics of our sample. 50% are male; participants are on average 35 years old and have almost 8 years of education. Participants answered about 80 percent of comprehension questions correctly on the first attempt, indicating fairly high levels of attention and comprehension for a task that was unusual and somewhat complex given the local context.

4.2 Experiment 1: Design

Participants play five rounds of the task, as illustrated in Figure 1, with no feedback between rounds.[18] Participants first play, in randomized order, an *Individual* round and a *Discussion* round. In each round, participants have access to two sets of draws with 1, 5, or 9 draws each.

***Individual* round.** In the *Individual* round, the participant first draws a set of balls from the urn with replacement, followed by a guess of how many red balls are in the urn. Then, they draw a second set of balls from the urn and make a second (and final) guess. All drawing and guessing is done privately, without any need to share information. This round serves as a control condition—a benchmark against which we compare the other treatments.

***Discussion* round.** The *Discussion* round models a common mode of social learning, where we learn from others' experiences through direct communication with them. Instead of drawing two sets of draws oneself as in the *Individual* round, participants'

[17]Each participant plays four of their five rounds with one randomly-assigned partner of a different gender, and one round with a randomly-assigned partner of the same gender. Participants were introduced to their partner at the start of each round. This variation was induced in order to study the effect of gender composition on learning and to contrast these findings with a study of learning between spouses. These results are reported in a companion paper. Here, we pool results across gender and both types of pairs.

[18]The full experimental script is provided in Appendix A.3.

partner's draws—accessible through a discussion—serve as their second set of draws. Each person first makes one set of draws followed by a private guess, exactly as in the *Individual* round. Next, the pair are asked to hold a face-to-face discussion and enter a joint guess.[19] After their discussion, the teammates are separated and each person makes one final, private guess.

Participants can take as long as they like for the unstructured, face-to-face discussion with their partner. They have an incentive to share information since one guess per team is randomly chosen to be paid for accuracy at the end of the experiment, with the payment split between the two partners. Participants also have an incentive to help their partner deliberate and make better guesses conditional on information, as in Cooper and Kagel (2005). We record the audio of the discussion (with participants' consent) and later analyze the transcripts, as reported in Table A.II.

Comparing each participant's final guesses in the *Individual* and *Discussion* rounds reveals whether they learn as much through a discussion with a partner as from information they uncovered themselves. By design, participants have access to the exact same number of draws to inform their final guess in these two rounds, provided they share information.[20] If participants are instead less sensitive to information collected by their partner, this implies either a failure of communication or a failure to aggregate information provided by one's partner.

Participants next play three more rounds, in randomized order, consisting of a *Discussion* round and two additional treatments in which the experimenter informs the participant of their partner's draws or guesses.

[19] The joint guess was included as a comparison to joint guesses made by teams composed of married couples, and is not the focus of this paper. Note that having to enter a joint guess might cause teammates to come closer to agreement about the optimal guess, which might be expected to reduce under-sensitivity to each others' information. Experiment 3 and most treatments in Experiment 2 do not include such a joint guess.

[20] In order to allow a particularly sharp comparison between the *Individual* and *Discussion* rounds, we ensure that exactly the same number of draws are available to each individual by the end of the both rounds. For instance, suppose that an individual (call them Person 1) gets n_1 draws first and n_2 draws second in the *Individual* round, for a total of $n_1 + n_2$ draws. We ensure that their partner ('Person 2') in turn receives n_2 and then n_1 draws in the *Individual* round. To make the *Discussion* round comparable, we ensure that Person 1 receives n_1 draws and Person 2 receives n_2 draws, such that, if they pool information in their discussion, each again has access to $n_1 + n_2$ draws to inform their final private guess. (n_1, n_2) are randomized across pairs. In the other rounds, (n_1, n_2) are randomized independently within-pair across rounds.

***Informed of Partner's Draws* round.** This round (which we abbreviate as the *'Informed'* round) is designed to shut down any communication frictions between the partners. It is identical to the *Discussion* round except that, after participants receive their first set of draws and enter their first guess, they are told their partner's draws (both number and composition) directly by the experimenter, e.g. "Your partner had five draws, of which three were red and two were white." Participants then make an additional private guess which can incorporate both sets of draws before moving on to the discussion and their final private guess.

Comparing the guess made after the experimenter informs the participant of their partner's signal (but before discussion) with the second guess in the *Individual* round allows us to directly test whether participants use information they gathered themselves in the same way as information collected by others but perfectly shared with them by a third party. In each case, there is no possibility of joint deliberation.[21] Comparing instead the post-discussion guess in the *Informed* round with that in the *Discussion* round holds fixed the possibility of joint deliberation while testing whether communication frictions in discussion inhibit information pooling.

***Informed of Partner's Guess* round.** This round is the same as the *Informed of Partner's Draws* round except that the experimenter informs each person of their partner's private guess (made based on their own draws only), rather than their partner's draws. The experimenter also shares the number of draws this guess was based on, e.g. "Your partner had 5 draws and, after seeing these draws, they guessed that the urn contains 12 red balls." Thus, while in the *Informed of Partner's Draws* round we directly transmit the signal received by one's partner, in the *Informed of Partner's Guess* round we transmit the action (guess) taken based on that signal as well as a measure of the precision of the signal. This round parallels more closely the literature which investigates social learning based on observing others' actions (Weizsäcker, 2010). In this treatment, less information is transmitted to the participant. Moreover, beliefs about others' competence might affect how these actions are interpreted and how much is learned about the signals.

[21] Note that this comparison requires controlling for order effects, since the *Individual* round is always in the first two rounds, while the *Informed* round falls in rounds 3-5.

4.3 Experiment 1: Results

4.3.1 Non-parametric results

We begin by examining participants' first guesses, which they make after drawing the first set of balls by themselves. Reassuringly, as shown in Figure 2 Panel A, the average number of red balls guessed increases in the number of "net red" draws uncovered oneself (pooling across all treatments), implying that participants respond to information they receive. We can compare this sensitivity to a normative benchmark by computing, for each guess that participants make, what a risk-neutral Bayesian seeking to maximize expected payoffs would guess given the same signals and faced with our incentive structure. Figure 2 shows that, on average, participants' individual guesses (blue dots and lines) are fairly close to this benchmark (pink dashed lines), though they are somewhat less sensitive to signals than a risk-neutral Bayesian would be.[22]

Figure 3 contrasts the sensitivity of participants' guesses to their second set of draws in the *Discussion* and *Informed* rounds, comparing each to the *Individual* round. The blue curve representing the *Discussion* round (left panel) is distinctly flatter than the grey curve representing the *Individual* round, revealing that participants' guesses are less sensitive to information gathered by their partner compared to information they gathered themselves. This difference is statistically significant: we can reject (F-test, $p = 0.001$) that the differences in average guesses across treatments for each 'net red' value are all zero (i.e., that each pair of dots in Figure 3 lie on top of each other).

Strikingly, the curve is even flatter in the *Informed* round (middle panel), in which we plot participants' guesses after their partners' information is *directly* communicated to them by the experimenter (and before any joint deliberation with their partner). Despite having been given *all* decision-relevant information about their partner's draws directly, participants react to this information much less than they do to information they collected themselves. We can again reject that average guesses conditional on each 'net red' value are always equal across treatments (F-test, $p < 0.001$).[23] This result

[22]The lower sensitivity compared to the risk-neutral Bayesian could be due to conservatism in updating, risk aversion, or noisy guessing combined with censoring. We do not seek to disentangle these explanations, as our focus is instead on testing whether guesses respond differently to information depending on the source by contrasting behavior *across* treatments. The structural estimation accounts for noisy guessing and censoring in the data.

[23]Note that this graph depicts the second private guess—after being informed of one's partner's draws but before having a chance to discuss with them. This provides a clean comparison with the

suggests that the key friction is not communication (i.e. participants never learning the information from their partner) but instead participants underweighting information uncovered by their partner, even when it is communicated. By design, this behavior cannot be explained by failure to communicate information or by mistrust of the partner's memory or motives.

Is lower sensitivity to others' signals necessarily evidence of worse learning? Recall that sensitivity to one's own signals is itself lower than that of a risk-neutral Bayesian (Figure 2). Since sensitivity to others' signals is lower still (Figure 3), this suggests that participants learn less effectively—are even further away from this benchmark—when some information is only available via a discussion with their partner.

4.3.2 Reduced-form and structural results

The reduced-form and structural models provide quantitative estimates of sensitivity to own and others' information. Figure 4 plots participants' average sensitivity to the second set of signals, by treatment, using reduced-form estimates from Equation 1. In their final private guesses in the *Discussion* round, participants are less than half as sensitive to their partner's signals compared to the corresponding signals in the *Individual* round (second bar, $p<0.01$). This implies they respond less to information collected by their partner compared to their 'own' information. Even more starkly, participants put close to zero weight on their partner's information in the *Informed* round, right after it is *directly* shared with them (third bar, $p<0.01$). Adding a face-to-face discussion with their partner after being informed of their draws somewhat increases participants' sensitivity to their partner's signals, but it remains significantly below the sensitivity to their own signals (fourth bar, $p=0.02$). Recall that these estimates hold the order of receiving the information fixed: we compare sensitivity to the second set of draws across treatments.

The corresponding regression estimates are presented in Table 2 Panel A (cols 1 to 4). Comparing the coefficient β_2 on the second set of information by treatment condition shows a clear result. Participants are 54 percent (0.28/0.52) less sensitive to information collected by their partner in the *Discussion* round relative to information they collected themselves in the *Individual* round ($p<0.01$). They are a striking 87 percent (0.45/0.52)

individual round: the only difference is drawing the signals oneself versus being informed of the signals one's partner drew. The right panel of Figure 3 shows *Informed* round guesses after the discussion.

less sensitive to their partner's draws in the pre-discussion *Informed* guess compared to in the *Individual* round (p<0.01), and 46 percent (0.24/0.52) less sensitive to their partner's draws in the post-discussion *Informed* guess compared to the *Individual* round (p=0.02). The face-to-face discussion increases sensitivity to the partner's information, presumably through joint deliberation regarding the right answer (since the information was already shared between partners).[24]

The structural estimates in Table 2 Panel B mirror the reduced-form results. Column 1 shows that participants put close to the Bayesian weight ($\beta_1 = 0.92$ vs. the Bayesian benchmark of 1) on their own first signal in the *Individual* treatment, and somewhat greater weight ($\beta_2^o = 1.50$) on their second signal in that round. In contrast, participants put 73% less weight (1.11/1.50, p<0.01) on their partner's signals in the *Discussion* round, and most strikingly put no weight at all on their partner's signals in the (pre-discussion) *Informed* round. In the post-discussion *Informed* round, they put 69% less weight on their partner's signal than on their own signal in the *Individual* round.[25]

Earnings implications. The expected earnings from guesses are a direct measure of performance in the experiment. Table 3 estimates average expected earnings from guesses as a function of the number of draws in the each set of signals. As expected, more draws in the second set of signals in the *Individual* round significantly increases earnings, by Rs. 2.79 per extra draw. However, participants earn significantly less for each extra draw their partner makes in the *Discussion* (p=0.03) and *Informed* (p=0.06) rounds. This provides further evidence that learning is worse when information is not all uncovered oneself.[26]

[24]The pattern of results in the *Informed of Partner's Guess* round are similar or more extreme than those that we find in the *Discussion* and *Informed of Partner's Draws* rounds. In the reduced-form estimates, participants are 90% less sensitive to their partner's information in this treatment. Because lower sensitivity to others' information in this treatment can be explained by additional factors such as guesses containing less information than draws or players' beliefs about their partners' ability to make good guesses, we leave analysis of the *Informed of Partner's Guess* round to Appendix A.1.

[25]The parameters of the quasi-Bayesian model have a different scale and interpretation than the reduced-form results discussed above. But frictionless social learning implies $\beta_2^o = \beta_2^p$ in both cases, where o and p refer to own and partner's draws respectively. Appendix A.2 shows that the reduced-form and structural estimates are consistent with each other: data simulated using the structural model produces the same reduced-form results as the empirical data.

[26]Table A.III in the appendix shows similar regressions but where the dependent variable is the absolute difference between participants' guesses and the true number of red balls in the urn. Mirroring the results in Table 3, additional draws reduce this error on average, and this improvement is smaller when these draws come from participants' partners in the *Discussion* and *Informed* rounds.

5 Experiment 2: Exploring Mechanisms and Confounds

Why do participants discount their partner's information even when it is directly communicated to them? Experiment 2 is designed to isolate potential mechanisms, rule out potential confounds, and evaluate the robustness of our findings.

5.1 Recruitment and Sample

Experiment 2 was run at the Behavioral Development Lab in Chennai, India between January and March 2020, after observing the results of Experiment 1. We recruited new participants following a similar procedure as Experiment 1. Data collection ended in March 2020 due to the Covid-19 pandemic, with a sample size of 292 participants (out of an intended sample of 800).[27] Compared to Experiment 1, participants have a similar average age (38 versus 35) and years of education (9 versus 8), but are less likely to be female (31% versus 50%), as reported in Column 2 of Table 1.

5.2 Experiment 2: Design

Participants played six rounds corresponding to different treatment conditions, with no feedback between rounds. They first played a *Discussion* round, exactly as in our first experiment, to provide a baseline and comparison with our previous sample. They then played five rounds in randomized order, consisting of a *Informed* round just as in Experiment 1 and four additional variations of *Informed*, described below.[28]

***Observe Partner's Draws* round.** In this round (which we abbreviate to *'Observe'*), both participants are in the same booth, so they can each watch their partner drawing balls from the urn with their own eyes. After both participants have drawn their signals, in randomized order, they are separated and each make a private guess. There is no discussion between partners and no need for the experimenter to share

[27]The pre-registered sample size was chosen in order to be powered to test for gender differences in treatment effects (which we explore in other work). Thus, even though the final sample size is much smaller than intended, we remain tolerably well-powered to estimate the treatment effects described here. For example, the minimum detectable effect size for the *Informed* treatment is around 50% lower sensitivity to partner's information relative to own information. This is close to the estimated effect in Experiment 1.

[28]Appendix Figure A.II, Panel A, also illustrates the design of the new treatment conditions in this experiment. The full experimental script is provided in Appendix A.3.

draws. Nor is there any scope for distrust of the experimenter or partner. Both one's own and one's partner's signals are perfectly observable, are revealed draw-by-draw, in randomized order across individuals. The *only* difference between the two sets of draws is who physically drew the balls from the urn. We designed this to be an extreme treatment, where we anticipated equal sensitivity to own and others' information. The remaining treatments are subtler and largely subsumed under this treatment.

Draw-by-Draw **round.** In the *Informed* treatment, participants learn about their own and their partner's information in different ways. One such difference is that they draw their own signals one at a time from the urn, while their partner's information is communicated in summary form in a single report ('2 red and 3 white balls'). Certain updating biases (e.g., base-rate neglect) could cause participants to respond differently to summary information than to learning information draw by draw. To test for this channel, the *Draw-by-Draw* round proceeds identically to the *Informed* round, except that the experimenter shares their partner's draws with each participant one draw at a time, e.g., by saying 'Your partner first drew a red ball', then after a brief pause, 'Your partner then drew a white ball, ...' and so on.

Reverse-Order **round.** In this round, one participant learns their partner's signal before making any draws themselves. They then makes a guess, make their own draws, and make another private guess. Since this treatment is only possible for one person in each pair, we only include guesses from the treated person while analyzing this round.

No-First-Guess **round.** This round was identical to the *Informed* round except that participants do not make a guess directly after making their own set of draws. We implemented this change to test whether, for example, people are more open to others' information when they have not yet taken an action or stated a belief based on their own information.

Higher-Stakes **treatment.** We increased the incentives for accurate guessing by 50% in a randomly-chosen 3 out of 6 rounds. The maximum amount each individual could earn from a guess and their loss in earnings per ball away from the truth were both increased by 50%, to Rs. 158 ($2.25) and Rs. 22.5 respectively. Participants were informed about the stakes at the beginning of each round.

5.3 Experiment 2: Results

Figure 5 shows the results from Experiment 2. Since this experiment does not include an Individual round, we simply compare the sensitivity to own information (β_1) and the partner's information (β_2) within round, estimating Equation 1 by OLS.[29] The corresponding regression coefficients are presented in Panel A of Table 4.[30]

We first replicate the main finding from Experiment 1: Figure 5 shows that participants are 87 and 58 percent less sensitive to their partner's information in the *Discussion* and *Informed* rounds, respectively, and we can reject $\beta_1 = \beta_2$ with $p<0.01$.[31] In addition, at least directionally, participants underweight their partner's information in *every* other treatment.

Most strikingly, participants are less sensitive to their partner's signals even in the *Observe* treatment, in which they see their partner drawing balls from the urn with their own eyes while sitting beside them. Yet, participants are still 41% less sensitive to their partner's information than to their own in this treatment ($p = 0.04$).

When participants learn their partner's signals before drawing their own signals, in the *Reverse Order* treatment, they are still 53% less sensitive to their partner's information ($p = 0.04$). While still sizable, the effects in the *Draw-by-Draw* and *No First Guess* treatments are somewhat less pronounced at 38% ($p = 0.18$) and 43% ($p = 0.12$), respectively. The latter two estimates are not statistically significant, given the lower-than-intended sample size, but the difference in point estimates is roughly comparable across all six treatments, and we cannot reject that it is the same in all treatments ($p = 0.82$).

The under-sensitivity to others' information is also not meaningfully affected by the size of the incentives for accurate guessing (Appendix Figure A.V and Table A.IV). In

[29]We did not include an *Individual* round since the previous experiment established that, if anything, participants are more sensitive to their most recent signals compared to earlier signals. Thus, if the partner's information is learned last, this biases us *against* finding less sensitivity to others' information.

[30]Appendix Figure A.III, Panel A shows non-parametric estimates, plotting participants' guesses first against their own signal and then against their partner's signal in the *Discussion*, *Informed* and *Observe* treatments. Like the reduced-form and structural results we discuss below, the non-parametric results indicate underweighting of others' information: the slope of guesses against own signal is steeper.

[31]To conserve space, in all rounds except the *Discussion* round, we focus in the main text on only the pre-discussion guesses, after the participant is informed of their partner's draws by the experimenter. Figure A.IV shows reduced-form results for the post-discussion guesses (except for in the *Observe* round in which there was no discussion and thus no post-discussion guess), which look broadly similar to those for the pre-discussion guesses.

particular, we see no significant change in underweighting in rounds that were randomly assigned to have 50% higher stakes.

The structural estimates (Panel B of Table 4) paint a similar picture, with participants putting significantly less weight on their partner's information in every round. The weight participants put on their own information tends to be at or above the Bayesian benchmark of $\beta_2^p = 1$, while they tend to underweight their partner's information (though, given the imprecision of these estimates, we typically cannot reject equality with the Bayesian benchmark). In particular, in the *Observe* round, participants place 46% less weight (0.66/1.43) on their partner's information than their own ($p < 0.01$).

Experiment 2 establishes a striking result: people are less sensitive to their partner's draws even when they can observe them with their own eyes. This rules out a number of confounds, including distrust of information communicated by others, order effects, or subtle differences in how information is communicated. Instead, the result suggests that the act of producing information (i.e., physically drawing balls from the urn) or of associating one piece of information with oneself as opposed to with one's partner may be driving factors. We designed Experiment 3 to further test these mechanisms.

6 Experiment 3: External Validity and Mechanisms

Experiment 3 is a large-scale, between-subjects online experiment with three goals. First, it further investigates mechanisms. We test for the importance of (i) visual salience and presentation of information; and (ii) taking some action to generate one's own signals; versus (iii) passively receiving information with labels indicating 'ownership' in causing lower sensitivity to others' information. Second, we test the external validity of our findings with higher-education participants from a different cultural context. Third, we develop a simple online design which allows our experimental paradigm to be easily adopted by other researchers.

6.1 Recruitment and Sample

We recruited 4,489 participants from the US and UK on the online survey platform Prolific in February 2022, asking participants to complete a "short decision-making experiment" that involved a 15-minute survey. We required participants to have completed at least 50 previous surveys on Prolific with an approval rating above 95%. Participants were paid \$2.50 for completing the survey, plus up to \$2.80 as a bonus for accurate guessing. The resulting sample is similar in age and gender to our Experiment 1 and 2 samples (Column 3 of Table 1). A key difference is that the sample is more highly educated, though participants' task comprehension and performance are comparable across the three experiments.[32]

6.2 Experiment 3: Design

Participants recruited on Prolific were directed to a Qualtrics survey which embedded the experiment. Each participant was randomly matched to a partner.[33] The experiment had a purely between-subjects design, with participants randomized to one of the treatments—variants of the *Informed* condition—described below. Each participant played five identical rounds of the same treatment without feedback. We randomized across participants whether they drew their own signals first or instead first learned about their partner's signals.[34]

***Informed of Partner's Draws* treatment.** This treatment sought to emulate the *Informed* round from Experiments 1 and 2 as closely as possible in an online format. Participants saw a virtual urn and clicked to draw balls from it one at a time. The drawing and replacement of the balls from the urn was animated. Participants were shown a summary of their partner's draws, as in the previous *Informed* treatments (e.g., '1 red and 4 blue'). A total of 1,008 participants were randomized into this treatment.

***Observe Partner's Draws* treatment.** This treatment (which we abbreviate to *'Observe'*) differed from the *Informed* treatment in that participants saw their partner's draws being revealed using the same ball-by-ball animations as their own draws.

[32] In Experiment 3, we included eight multiple-choice comprehension questions asking participants to explain aspects of the instructions. Participants had to answer each question correctly before they could proceed. The average participant answered 92% of these questions on the first attempt, and more than 80% did so for all eight questions. The results are unchanged if we include only those who answered all questions correctly.

[33] Since the experiment did not include any direct communication between partners (as there was no *Discussion* round), it was not necessary for partners to be playing the game at the same time. Instead, we pre-generated the signals for each partner from the same 'urn'.

[34] The script and a link to the online experiment are provided in Appendix A.3. Appendix Figure A.II Panel B illustrates the design of the different treatments. Selected screenshots showing how draws were presented to participants are reproduced in Appendix Figure A.VI.

The goal was to make the mode of presentation of the two sets of draws as similar as possible. Comparing the *Observe* and *Informed* treatments isolates the role of the presentation of others' information, including its visual presentation and whether information is delivered in summary form or signal-by-signal. A total of 1,497 participants were randomized into this treatment.

***Labels Only* treatment.** This treatment was the same as the *Observe* treatment, except that participants no longer had to click a button to generate each of their draws. The only difference between one's own and one's partner's signals was one word in the text that appeared below the animation (e.g. 'Your first marble' versus 'Partner's first marble'). If participants are less sensitive to their partner's draws even in this minimal treatment, it implies that a subtle label is enough to generate a sense of ownership. In turn, comparing this treatment with the *Observe* treatment isolates the effect of taking an action to generate your own information. Taking some such action to generate information might be necessary to create a sense of ownership or to make that information more salient or vivid. A total of 1,487 participants were randomized into this treatment.[35]

Non-Rivalry treatment. This treatment aimed to reduce any sense of competition with one's partner. A randomly-selected half ($N = 505$) of the participants in the *Informed* treatment were truthfully informed that their partner would not be guessing the contents of the urn. Instead, the partner would only draw signals and be asked to remember them.

***Higher-Stakes* treatment.** We randomized across participants the size of the incentives for accurate guessing. Half of those in each treatment, a total of 2,196 participants, earned a \$1.40 bonus minus \$0.20 cents times the absolute difference between their guess and the true number of red balls in the urn. For the other half of participants, the incentives were doubled.

Survey. After completing the five rounds of the experiment, participants completed a short survey. In the survey, without prior warning, we measured their recall of their own and their partner's draws from the last round as a measure of attention and memory. We also elicited participants' perceptions of whether they used their own and their partner's signals equally in informing their guesses.

[35] We recruited more people into the *Observe* and *Labels Only* treatments because we were particularly interested in comparing the two treatments.

6.3 Experiment 3: Results

To test whether participants are less sensitive to their partner's information, we simply estimate equation (1) within each treatment condition and test $\beta_1 = \beta_2$. Since the order of learning one's own and one's partner's signals was randomized with equal probabilities, order effects do not confound this comparison. Figure 6 and Table 5 Panel A report the reduced-form results.[36]

In the *Informed* treatment, we qualitatively replicate our previous findings: participants are 17% less sensitive to their partner's information than their own ($p < 0.01$). The magnitude of this difference is sizable but notably smaller than in Experiments 1 and 2, as anticipated given the documented tendency for lower sensitivity to treatments in online experiments (Gupta et al., 2021). Intuitively, the sense that some information was uncovered by another person may be weaker in the online experiment since there is no interaction with the other individual and the participant never sees them or learns anything about them. Similarly, the vividness and sense of ownership of one's own signals may be weaker since the signals are not physically drawn oneself but rather are generated by a computer and appear on the screen. Other differences such as a higher-education sample might also play a role, although we do not find stronger effects among lower-education participants within any of the three experiments (Table A.VI).

The design of Experiment 3 permits an even simpler test of sensitivity to own and others' information. Since participants were randomized to receive their own or their partner's signals first, we can examine the *first* guess they make—after seeing only the first set of draws—and test whether this guess was less sensitive to draws made by their partner. Appendix Table A.V Column 1 reports these results. Once again, we find that participants' guesses are 17% less sensitive to their partner's signal than to their own ($p<0.01$). Overall, we view the results as providing strong evidence of lower sensitivity to others' information even with a very different sample and experimental format.

In the *Observe* treatment, participants continue to be significantly less sensitive to their partner's information ($p<0.01$). Indeed, the magnitudes are nearly identical to the *Informed* treatment (19% vs. 17%, p=0.74). Consistent with the findings of Experiment 2, this suggests that differences in presentation of own and others' information

[36] Appendix Figure A.III, Panel B, reports non-parametric results for Experiment 3, plotting participants' guesses against their own signal and then against their partner's. The pattern of results is similar to our reduced-form results, showing a greater responsiveness to own signal in the *Informed* and *Observe* treatments, but a more equal responsiveness in *Labels Only*.

does not explain the lower sensitivity to others' information. Appendix Table A.V Column 2 shows that this also holds for the first guess (10% lower sensitivity to others' information, $p<0.01$).

By contrast, participants in the *Labels Only* treatment were only 4% less sensitive to their partner's information, a difference which was not statistically significant in the reduced-form estimates ($p=0.27$). The difference in sensitivity to own and partner's information ($\beta_1 - \beta_2$) is significantly lower in the *Labels Only* treatment than in the *Informed* ($p=0.02$) and *Observe* ($p<0.01$) treatments. We find a similar pattern in the first guess (Appendix Table A.V Column 3). We interpret this result as showing that taking an action to gather information—which, plausibly, generates a sense of ownership and/or increases the salience of the information—plays a key role. Merely labeling information as 'own' versus 'partner's' may not generate a sense of ownership when the participant receives the information passively.

The structural estimates presented in Table 5 Panel B again show clear evidence of underweighting of others' information in the *Informed* and *Observe* treatments, by 31% and 33%, respectively (each $p<0.01$). Again, the difference in weights is significantly smaller in the *Labels Only* treatment compared to the *Observe* treatment ($p=0.04$), implying that taking an action to generate one's own draws increases the weight on own relative to others' information. However, in contrast to the reduced-form estimates, the structural estimates show significant underweighting of partners' information even in the *Labels Only* round ($p<0.01$).[37] However, this underweighting is significantly lower than in the *Observe* treatment ($p=0.04$).

Stakes and awareness. The relative sensitivity to own vs. others' information is not affected by the size of the incentives that participants faced for accurate guesses (Figure A.V, Panel B). For all three treatments, the differential sensitivity to own and partner's signals is very similar (and statistically indistinguishable) between the low- and high-stakes groups. This finding suggests that participants are either unaware that they are less sensitive to others' information or that they mistakenly believe it is optimal to discount others' information. Consistent with the former interpretation,

[37]The structural estimates account for the full information content of the signal. For example, a person should place more weight on seeing 9 draws (5 red and 4 white) than on seeing just 1 red draw, whereas the reduced-form analysis treats these as identical (1 net red draw). The structural model also accounts for noisy choices and the fact that guesses are constrained to be between 4 and 16. These differences may explain the small discrepancy in the reduced-form and structural analysis of the *Labels Only* treatment.

77% of participants reported in the debriefing survey that they treated both pieces of information the same. Yet these same participants were 17% less sensitive to their partner's information in the *Informed* treatment, identical to the result in the full sample (Table A.VI Panel C).[38]

Memory and attention. We also provide tentative evidence on whether up-front attention or imperfect memory mediate the under-sensitivity to others' information (Appendix Figure A.VII and Table A.VII). In the debriefing survey, participants were asked to recall their own and their partner's draws in the final round. Recall of one's own draws was slightly higher on average (60% vs 55%, p<0.01).[39] However, even when restricting the sample to those who perfectly remember *both* sets of draws, participants still place significantly more weight on their own information (Appendix Figure A.VIII and Table A.VI Panel C). Despite being able to recall this information when specifically asked to, they fail to apply it to their choices in the same way that they do their own information.

Competition. Despite the incentives to make accurate guesses, one concern could be that participants underweight their partner's information out of a sense of competitiveness: e.g., they may enjoy 'winning' by making good guesses precisely when their partner guesses poorly. This could lead to a strategy of ignoring the partner's draws. However, the *Non-Rivalry* treatment—a sub-treatment of *Informed* in which the partner does not make any guesses—does not increase sensitivity to the partner's signals (Appendix Figure A.IX and Table A.VIII).

7 Interpretation, Mechanisms, and Potential Confounds

Our main finding is that people are more sensitive to information they uncover themselves compared to equally-relevant information uncovered by others. This result holds in three separate pre-registered experiments, when (i) participants can learn their

[38] 14% instead reported using their own information more while 8% reported using their partner's information more. In open-ended responses, participants who reported using (say) their own information more often explained that this was because they (randomly) received more draws than their partner. A 10 percentage point increase in the share of draws received oneself is associated with a 12 percentage point increase in the likelihood of reporting using one's own information more (p<0.01).

[39] The difference in recall is significant in all treatments, although it is smaller in the *Labels Only* treatment. Specifically, recall of own vs. partner's draws in the different treatments are 64% vs 56% for the *Informed* treatment, 60% vs 55% for *Observe*, and 58% vs 55% for *Labels Only*. We can reject equal memory gaps in the *Labels Only* and the *Informed* treatments (p=0.01).

partner's information via a face-to-face discussion (Experiments 1 and 2); (ii) they are directly informed of their partner's information by the experimenter (Experiments 1, 2 and 3); (iii) they observe their partner drawing balls from the urn with their own eyes (Experiment 2); (iv) the visual presentation of own and others' information is identical (Experiments 2 and 3); (v) the order of learning one's own and others' information is randomized or controlled for (Experiments 1 and 3). The result holds among participants who perfectly recall others' signals and even among those who report using their own and others' signals equally (Experiment 3).

Having considered and rejected a number of alternative mechanisms, we speculate that the effect is driven by some sense of ownership—broadly construed—where generating information through one's own efforts or experiences causes that information to influence one's beliefs or decisions more. What's more, passively receiving information labeled as 'yours' versus 'others' yields a significantly smaller difference in sensitivity (Experiment 3), suggesting that taking some action to generate the information may be necessary to generate this psychology.

Our findings cannot be explained by the possibility that participants find probabilistic reasoning difficult and generally deviate from Bayesian updating in systematic ways, for example by being conservative in belief updating, by overweighting small samples, or by neglecting base rates (Benjamin et al., 2019). Our empirical test does not require participants to be Bayesian. Instead, it simply asks if information drawn oneself is treated similarly to identical information drawn by others. More generally, our results do not appear to be driven by simple confusion. They hold in both low-education samples in India and in high-education samples in the US and UK. Performance on comprehension questions was good, and we do not detect any significant within-experiment heterogeneity by comprehension scores or education (Appendix Table A.VI).

Another concern is that participants react less to their partner's information due to *distrust* of the communicated information. They might distrust what their partner tells them in the face-to-face discussion (despite the partner having incentives to share information) and distrust the message from the experimenter in the *Informed* condition (since the experimenter's incentives are unclear). However, several pieces of evidence suggest distrust of communicated information does not drive our results. First, watching one's partner drawing balls from the urn with one's own eyes, while being seated beside them, still results in lower sensitivity to the partner's draws (Experiment 2). Second, in Experiment 3, both one's own and one's partner's draws are simply displayed on the computer screen, such that it is not clear why one would trust draws assigned to oneself more. Finally, people report treating their own and their partner's information the same despite being less sensitive to their partner's information (Experiment 3). People therefore do not appear to explicitly distrust others' information in that experiment.

Communicated information is often *presented* differently than information uncovered oneself. For example, people usually share their information or advice with others in summary form whereas one's own experiences may uncover information in piecemeal fashion. Such differences in presentation also do not explain our results, since directly observing others' draws as they are uncovered does not reduce under-sensitivity to them.

Factors such as *overconfidence* are also unlikely to explain our results. Specifically, confidence about one's ability to use information to make accurate guesses should not cause individuals to weight information differently based on the source, once they learn that information. People would instead need to believe that they are especially skilled or lucky at drawing signals.

Competitiveness towards their partner also does not appear to explain our findings. Competing over the average accuracy of their guesses should cause participants to fully use all available information. Moreover, in a treatment in which the partner does not make any guesses, and merely draws balls, participants are still less sensitive to signals drawn by their partner (Experiment 3).

The experimental scripts also tried to avoid any *experimenter demand* effects to underweight others' information. The instructions repeatedly mentioned that participants' goal was just to guess the number of red balls in the urn, and that their and their partner's draws were coming from the same urn. Participants were asked to make guesses both after seeing their draws and after seeing the partner's draws, which might—if anything—suggest that the experimenter expects them to incorporate both sets of information. Next, the smaller/null effects in the *Labels Only* treatment argue against experimenter demand effects in Experiment 3 since the experimental scripts were otherwise identical. And finally, most participants explicitly report using their and their partner's draws equally, and yet these same participants nonetheless display under-sensitivity to their partner's signal (Experiment 3).

8 Conclusion

This paper presents evidence of a powerful and potentially far-reaching barrier to social learning: people place more weight on information gathered themselves than on information gathered by others. They discount information uncovered by another person when they can learn it via a conversation with that person, when the information is shared by a trusted third party, and even when they have seen it with their own eyes. This phenomenon appears to be robust: we find evidence of it across three experiments with very different study populations, cultural contexts, and experimental formats.

Existing research shows that, when faced with complex social learning problems, people deviate from Bayesian inference by, e.g. overweighting private signals relative to public information (Weizsäcker, 2010), neglecting selection or correlation (Eyster et al., 2015; Enke, 2020), and averaging beliefs as in DeGroot learning (Chandrasekhar et al., 2020). Even in a relatively simple setup with perfectly observed signals, we find that people strongly underweight information learned from others relative to their own information. An open question is how under-weighting of others' information plays out in more complex real-life settings. In some cases, under-weighting others' information could counteract other biases. For example, correlation neglect might cause people to overreact to redundant information reaching them from multiple sources (Enke and Zimmermann, 2019). In this case, being less sensitive to information from others might improve overall learning. However, in other cases, people's under-sensitivity to others' information might be exacerbated by other forces, e.g., a tendency to distrust information coming from socially dissimilar people or from someone with lower social status (BenYishay and Mobarak, 2019).

While precise and closely controlled, a weakness of our lab setting is that it is fairly abstract and with moderate stakes at best (up to about half a day's income in Experiments 1 and 2). An open question is to what extent similar findings will emerge in ecologically valid settings and with higher stakes. We speculate that the mechanism we document may underlie previously documented failures of social learning, whether in information cascade experiments (Weizsäcker, 2010), farmers learning more from their own plots than from neighbors (Foster and Rosenzweig, 1995), or central bankers being sensitive to their own personal economic experiences beyond aggregate data (Malmendier et al., 2021). But underweighting of others' information could play a role in numerous other settings where social learning is possible.

We document this phenomenon in teams of strangers. In a companion paper, we find that the marital setting—learning from one's spouse—appears to counteract the discounting of others' information for women but not for men (Conlon et al., 2022). Future work should study the underlying mechanisms behind these differences and, more generally, what types of social or work relationships and contexts shape how effectively people learn from each others. For example, do people learn better from friends and colleagues? How do social status hierarchies affect the weight placed on a person's independent information?

We find a crucial role for taking some action to obtain new information in generating our effects; merely labeling information as one's own has a significantly smaller effect. Our interpretation is that taking an action to acquire information activates a feeling of ownership of this information or makes it more vivid or salient, which in turn leads people to be more sensitive to it. Future work should investigate what types of actions, efforts, or experiences that generate new information create—or fail to create—this effect in natural settings. This includes investigating situations where people exert effort to actively discover others' information, for example by seeking out those with experience or searching for information online.[40] Field evidence that compares weights people put on their own and others' information in a variety of contexts is needed to better understand the relevance and real-world costs of this phenomenon.

[40] In Experiment 1, we do in fact measure a type of action taken to obtain information: whether participants explicitly ask their partner about their draws during the discussion. We find that participants who ask underweight their partner's signal just as much as others (Appendix Table A.IX). While this variable is of course endogenous, this result suggests that the effect may not be simply about active information-seeking in general, but something more specific such as generating information yourself.

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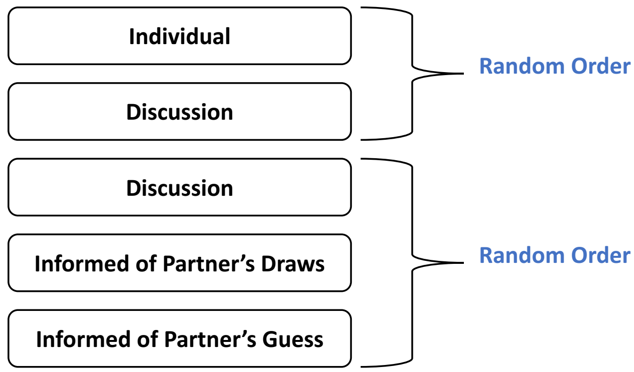
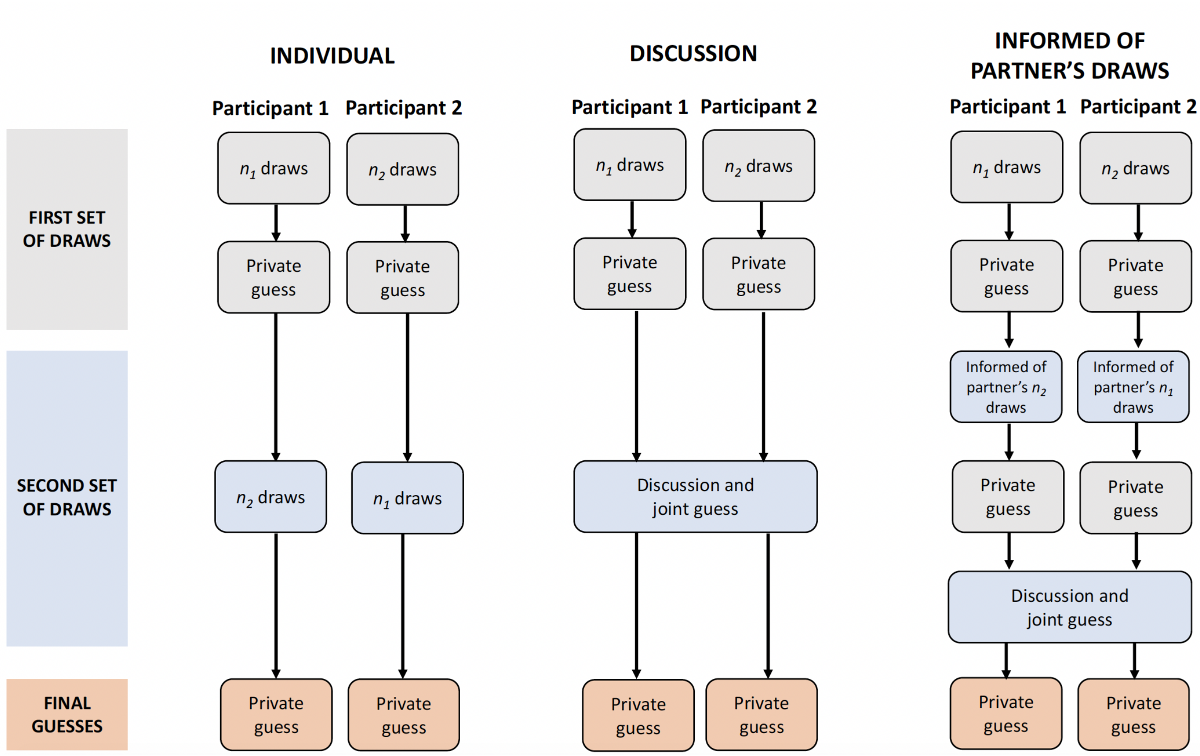
Figure 1: Experimental Design

Panel A: Randomization of Rounds



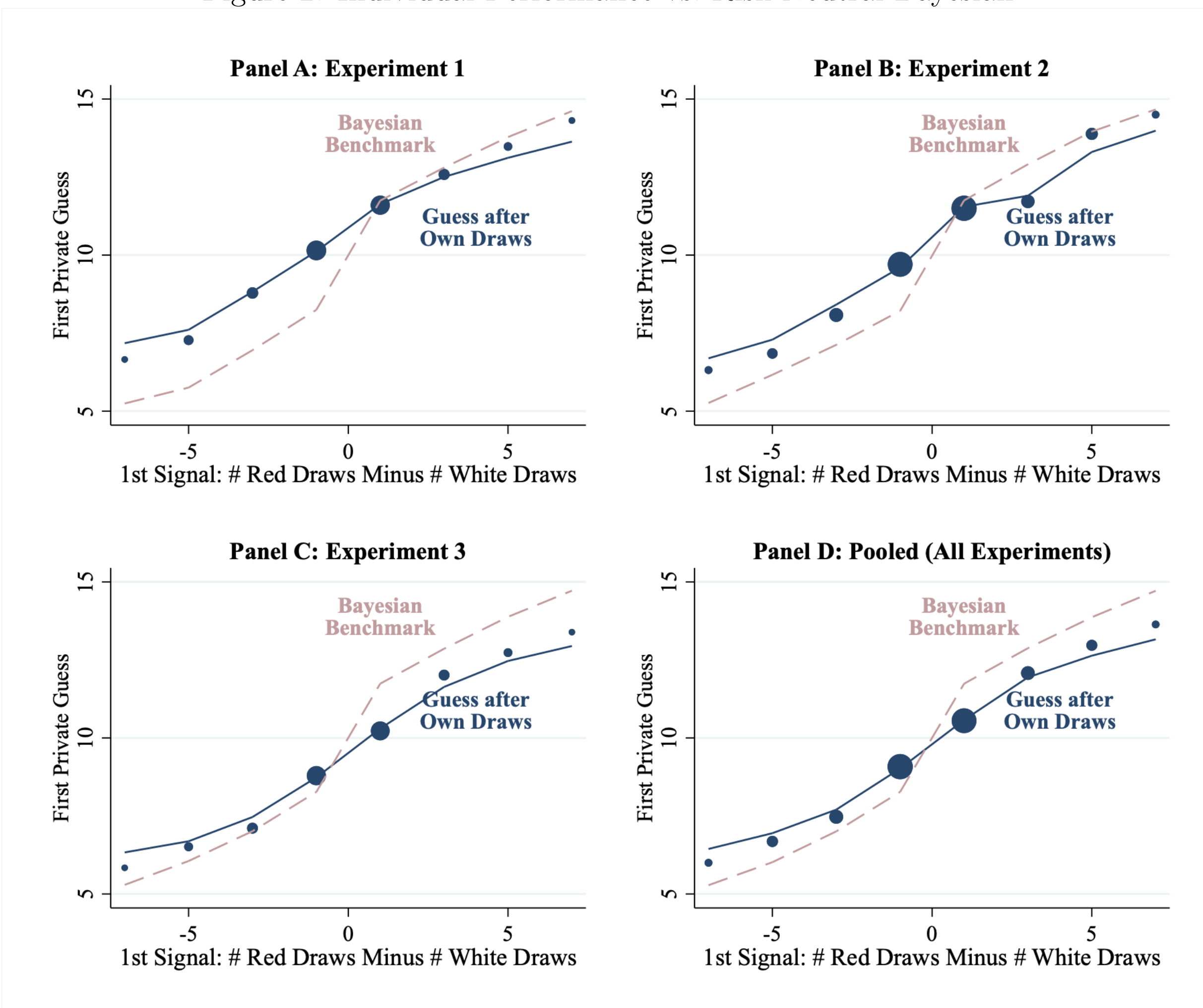
Panel B: Structure of Individual, Discussion, and Informed Rounds



Panel A shows the five rounds of Experiment 1. All participants get matched to a previously unknown partner and complete all five rounds with this partner (with the exception that in one randomly-selected *Discussion* round, participants were re-matched for that round only to generate variation in the relative gender of the partners. We do not exploit this variation in our paper). We randomized the order of the first two rounds (*Individual*, *Discussion*) and the order of the following three rounds: *Discussion*, *Informed of Partner's Guess*, and *Informed of Partner's Draws*.

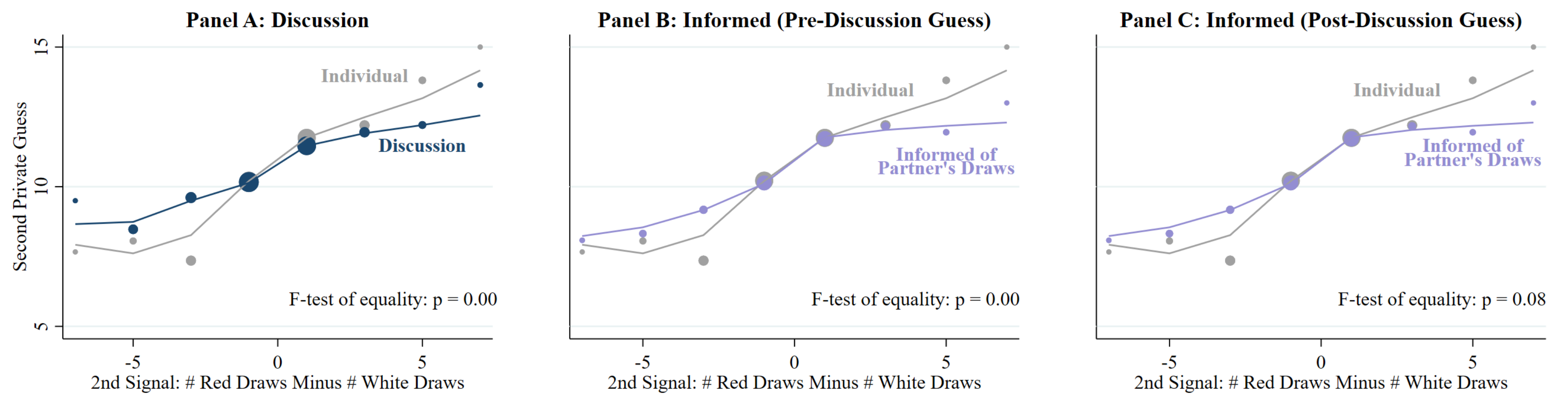
Panel B describes the structure of the different rounds. In the *Individual* round, each participant gets two sets of private draws from the urn and makes a private guess after each set of draws. In the *Discussion* round, each participant makes one set of draws followed by a private guess. The two participants are then asked to discuss and make a joint guess, before each making a final private guess. The *Informed of Partner's Draws* round is identical to the *Discussion* round, except that pre-discussion, each participant is informed about their partner's first set of draws, and then asked to make a private guess. In the *Informed of Partner's Guess* round (Appendix A.1), each participant is instead informed pre-discussion about their partner's first private guess, and then asked to make a private guess.

Figure 2: Individual Performance vs. Risk-Neutral Bayesian



Notes: This figure plots participants' first private guess against the net number of red draws (red draws minus white draws) in participants' own first (private) signal. For each experiment we use the participants' first private guess (after seeing only the first set of draws). We only include observations where participants saw their own signal first privately (in Experiment 1, this is all observations). The blue solid curve shows locally-weighted means (lowess). The pink dotted lines show the average of a risk-neutral Bayesian's guesses given the same signals. Dot size indicates number of observations for each net number of red draws. Panels A through C show data from each of the three experiments separately. Panel D shows pooled data from all three experiments.

Figure 3: Experiment 1: Non-Parametric Results

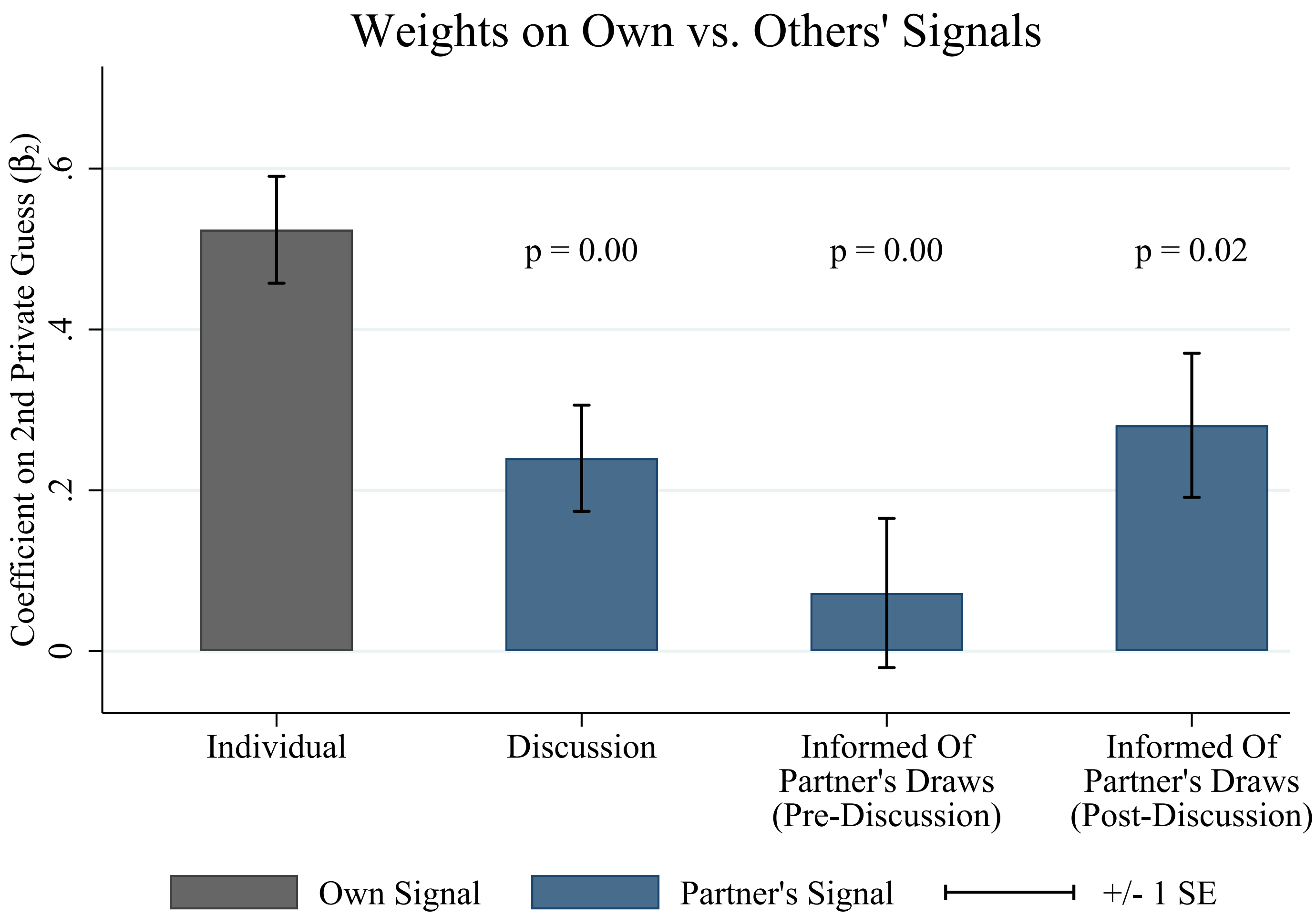


Notes: This figure shows average second private guess of participants in Experiment 1. The x-axis shows the net number of red draws (i.e. red draws minus white draws) in the second signal of the round. Dot size indicates number of observations for each net number of red draws. Lines show locally-weighted means (lowess).

- In **Panel A**, the gray dots indicate average guesses in the *Individual* Round, where participants made the second set of draws themselves. The dark-blue dots in the graphs on the left show guesses in the *Discussion* Round, where the second set of draws had to be communicated to the participant via discussion.
- In **Panel B**, the lavender dots show average guesses in the *Informed of Partner's Draws* round, after the respondent is told of his/her partner's draws by the experimenter (but before the joint discussion).
- In **Panel C**, the lavender dots show average guesses in the *Informed of Partner's Draws* round after the joint discussion.

'F-test of equality' in the bottom right shows the p-value of a test of the joint hypothesis that the mean guess is equal across the two rounds at every value of net red draws.

Figure 4: Experiment 1: Reduced-Form Estimates



Notes: This figure shows the weights participants put on different signals in Experiment 1. We estimate equation (1) and then display β_2 for each of the following four types of private guesses:

(a) *Individual*, in which participants collect all information on their own. For this round, we report the coefficient on the net red draws in the participant's second set of draws, which replaces *Partner's Signal* in equation (1);

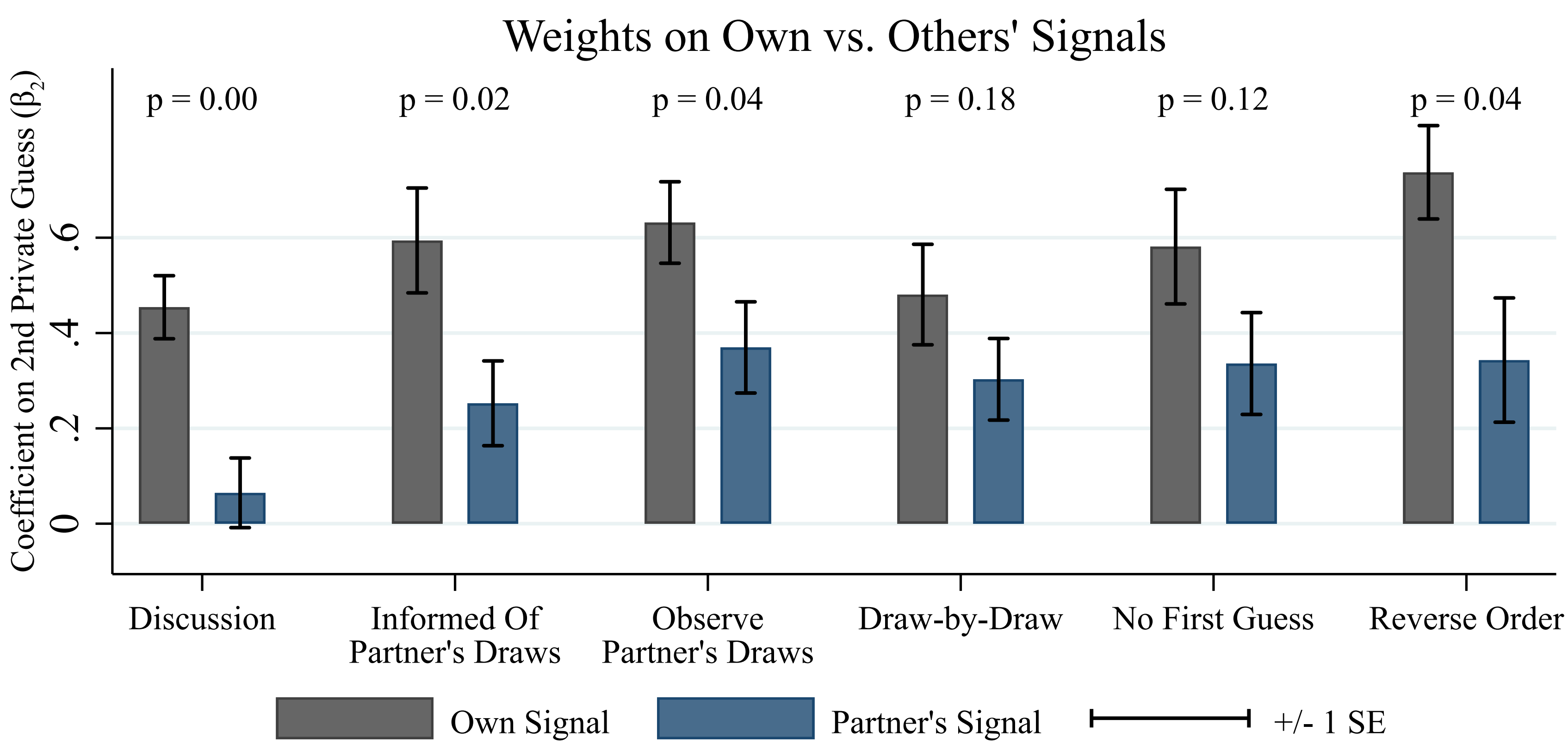
(b) *Discussion*, in which participants collect the first signal on their own and the second signal (their partner's) is only accessible via discussion;

(c) *Informed of Partner's Draws (pre-discussion)*, where participants receive the second set of information directly from the experimenter but before any discussion with their partner;

(d) *Informed of Partner's Draws (post-discussion)*, in which participants receive the second set of information directly *and* have the chance to discuss it with their partner.

For each of the dark-blue bars, we show the p-value of testing whether the weight in that round equals the corresponding weight in the *Individual* round (gray bar).

Figure 5: Experiment 2: Reduced-Form Estimates



Notes: This figure shows the weights participants put on different signals in Experiment 2. We estimate equation (1) and then display β_1 in gray and β_2 in dark blue for each treatment, except the *Discussion* round. In the *Discussion* round, it is the post-discussion guess as there was no pre-discussion guess. In addition to the *Discussion* and *Informed of Partner's Draws* rounds, we look at the following treatments:

(a) *Observe Partner's Draws*, in which each participant directly observes their partner's draws (as well as making their own);

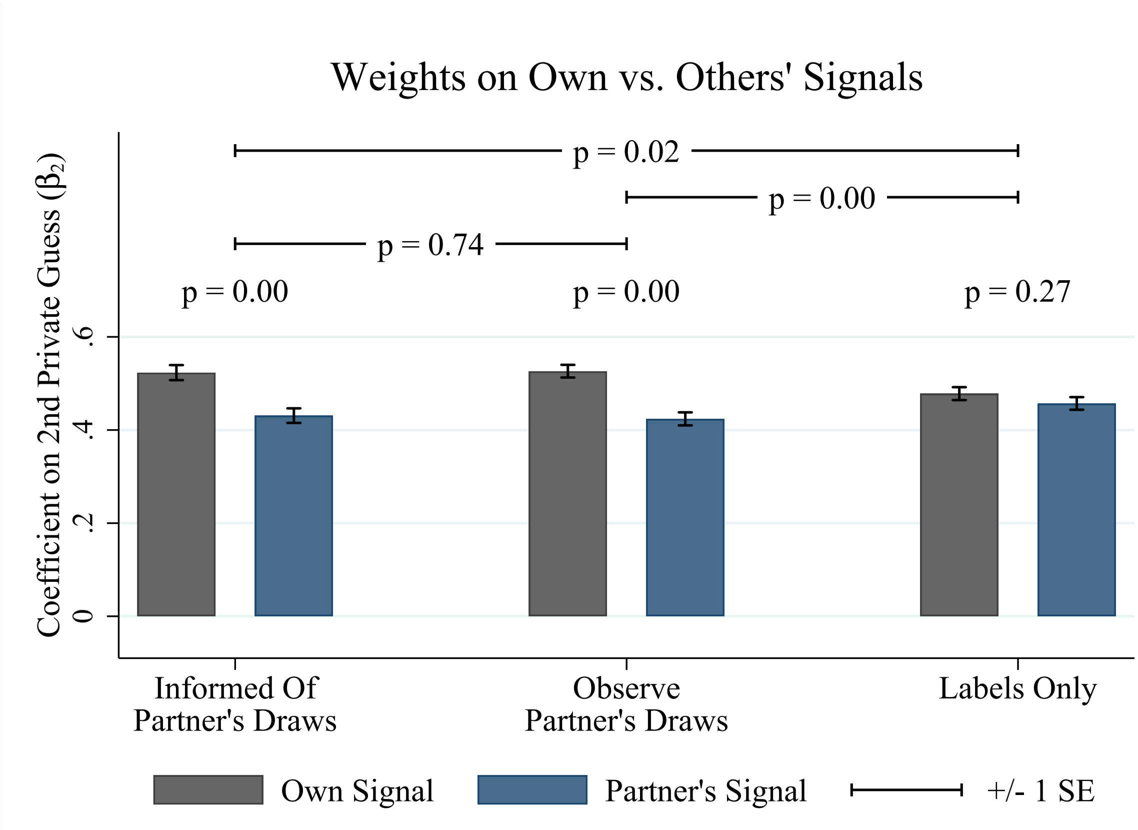
(b) *Draw-by-Draw*, in which participants receive the second set of signals directly one draw at a time;

(c) *No First Guess*, in which participants receive their partner's signals (and their own) before making their first and only private guess;

(d) *Reverse Order*, in which one participant receives their partner's signals first and makes their first private guess, and then receives their own signals and makes their second private guess.

For each round, we show the p-value of testing whether the weight on their signal (β_1) equals the corresponding weight on their partner's signal (β_2) in that round.

Figure 6: Experiment 3: Reduced Form Estimates



Notes: This figure shows the weights participants put on different signals in Experiment 3. We estimate equation (1) and then display β_1 in gray and β_2 in dark blue for each treatment.

- The first set of bars show the weights participants put on signals in the *Informed of Partner's Draws* treatment, in which participants clicked to draw their own balls one at a time and were told their partner's number of red and white draws.
- The second set of bars represent the *Observe Partner's Draws* treatment, in which participants clicked to draw their own balls one at a time and directly observed their partner's draws appearing from the urn one at a time.
- The third set of bars corresponds to the *Labels Only* treatment, in which participants did not take any actions and instead passively observed their own and their partner's labeled draws one by one in the exact same format.

For each round, we show the p-value of testing whether the weight on their signal (β_1) equals the corresponding weight on their partner's signal (β_2) in that round.

Table 1: Sample Characteristics

	Experiment 1 (1)	Experiment 2 (2)	Experiment 3 (3)
Female	0.50 (0.50)	0.31 (0.46)	0.57 (0.50)
Age	34.66 (8.58)	38.40 (7.31)	37.70 (13.87)
Years Of Education	7.86 (3.94)	9.02 (3.49)	15.04 (2.03)
Expected Earnings (Relative to Bayesian)	0.82 (0.11)	0.84 (0.12)	0.89 (0.10)
Fraction of Comprehension Questions Correct	0.79 (0.14)	0.79 (0.13)	0.92 (0.13)
Number of Participants	500	293	4489

Notes: This table shows averages of key background characteristics for individuals in each of our three experiments. Standard deviations are in brackets. "Expected Earnings (Relative to Bayesian)" is calculated as the expected payoff of the participant's guess given the draws they observed, divided by the expected payoff that the Bayesian risk-neutral guess (i.e., expected payoff-maximizing guess) would make given those same draws. "Fraction of Comprehension Questions Correct" shows the proportion of participants who correctly answer questions about the task (summary of questions in Table A.I).

Table 2: Experiment 1: Reduced-Form and Structural Estimates

	Individual (1)	Discussion (2)	Informed (Pre) (3)	Informed (Post) (4)
	Panel A: Reduced-Form Estimates			
β_1: Own First Signal	0.43	0.56	0.56	0.36
	(0.06)	(0.06)	(0.09)	(0.09)
β_2^o: Own Second Signal	0.52			
	(0.07)			
β_2^p: Partner's Signal		0.24	0.07	0.28
		(0.07)	(0.09)	(0.09)
Constant	10.71	10.73	10.64	10.66
	(0.16)	(0.16)	(0.23)	(0.23)
$\boldsymbol{\beta_2^p - \beta_2^o}$		**-0.28*****	**-0.45*****	**-0.24****
		(0.08)	**(0.11)**	**(0.10)**
	Panel B: Structural Estimates			
β_1: Own First Signal	0.92	0.87	1.02	0.57
	(0.63)	(0.18)	(0.41)	(0.31)
β_2^o: Own Second Signal	1.50			
	(0.74)			
β_2^p: Partner's Signal		0.40	-0.01	0.46
		(0.13)	(0.37)	(0.26)
$\boldsymbol{\beta_2^p - \beta_2^o}$		**-1.11*****	**-1.51*****	**-1.04****
		(0.71)	**(0.71)**	**(0.73)**
N	500	1000	500	500

Notes: This table shows reduced-form and structural estimates for the weights on signals in Experiment 1. The dependent variable is participants' private guess. 'Informed (Pre)" means the second private guess from the *Informed of Partner's Draws* round, after the participant was directly told their partner's signal but before the joint discussion. "Informed (Post)" means the third private guess, after the discussion. All standard errors are clustered at the pair (of two participants) level. Standard errors of the structural estimates are bootstrapped. *, **, and *** indicate significance at the p<0.10, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_2^o$.

Reduced-form coefficients: Panel A shows reduced-form results, estimating equation 1 by OLS. "Own First Signal" is the net number of red draws (i.e., red draws minus white draws) in the participant's first set of draws, which they drew themselves in all rounds. "Own Second Signal" is the net number of red draws in the participant's second set of draws in the individual round. "Partner's Signal" is the net number of red draws in the set of draws by the participant's partner, which was the second signal available to the participant in the *Discussion* and *Informed of Partner's Draws* rounds. All regressions include order fixed effects interacted with the participants' first and second signal.

Structural parameters: Panel B shows estimates of the structural model described in Section 3.3. "Own First Signal", "Own Second Signal" and "Partner's Signal" indicate the weights placed on the first set of signals, second set in the *Individual* round, and second (partner's) set in each other round in the agents' quasi-Bayesian updating rule.

Table 3: Experiment 1: Expected Earnings by Type of Guess and Number of Draws

	Individual	Discussion	Informed (Pre)	Informed (Post)
	(1)	(2)	(3)	(4)
γ_1: # Own First Draws	1.51	2.26	3.12	2.46
	(0.84)	(0.58)	(0.78)	(0.77)
γ_2^o: # Own Second Draws	3.31			
	(0.90)			
γ_2^p: # Partner's Draws		0.57	0.50	2.10
		(0.61)	(0.78)	(0.80)
Constant	102.45	105.32	97.46	96.63
	(5.37)	(4.44)	(6.09)	(5.88)
N	500	1000	500	500
$\boldsymbol{\gamma_2^p - \gamma_2^o}$		**-2.73*****	**-2.81****	**-1.21**
		(1.02)	**(1.14)**	**(1.21)**
N	500	1000	500	500

Notes: This table compares participants' expected earnings in the *Discussion* and *Informed of Partner's Draws* rounds to their earnings in the *Individual* round. The table shows OLS estimates of the following equation for the *Discussion* and *Informed of Partner's Draws* rounds:

$$\textit{Expected Earnings}_i = \alpha + \gamma_1 \# \textit{ Own First Draws}_i + \gamma_2^p \# \textit{ Partner's Draws}_i + \epsilon_i \tag{4}$$

and OLS estimates of the following equation for the *Individual* round:

$$\textit{Expected Earnings}_i = \alpha + \gamma_1 \# \textit{ Own First Draws}_i + \gamma_2^o \# \textit{ Own Second Draws}_i + \epsilon_i \tag{5}$$

where $\textit{Expected Earnings}_{irt}$ is the expected earnings from i's guess in the round in question, given the signals, and $\#$ *Own First Draws*$_i$ indicates the number of draws in the first set of signals, drawn oneself. $\#$ *Own Second Draws* is the number of draws in the participant's second set in the Individual round and $\#$ *Partner's Draws* is the participant's partner's number of draws, in the *Discussion* and *Informed of Partner's Draws* rounds. In estimation, we stack the estimating equations for all treatment and estimate them jointly including controls for round order fixed effects. Standard errors are clustered at the pair level. *, **, and *** indicate significance at the $p<0.10$, 0.05, and 0.01 levels of the difference $\gamma_2^p - \gamma_2^o$.

Table 4: Experiment 2: Reduced-Form and Structural Estimates

	Discussion (1)	Informed (2)	Observe (3)	Draw-by-Draw (4)	No First Guess (5)	Reverse Order (6)
	Panel A. Reduced Form Estimates					
β_1: Own Signal	0.45	0.59	0.63	0.48	0.58	0.74
	(0.07)	(0.11)	(0.09)	(0.11)	(0.12)	(0.10)
β_2^p: Partner's Signal	0.06	0.25	0.37	0.30	0.34	0.34
	(0.07)	(0.09)	(0.10)	(0.09)	(0.11)	(0.13)
Constant	10.66	10.64	10.63	10.45	10.51	10.38
	(0.19)	(0.22)	(0.22)	(0.21)	(0.24)	(0.26)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.39*****	**-0.34****	**-0.26****	**-0.18**	**-0.25**	**-0.39****
	(0.09)	**(0.14)**	**(0.13)**	**(0.13)**	**(0.16)**	**(0.19)**
	Panel B. Structural Estimates					
β_1: Own Signal	0.48	1.32	1.51	1.01	1.25	1.29
	(0.11)	(0.60)	(0.70)	(0.69)	(0.72)	(0.82)
β_2^p: Partner's Signal	0.07	0.23	0.60	0.33	0.48	0.52
	(0.08)	(0.36)	(0.45)	(0.41)	(0.55)	(0.80)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.41*****	**-1.08*****	**-0.91*****	**-0.68****	**-0.78****	**-0.77***
	(0.10)	**(0.44)**	**(0.43)**	**(0.49)**	**(0.41)**	**(0.52)**
N	288	292	292	292	292	146

Notes: This table shows reduced-form and structural estimates for rounds in Experiment 2 (our second lab experiment).

Reduced-form coefficients: Panel A shows reduced-form results, estimating equation 1 by OLS. The dependent variable is participants' private guess. "Informed" refers to the *Informed of Partner's Draws* round and "Observe" to the *Observe Partner's Draws* round. "Own Signal" indicates the net number of red draws (i.e., red draws minus white draws) in the participant's own set of draws. Similarly, "Partner's Signal" indicates the net number of red draws in their partner's set of draws. In estimation, we stack the estimating equations for all treatment and estimate them jointly. The joint regression also includes fixed effects for the order in which participants played treatment conditions, interacted with "Own Signal" and "Partner's Signal." Standard errors are clustered at the pair level. *, **, and *** indicate significance at the p<0.10, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

Structural parameters: Panel B shows estimates of the structural model described in Section 3.3. "Own Signal" and "Partner's Signal" indicate the weights placed on their own and their partner's set of draws in the agents' quasi-Bayesian updating rule. Bootstrapped standard errors (clustered at the pair level) in parentheses. *, **, and *** indicate significance at the p<0.10, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

Table 5: Experiment 3: Reduced-Form and Structural Estimates

	Informed (1)	Observe (2)	Labels Only (3)
Panel A. Reduced Form Estimates			
β_1: Own Signal	0.52	0.53	0.48
	(0.02)	(0.01)	(0.01)
β_2^p: Partner's Signal	0.43	0.42	0.46
	(0.02)	(0.01)	(0.01)
Constant	9.56	9.55	9.61
	(0.04)	(0.03)	(0.03)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.09*****	**-0.10*****	**-0.02**
	(0.02)	**(0.02)**	**(0.02)**
p-value: $\beta_2^p - \beta_1$ same as in Informed		0.74	0.02
p-value: $\beta_2^p - \beta_1$ same as in Observe			0.00
Panel B. Structural Estimates			
β_1: Own Signal	0.49	0.51	0.46
	(0.04)	(0.04)	(0.03)
β_2^p: Partner's Signal	0.34	0.34	0.36
	(0.03)	(0.03)	(0.03)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.15*****	**-0.17*****	**-0.10*****
	(0.04)	**(0.03)**	**(0.03)**
p-value: $\beta_2^p - \beta_1$ same as in Informed		0.52	0.25
p-value: $\beta_2^p - \beta_1$ same as in Observe			0.04
N	5040	7485	7435

Notes: This table shows reduced-from and structural estimates for rounds in Experiment 3 (the online experiment).

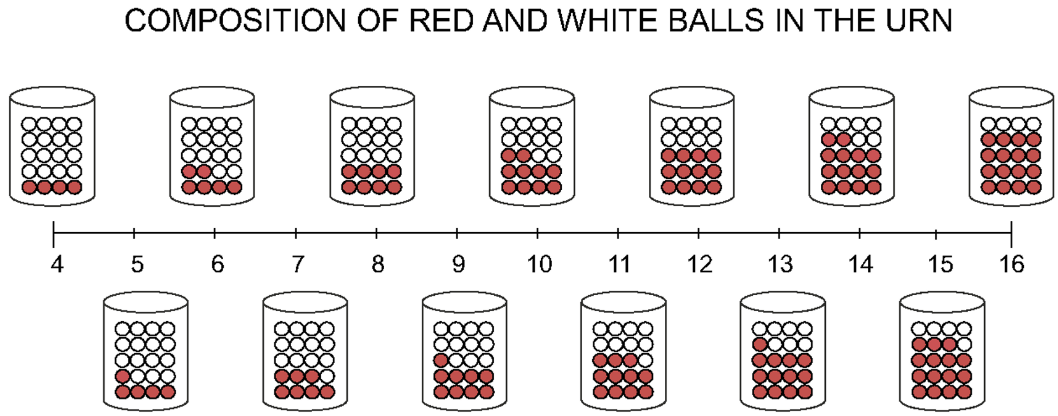
Reduced-form coefficients Panel A shows reduced-form results, estimating equation 1 by OLS. The dependent variable is participants' private guess. "Informed" refers to the *Informed of Partner's Draws* round and "Observe" to the *Observe Partner's Draws* round. "Own Signal" indicates the net number of red draws (i.e., red draws minus white draws) in the participant's own set of draws. Similarly, "Partner's Signal" indicates the net number of red draws in their partner's set of draws. Randomization was between participants in this experiment so we estimate the equation separately for each treatment condition. Standard errors are clustered at the pair level. *, **, and *** indicate significance at the p<0.10, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

Structural parameters: Panel B shows estimates of the structural model described in Section 3.3. "Own Signal" and "Partner's Signal" indicate the weights placed on their own and their partner's set of draws in the agents' quasi-Bayesian updating rule. Bootstrapped standard errors (clustered at the pair level) in parentheses. *, **, and *** indicate significance at the p<0.10, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

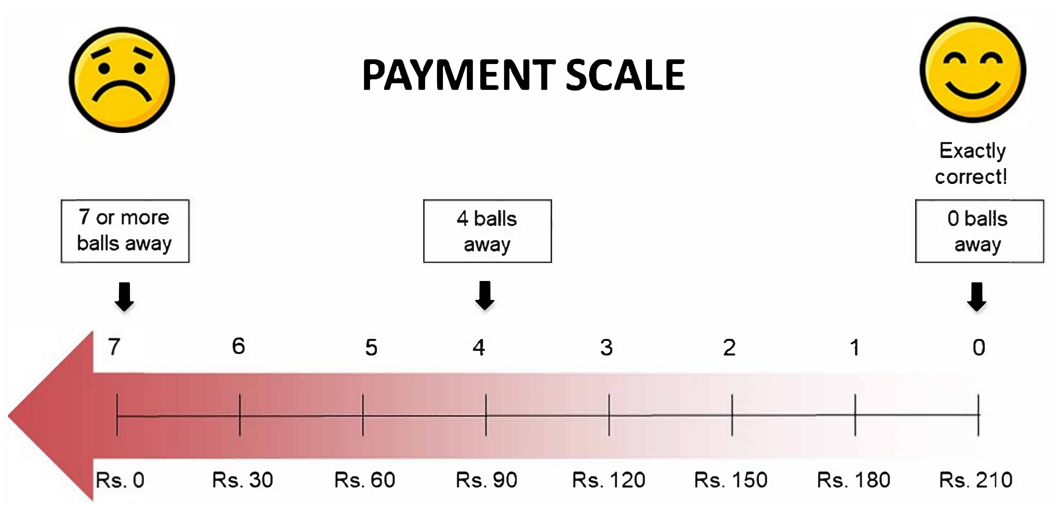
A Learning in the Household: Online Appendix

Figure A.I: Visual Aids

(a) **Guess Scale**



(b) **Payment Scale**



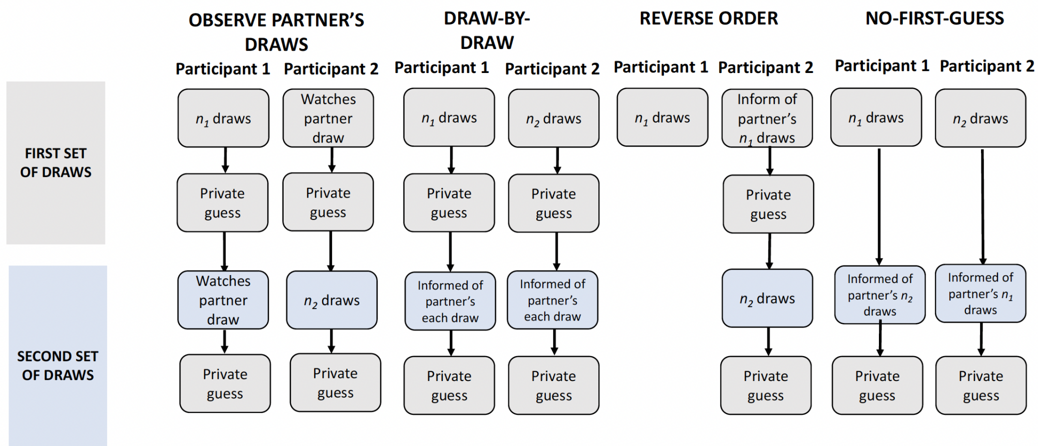
Notes: This figure shows the visual aids used to explain the experiment to study participants in Experiment 1 and Experiment 2.

Panel A: The figure shows the scale which participants used to make their guesses. It shows the 13 possible urn compositions ranging from 4 to 16 red balls (among 20 balls in total). We induced common priors: participants were informed that in each round, each of these compositions were equally likely (probability 1/13 each). Participants guessed by placing a small token on top of the corresponding number.

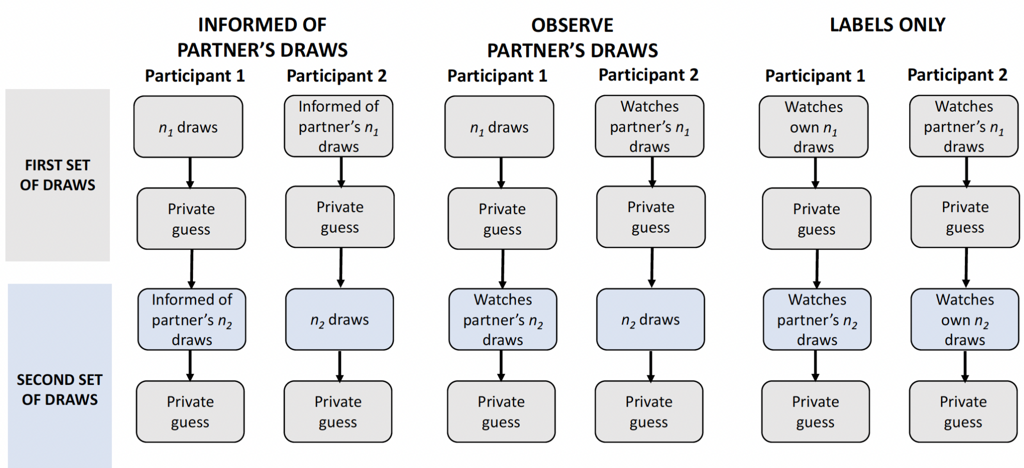
Panel B: The figure shows the scale used to explain the incentives for accurate guessing to participants. For each pair of participants, one of their guesses was randomly selected to determine the pair's payment. In Experiments 1 and 2, on top of their participation fee, each individual receives an amount in Rupees (Rs.) equal to $\max\{(105 - 15 \times |g - r|), 0\}$, where g is the guess and r the true number of red balls for the randomly-selected guess. See more detail in Section 2.1.

Figure A.II: Experimental Design for Experiment 2 and 3

Panel A: Experiment 2



Panel B: Experiment 3

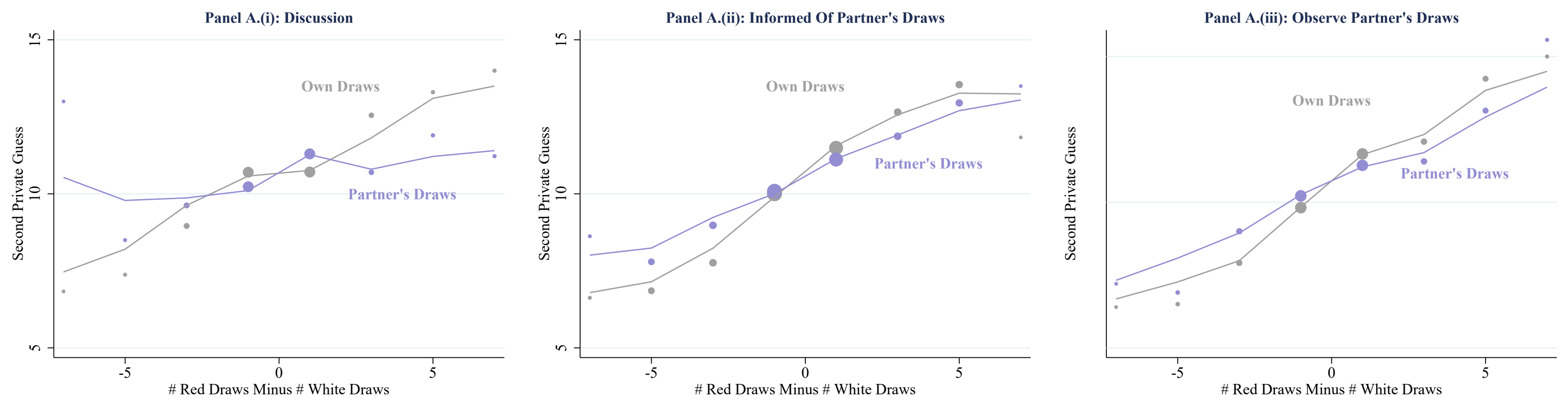


Panel A describes the structure of the different rounds in Experiment 2. In addition to the *Discussion* and *Informed of Partner's Draws* rounds, participants played four variations of the *Informed of Partner's Draws* round. In the *Observe Partner's Draws* round, each participant makes one set of draws while their partner is present, followed by a private guess after each set of draws. The *Draw-by-Draw* round is the same as the *Informed of Partner's Draws* round except each participant is informed about their partner's draws one draw at a time. In the *Reverse-Order* round, one participant learns about their partner's draws first and makes a private guess, and then makes their own set of draws and makes another private guess. In this round, the treatment is only for one participant from the pair. The *No-First-Guess* round is the same as the *Informed of Partner's Draws* round except participants only make one private guess after both sets of draws.

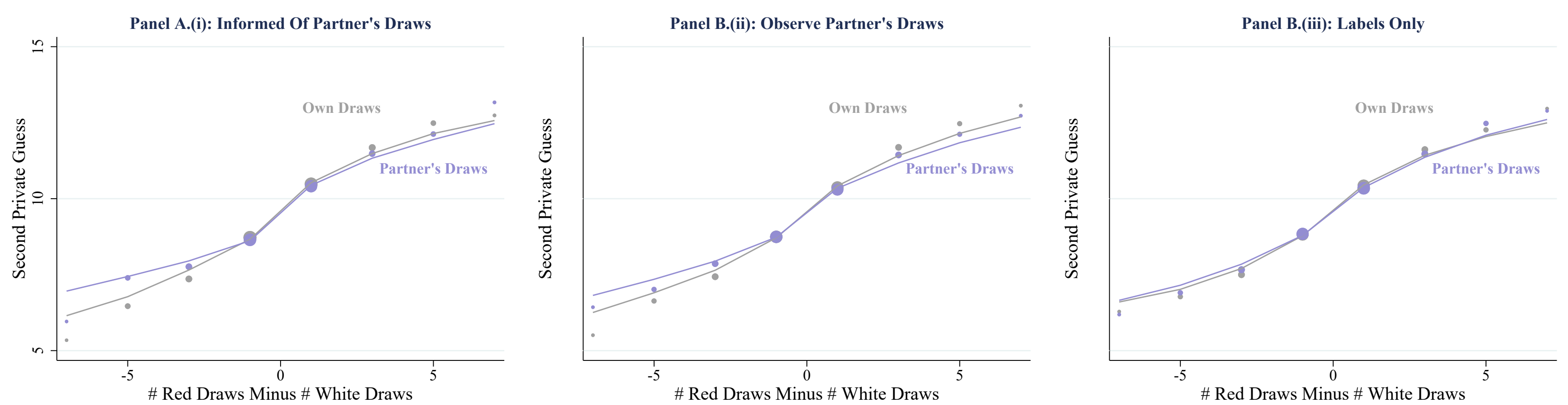
Panel B describes the structure of the different rounds in Experiment 3. In this experiment, the participant's own information and partner's information was presented in the Qualtrics survey using a virtual urn. In the *Informed of Partner's Draws* round, each participant makes one set of draws followed by a private guess. They are informed of their partner's draws and asked to make another private guess. In this experiment, participants played two additional variations of the *Informed of Partner's Draws* round. The *Observe Partner's Draws* round is the same as the *Informed of Partner's Draws*, except each participant watches their partner's draws, followed by a private guess after each set of draws. The *Labels Only* round is identical to the *Informed of Partner's Draws* round, except participants watch both their own draws and their partner's draws, and make a private guess after each set of draws.

Figure A.III: Experiments 2 and 3: Non-Parametric Estimates

Panel A: Experiment 2

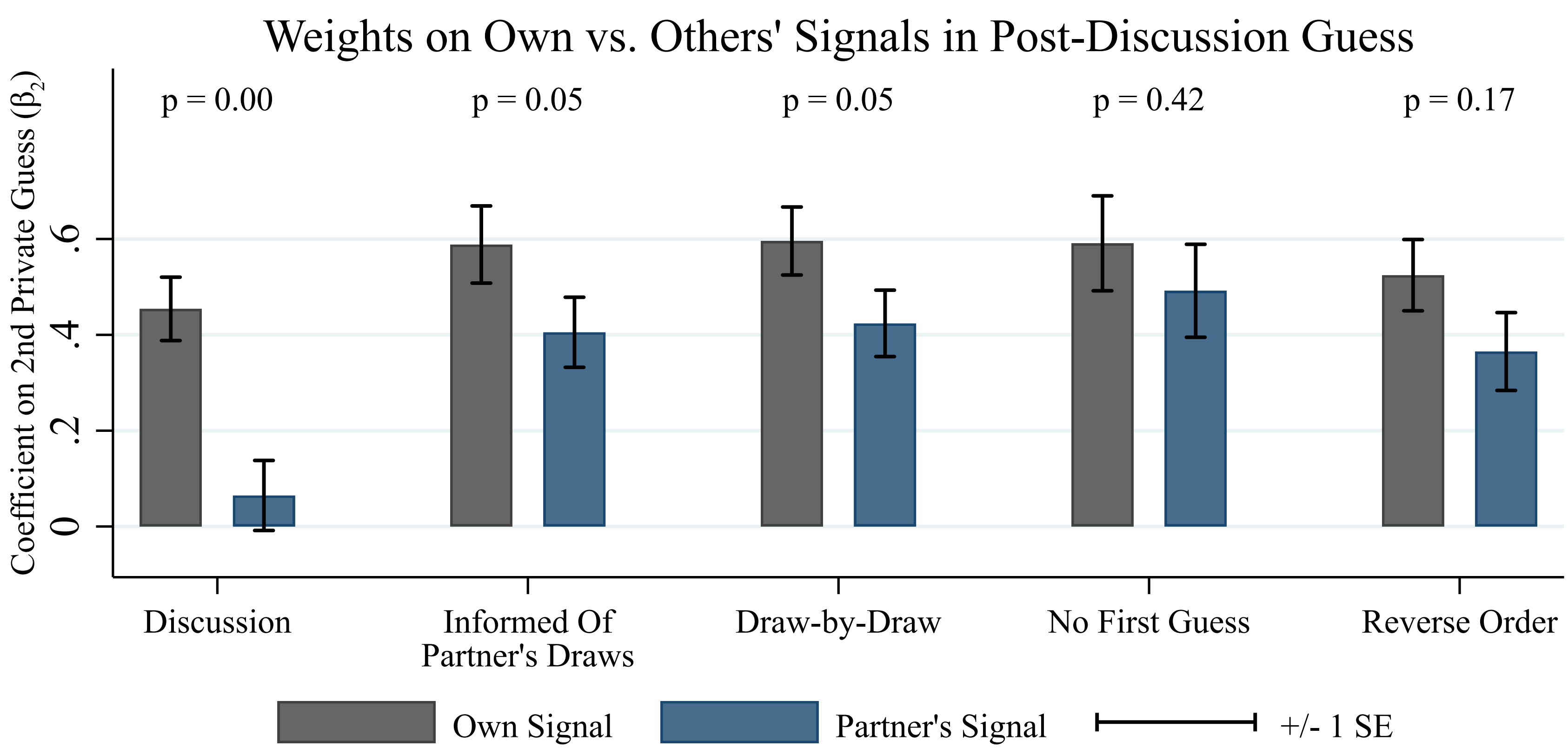


Panel B: Experiment 3



Notes: This figure shows the average second private guesses of participants in Experiment 2 and 3. In each graph, we plot this first against the participant's own signal (unconditional on partner's signal) in gray, and then again against their partner's signal (unconditional on own signal), in blue. The x-axis shows the net number of red draws (i.e. red draws minus white draws) in a given signal. Dots indicate average guesses, with dot size indicating number of observations, while the solid curves show locally-weighted means (lowess). Because the signals are symmetrically distributed, equal weighting of own and others' information would imply the two curves should be equally steep. **Panel A** shows the average second private guess in Experiment 2. We show this for A.(i) *Informed of Partner's Draws*, where participants receive the second set of draws directly from the experimenter (and the second guess is before any discussion with their partner); and A.(ii) *Observe Partner's Draws*, where participants watch their partner drawing from the urn. **Panel B** shows the average second guess of participants in Experiment 3. We show results for: B.(i) *Informed of Partner's Draws*, where participants are given a summary of their partner's draws; B.(ii) *Observe Partner's Draws*, where participants watch their partner's draws appear from the urn; and B.(iii) *Labels Only*, where participants passively watch their own as well as their partner's draws appear from the urn.

Figure A.IV: Experiment 2: Reduced-Form Estimates



Notes: This figure shows the weights participants put on different signals when making their post-discussion private guess in Experiment 2. We estimate equation (1) and then display β_1 in gray and β_2 in dark blue for each treatment, except the *Observe Partner's Draws* round (in which there was no discussion and thus no post-discussion guess). In addition to the *Discussion* and *Informed of Partner's Draws* rounds, we look at the following treatments:

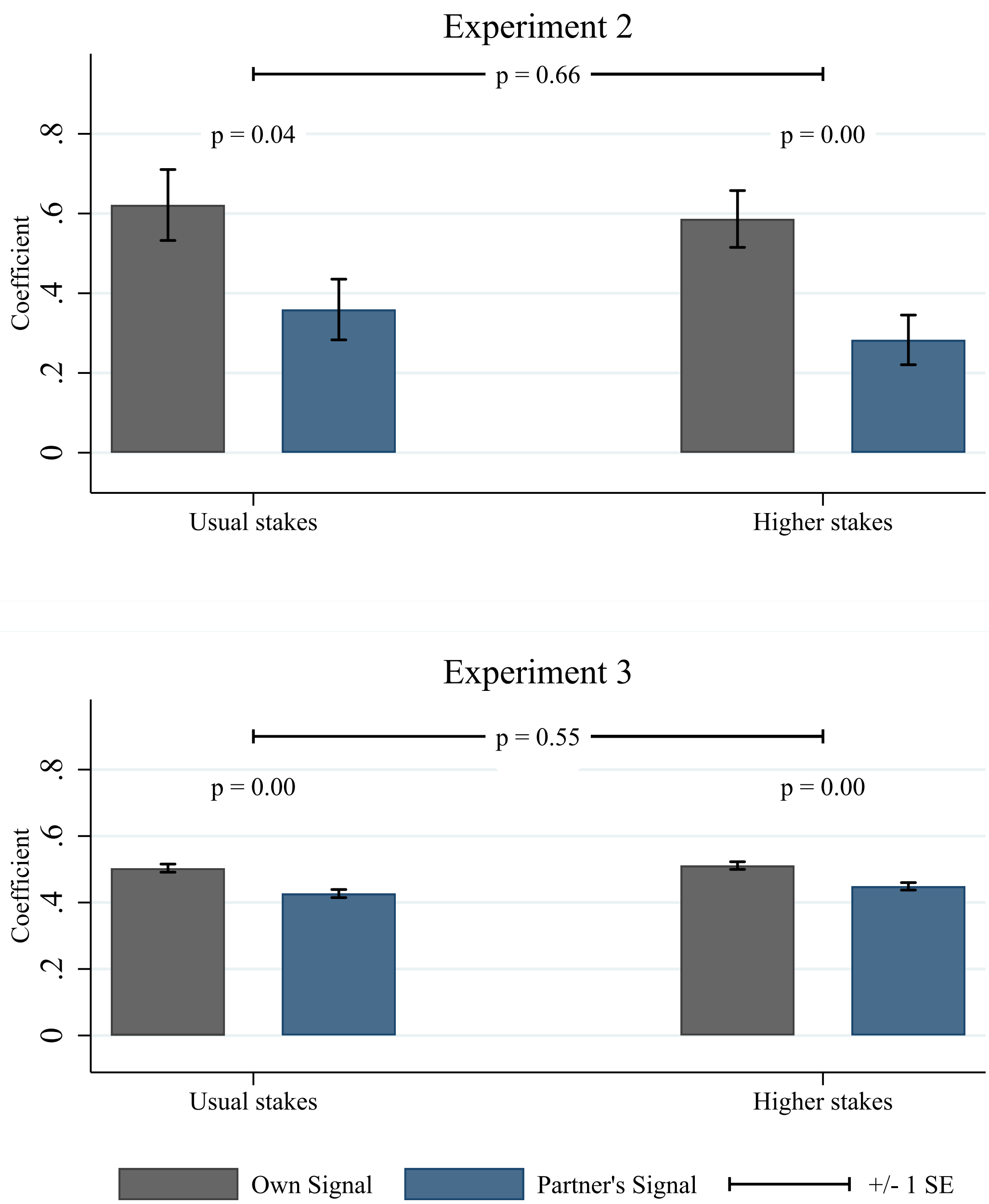
(a) *Draw-by-Draw*, in which participants receive the second set of signals directly one draw at a time;

(b) *No First Guess*, in which participants receive their partner's signals (and their own) before making their first and only private guess;

(c) *Reverse Order*, in which one participant receives their partner's signals first and makes their first private guess, and then receives their own signals and makes their second private guess.

For each round, we show the p-value of testing whether the weight on their signal (β_1) equals the corresponding weight on their partner's signal (β_2) in that round.

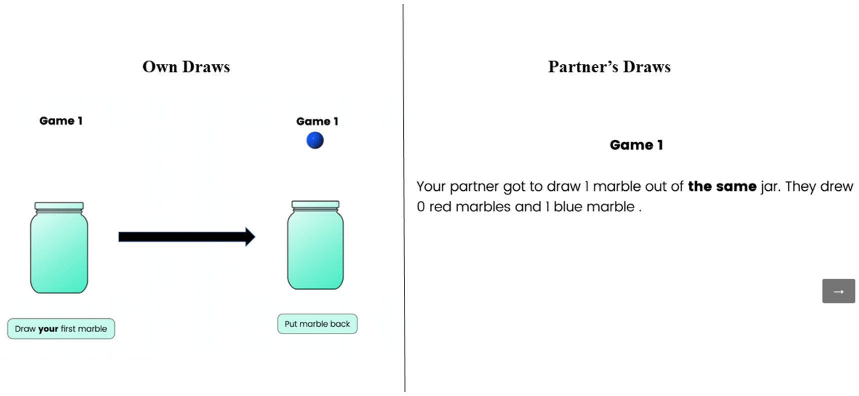
Figure A.V: Weights on Own vs. Others' Signals under Usual vs. Higher Stakes



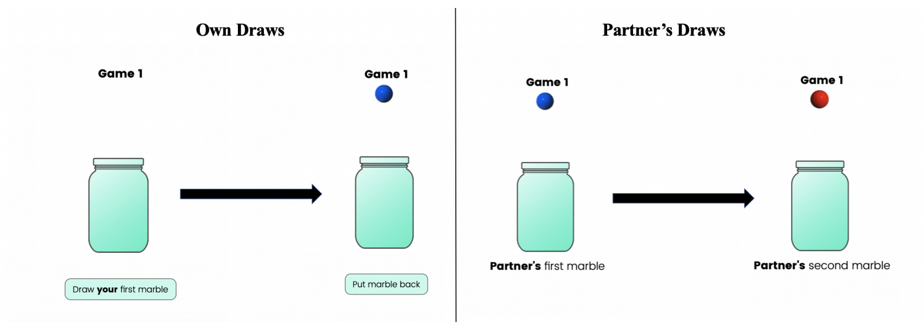
Notes: This figure shows OLS estimates of equation 1 in Experiments 2 and 3, pooling the different treatments, separately by whether participants faced lower or higher stakes (incentives). Above each pair of bars, we show the p-value of testing whether the weight on own information (gray) equals the weight on partner's information (dark blue). The higher, centered p-value in each graph is the p-value of testing whether the difference in weights is the same in the usual and the high stakes condition. In both experiments, we cannot reject that it is.

Figure A.VI: Visual Presentation of Draws in Experiment 3

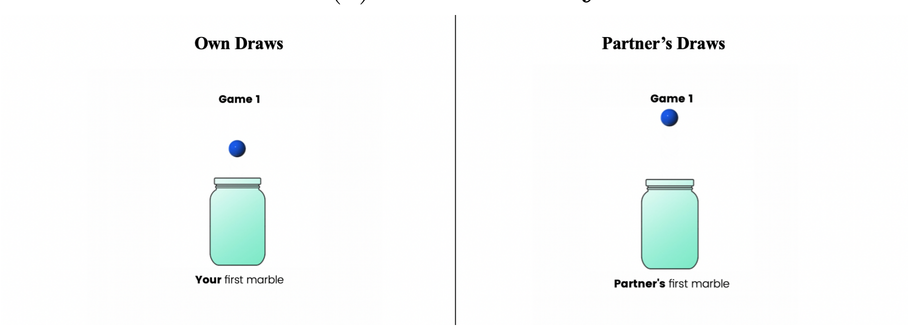
(a) **Informed Of Partner's Draws**



(b) **Observe Partner's Draws**

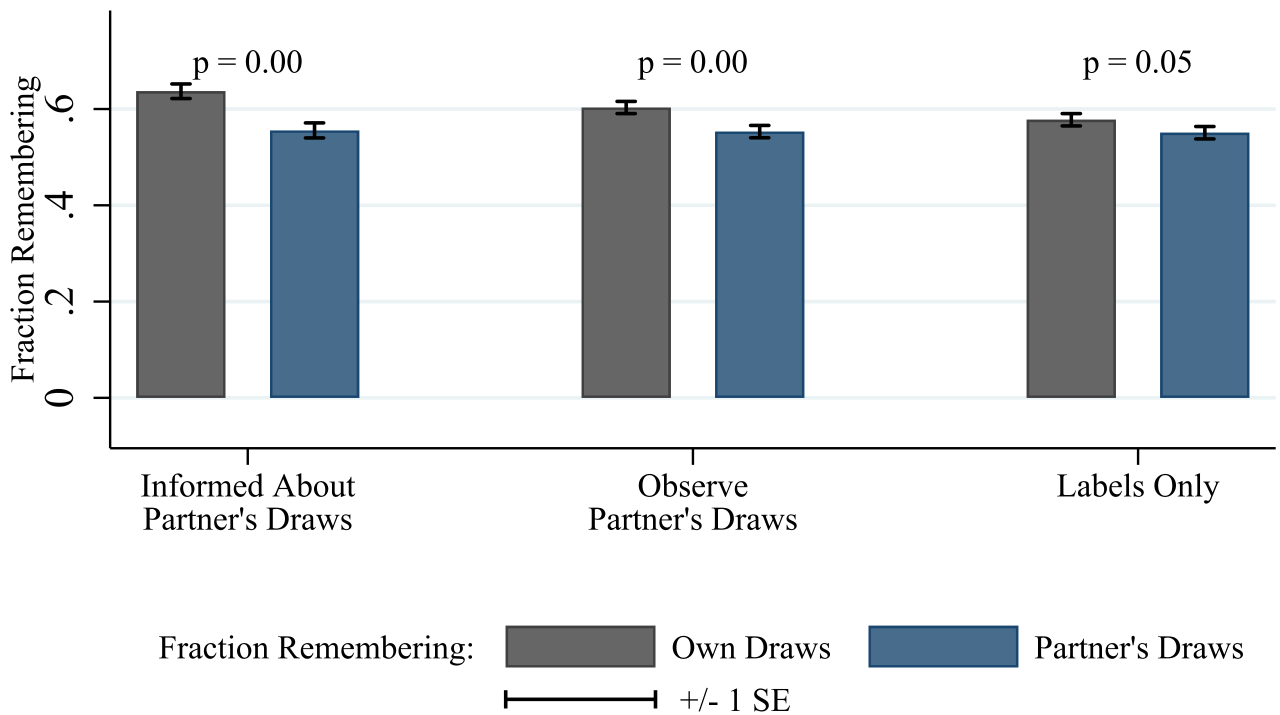


(c) **Labels Only**



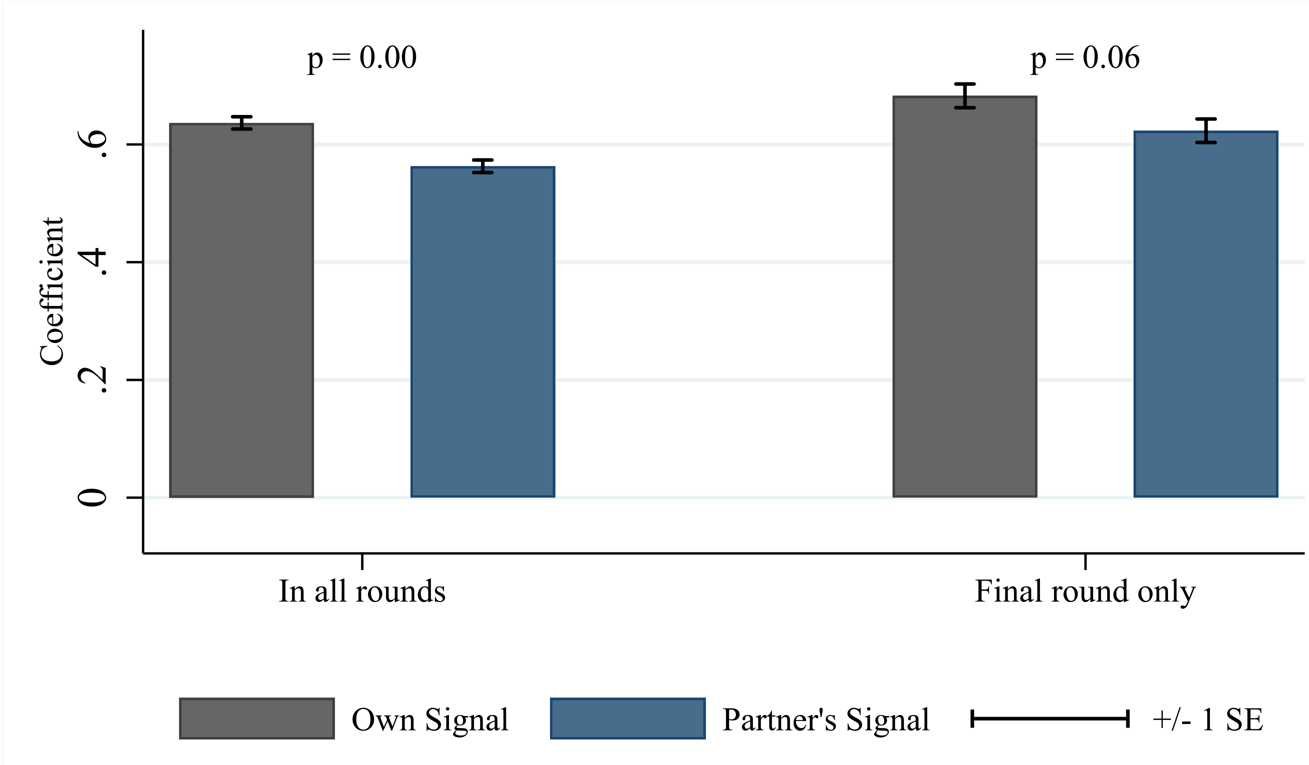
Notes: This figure shows how the participant's own information and partner's information was presented in the Qualtrics survey for the different treatments in Experiment 3. The left panel of the figure shows how their own information was presented, and the right panel shows how their partner's information was presented. The arrows indicate subsequent screens. In all treatments, we emphasized that own and partner's draws were made from the same urn. **Panel A** shows how draws were presented in the *Informed of Partner's Draws* treatment. To obtain their own draws, participants clicked to draw balls one by one from a virtual urn, and after each ball was shown, clicked again to put it back in the urn, which was then animated to shuffle. In contrast, participants learned their partner's draws in summary form as shown in the right part of the panel. **Panel B** shows how draws were presented in the *Observe Partner's Draws* treatment. Participants obtained their own draws in exactly the same way as in the *Informed of Partner's Draws* round. For their partner's draws, participants were shown the same virtual urn and saw their partner's draws being revealed by the same ball-by-ball animation. However, the draws appeared one by one *without* clicking on the urn to obtain them. **Panel C** shows how draws were presented in the *Labels Only* treatment. The participants were shown a virtual urn and saw their own draws revealed by the same ball-by-ball animation, without having to click. Their partner's draws were revealed in exactly the same way.

Figure A.VII: Memory of Own vs. Others' Signals in Experiment 3



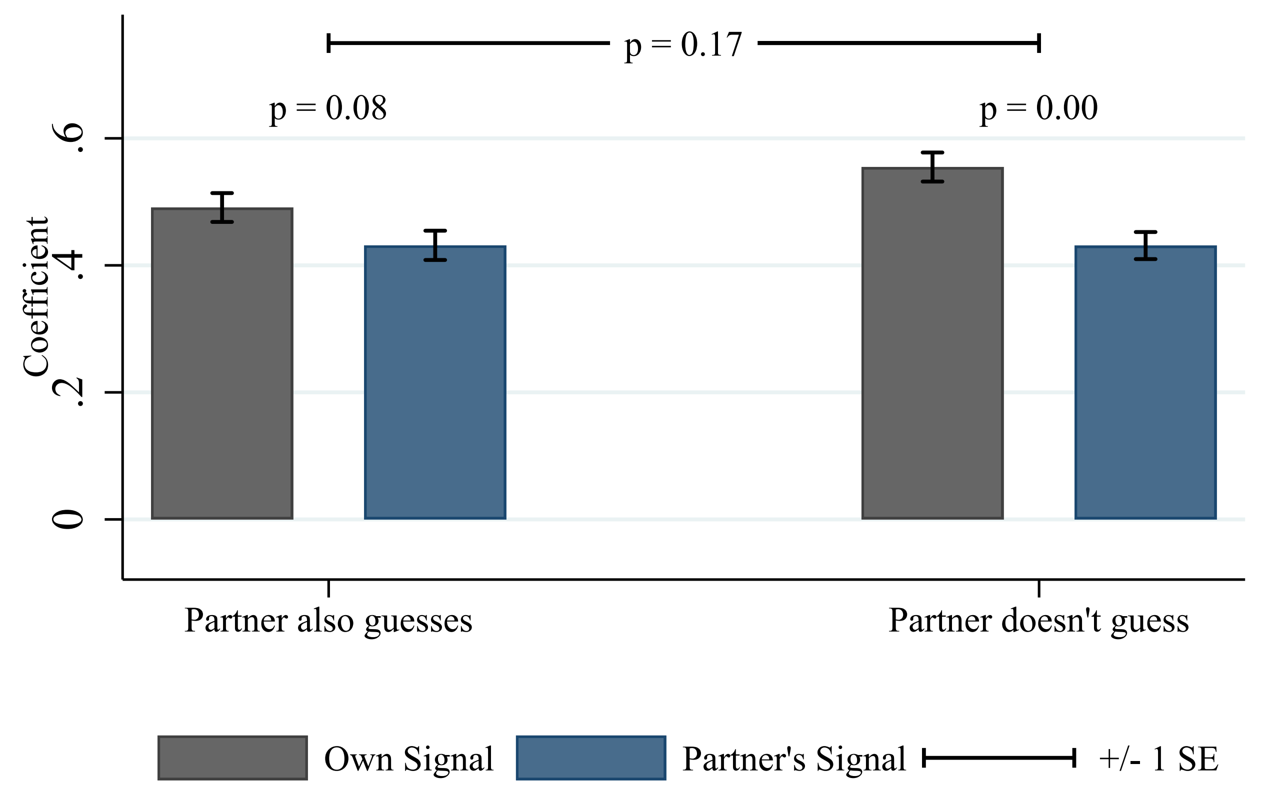
Notes: Participants in Experiment 3 were asked at the end of their final round (out of 5) if they remembered their own and their partner's draws—both number and color composition—from that round. The question was unannounced and unincentivized. This figure shows the fraction of participants correctly remembering their own (gray bar) versus their partner's (blue bar) draws in each treatment in Experiment 3. For each pair of bars, we show the p-value of testing that the same fraction remembered their own draws as remembered their partner's draws. See Table A.VII for the underlying numbers used in this figure.

Figure A.VIII: Weights on Own vs. Others' Signals for Participants Who Remember All Draws (Experiment 3)



Notes: Participants in Experiment 3 were asked at the end of their final round (out of 5) if they remembered their own and their partner's draws from that round. This question was unannounced and unincentivized. This figure shows OLS estimates of equation 1 in Experiment 3 for participants who correctly remembered both, pooling across treatments. The left pair of bars shows these participants' weights pooling all five rounds and the right set their weights in the final round only (i.e., the round for which they correctly remembered). Above each pair of bars, we show the p-value of testing whether the weight on own information (gray) equals the weight on partner's information (dark blue).

Figure A.IX: Experiment 3: Reduced-Form Estimates – Guessing vs. Non-guessing Partner in the *Informed* Treatment



Notes: This figure shows OLS estimates of equation 1 for participants in the *Informed of Partner's Draws* treatment in Experiment 3, separately by whether they were also assigned to the *Non-Rivalry* treatment, i.e., by whether their partner also guessed ('Guessing partner') or not ('Non-guessing partner'). For each of the dark-blue bars, we show the p-value of testing whether the weight on own information (gray bar) equals the weight on partner's information (blue bar). The higher, centered p-value is the p-value of testing whether the difference in weights is the same across the two treatments. We cannot reject that it is. See Table A.VIII for the underlying numbers displayed in this figure.

Table A.I: Comprehension and Memory

Question	Experiment 1	Experiment 2
A. Basic Design		
Number of balls	0.97	0.99
Colors of balls	1.00	1.00
B. Common Prior		
Possible $<$ 4 red	0.93	0.96
Possible $>$ 16 red	0.93	0.97
Who chooses number of red balls	0.81	0.84
Likelihood of each number	0.78	0.61
C. Signals		
Learn more from more balls	0.88	0.88
Possible have 4 draws	0.76	0.69
How number draws differs	0.47	0.47
How spouse's draws differ	0.61	0.63
D. Incentives		
Payment if 1 off	0.90	0.95
Payment if way off	0.85	0.92
Payment if 4 off	0.92	0.93
E. Memory		
Correctly remembered own guess	0.92	
Correctly remembered # of own draws	0.97	0.96
Correctly remembered # of own red draws	0.85	0.80
Correctly remembered # of partner's draws		0.89
Correctly remembered # of partner's red draws		0.70

Notes: This table shows summary statistics of participants' comprehension of the task and their memory of previous draws and guesses. Column 1 shows the sample of 500 individuals of Experiment 1; and column 2 shows the sample of 292 individuals of Experiment 2. Panels A through D show the fraction of participants who answered each question correctly. For each question, we corrected the participant if they gave a wrong answer. Panel E shows the fraction of people who correctly remembered their own and their partner's in some of the rounds.

- **Panel A** shows answers to questions "How many balls are in the urn?" (correct answer: 20), and "What colors are the balls?" (red and white).
- **Panel B** "Is it possible to have less than 4 /more than 16 red balls?" (no); "Who chooses how many balls are red?" (the computer), and "Are some numbers more likely than others?" (no).
- **Panel C** "Do you learn more from one draw or five draws?" (five); "Can you get exactly 4 draws in any round?" (no); "Will you have the same or different numbers of draws across rounds?" (could be same or different); "Will your partner have the same or different number to you?" (could be same or different).
- **Panel D** shows the fraction of people who could correctly indicate their payment on the scale if their guess was 1, 11, or 4 balls off.
- **Panel E** shows the proportion of participants who correctly remember their own guess and draws. "Correctly remembered own guess" correspond to the fraction of people who correctly remember their own guess in the *Informed of Partner's Guess* round of Experiment 1. "Correctly remembered # of own draws" and "Correctly remembered # of own red draws" correspond to the fraction of people who correctly remember their own draws in the in the *Informed of Partner's Draws* round in Experiment 1, and correspond to results pooled across 4 rounds, including the *Observe Partner's Draws* round in Experiment 2. "Correctly remember # of partner's draws" and "Correctly remembered # of partner's red draws" correspond to the *Observe Partner's Draws* round in Experiment 2.

Table A.I: (continued) Comprehension - Experiment 3

	Experiment 3
Goal of task	0.81
Number of balls	0.93
Possible numbers of red balls	0.97
Playing with partner	0.88
Drawing with replacement	0.90
Same urn as partner	0.91
Urn re-randomized across rounds	0.93
Incentive scheme	0.99

Notes: This continues Table A.I, showing summary statistics of participants' comprehension of the task in Experiment 3. Participants were asked 8 multiple-choice questions; if they got a question wrong, they had to retry until they got it right (they could re-read the relevant instruction). Shown are the fraction of participants answering each question correctly first time. The questions are shown below, with the correct answer in brackets.

- Goal of task – "What is the goal of the game you are playing today?" (To guess the number of red marbles in a virtual jar)
- Number of balls – "How many marbles are in the jar total?" (20)
- Possible numbers of red balls – "And how many red marbles could possibly be in the jar?" (Between 4 and 16 red marbles)
- Playing with a partner – "Who are you playing this game with?" (a real person who is taking the survey at about the same time with me). Note that in the *Non-rivalry* treatment, the correct answer was 'A real partner who is taking the survey at around the same time as me but doing a different task than what I'm doing'.
- Drawing with replacement – "Which of the following statements is correct: After each draw, the marble is not put back in the jar / After each draw, the marble gets put back and the contents get shuffled" (After each draw, the marble gets put back and the contents get shuffled)
- Same urn as partner – "Which of these statements is correct: My partner and I are drawing marbles from the same jar with the same number of red marbles / ... different number of red marbles / I am drawing marbles from the jar, and my partner is not / My partner is drawing marbles from the jar, and I am not" (My partner and I are drawing marbles from the same jar with the same number of red marbles)
- Urn re-randomized across rounds – "Which of these statements is correct: I will only play this game once / I will play this game 5 times with the contents of the jar always being the same / I will play this game 5 times with the contents of the jar being re-randomized each time" (I will play this game 5 times with the contents of the jar being re-randomized each time)
- Incentive scheme – "How can you affect the outcome of your bonus payment?" (For a randomly chosen guess, the closer I was to the true number of red marbles in the jar, the higher is my bonus)

Table A.II: Transcripts of Joint Discussions: Summary Statistics

	Experiment 1
Asked for Other's Information	0.36
Explained Task to Partner	0.00
Shared Guess	0.29
Shared Number of Draws	0.19
Shared Composition of Draws	0.23
Suggested Final Guess	0.53
Length of Discussion (mins)	0.92

Notes: This table shows averages of key characteristics of the discussion among participants for Experiment 1. These variables were constructed using transcripts of the discussions between participants before the joint guesses were made. Except for the length of discussion, each variable is at the participant level (as opposed to at the pair level)

- We pool the discussions across 3 rounds, and exclude the *Individual* round and *Discussion* round with same-gender pairs. The latter was excluded due to challenges in identifying the two participants.
- "Shared Number of Draws" equals 1 if participants shared their total draws or mentioned the specific composition of their draws, ("I drew 4 red balls and 1 white ball"). "Shared Composition of Draws" equals 1 if participants shared the specific composition of draws ("I drew 4 red balls and 1 white ball") or mentioned that they drew more of one color ("I drew more red balls than white").
- 83% of our transcripts were audible, so the remaining have been excluded from this table.

Table A.III: Experiment 1: Error in Guess by Type of Guess and Number of Draws

	Individual (1)	Discussion (2)	Informed (Pre) (3)	Informed (Post) (4)
γ_1: # Own First Draws	-0.13 (0.06)	-0.09 (0.04)	-0.09 (0.05)	-0.02 (0.05)
γ_2^o: # Own Second Draws	-0.15 (0.07)			
γ_2^p: # Partner's Draws		-0.04 (0.04)	0.02 (0.05)	-0.02 (0.06)
Constant	4.10 (0.46)	3.58 (0.32)	3.45 (0.45)	3.22 (0.46)
$\boldsymbol{\gamma_2^p - \gamma_2^o}$		**0.11***** **(0.07)**	**0.17**** **(0.08)**	**0.14*** **(0.08)**
N	500	1000	500	500

Notes: This table compares the error in participants' guesses (the absolute difference between their guess and the true number of red balls in the urn) in the *Discussion*, *Informed of Partner's Draws*, and *Individual* round. The table shows OLS estimates of the following equation for the *Discussion* and *Informed of Partner's Draws* rounds:

$$|\textit{Guess - Truth}|_{irt} = \alpha + \gamma_1 \#\ \textit{Own First Draws}_i + \gamma_2^p \#\ \textit{Partner's Draws}_i + \epsilon_i \quad (6)$$

and OLS estimates of the following equation for the *Individual* round:

$$|\textit{Guess - Truth}|_{irt} = \alpha + \gamma_1 \#\ \textit{Own First Draws}_i + \gamma_2^o \#\ \textit{Own Second Draws}_i + \epsilon_i \quad (7)$$

where $|\textit{Guess - Truth}|_{irt}$ is the absolute value of difference between i's guess and the true number of red balls in the urn in the round in question, and *# Own First Draws*$_i$ indicates the number of draws in the first set of signals, drawn oneself. *# Own Second Draws* is the number of draws in the participant's second set in the Individual round and *# Partner's Draws* is the participant's partner's number of draws, in the *Discussion* and *Informed of Partner's Draws* rounds. In estimation, we stack the estimating equations for all treatment and estimate them jointly including controls for round order fixed effects. Standard errors are clustered at the pair level. *, **, and *** indicate significance at the p<0.10, 0.05, and 0.01 levels of the difference $\gamma_2^p - \gamma_2^o$.

Table A.IV: Weights on Own vs. Others' Signals under Usual vs. Higher Stakes

	Usual Stakes (1)	Higher Stakes (2)
Panel A: Experiment 2		
β_1: Own Signal	0.62	0.59
	(0.09)	(0.07)
β_2^p: Partner's Signal	0.36	0.28
	(0.08)	(0.06)
Constant	10.47	10.44
	(0.12)	(0.11)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.26****	**-0.30*****
	(0.13)	**(0.11)**
p**-value:** $\boldsymbol{\beta_2^p - \beta_1}$ **equal across treatments**	**0.66**	
N	1602	1602
Panel B: Experiment 3		
β_1: Own Signal	0.50	0.51
	(0.01)	(0.01)
β_2^p: Partner's Signal	0.43	0.45
	(0.01)	(0.01)
Constant	9.56	9.58
	(0.03)	(0.03)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.08*****	**-0.06*****
	(0.02)	**(0.02)**
p**-value:** $\boldsymbol{\beta_2^p - \beta_1}$ **equal across treatments**	**0.55**	
N	9770	10190

Notes: This table shows OLS estimates of equation 1 separately by whether participants faced usual or higher stakes (incentives). This table reports the same estimates as Figure A.V. *, **, and *** indicate significance at the $p<0.10$, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

Table A.V: Experiment 3: Sensitivity of First Guesses to Own vs Other's Signal

	Informed (1)	Observe (2)	Labels Only (3)
β_1:First Signal $\cdot\mathbb{1}$(Own)	0.66	0.67	0.61
	(0.02)	(0.02)	(0.02)
β_2^p:First Signal $\cdot\mathbb{1}$(Partner's)	0.55	0.59	0.63
	(0.02)	(0.02)	(0.02)
Constant	9.45	9.52	9.64
	(0.04)	(0.03)	(0.03)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.11*****	**-0.07*****	**0.02**
	(0.03)	**(0.03)**	**(0.03)**
p-value: $\beta_2^p - \beta_1$ same as in Informed		0.68	0.01
p-value: $\beta_2^p - \beta_1$ same as in Observe			0.01
N	5040	7485	7435

Notes: This table shows reduced-form results, estimating the following equation by OLS:

$$FirstGuess_i = \alpha + \beta_1 \cdot First\ Signal_i \cdot \mathbb{1}(Own) + \beta_2^p \cdot First\ Signal_i \cdot \mathbb{1}(Partner's) + \epsilon_i$$

where the dependent variable $FirstGuess_i$ is participant i's *first* private guess (before seeing the second signal). $First\ Signal_i$ indicates the net number of red draws (i.e., red draws minus white draws) in the first signal that the participant saw, $\mathbb{1}(Own)$ is a dummy variable indicating whether this was i's own signal, and $\mathbb{1}(Partner's)$ is a dummy variable indicating whether this was i's partner's signal. "Informed" refers to the *Informed of Partner's Draws* round and "Observe" to the *Observe Partner's Draws* round. Standard errors are clustered at the pair level. *, **, and *** indicate significance at the $p<0.10$, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

Table A.VI: Heterogeneity

	Comprehension: Below median	Comprehension: Above median	Education: Below median	Education: Above median	Performance Belief: Below median	Performance Belief: Above median
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Experiment 1						
β_1: Own Info	0.47	0.52	0.41	0.58	0.50	0.49
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
β_2^p: Partner's Info	0.26	0.32	0.28	0.30	0.30	0.27
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.21*****	**-0.20*****	**-0.13****	**-0.28*****	**-0.24*****	**-0.14****
	(0.06)	**(0.06)**	**(0.06)**	**(0.06)**	**(0.06)**	**(0.06)**
p-val.: $\boldsymbol{\beta_2^p - \beta_1}$ equal	**0.90**		**0.11**		**0.23**	
Panel B: Experiment 2						
β_1: Own Info	0.50	0.64	0.48	0.63		
	(0.04)	(0.04)	(0.05)	(0.04)		
β_2^p: Partner's Info	0.30	0.31	0.24	0.36		
	(0.04)	(0.04)	(0.04)	(0.05)		
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.20*****	**-0.33*****	**-0.25*****	**-0.27*****		
	(0.06)	**(0.06)**	**(0.07)**	**(0.06)**		
p-val.: $\boldsymbol{\beta_2^p - \beta_1}$ equal	**0.15**		**0.82**			
Panel C: Experiment 3						
					Remember All Draws	Say Treat Same
β_1: Own Info	0.45	0.54	0.48	0.53	0.68	0.53
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
β_2^p: Partner's Info	0.36	0.48	0.41	0.46	0.62	0.45
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.08*****	**-0.06*****	**-0.08*****	**-0.06*****	**-0.06***	**-0.08*****
	(0.02)	**(0.01)**	**(0.02)**	**(0.02)**	**(0.03)**	**(0.01)**
p-val.: $\boldsymbol{\beta_2^p - \beta_1}$ equal	**0.36**		**0.61**			

This table shows estimates of equation 1 estimated on subsets of the data. Columns 1 and 2 show estimates by whether comprehension (the percentage of comprehension questions answered correctly first time) is above or below median. The median was 79% in Experiments 1 and 2, and 100% in Experiment 3 (so 'above median' means everyone who got all questions right). Columns 3 and 4 show estimates by whether years of education is above or below median. Columns 5 and 6 show in Panel A estimates by whether the guesser's belief about their own performance – specifically, how much they expected their guesses to earn on average – is above or below median. This was only asked about in Experiment 1. In Panel C, column 5 restricts the Experiment 3 data to the final round of the experiment and to participants who correctly remember both their own and their partner's draws (asked after the round ended), while column 6 restricts the Experiment 3 data to participants who answered in a debriefing question at the end of the survey that they "treated my draws and my partner's draws the same." For each pair of columns, "p-val.: $\beta_2^p - \beta_1$ equal" is the p-value from testing the hypothesis that $\beta_2^p - \beta_1$ is the same in each subsample. The data pools all treatments except the *Individual* round in Experiment 1. Standard errors in parentheses. *, **, and *** indicate significance at the p<0.10, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

Table A.VII: Memory of Own vs. Others' Draws in Experiment 3

	Informed (1)	Observe (2)	Labels Only (3)
Fraction Remembering:			
Own Draws	0.64	0.60	0.58
	(0.02)	(0.01)	(0.01)
Partner's Draws	0.56	0.55	0.55
	(0.02)	(0.01)	(0.01)
p-val.: Equal memory of own and partner's	0.00	0.00	0.05
N	2016	2994	2974

Notes: Participants in Experiment 3 were asked at the end of their final round (out of 5) if they remembered their own and their partner's draws – both number and color composition – from that round. This question was unannounced and unincentivized. This table shows the fraction of participants correctly remembering their own versus their partner's information in each treatment in Experiment 3. In each column we show the p-value of testing whether the fraction remembering own and partner's draws is the same within that treatment. Standard error of the mean in parentheses. This table reports the same estimates as Figure A.VII.

Table A.VIII: Experiment 3: Reduced-Form Estimates – Rivalry

	Partner also guesses (1)	Partner doesn't guess (2)
β_1: Own Signal	0.49	0.55
	(0.02)	(0.02)
β_2^p: Partner's Signal	0.43	0.43
	(0.02)	(0.02)
Constant	9.54	9.59
	(0.07)	(0.06)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.06***	**-0.12*****
	(0.03)	**(0.03)**
p-value: $\boldsymbol{\beta_2^p - \beta_1}$ equal across treatments	**0.17**	
N	2525	2515

Notes: This table shows OLS estimates of equation 1 for participants in the *Informed of Partner's Draws* treatment in Experiment 3, separately by whether their partner also guessed or did not guess (the *Non-Rivalry* treatment). This table reports the same estimates as Figure A.IX. The bottom row shows the p-value of testing whether the difference in weights is the same across the two treatments. Standard errors in parentheses. *, **, and *** indicate significance at the $p<0.10$, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

Table A.IX: Experiment 1: Reduced-Form Results by Whether Participants Asked for Their Partner's Draws (*Discussion* Round)

	Asked for Partner's Draws (1)	Did not ask for Partner's Draws (2)
β_1: Own Signal	0.61	0.47
	(0.08)	(0.07)
β_2^p: Partner's Signal	0.26	0.31
	(0.10)	(0.08)
Constant	10.86	11.41
	(0.22)	(0.22)
$\boldsymbol{\beta_2^p - \beta_1}$	**-0.36****	**-0.16**
	(0.15)	**(0.12)**
p**-value:** $\boldsymbol{\beta_2^p - \beta_1}$ **equal**	**0.32**	
N	141	207

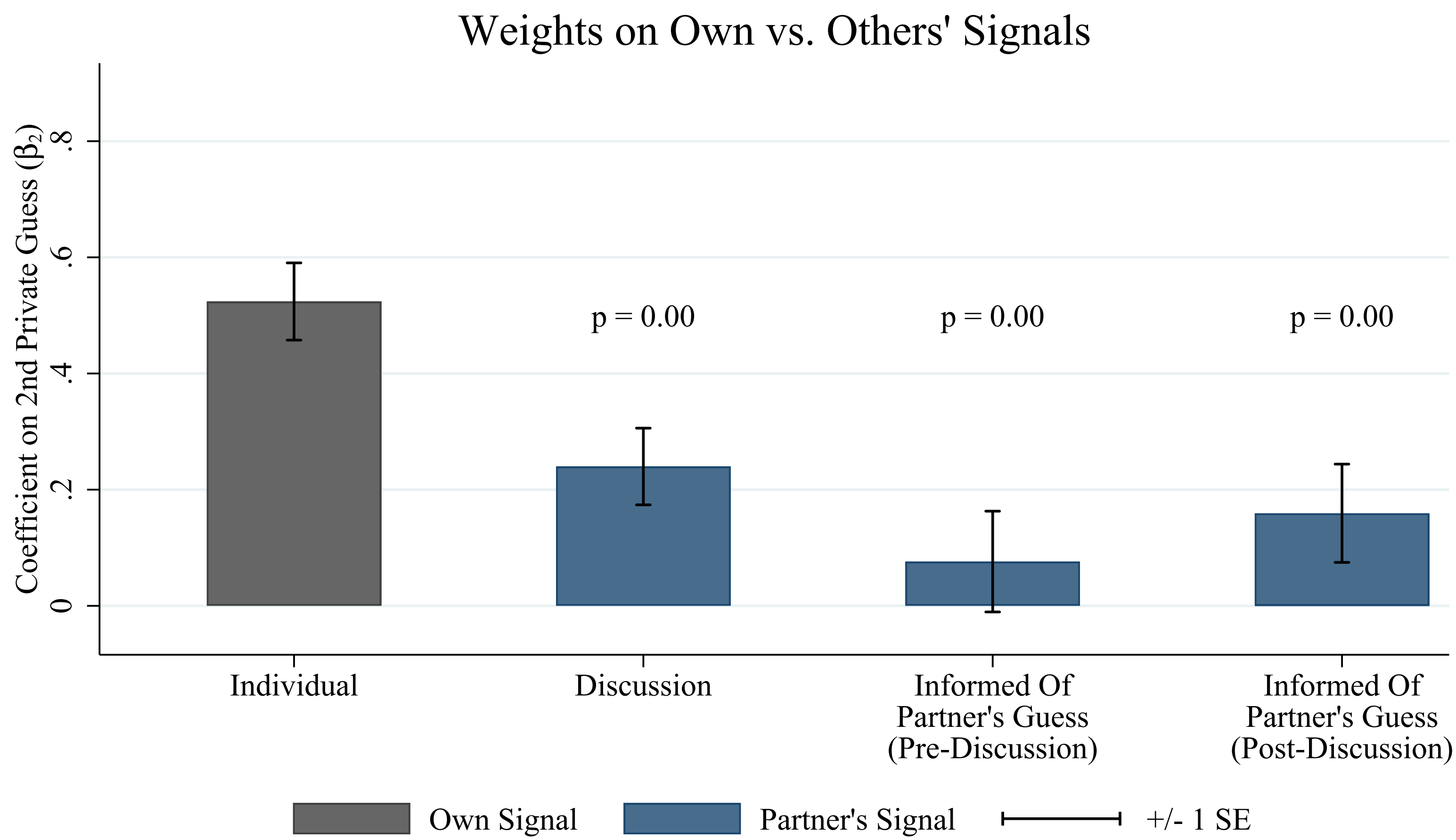
Notes: This table shows OLS estimates of equation 1 for the *Discussion* treatment in Experiment 1, separately by whether participants asked their partner anything about their draws during the discussion. The bottom row shows the p-value of testing whether the difference in weights on own and partner's signals is the same in both cases. Standard errors in parentheses. *, **, and *** indicate significance at the $p<0.10$, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_1$.

A.1 *Informed of Partner's Guess* Round in Experiment 1

The *Informed of Partner's Guess* round in Experiment 1 is identical to the *Informed of Partner's Draws* round, except that instead of sharing with each person the number of balls of each color their partner drew, the surveyor shares their partner's guess and the total number of draws (1, 5 or 9) on which that guess was based. Figure A.X shows estimates for the *Individual*, *Discussion*, and *Informed of Partner's Guess* rounds. The results look similar to those for the *Informed of Partner's Draws* round. People strongly discount their partner's information relative to their own in both the pre-discussion and post-discussion guesses. This could be explained by differential processing of own compared to others' information, but also by other (potentially rational) reasons, such as mistrust of partners' guesses or the increased computational difficulty of backing out what the partner's information must have been given their guess. Table A.X shows the corresponding reduced-form and structural estimates, which confirm the visual impressions from Figure A.X.[41]

[41]Note that the structural estimates assume that participants are able to back out from their partner's guess what their information must have been. Less weight on partner's information could therefore reflect not just intrinsic discounting others info but also the extent to which that this is a difficult problem for participants to solve (or one they do not attempt to solve).

Figure A.X: Experiment 1: Reduced Form Estimates – Informed of Partner's Guess Round



Notes: This figure shows the weights participants put on different signals in Experiment 1. We estimate equation (1) and then display β_2 for each of the following four types of private guesses:

(a) *Individual*, where participants collect all information on their own. For this round, we replace *Partner's Info* in equation (1) by the net red draws in the participant's second set of signals;

(b) *Discussion*, in which participants collect the first set of information on their own and the second set (their partner's) is only accessible via discussion;

(c) *Informed of Partner's Guess (pre-discussion)*, where participants have learned their partner's guess and number of draws directly from the experimenter but before any discussion with their partner;

(d) *Informed of Partner's Guess (post-discussion)*, where participants have learned their partner's guess and number of draws *and* had the chance to discuss it with their partner.

For each of the dark-blue bars, we show the p-value of testing whether the weight in that round equals the corresponding weight in the *Individual* round (gray bar).

Table A.X: Reduced-Form Estimates in the Informed of Partner's Guess Round

	Individual	Discussion	Informed (Pre)	Informed (Post)
	(1)	(2)	(3)	(4)
β_1: Own First Signal	0.43	0.56	0.50	0.40
	(0.06)	(0.06)	(0.10)	(0.10)
β_2^o: Own Second Signal	0.52			
	(0.07)			
β_2^p: Partner's Signal		0.24	0.08	0.16
		(0.07)	(0.09)	(0.08)
Constant	10.71	10.73	10.58	10.65
	(0.16)	(0.16)	(0.22)	(0.22)
$\boldsymbol{\beta_2^p - \beta_2^o}$		**-0.28*****	**-0.45*****	**-0.36*****
		(0.08)	**(0.10)**	**(0.10)**
N	500	1000	500	500

Notes: This table shows reduced-form estimates of equation 1 for the *Individual*, *Discussion* and *Informed of Partner's Guess* rounds in Experiment 1. The dependent variable is participants' private guess. 'Informed (Pre)" means the second private guess from the *Informed of Partner's Guess* round, after the participant was directly told their partner's guess but before the joint discussion. "Informed (Post)" means the third private guess, after the discussion. "Own First Signal" is the net number of red draws (i.e., red draws minus white draws) in the participant's first set of draws, which they drew themselves in all rounds. "Own Second Signal" is the net number of red draws in the participant's second set of draws in the individual round. "Partner's Signal" is the net number of red draws in the set of draws by the participant's partner, which was the second signal available to the participant in the *Discussion* and *Informed of Partner's Guess* rounds. All regressions include order fixed effects interacted with the participant's first and second signal. All standard errors are clustered at the pair (of two participants) level. *, **, and *** indicate significance at the $p<0.10$, 0.05, and 0.01 levels of the difference $\beta_2^p - \beta_2^o$.

A.2 Comparing Structural to Non-Structural Results

In this section we consider whether the estimates of the structural model outlined in Section 3.3 are consistent with the main non-structural results presented elsewhere in Section 4.3. To do so, we simulate, using the estimates of the parameters of the model, what guesses participants in Experiment 1 would make given the signals they had. To eliminate unnecessary noise, instead of simulating just once for each guess of what the participant would choose (which is noisy), we calculate the expected guess. We then produce a version of Panel A of Table 2 using the simulated data. The question these analyses allow us to answer is, "Are the estimated biases from the structural model sufficient to explain the patterns found in the reduced-form and non-structural results?" If the model implied that the non-structural analyses would look very different than in fact they do, this would suggest that the model is not capturing something important about the biases we document.

Panel A of Table A.XI replicates Panel A of Table 2, our main reduced-form results for Experiment 1. Panel B shows the same regressions but using the model-implied expected guesses as the dependent variable rather than participants' true guesses. Note that these variables, because they are expectations rather than single draws from the distribution of guesses, are mechanically much less noisy than the actual guesses. However, as Table A.XI shows, the *size* of the coefficients are quite similar (i.e., comparing within column across panels). Our interpretation of these results is that the model estimates are sufficient to explain the pattern of results shown in the reduced-form analyses.

Figure A.XI compares the non-parametric results from Figure 3 with similar estimates using the model-simulated data. There are four panels, representing the *Individual* round, *Discussion* round, *Informed of Partner's Draws* round (pre-discussion), and *Informed of Partner's Draws* round (post-discussion). Each panel shows the estimates given the actual guesses that participants make (in gray) along with the model-simulated expected guesses (in blue). As expected, actual guesses are noisier, but the slopes of the curves are extremely similar within each panel, suggesting that the non-parametric and structural effect sizes are of comparable magnitude. Note that there is a slight bias in the actual data toward guessing more red balls in the urn, which the structural model by construction cannot deliver (as evidenced by the gray tending to lie above the blue curve).

Table A.XI: Comparing Reduced-Form to Structural Results

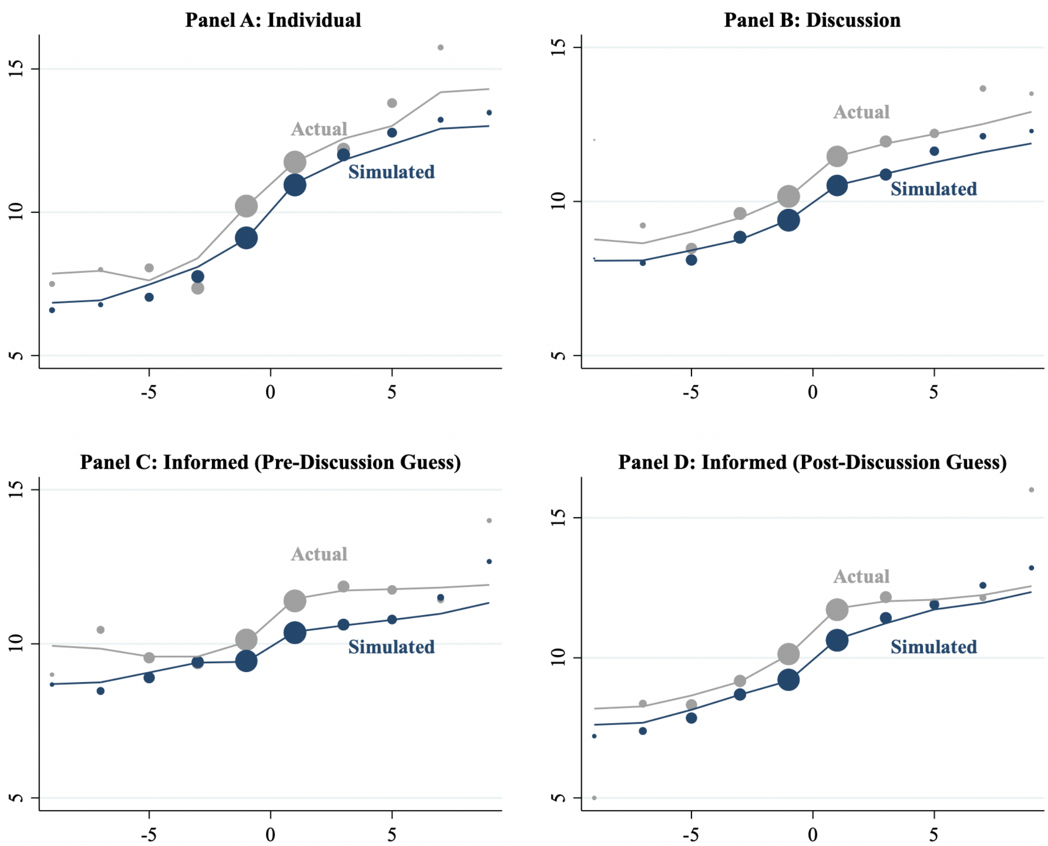
	Individual	Discussion	Informed (Pre)	Informed (Post)
	(1)	(2)	(3)	(4)
Panel A: Actual Guesses				
β_1: Own First Signal	0.43	0.56	0.56	0.36
	(0.06)	(0.06)	(0.09)	(0.09)
β_2^o: Own Second Signal	0.52			
	(0.07)			
β_2^p: Partner's Signal		0.24	0.07	0.28
		(0.07)	(0.09)	(0.09)
Constant	10.71	10.73	10.64	10.66
	(0.16)	(0.16)	(0.23)	(0.23)
$\boldsymbol{\beta_2^p - \beta_2^o}$		**-0.28*****	**-0.45*****	**-0.24****
		(0.08)	**(0.11)**	**(0.10)**
Panel B: Model-Implied Expected Guesses				
β_1: Own First Signal	0.41	0.48	0.54	0.38
	(0.01)	(0.01)	(0.02)	(0.01)
β_2^o: Own Second Signal	0.58			
	(0.02)			
β_2^p: Partner's Signal		0.24	0.04	0.27
		(0.01)	(0.01)	(0.01)
Constant	9.98	9.98	9.98	9.98
	(0.03)	(0.02)	(0.03)	(0.03)
$\boldsymbol{\beta_2^p - \beta_2^o}$		**-0.34*****	**-0.54*****	**-0.31*****
		(0.02)	**(0.02)**	**(0.02)**
	500	1000	500	500

This table shows reduced-form weights on information in the Individual, Discussion and Informed of Partner's Draws rounds in Experiment 1. "Informed of Partner's Draws (Pre-Discussion)" means the dependent variable is the second private guess from the Informed of Partner's Draws round, after the participant was directly told their spouse's information but before discussing it with their spouse. "Informed of Partner's Draws (Post-Discussion)" means the dependent variable is the third private guess, after the discussion.

Actual Guesses: Panel A shows reduced-form results, estimating equation 1 by OLS. The dependent variable is participants' actual private guess. "Own First Signal" is the net number of red draws (i.e., red draws minus white draws) in the participant's first set of signals, which they drew themselves in all rounds. "Own Second Signal" is the net number of red draws in the participant's second set of signals in the individual round. "Partner's Signal" is the net number of red draws in the set of signals drawn by the participant's teammate, which was the second set of signals available to the participant in the Discussion and Informed of Partner's Draws rounds. All regressions include order fixed effects interacted with the participant's first and second info.

Model-Implied Expected Guesses: show the same regressions as Panel A, but use the expected guesses (conditional on actual signals) implied by the structural estimates presented in Panel B of Table 2.

Figure A.XI: Simulated Guesses in Individual, Discussion, and Informed of Partner's Draws Rounds



Notes: This figure compares average actual guesses in Experiment 1 to the average *simulated* guess of participants using the structural model in Section 3.3. The x-axis shows the net number of red draws (i.e. red draws minus white draws) in the second signal of the round. The gray dots indicate average actual guesses, while blue dots indicate average simulated guesses. Panel A includes final private guesses in the *Individual* Round, where participants made the second set of draws themselves. Panel B includes final private guesses in the *Discussion* Round, where the second set of draws had to be communicated to the participant via discussion. Panel C includes the second private guesses in the *Informed of Partner's Draws* round, after the respondent is told of his/her partner's draws by the experimenter but before the joint discussion. Panel D includes final private guesses in the *Informed of Partner's Draws* round, after the joint discussion.