Why Are Rational Expectations Violated in Social Interactions?

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Abstract

Individuals often interact with each other through observation — they observe the choices of other people who possess private information. In such social interactions, it is typically assumed that decision makers have rational expectations, therefore they can infer what other decision makers know via observation of their choices. In this study, I assess the validity of the rational expectations assumption in a social interaction experiment. I use a simple and transparent experimental setting to show that decision makers often fail to exhibit rational expectations in social interactions and this behavior is independent of commonly documented errors in statistical reasoning: subjects exhibit a higher level of irrationality in the presence than in the absence of social interaction, even when they receive informationally equivalent signals across the two conditions. A series of treatments aimed at identifying mechanisms suggests that the behavior of other people are often "ambiguous" to a decision maker who observes their choices. So, the decision maker behaves as if she has limited ability to infer the relationship between what other people choose and what they know.

Keywords— Rational expectations, Ambiguity, Social interaction, Decision-making error

JEL Codes: C91, C92, D01, D81, D83

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1 Introduction

Understanding the interactions of individuals who know that other individuals possess private information is a central concern in the economics of information (Manski, 2000). Observation of chosen actions may reveal private information; for instance, product choices may reveal consumers' private knowledge about their quality and acceptance of job offers may reveal workers' skills (Akerlof, 1970). In general, a decision maker's action may impact the actions of other decision makers through three channels: constraints, preferences, and expectations (Schelling, 1971; Manski, 2000). Econometric analysis of choice data often reduces the empirical inference to revelation of preferences by assuming that individuals have specific expectations that are objectively correct, i.e., rational expectations (Manski, 2004). However, decision makers often do not directly observe the expectations of other decision makers, so they may not have perfect forecast about other decision makers' behavior.

Studies that impose the assumption of rational expectations often do not explain why decision makers may have such optimal forecasts. Conditions that may or may not lead to the failure of this assumption has been the focus of a limited literature in economics (Cyert & DeGroot, 1974; Smith, 1991; Kalai & Lehrer, 1993). Yet there is no consensus on why individuals may fail to exhibit rational expectations in social interactions. This is specially important in that it can lead to a socially inefficient outcome in situations where information is transmitted by observation (Eyster, 2019).

In this paper, I employ a set of relatively simple and transparent laboratory experiments to uncover why the rational expectations assumption might be violated in social interactions (SI). In the experiment, subjects need to guess about an *ex ante* unknown state of the world and are paid for accuracy. The state is binary and its possible realizations are represented by two boxes that contain ten balls of black and white color. The combination of black and white balls can be different across the two boxes and the content of each box is known to subjects. The true state is randomly realized in the beginning of the experiment, i.e., one box is selected by flipping a fair coin. Subjects do not observe the true state, but they receive a signal about it. They then guess which box is the true state. The key manipulation of the experimental design is the source of the signals: across conditions, subjects receive informationally-equivalent signals that vary only in whether or not the signal arises from a social interaction. In the *Individual* condition (control), a subject observes a ball randomly drawn from the true state. In the *Social* condition (treatment), the subject does not directly observe a ball, but she observes the choice of another participant, called *neighbor* in the experiment, who has observed a ball randomly drawn from the true state. Subjects know the precise signal-generating process and that all participants are incentivized to make a correct choice. So, the provided signal is informationally equivalent across the two conditions: under rational expectations, the choices of the subjects should be identical in the two conditions.

In order to identify individual errors that are associated with the failure of rational expectations, I use a within-subject design. I compare subjects' choices across the individual and the social conditions and present clean evidence that, despite extensive instructions, subjects exhibit on average a higher level of irrationality in the social condition (in the presence of SI) than in the individual condition (in the absence of SI) when they receive informationally equivalent signals across the two conditions. That is, they neglect the provided information relatively more in the social condition than in the individual condition.[1]

This finding extends the results of a long literature in psychology and economics, that examines why individuals may deviate from the neoclassical theory of probabilistic decision-making in isolated environments (Phillips & Edwards, 1966; Kahneman & Tversky, 1972; Ambuehl & Li, 2018), to a social setting. The within subject design plays a critical role here, because it allows the identification of the errors that are associated with SI (i.e. the rational expectations assumption) while controlling for any other error that is independent of SI, e.g., errors in statistical reasoning (Benjamin, 2019).[2] In my setting, SI has a particularly simple form so that there is little concern regarding the complexity of the decision problem, which has previously been shown to affect individuals' mistakes (Charness & Levin, 2009; Enke & Zimmermann, 2019).

A plausible explanation for the unexpected tendency to neglect information in the SI is the

[1] Throughout, I use "irrationality" and "neglect" interchangeably.

[2] A notable difference between my work and the belief updating literature is that I examine individuals' sub-optimal "choice" under uncertainty, while this literature examines how individuals form their posterior "belief". The papers in this literature either do not collect data on actual choices or ignore the fact that having a Bayesian (non-Bayesian) belief is not necessarily equivalent to making a correct (incorrect) choice. As a result, the notion of "bias" in the belief updating literature is completely different than the notion of "error" in my study. A *biased belief* is defined as a belief that is not Bayesian. However, an *error in choice* is defined as an action that fails to optimize the individual's payoff based on the available information. It can be shown that neither does a biased belief necessarily lead to an error in the choice, nor is an error in the choice necessarily a result of a bias in the belief.

subject's inability in inferring the relationship between what other participants choose and what they know. That is, subjects might not be able to predict how their neighbors make decision based on their private information. This *ambiguity* may lead subjects to mistrust their neighbors' choices or assign a higher error rate to the neighbors' choices than what neighbors actually exhibit (Weizsäcker, 2003; Kubler & Weizsacker, 2004). If ambiguity is the reason behind the extra neglect in the SI, then providing additional information about neighbors' behavior may help subjects to better extract the information contained in their neighbors' choices.

To test the role of ambiguity about neighbor's behavior in the subject's irrationality, I develop three sets of treatment variations. In each treatment, I exogenously manipulate subjects' knowledge about their neighbors by providing additional information about the neighbors. First, I present to the subjects the demographic information of their neighbors. Specifically, subjects in this treatment observe their neighbors' age, gender, years of education, and whether the neighbors have taken Probability/Statistics courses. If demographics provide information about the behavior of neighbors, one expects to see a lower level of neglect in the SI for this treatment than the base experiment. The results indicate that providing demographic information about the neighbor has a small and insignificant effect on the subjects' irrationality in the SI.[3]

Second, I design a treatment in which the neighbor is replaced by a "computer bot", whose behavior is clearly described to the subjects. The idea here is to create a social environment where there is less ambiguity in the neighbor's behavior than the baseline experiment. In this treatment, subjects are told that their neighbor is a computer bot that chooses the box with more black balls when it observes a black ball, and chooses a box with more white balls when it observes a white ball. The results of this low ambiguity treatment show that the neglect in the social condition significantly drops compared to the baseline experiment. This finding highlights that the ambiguity of neighbor's behavior can play an important role in individual decision-making when social interaction happens through observation. In fact, the violation of rational expectations might be a result of the ambiguity in other decision makers' behavior.

Third, I devise a treatment where the subject observes both her neighbor's choice and the ball

[3] I also examine the role of subjects' observable characteristics in driving the unexpected irrationality observed in the SI. I find that typical demographics such as: age, gender, education, and taking Probability/Statistics courses cannot explain the additional neglect in the social condition.

that her neighbor has seen. If the additional neglect in the SI was largely about the ambiguity in the neighbor's behavior, then the observed difference between the irrationality across the social and the individual condition should disappear in this treatment. The results support this prediction: when subjects are provided with both their neighbors' choices and the signals behind those choices, there is no statistically significant difference between the level of irrationality (neglect) across the social and the individual condition. This suggests that the failure of rational expectations in the social condition is mainly driven by the ambiguity of other people's behavior, i.e., subjects behave as if they lack knowledge about how others make choice based on their private information. As a consequence, even though subjects know that others' choices are based on useful information, they may choose to neglect them.

Economists are increasingly interested in the mechanisms behind reduced-form errors in decision-making due to the view that this may help develop new behavioral models that can explain real world behavior (Enke, 2020). In the final part of the paper, I develop a model of decision-making to explain the sources of individual error in social interactions. This model uncovers the mechanisms that may lead a subject to make an irrational choice in the context of my experiment, and identifies the channel associated with the violation of the rational expectations.

In the current study, the individual's decision-making process can be modelled as a two stage procedure: upon obtaining a signal, a subject needs to 1) update her belief, and 2) make a binary choice based on her belief. Here, an irrational choice can be a result of one of the following two errors. First, it might be the case that the subject updates her belief in a wrong direction, i.e., the updated belief contradicts the observed signal. In the context of my experiment, this happens when the signal supports a specific state, but the subject mistakenly believes that the other state is more likely, and thus she makes a choice that, from the experimenter's point of view, is irrational. I call this mistake a *posterior error*.[4]

Second, the subject may update her belief in a correct direction, but she may fail to pick the right choice based on her belief.[5] In my experiment, this happens when both the signal and the

[4]The posterior error is a choice that is consistent with the subject's belief, but from the experimenter's point of view is irrational because it fails to optimize the subject's payoff.

[5]The idea that subjects may choose all option with positive probability has been documented in prior literature (McKelvey & Palfrey, 1995).

subject's posterior belief favor the same state, but the subject makes a choice that contradicts her belief. I call this mistake a *reasoning error*.

To distinguish between a posterior error and a reasoning error, I add a survey question to each choice that subjects make during the experiment. The purpose of this survey question is to measure the "relative" direction of the subject's posterior belief.[6] Specifically, it asks about the probability that the subject believes her choice is correct. This survey question along with the subject's actual choice allow me to identify both the posterior error and the reasoning error in subjects' behavior. I find that both of these errors contribute to subjects' mistakes in the experiment, with posterior error being the dominant one.[7] I then compare the magnitude of these errors across the individual condition and the social condition. The result shows that the additional neglect in the social condition is mainly driven by posterior error. That is, while the magnitude of the reasoning error remains unchanged across the individual and the social conditions, the posterior errors are significantly higher in the social condition. This evidence is consistent with the earlier finding that there is ambiguity in other people's behavior and provides an explanation for why an individual may fail to exhibit rational expectations in SI.

My study is also related to the experimental literature on social learning (Anderson & Holt, 1997; Kubler & Weizsacker, 2004; Weizsacker, 2010)[8]. Yet there are several differences between the current experimental setting and the conventional setting in this literature (Anderson & Holt, 1997). First, in my study, unlike the social learning experiments, the private signal and the choice of predecessor is studied separately. Subjects encounter only one of these two sources of information at a time. In the individual condition, subjects encounter a private signal, and in the social condition, they encounter the choice of a predecessor. The comparison of choices across these two conditions helps to causally identify the irrationality that is associated with the SI.[9]

Second, the social learning experiment is a dynamic setting in nature: the number of predecessors increases for subjects who arrive later in the experiment. This implies that the complexity of

[6] See Manski (2004) for a detailed discussion of how survey data on probabilistic expectations can enable experimental economists to overcome identification problems.

[7] The joint identification of reasoning error and posterior error has not been explored in the prior literature.

[8] See Eyster (2019) for a recent literature review.

[9] In my experiment, subjects are instructed so that they view the social condition and the individual condition as two separate parts. However, in social learning experiments, there is no such distinction.

information increases for later participants. This is important because the complexity of the decision problem can be an important factor in driving individual errors (Charness & Levin, 2009; Enke & Zimmermann, 2019). However, both of the conditions in my experiment are very simple and static, in the sense that the complexity of problem does not change across subjects within a condition. In the individual condition, all subjects obtain only one private signal. Similarly, in the social condition, all subjects only observe the choice of one predecessor.[10]

Third, the studies in the social learning literature usually impose strong assumptions to be able to estimate a behavioral model that can explain the observed choices in the data. For example, they often abstract away from the biases in belief updating (that are usually prevalent in the absence of SI) and presume that individuals update their beliefs according to Bayes rule. They then assume that the subject's choice probabilities follow a logit function.[11] These assumptions allow the researcher to estimate all the observed errors by one parameter, which is typically called *response precision*. In my setting, none of these assumptions are needed because my main analysis is based on the comparison of choices in the absence and in the presence of SI. I do not need to take a stand on how individuals update their beliefs because the within-subject design allows me to control for any individual error that is not related to the social environment (Benjamin, 2019), and isolate the errors associated with SI under a set of weak assumptions.[12]

The remainder of the paper proceeds as follows. Section 2 describes the experimental design. Section 3 presents the main results of the paper. In Section 4, I develop a model to explain the sources of irrational choices in individual behavior and identify the channel that is influenced by SI. Finally, Section 5 concludes the paper.

[10] This also distinguishes my research from the studies that examine consensus of beliefs in social networks (Golub & Jackson, 2010; Grimm & Mengel, 2013; Chandrasekhar et al., 2014; Brandts et al., 2015)

[11] This can be justified by assuming that there is a random shock in the individual's utility function that follows a type-I extreme value distribution (McKelvey & Palfrey, 1995; Anderson & Holt, 1997).

[12] In fact, my analysis in the appendix indicates that imposing the assumption of Bayesian updating can bias the estimated response precision parameter. This highlights the importance of collecting expectations data to relax unnecessary assumptions about probabilistic expectations (Manski, 2004).

2 Experimental Design

Subjects are randomly assigned to one of four treatments (Figure 1). The experiment in each treatment consists of two consecutive parts and the order of these two parts is randomized. In one part, the subject performs a task in isolation — without social interaction (*individual condition*). In the other part, she performs the same task with social interaction (*social condition*). As noted earlier, the order of these two parts is randomized, i.e., given a treatment, some subjects first see the individual condition and then proceed to the social condition, and others see them in reverse order (see Figure 1).

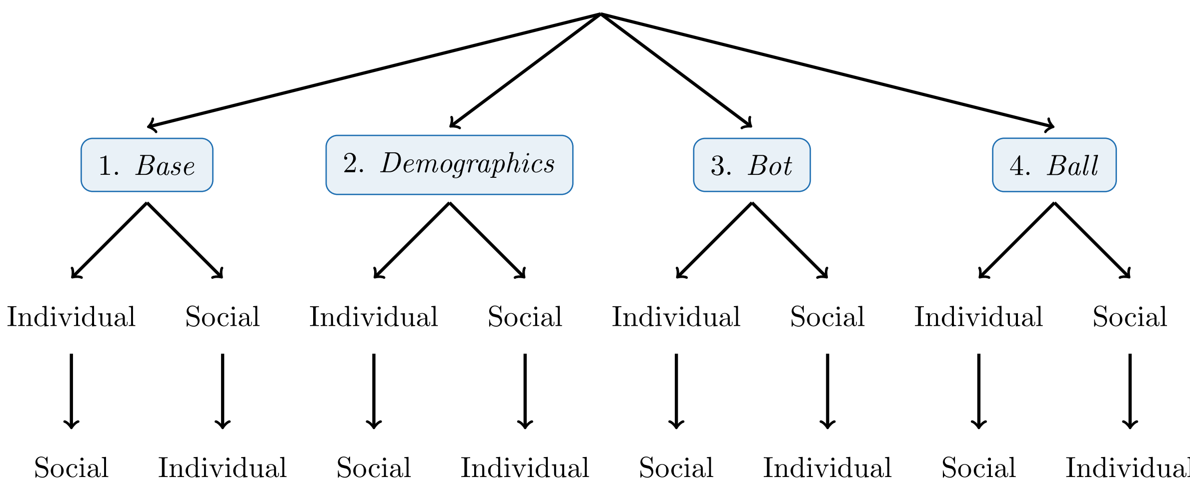


Figure 1: The experimental design

The individual condition is the same in all four treatments, but the social condition differs across treatments. The idea is to exogenously manipulate the subject's knowledge about the participants with whom she is interacting across treatments. I will elaborate on the differences between treatments as I proceed in the following.

2.1 Individual Condition

The *individual condition* is a benchmark which measures the subjects' behavior in the absence of social interaction. It consists of 21 rounds. In each round, two boxes are shown to the subject. Each box contains 10 balls of white or black color (see Figure 2 for an example). These boxes represent the possible states of the world, $\omega \in \{X, Y\}$. In the beginning of each round, a fair coin is anonymously flipped. If the coin is **Head**, the state is **X** and one ball is randomly drawn from box X. If the coin is **Tail**, the state is **Y** and one ball is randomly drawn from box Y.[13] The subject does not observe the coin. She observes the ball, and then is asked to guess what the state is. The combination of white and black balls randomly changes over 21 rounds. Denote the fraction of white balls in box X by θ_X and the fraction of black balls in box Y by θ_Y. The combinations used in the experiment include a wide range of symmetric and asymmetric information structures: $\left\{(\theta_X, \theta_Y) \;\middle|\; \theta_X, \theta_Y \in \{0.5, 0.6, 0.7, 0.8, 0.9, 1\} \text{ , } \theta_X \geq \theta_Y\right\}$.

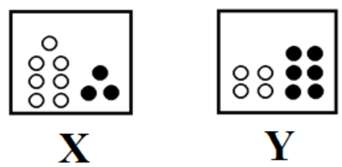


Figure 2: These two boxes represent possible states of the world (Here, for instance $\theta_X = 0.7$ and $\theta_Y = 0.6$)

Subjects are incentivized to make a correct guess:[14] it is best for a subject to pick a box with more black (white) balls when she observes a black (white) ball. In addition to collecting the subjects' choices, I add a survey question at the end of each round that asks for the subject's posterior belief. Specifically, the subject answers the following question after she reports her choice in each round: *with what probability do you think your guess is correct?*.[15] Unlike the choice, the survey question is not incentivized in the experiment for a few reasons. First, I found that the experiment lasts too long when subjects are required to go through an incentive compatible elicitation procedure for each of the posterior beliefs that they submit during the experiment. So, it may cause fatigue and contaminate the choice data that is vital for the main analysis. Second, I did use monetary incentives for posteriors in a pilot study using a revised version of Quadratic Scoring Rule (Brier,

[13]This induces a prior probability of $\frac{1}{2}$ for each box. The language used in the actual experiment was slightly different: I used *box H* (head) and *box T* (tail) instead of box X and box Y to remind individuals about the randomization (see the appendix for experiment instructions).

[14]The idea is to randomly choose some rounds and pay the subject for each correct guess in those rounds. I explain the payment scheme in more details later.

[15]As I explain later, I am interested in knowing which state is more likely from the subject's perspective when she makes a choice. Effectively, I only need to know whether the subject chooses a state that she believes has a higher (>50%) or lower (<50%) chance of being correct.

1950).[16] The pilot results suggested that the incentivized posteriors are not significantly different than the posteriors that are not incentivized. The prior literature has also shown that responses to this type of survey questions, in the absence of incentives for honest revelation of expectations, do possess face validity when the questions concern well-defined events; see Manski (2004) for a detailed discussion. Forth, the main analysis in this study does not require posterior belief. So, the main findings do not rely on whether or not the survey question is incentivized. I kept the survey question very standard and easy to understand so that it is unlikely that the subject does not understand the survey question or incurs a cognitive cost to think about the answer (Smith, 1991). So, one can expect the reported posterior probabilities to be close to the subjective probabilities in the subject's mind.[17]

2.2 Social Condition

The *social condition* is designed to study the subjects' behavior in the presence of social interaction. The structure of the task is similar to that of the individual condition. The social condition consists of 21 rounds. In each round, the subject is randomly connected to another participant, called *neighbor* in the experiment, and receives information from one of the rounds in the neighbor's individual condition. The subject observes the content of two boxes that has been shown to the neighbor. Her task is to guess what the state (selected box) is, based on the information that she obtains from the neighbor. As noted earlier, there are four treatments in the experiment and the transmitted information in the social condition is different across treatments. I explain the treatments in the following.

The first treatment is called *base*. In this treatment, the information coming through social inter-

[16] For the subjects who are incentivized for both the choice and the posterior, I randomly select one posterior and one choice for payment (the selection is independent).

[17] I also did a robustness check at the end of my main experiment and incentivized all subjects according to Quadratic Scoring Rule. The elicited posteriors were very similar to those that were collected from the survey questions during the experiment. But I do not use these incentivized posteriors in my analysis because the incentive compatible elicitation of posteriors were always happening at the end of the experiment, after both the individual condition and the social condition had been finished. The fact that the incentivized posteriors were always collected after the end of the experiment might make the results inconclusive (the subjects were answering the same survey questions as they had observed during the experiment. The concern is that subjects might not think about the questions anymore because they had already seen the same questions before. Hence, elicitation mechanism might not have an impact on subjects' posteriors.)

action is the neighbor's guess.[18] Note that a neighbor here is a random subject who has previously participated in the experiment. The subject knows that the neighbor's guess is incentivized and is based on a randomly drawn ball from the realized state (box). To summarize, in each round, the subject observes two boxes and the guess of a neighbor, but not the ball that the neighbor has observed. Then, the subject is asked to guess about the realized state. The experiment is designed such that the neighbor randomly changes in each round. Hence, the subject does not interact with the same neighbor over time and it is unlikely that the subject learns about a specific neighbor's behavior over the course of 21 rounds in the social condition.

The second treatment is called *demographics*. There is a slight difference between the social condition in this treatment and in the base treatment: on top of the neighbor's guess, the subject observes the neighbor's demographic information such as age, gender, years of education, and whether the neighbor has taken any probability/statistics courses. This treatment is designed to examine whether providing demographic information about the neighbor can alleviate the irrationality associated with the ambiguity of neighbor's behavior in the social interaction. If demographics provide additional information about the behavior of neighbor, the ambiguity might be lower in this treatment than the base treatment.

The third treatment is called *bot*. Everything in this treatment is the same as in the base treatment, except that the neighbor is a computer bot which is programmed to exhibit a specific behavior (i.e. rational). This means when the bot observes a white ball, it chooses the box with more white balls, and when it observes a black ball, it chooses the box with more black balls. The behavior of the bot is explained in details to the subjects in this treatment. Subjects see the guess of the bot in this treatment and then submit their own guesses about the realized state. The social interaction in this treatment is relatively more transparent than the earlier two treatments. So, one expects the irrationality associated with the ambiguity of neighbor's behavior to be significantly lower in this treatment than the base treatment.

The fourth treatment, which is called *ball*, is an augmented version of the base treatment in which the subject observes both the (human) neighbor's guess and the ball which has been shown to the

[18] By "guess" I mean the actual choice of the neighbor. The subject does not observe the neighbor's posterior belief (the answer to the survey question).

neighbor. The ambiguity effect is expected to completely disappear in this treatment because the subject is provided with all the relevant information regarding her neighbor's choice.

2.3 Payment Scheme

Each subject receives $6 show-up fee for participation. In addition to that, two rounds of the experiment are randomly selected and the subject wins $12 for each correct guess in those two rounds.

3 Results

In this section, I first define the criteria for recognizing individual errors in the context of my experiment. I then analyse subjects' choices in the experiment to measure the frequency of these errors and examine the relation between them in the individual condition and in the social condition. The comparison between errors in the individual and in the social condition identifies the errors that are associated with the social interaction (e.g. the violation of rational expectations).

In the individual condition, a Bayesian rational subject should choose a box with more black balls when she observes a black ball, and a box with more white balls when she observes a white ball. Accordingly, I define an *individual irrationality* as an observation which deviates from this prediction.

Definition 1. *Individual Irrationality: A choice in the individual condition where the subject observes a white (black) ball, but chooses a box with more black (white) balls.*

In the social interaction, the conventional assumption in economics is that individuals have rational expectations about each other (and rationality is common knowledge). In the context of the current experiment, this implies that the subject should follow her neighbor's guess and choose the same box as the neighbor in the social condition. Accordingly, a *social irrationality* is defined as follows.

Definition 2. *Social Irrationality: A choice in the social condition where the subject chooses a box different from her neighbor's guess.*[19]

[19]The definition of social irrationality in the *Ball* treatment is a little bit different because the subject observes

In the next section, I analyse the experimental data to measure the magnitude of individual irrationality and social irrationality in subjects' choices and to elaborate on the differences.

3.1 Data

The main experiment was conducted at Toronto Experimental Economics Laboratory (TEEL) in University of Toronto during December 2019. The experiment was programmed in oTree (Chen et al., 2016). In total, 151 subjects were recruited from the subject pool using Online Recruitment System for Economic Experiments (Greiner, 2015). The average payment across subjects was \$25.26.[20] Table 1 provides evidence that individual characteristics are relatively balanced across the four treatments, confirming that the randomization was successful.

Table 1: Summary Statistics

	Treatment			
	Base	Demographics	Bot	Ball
Female (%)	77.5	73.5	78.9	61.5
Prob/Stat course (%)	75	64.7	68.4	69.2
Years of Education	15.0	14.85	14.73	14.48
	(1.5)	(2.11)	(2.24)	(1.82)
Age	20.25	19.38	20.02	20.28
	(1.81)	(1.39)	(2.04)	(1.88)
Number of Subjects	40	34	38	39

Note: Standard errors are presented in parentheses. The second row shows the percentage of subjects who have taken Probability/Statistics courses.

In the following, I exclude the cases in which both boxes have 5 black balls and 5 white balls,

both the ball and the neighbor's guess when she is connected to the neighbor. In that case, I define social irrationality as a choice in which the subject chooses a box different from her neighbor's guess, given that the neighbor's guess is rational (i.e., does not contradict with the signal).

[20] No subject participated in more than a single treatment. Subjects needed to be at least 18 years old to be eligible to participate in the experiment. The human neighbors in the social condition were 94 subjects who had participated in the experiment a few months before the main experiment.

$\theta_X = \theta_Y = 0.5$, because theory does not have a prediction about the subject's behavior in those cases. Subjects are expected to behave randomly in those rounds, a result that is supported by the data.[21]

3.2 How Do Errors Differ across the Individual and the Social Conditions?

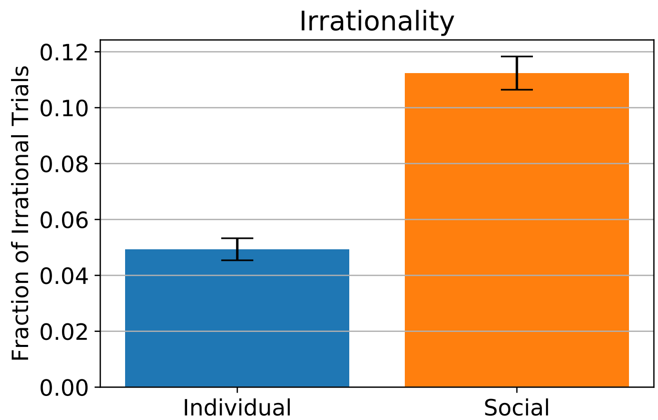


Figure 3: Individual irrationality and social irrationality (pooled data)

My first result examines the aggregate fraction of irrational choices in the individual condition and in the social condition. Figure 3 illustrates that the individual irrationality and the social irrationality are significantly greater than zero, even though subjects are incentivized for being correct. In the individual condition, subjects on average deviate from the theoretical prediction (Bayesian rational behavior) with a probability of 0.049 (p-$value < 0.001$).[22] In the social condition, even though subjects know that their neighbor's guess is incentivized with money, they on average do not follow the choice of their neighbor with a probability of 0.112 (p-$value < 0.001$). Surprisingly, the social irrationality is significantly higher than the individual irrationality (p-$value < 0.001$). This evidence suggests that subjects neglect the information more in the social condition than in the

[21] In the individual condition, when the two boxes have the same combination of balls (5 white and 5 black balls), subjects choose the left box with probability 0.44. Here, the null $H_0 : p = 0.5$ cannot be rejected at the 5% significance level (p-$value = 0.14$). Similarly, in the social condition, when both boxes have 5 white and 5 black balls, subjects do not follow their neighbor's guess with probability 0.48 (p-$value = 0.74$ for the null $H_0 : p = 0.5$).

[22] This is lower than the error rate reported in prior literature for the individuals who arrive first in a standard social learning experiment (Anderson & Holt, 1997; Kubler & Weizsacker, 2004). In Anderson and Holt (1997) 10% of the subjects whose information set was a private signal, did not follow their signal. In Kubler and Weizsacker (2004), this behavior was observed in about 7% of all cases where first players saw only a private signal.

individual condition, a result that can be associated with the violation of rational expectations.[23]

Figure 4 presents the distribution of individual irrationality and social irrationality across subjects. The blue histogram shows that about 63% of subjects have no individual irrationality over the course of 21 rounds in the individual condition. In addition, 19.8% of subjects have exactly one individual irrationality, and the remaining 17.2% have more than one individual irrationality. So, the individual irrationality is not negligible for a considerable fraction of subjects.[24] On the other hand, the orange histogram indicates that 54.3% of subjects have no social irrationality, 10.6% have exactly one social irrationality, and the remaining 35.1% have more than one. Comparing the two distributions, one can observe that the upper tail of the distribution is thicker in the social condition than in the individual condition. So, there is a clear shift in the error rate of subjects across the two conditions.

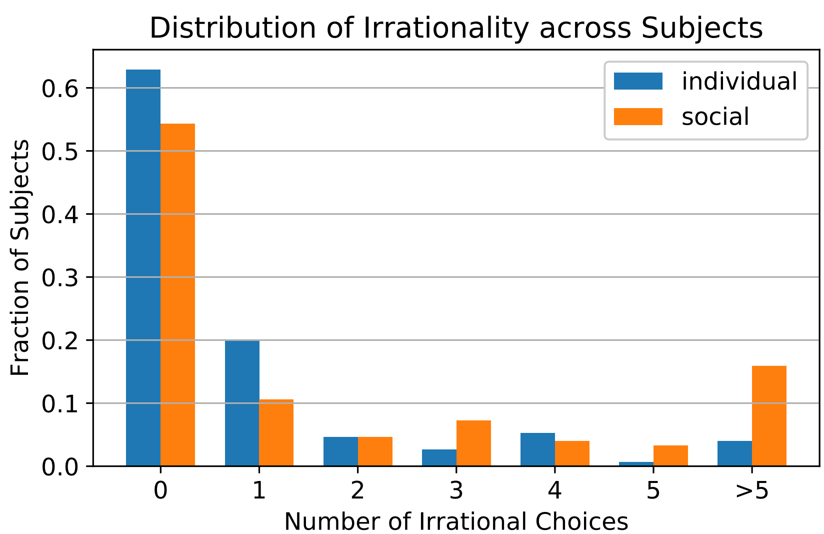


Figure 4: The distribution of individual irrationality and social irrationality across subjects

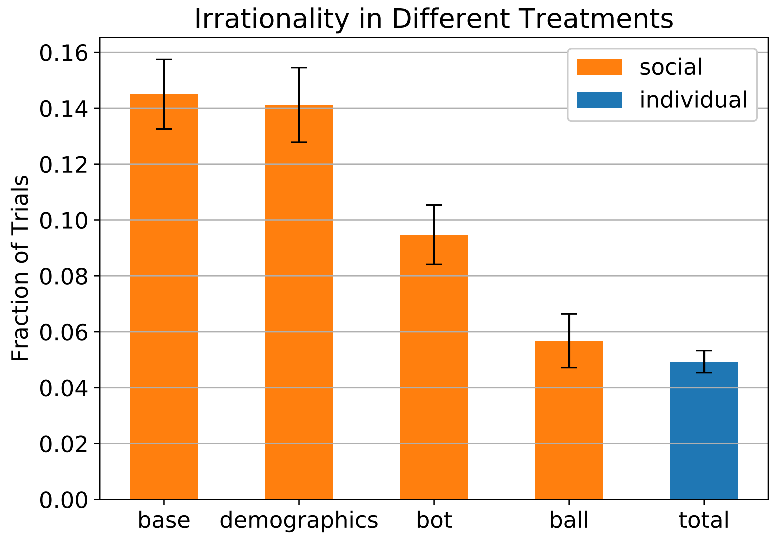


Figure 5: Social irrationality in different treatments

3.3 The Role of Ambiguity

In this section, I examine the mechanisms behind the additional neglect in the social condition. The hypothesis is that the additional irrationality in the social condition is most likely due to the violation of rational expectations, which arises from the ambiguity of the neighbor's behavior. In other words, because the neighbor's decision-making process is ambiguous to the subjects, they cannot correctly extract the neighbor's private information from observation of their choices, and thus violate the rational expectations. To test this idea, as noted earlier, I exogenously manipulate the subject's knowledge about the neighbor across four treatments. Figure 5 illustrates the social irrationality in each treatment along with the aggregate individual irrationality.[25] The treatment "*base*" is a benchmark treatment in which subjects only observe the guess of their neighbor. The result in this treatment echos the earlier finding about the larger magnitude of neglect (irrationality) in the social condition than in the individual condition.

[23]Note that the comparisons in this section are within-subject, i.e., the same subjects are making on average more errors in the social condition than in the individual condition. Given my experimental design, it is also possible to do the analysis between-subject. The details of the between-subject analysis are provided in the appendix. The results are qualitatively similar there.

[24]This result is consistent with Ambuehl and Li (2018) who report that 17% of their subjects made at least one irrational choice out of six trials.

[25]Recall that the individual condition is identical in all treatments. So, I do not break down the individual irrationality here and only report the aggregate individual irrationality for ease of exposition.

In the treatment "*demographics*", subjects are provided with some demographic information about their neighbor (Age, Gender, Years of Education, Whether the neighbor took probability/statistics courses), on top of the neighbor's guess. The result of this treatment shows that providing demographics slightly decreases the social irrationality compared to the base treatment, from 0.145 to 0.1411. But this effect is not statistically significant ($p\text{-}value = 0.83$).

In the treatment "*bot*", subjects observe the guess of a computer bot. Here, the bot's behavior is known to subjects: it picks a box with more white balls when it observes a white ball, and picks a box with more black balls when it observes a black ball. The social irrationality in this treatment significantly drops to 0.094 compared to the base treatment ($p\text{-}value < 0.01$). This evidence is consistent with the hypothesis that the difference between the social irrationality and the individual irrationality is due to the ambiguity about the neighbor's behavior.[26]

Finally, in the treatment "*ball*", subjects are provided with both the neighbor's guess and the ball which was shown to the neighbor. Figure 5 shows that the social irrationality in this treatment is significantly lower than all other treatments ($p\text{-}value < 0.01$). Here, the difference between the social irrationality and the individual irrationality is no longer statistically significant. This result verifies that when there is no ambiguity about the neighbor's behavior in the social condition, the magnitude of social irrationality is the same as the magnitude of individual irrationality. So, the additional neglect in the social condition disappears from the subject behavior.

3.4 The Observed Heterogeneity in Subjects' Behavior

In this section, I run some regressions to examine the observed heterogeneity in the subjects' behavior. My data contains demographic information about all the subjects and each of their neighbors. So, I can investigate how subjects' characteristics and those of their neighbors explain the observed irrationality in the experiment.

First, I investigate the role of the subject's characteristics. Specifically, I estimate the following

[26] Note that although the social irrationality is alleviated in the bot treatment, it is still significantly higher than the individual irrationality. One natural question rises here: why is there a difference between the individual irrationality and the social irrationality in the bot treatment? Responses from an open survey question that was collected at the end of the experiment show that some of the subjects mistrust bots. This might explain why the social irrationality in the bot treatment remains significantly higher than the individual irrationality.

regression,

$$Y_i \times 100 = \alpha + X_i\gamma + \epsilon \tag{1}$$

where Y_i is the fraction of irrational choices by subject i, X_i includes the subject's observed characteristics: gender (dummy for female), years of education, age, and whether the subject has taken Probability/Statistics courses. The estimation results are provided in Table 2.

Table 2: The observed heterogeneity in the subject's irrationality

	Data	
	Individual	Social
	(1)	(2)
DV	$Y_{ic} \times 100$	$Y_{ic} \times 100$
Gender (Female)	0.47	5.58*
	(1.84)	(2.88)
Education	1.00**	0.11
	(0.49)	(0.78)
Age	− 0.51	− 1.36
	(0.54)	(0.85)
Prob/Stat course	− 4.02**	− 6.85**
	(1.89)	(2.95)
Constant	2.81	37.19**
	(9.35)	(14.64)
Observations	151	151
R^2	0.063	0.097
Adjusted R^2	0.037	0.073
Note:	*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$	

Columns (1) in Table 2 indicates that in the individual condition, all else equal, subjects who have taken Probability/Statistics courses make 4.02 percentage points less errors than subjects who have not. This result suggests that the individual irrationality is mainly driven by the lack of knowledge in probability and statistics. Column (2) illustrates that in the social condition, all else equal, the subjects who have taken Probability/Statistics courses make 6.85 percentage points less errors than subjects who have not. However, the subject's observable characteristics cannot explain the additional irrationality that is associated with the ambiguity of the neighbor's behavior in the social condition (i.e. violation of rational expectations).

Next, I examine the effect of the neighbor's observable characteristics on the subject's social irrationality. Note that only the subjects who are in the treatment *demographics* observe their neighbor's characteristics. So, I need to restrict the data in this section to the choices made in the social condition of the demographics treatment. Here, the dependent variable is a binary choice. Hence, I estimate the following logistic regression,

$$Pr(D_{ij} \text{ is irrational}) = \frac{\exp\,(\alpha + X_i\gamma + X_j\delta)}{1 + \exp\,(\alpha + X_i\gamma + X_j\delta)} \tag{2}$$

where D_{ij} is the choice of subject i in round j, X_i includes the subject's observable characteristics, and X_j includes the neighbor's observable characteristics in round j (recall that the neighbor randomly changes in each round). As before, observable characteristics include gender, years of education, age, and whether the individual has taken Probability/Statistics course. The estimation results are shown in Table 3.

Columns (1) and (2) in Table 3 present the estimated coefficients for equation (2). The coefficients are insignificant in the first column. However, the second column shows that the neighbor's observable characteristics have a statistically significant effect on the subject's behavior: *ceteris paribus*, the subject is more likely to follow a neighbor whose age is higher, whose gender is female (versus male), and who has taken Probability/Statistics courses.

The coefficients of a logistic regression are not quantitatively interpretable. So, I report the average marginal effects in columns (3) and (4) of Table 3. The results in column (4) imply that, *ceteris paribus*, a subject is likely to follow a neighbor who has taken Probability/Statistics courses 5.8 percentage points more than a neighbor who has not. In addition, all else equal, a subject is 4.7 percentage points less likely to make an irrational guess when interacting with a female versus a male neighbor (4.7 percentage points more likely to follow the neighbor). The effect of

Table 3: The observed heterogeneity in the social condition of treatment "*demographics*" (Equation 2)

	Logit Coefficients		Average Marginal Effects	
	(1)	(2)	(3)	(4)
Subject's Gender (Female)	0.52	0.48	0.062	0.056
	(0.59)	(0.60)	(0.071)	(0.07)
Subject's Education	−0.139	− 0.159	− 0.016	− 0.018
	(0.17)	(0.17)	(0.02)	(0.02)
Subject's Age	− 0.08	− 0.075	− 0.009	− 0.008
	(0.23)	(0.23)	(0.0267)	(0.026)
Subject's Prob/Stat course	− 0.44	− 0.46	− 0.052	− 0.052
	(0.63)	(0.64)	(0.076)	(0.076)
Neighbor's Gender (Female)		− 0.41**		− 0.047*
		(0.20)		(0.025)
Neighbor's Education		− 0.04		− 0.005
		(0.032)		(0.003)
Neighbor's Age		− 0.025**		− 0.003***
		(0.01)		(0.001)
Neighbor's Prob/Stat course		− 0.51***		− 0.058**
		(0.196)		(0.025)
Constant	2.18	4.19		
	(3.2)	(3.51)		
Observations	680	680	680	680
Pseudo R^2	0.035	0.061	0.035	0.061

Note: Standard errors are clustered at the subject level.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

the neighbor's age is very small though, i.e., one year increase in the neighbor's age increases the likelihood of being followed by the subject by 0.3 percentage points.

4 A Model of Decision-making

In this section, I introduce a framework to describe the individual decision-making process in the context of my experiment. I then provide two explanations for an observed error in the individual's choice. Finally, I combine the subjects' choice data with their responses to the survey questions, that measure their relative posterior beliefs in each round, to uncover the channel that is associated with the violation of rational expectations.

In the context of my experiment, the individual's decision-making process can be modeled as a two stage procedure. Upon observing a signal, the subject first updates her belief and then picks one of the two possible states based on her posterior. This process is shown in Figure 6.

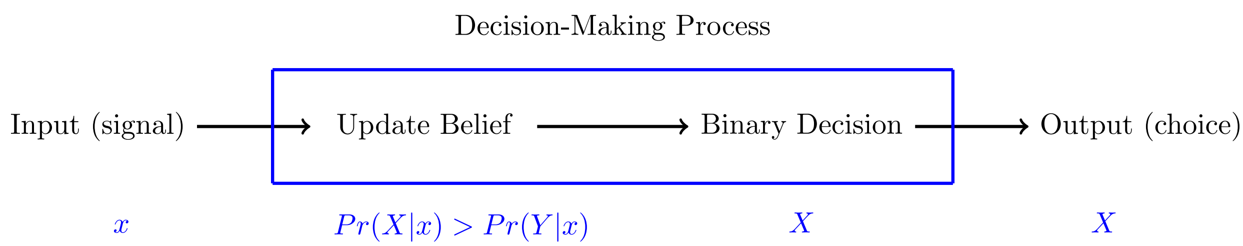


Figure 6: The individual decision-making process

As an example, suppose an individual observes signal x. In theory, the individual should update her belief in favor of state X in the first stage, $Pr(X|x) > Pr(Y|x)$, and then choose state X in the second stage. However, as I showed earlier, the individual's choice (output) does not always comply with the signal (input). Individuals frequently make errors in this simple task. Now, consider a case in which a subject obtains signal x, but her final guess is Y (Figure 7). There are two explanations for this observation:

1. **Posterior Error**: It might be that the subject's posterior is mistakenly in favor of state Y, $Pr(Y|x) > Pr(X|x)$, and this causes the subject to make an erroneous decision. This

means that the subject's posterior is in a wrong direction, but her choice is consistent with her incorrect posterior.[27]

2. **Reasoning Error**: It might be that the subject's posterior is correctly in favor of state X, $Pr(X|x) > Pr(Y|x)$, but she mistakenly chooses state Y.

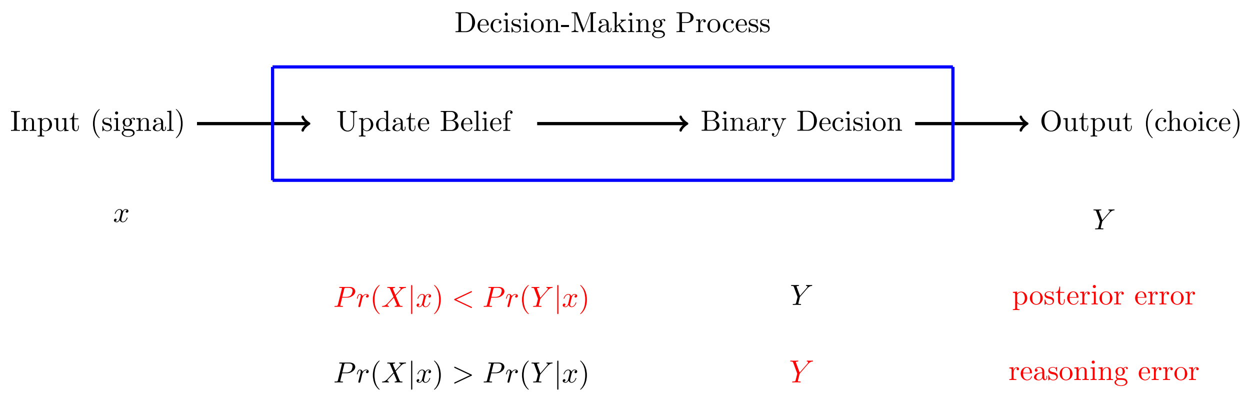


Figure 7: Two explanations for an observed error in the individual's choice

In general, it is not possible to distinguish between these two explanations by only observing the subject's choice. However, as stated before, my data includes both the subjects' choices and their self-reported posteriors. So, I can distinguish between a posterior error and a reasoning error in the data.[28]

Figure 8 illustrates the break down of the observed individual irrationality and social irrationality into posterior error and reasoning error. The figure shows that the probability of a reasoning error is equal to 0.018 in both the individual condition and the social condition. However, there is a statistically significant difference between the magnitude of posterior error across the two conditions; it is 0.031 in the individual condition, but 0.095 in the social condition (p-$value < 0.01$).

[27]It is important to notice that the posterior error is different from what is commonly known as "belief updating bias" in the literature (Kahneman & Tversky, 1972; Benjamin, 2019). A biased belief is not necessarily in a wrong direction, i.e., the biased belief and the Bayesian belief can both favor the same state while assigning different likelihoods to that state. For example, when the signal implies a 70% chance (in theory) to an event, a biased belief may assign a 60% chance to it (both are greater than 50%). However, a posterior error is the consequence of a severe bias that switches the direction of the posterior probability, i.e., an updated belief that is in a wrong direction (e.g. a belief of less than 50% in the earlier example).

[28]The framework that is introduced here applies to both the individual condition and the social condition of my experiment. The only difference is that the signal (input) is a ball in the individual condition, while it is the guess of a neighbor (and any additional information coming along the neighbor's choice) in the social condition.

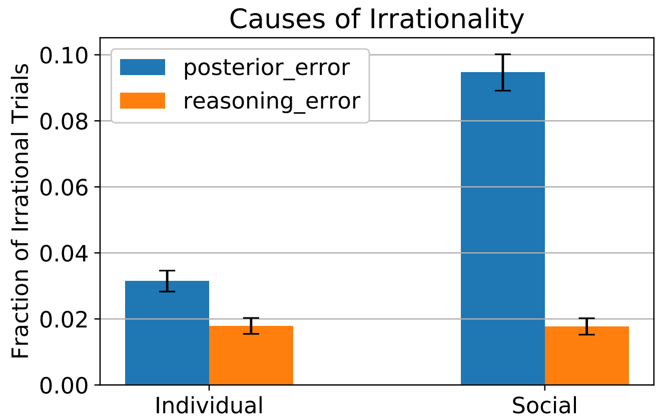


Figure 8: The break down of individual irrationality and social irrationality into posterior error and reasoning error

Figure 8 provides an important insight about the mechanism behind the violation of rational expectations in the social interaction. It suggests that the ambiguity about the neighbor's behavior makes the belief updating more difficult in the social condition than in the individual condition. That is, subjects make more errors when they update their beliefs (e.g. the first stage of the decision-making process) in the social condition than in the individual condition. However, this ambiguity does not influence the second stage of the decision-making process, i.e., once posterior beliefs are formed, subjects follow the same reasoning procedure, and thus the magnitude of the reasoning error remains unchanged across the individual condition and the social condition.

Distinguishing between posterior errors and reasoning errors identifies a critical touchpoints in the decision-making process and may provide solutions to nudge individuals towards making better decisions in social environments. It suggests that the violation of rational expectations may not necessarily result from the lack of math/Stats knowledge, but may be more about how uncertain subjects are about their neighbor's behavior. In addition, failing to control for individual errors that are independent of the social environments (e.g. reasoning errors) may lead to unintended consequences. In appendix C, I estimate a unified model of individual behavior by borrowing techniques from the social learning literature (Grether, 1980; Anderson & Holt, 1997). There, I show that not accounting for different sources of error (posterior error versus reasoning error) can bias the estimated response precision parameter that intends to describe the individual behavior.[29]

[29]The predominant approach in the social learning literature is to derive predictions under the assumption that all

5 Conclusion

Individuals often interact with each other via observation of choices. Such social interactions affect people's beliefs and can help them to make informed decisions. The conventional assumption in the literature is that decision makers have rational expectations about each other. However, individuals often do not observe other decision makers' expectations. So, they may not always have precise predictions about other people' behavior, and this may lead to a socially inefficient equilibrium when information is transmitted by observation.

In this study, I conduct a series of laboratory experiments to examine why individuals may fail to exhibit rational expectations in social interactions. I use a relatively simple and novel experimental setting to disentangle between individual errors that are independent of the social environment, and the errors that lead to the violation of rational expectations. In a within-subject design, I compare subjects' choices across an isolated condition and a social condition, and show that subjects make more errors in the presence than in the absence of social interaction, even when they receive informationally equivalent signals across the two conditions. That is, they neglect the provided information more when they interact with others than when they do not. Here, the additional neglect is associated with the violation of rational expectations.

To uncover the mechanism behind the additional neglect in the social condition, I design a series of treatment variations by exogenously manipulating the subject's knowledge about her neighbor. I find that the unexpected irrationality in the social condition is mainly driven by the ambiguity of other people's behavior: subject's behave as if they lack knowledge of how others make decision based on their private signals. The implication of this result is that social interactions might not be as effective as one expects in theory. So, one should take careful considerations in examining the effects of social interactions in real world.

Finally, I introduce a model of decision-making to explain the sources of error in individual behavior and identify the channel that is associated with the violation of rational expectations. I show that there are two sources of error in decision-making: 1) posterior error: when a subject's

other players obey a given model solution, for instance Perfect Bayesian Equilibrium or Quantal Response Equilibrium. But despite their undisputable usefulness, these solutions are often inaccurate descriptions of behavior and thus yield imperfect benchmarks (Weizsacker, 2010).

posterior belief contradicts the signal that she observes, and 2) reasoning error: when a subject chooses an option that contradicts her own belief. I show that the violation of rational expectations mainly contributes to the posterior errors. In other words, while the reasoning error remains unchanged across the individual and the social condition, the posterior error significantly increases when social interaction is introduced into the experiment. This model provides an explanation for why decision makers may fail to exhibit rational expectations in social interactions.

References

Akerlof, G. (1970). The market for 'lemons': Quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, *84*, 488–500.

Ambuehl, S., & Li, S. (2018). Belief updating and the demand for information. *Games and Economic Behavior*, *109*, 21–39.

Anderson, & Holt, C. A. (1997). Information cascades in the laboratory. *American Economic Review*, *87(5)*, 847–862.

Benjamin, D. J. (2019). Errors in probabilistic reasoning and judgment biases. *Handbook of Behavioral Economics: Applications and Foundations*, *2*, 69-186.

Brandts, J., Giritligil, A. E., & Weber, R. A. (2015). An experimental study of persuasion bias and social influence in networks. *European Economic Review*, *80*, 214–229.

Brier, G. W. (1950). Verification of forecasts expressed in terms of probability. *Monthly Weather Review*, *78*, 1–3.

Chandrasekhar, A., Larreguy, H., & Xandri, J. (2014). Testing models of social learning on networks: Evidence from a framed field experiment. *mimeo*.

Charness, G., & Levin, D. (2009). The origin of the winner's curse: A laboratory study. *American Economic Journal: Microeconomics*, *1 (1)*, 207-236.

Chen, D., Schonger, M., & Wickens, C. (2016). otree - an open-source platform for laboratory, online and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88-97.

Cyert, R., & DeGroot, M. (1974). Rational expectations and bayesian analysis. *Journal of Political Economy*, *82*, 521–536.

Enke, B. (2020). What you see is all there is. *Quarterly Journal of Economics*, *135(3)*, 1363-1398.

Enke, B., & Zimmermann, F. (2019). Correlation neglect in belief formation. *Review of Economic Studies*, *86*, 313–332.

Eyster, E. (2019). Errors in strategic reasoning. *Handbook of Behavioral Economics: Applications and Foundations*, *2*, 187-259.

Golub, B., & Jackson, M. (2010). Naive learning in social networks and the wisdom of crowds. *American Economic Journal: Microeconomics*, *2(1)*, 112-149.

Greiner, B. (2015). Subject pool recruitment procedures: Organizing experiments with orsee. *Journal of the Economic Science Association*, *1*, 114–125.

Grether, D. (1980). Bayes rule as a descriptive model: the representatives heuristic. *The Quarterly Journal of Economics*, *95(3)*, 537-557.

Grimm, V., & Mengel, F. (2013). An experiment on belief formation in networks. *working paper*.

Kahneman, D., & Tversky, A. (1972). Subjective probability: a judgment of representativeness. *Cognitive Psychology*, *3 (3)*, 430-454.

Kalai, E., & Lehrer, E. (1993). Rational learning leads to nash equilibrium. *Econometrica*, *61*, 1019–1045.

Kubler, D., & Weizsacker, G. (2004). Limited depth of reasoning and failure of cascade formation in the laboratory. *Review of Economic Studies*, *71*, 425-441.

Manski, C. F. (2000). Economic analysis of social interactions. *Journal of Economic Perspectives*, *14 (3)*, 115–136.

Manski, C. F. (2004). Measuring expectations. *Econometrica*, *72(5)*, 1329–1376.

McKelvey, R., & Palfrey, T. (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior*, *10*, 6-38.

Phillips, L., & Edwards, W. (1966). Conservatism in a simple probability inference task. *Journal of Experimental Psychology*, *72(3)*, 346-354.

Schelling, T. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *1*, 143–86.

Smith, V. L. (1991). Rational choice: The contrast between economics and psychology. *Journal of Political Economy*, *99(4)*, 877- 897.

Weizsacker, G. (2010). Do we follow others when we should? a simple test of rational expectations. *American Economic Review*, *100 (5)*, 2340-2360.

Weizsäcker, G. (2003). Adolescent econometricians: How do youth infer the returns to schooling? *Games and Economic Behavior*, *44*, 145–171.

Appendix A1: Experiment Instructions

Welcome and thank you for participating in this experiment. Please read this instruction carefully. All participants in this experiment are recruited in the same way as you and read the same instructions as you do. It is important that you do not discuss the details of this experiment with anyone else after the experiment.

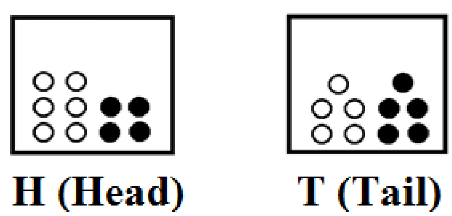
You will receive $6 for participating in this experiment. During the course of the experiment you can earn more. Your earning will depend on your performance during the experiment. All your decisions and your earning will be treated confidentially.

This session is part of an experiment about how humans make decision under uncertainty. The experiment consists of multiple parts. You need to read the following instruction to understand what will happen in each part of the experiment.

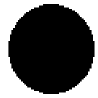
FIRST PART:

In the first part of the experiment, you'll face 21 rounds of decision-making. Each round proceeds as follows:

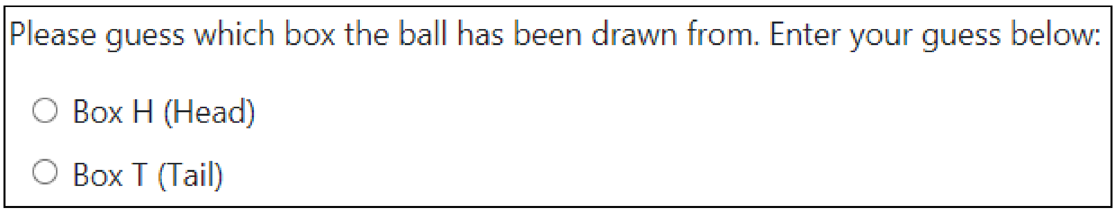
Two boxes are shown to you. Each box contains 10 balls. The combination of BLACK and WHITE balls can be different in each round. You can see an example below.



Then, a fair coin is flipped. If the coin is **Tail**, one ball is randomly drawn from **box T (Tail)**. If the coin is **Head**, one ball is randomly drawn from **box H (Head)**. You do not observe the coin, but you see the ball. For example if the ball is black, you see the following:



You then guess which box the ball has been drawn from. Specifically, you will answer the following question:



Please guess which box the ball has been drawn from. Enter your guess below:

○ Box H (Head)

○ Box T (Tail)

Remember that your answers during the experiment determine your payment at the end of the experiment. So, if you guess the correct box, you will likely receive more money at the end of the experiment. At the end of the experiment, two of your guesses will be selected at random and you will receive $12 for each correct guess.

To summarize part 1 of the experiment, you will face 21 rounds. In each round, you experience the following steps:

1. A fair coin is flipped. If the coin is Tail, one ball is randomly drawn from box T (Tail). If the coin is Head, one ball is randomly drawn from box H (Head).
2. You see the ball.
3. You guess which box the ball has been drawn from.

Note that you should consider each round as an independent experiment. There is no relation between different rounds.

SECOND PART: (Treatment *Base*)

In the second part of the experiment, you again go through 21 rounds. Each round proceeds as follows:

You are randomly connected to another participant, who is called your "NEIGHBOR". Your neighbor is an individual who has participated in this experiment before. He/She is not present in the lab right now. You then receive information about one of the rounds that your neighbor has gone through. The setting of your neighbor's experiment was the same as what you saw in the previous part. In each round, the neighbor was observing one ball, randomly drawn from one of the two available boxes, and then he/she was submitting a guess.

Your task is as follows: you first see the two boxes that has been shown to your neighbor. You then observe your neighbor's guess. Finally, you guess what the correct box is in your neighbor's experiment. Remember that your neighbor's guesses were for money. It means that a correct guess by your neighbor was increasing his/her chances of getting money.

To summarize the second part of the experiment, you will face 21 rounds. In each round, you are randomly connected to another participant, who is called your "NEIGHBOR". Then, you proceed as follows:

1. You see two boxes which were shown to your neighbor.

2. You see your neighbor's guess (your neighbor's guess was based on a ball randomly drawn from one of the boxes).

3. You guess which box is the correct choice in your neighbor's experiment.

Please keep in mind that you perform this task in multiple rounds and you might be connected to a different person in each round. So, you are not necessarily interacting with the same person in all rounds.

SECOND PART: (Treatment *Demographics*)

In the second part of the experiment, you again go through 21 rounds. Each round proceeds as follows:

You are randomly connected to another participant, who is called your "NEIGHBOR". Your neighbor is an individual who has participated in this experiment before. He/She is not present in the lab right now. You then receive information about one of the rounds that your neighbor has gone through. The setting of your neighbor's experiment was the same as what you saw in the previous part. In each round, the neighbor was observing one ball, randomly drawn from one of the two available boxes, and then he/she was submitting a guess.

Your task is as follows: you first see the two boxes that has been shown to your neighbor. You then observe your neighbor's guess (you will also see some demographic information about your neighbor such as: gender, age, years of education, and whether he/she has taken any probability/Statistics course). Finally, you guess what the correct box is in your neighbor's experiment. Remember that your neighbor's guesses were for money. It means that a correct guess by your neighbor was increasing his/her chances of getting money.

To summarize the second part of the experiment, you will face 21 rounds. In each round, you are randomly connected to another participant, who is called your "NEIGHBOR". Then, you proceed as follows:

1. You see two boxes which were shown to your neighbor.
2. You see your neighbor's guess (your neighbor's guess was based on a ball randomly drawn from one of the boxes). You also observe some demographic information about your neighbor.
3. You guess which box is the correct choice in your neighbor's experiment.

Please keep in mind that you perform this task in multiple rounds and you might be connected to a different person in each round. So, you are not necessarily interacting with the same person in all rounds.

SECOND PART: (Treatment *Bot*)

In the second part of the experiment, you again go through 21 rounds. Each round proceeds as follows:

You are connected to a bot, which is called your "NEIGHBOR". The setting of the experiment is similar to what you saw in the previous part. Two boxes are shown to you and the bot. Then, a ball is randomly drawn from one of the boxes. We show the ball to the bot (not you) and let the bot guess which box the ball is drawn from.

The bot is programmed such that when it observes a white ball, it picks the box with more white balls, and when it observes a black ball, it picks the box with more black balls. You then see the bot's guess. Finally, you guess which box the ball has been drawn from.

To summarize the second part of the experiment, you will face 21 rounds. In each round, you are connected to a bot that is called your "NEIGHBOR". Then, you proceed as follows:

1. You and your neighbor (BOT) see two boxes.

2. You see your neighbor's guess (your neighbor's guess is based on a ball randomly drawn from one of the boxes).

3. You guess which box is the correct choice.

NOTE: The bot is programmed such that it picks the box with more black balls when it observes a black ball, and it picks the box with more white balls when it observes a white ball.

SECOND PART: (Treatment *Ball*)

In the second part of the experiment, you again go through 21 rounds. Each round proceeds as follows:

You are randomly connected to another participant, who is called your "NEIGHBOR". Your neighbor is an individual who has participated in this experiment before. He/She is not present in the lab right now. You then receive information about one of the rounds that your neighbor has gone through. The setting of your neighbor's experiment was the same as what you saw in the previous part. In each round, the neighbor was observing one ball, randomly drawn from one of the two available boxes, and then he/she was submitting a guess.

Your task is as follows: you first see the two boxes that has been shown to your neighbor. You then observe your neighbor's guess and the ball that has been shown to him/her. Finally, you guess what the correct box is in your neighbor's experiment. Remember that your neighbor's guesses were for money. It means that a correct guess by your neighbor was increasing his/her chances of getting money.

To summarize the second part of the experiment, you will face 21 rounds. In each round, you are randomly connected to another participant, who is called your “NEIGHBOR”. Then, you proceed as follows:

1. You see two boxes which were shown to your neighbor.

2. You see your neighbor’s guess as well as the ball that had been shown to your neighbor.

3. You guess which box is the correct choice in your neighbor’s experiment.

Please keep in mind that you perform this task in multiple rounds and you might be connected to a different person in each round. So, you are not necessarily interacting with the same person in all rounds.

PAYMENT:

You will receive $6 for showing up. In addition to that, two of your guesses during the experiment will be randomly selected and you get an extra $12 for each correct guess.

Note: Your payment will be determined at the end of the experiment session after you finish all parts of the experiment. You will not know how much you earn in each part during the experiment.

Appendix A2: Experiment Interface (oTree)

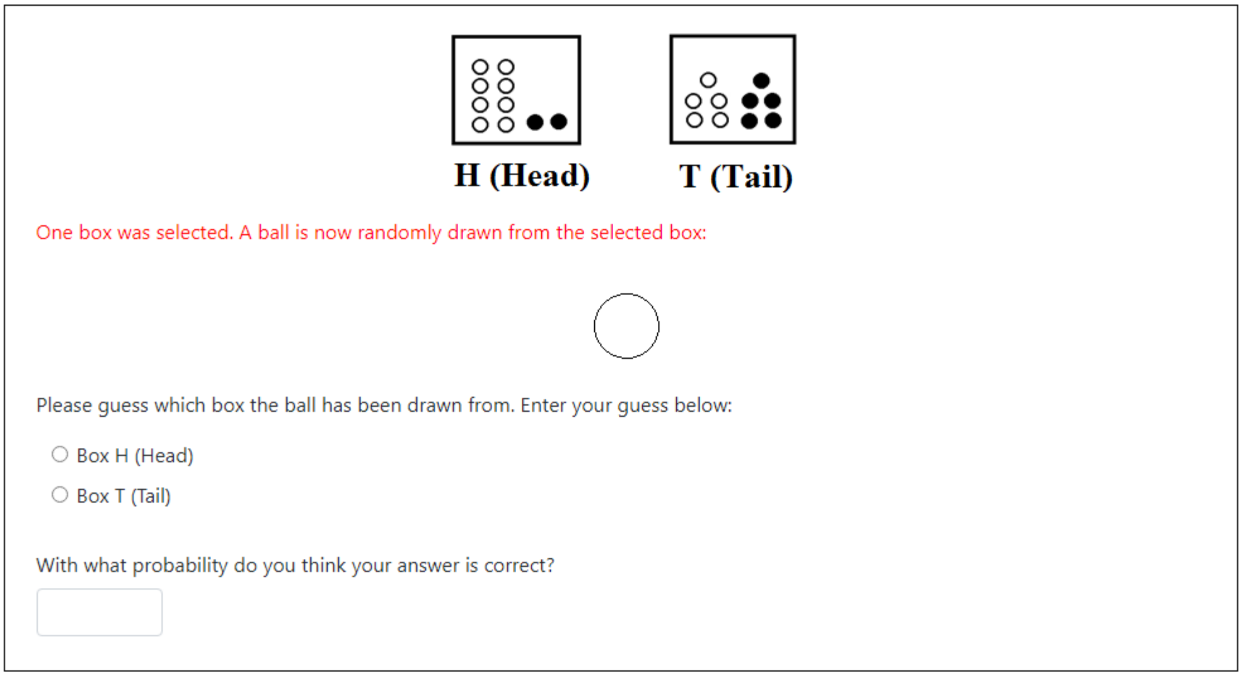


Figure 9: Individual Condition

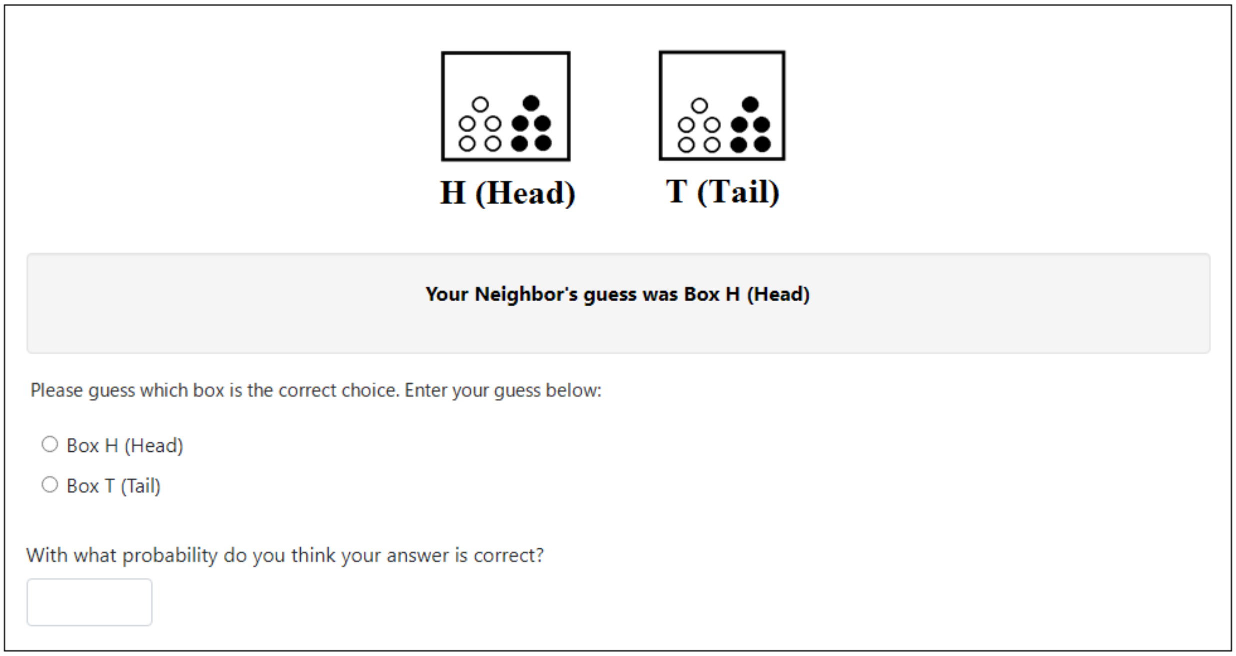


Figure 10: Social Condition (Base)

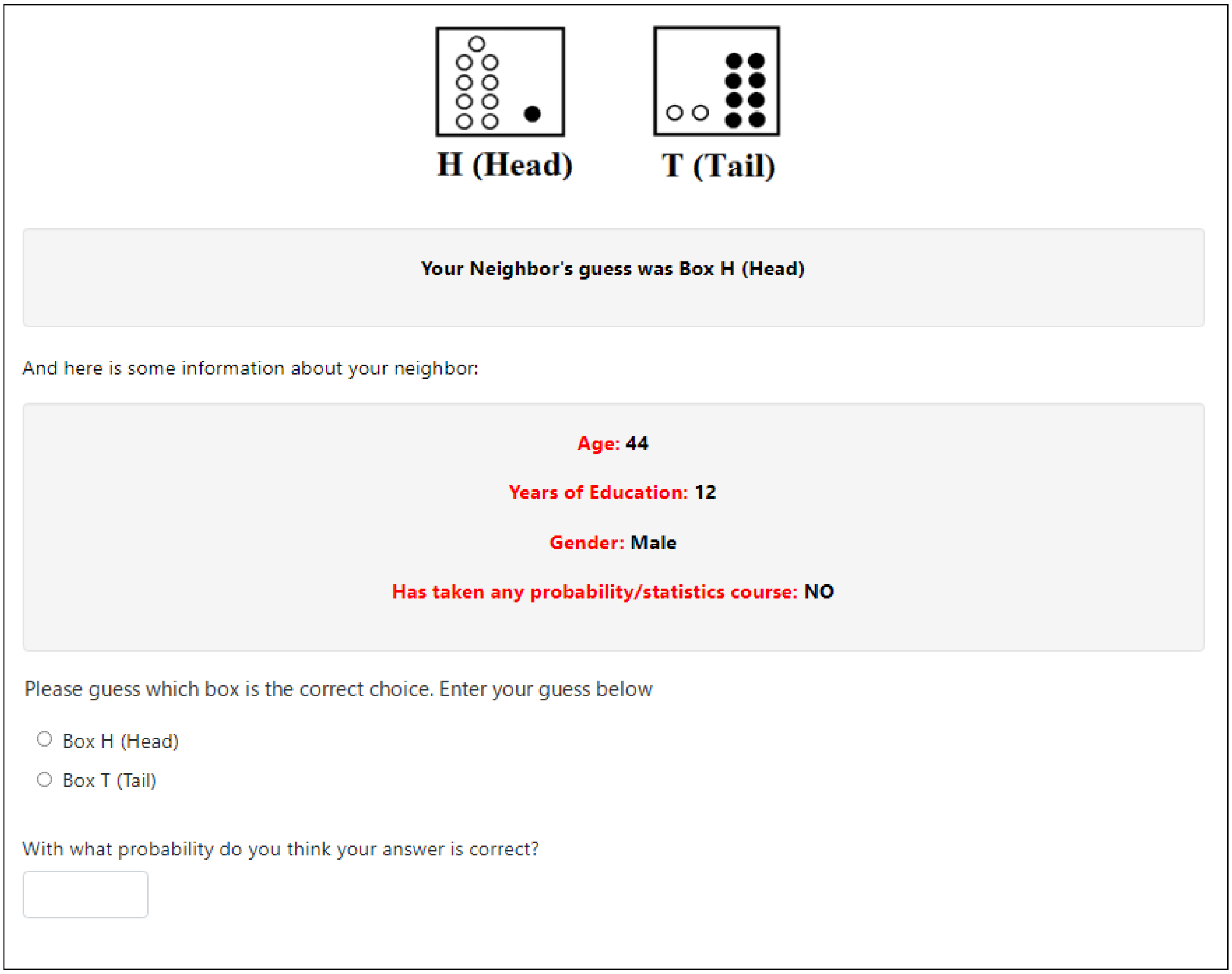
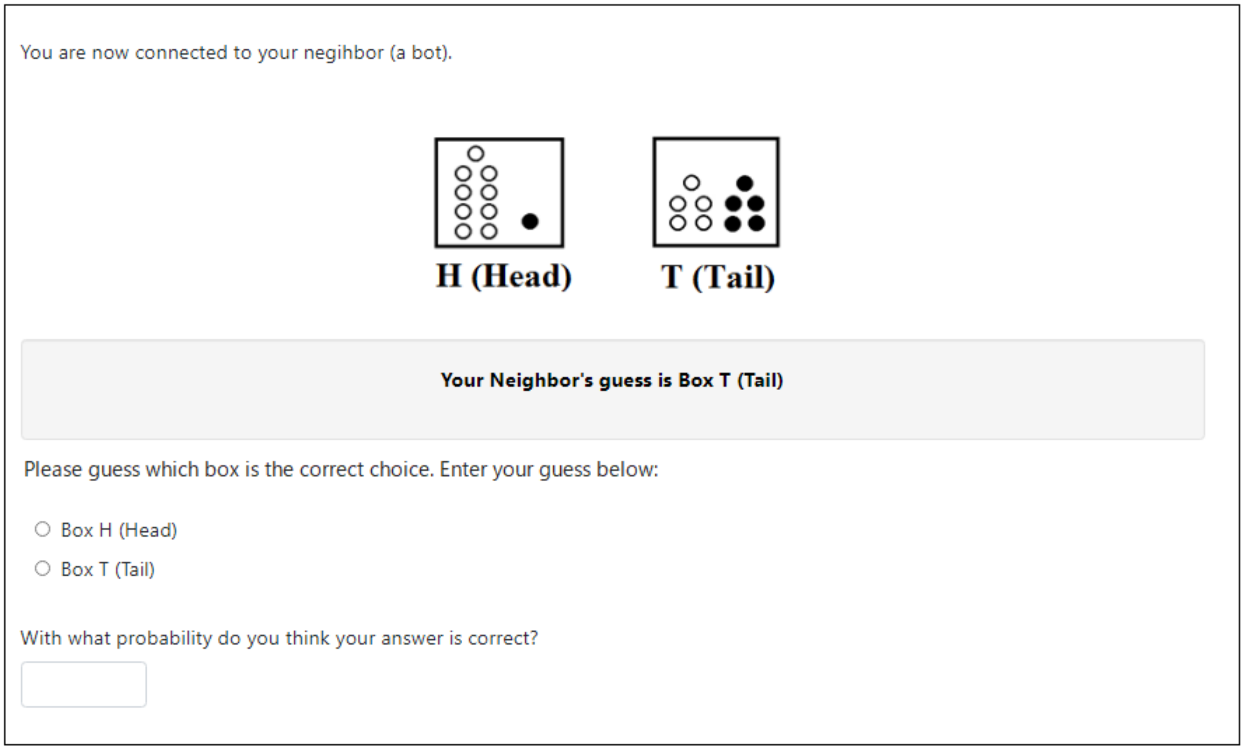


Figure 11: Social Condition (Demographics)


You are now connected to your negihbor (a bot).

H (Head)

T (Tail)

Your Neighbor's guess is Box T (Tail)

Please guess which box is the correct choice. Enter your guess below:

- Box H (Head)
- Box T (Tail)

With what probability do you think your answer is correct?

Figure 12: Social Condition (Bot)

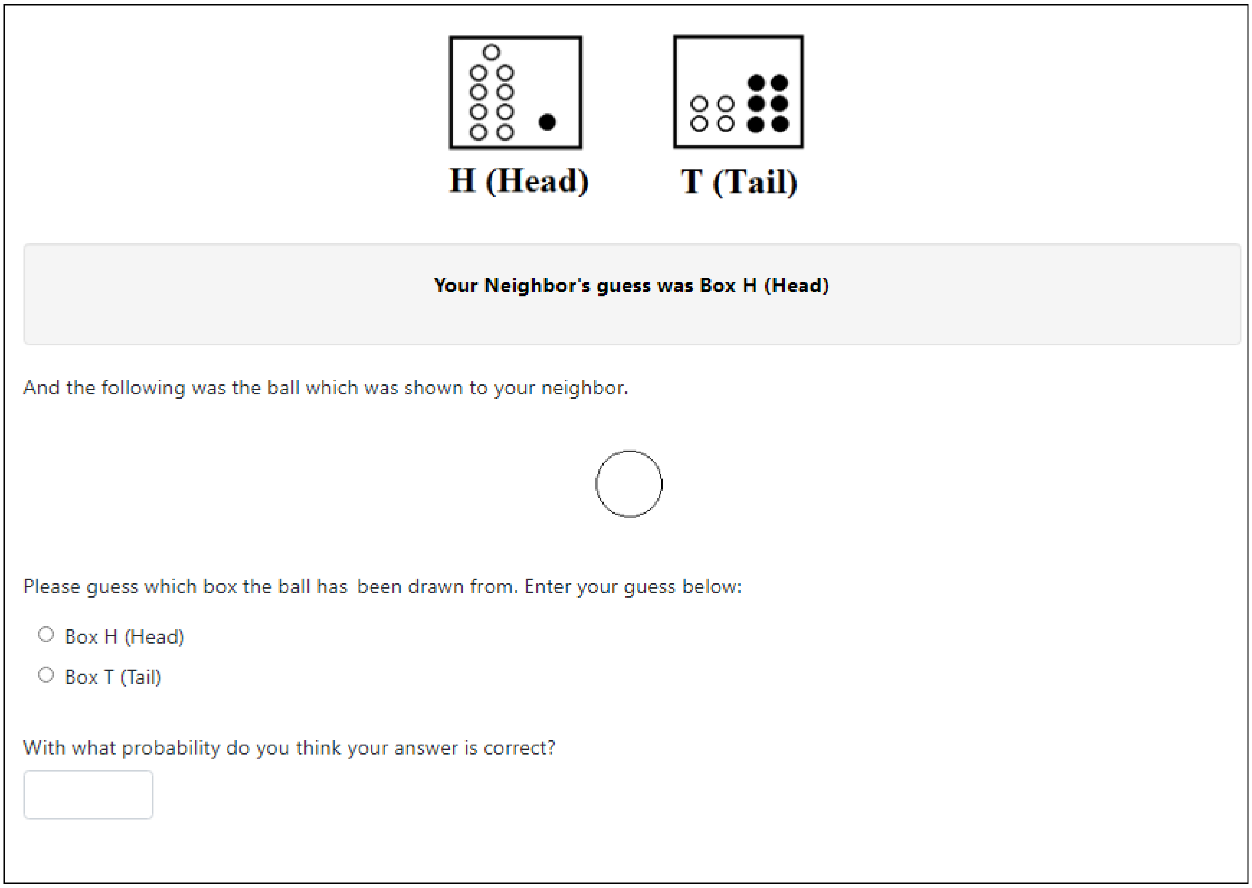


Figure 13: Social Condition (Ball)

Appendix B: Between-Subject Analysis

In the previous sections, the analysis was done on a pooled data, meaning that the data for each subject consists of decisions in both the individual and the social conditions. This means the earlier results were based on a "within-subject" analysis. In this section, I do a robustness check and examine whether the results hold if the analysis is done "between-subject". To achieve this, I need to compare the individual irrationality of subjects who see the individual condition first, with the social irrationality of subjects who see the social condition first. The results of this between-subject analysis is shown in Figure 14. This figure verifies that the main finding holds even if the analysis is done *between-subject*.

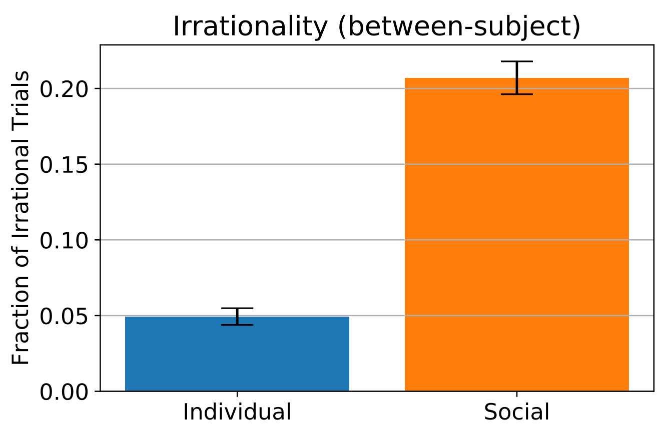


Figure 14: Individual Irrationality and Social Irrationality (between-subject analysis)

I can also redo the underlying analysis of Figure 5 at a between-subject level. The results, which are shown in Figure 15, are qualitatively similar to those presented in the body of the article.

Appendix C: A Unified Model of Individual Behavior

In this section, I present and estimate a behavioral model that corresponds to the two-stage decision-making process introduced in Section 4. The model combines two frameworks from the existing literature: for the first stage of the decision-making process, the model adapts a standard framework that was introduced in Grether (1980). For the second stage of the decision-making process, the model uses logistic response functions to determine choice probabilities (McKelvey & Palfrey, 1995;

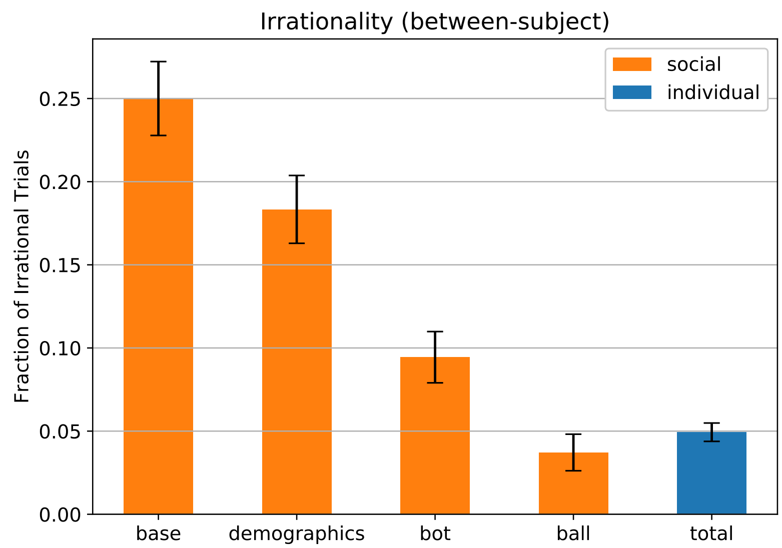


Figure 15: Social irrationality in different treatments (between-subject analysis)

Anderson & Holt, 1997). The model parameters are estimated by a two-step method. In the fist step, I use the data from the individual condition to estimate the individual errors that are independent of the social condition. These estimates are then used in a second step to estimate the subject's belief about the neighbor's behavior in the social condition. This two step method uncovers the impact of the ambiguity about the neighbor's behavior on the subject's error rate in the social condition.

The Behavioral Model

My goal in here is to build a comprehensive model that incorporates the two stages of the decision-making process shown in Figure 6. For the first stage, I use the traditional framework of Grether (1980). In this framework, when an individual obtains signal s, she updates her belief as follows:

$$\pi(X|s) = \frac{p(s|X)^c\ p(X)}{p(s|X)^c\ p(X) + p(s|Y)^c\ p(Y)} \tag{3}$$

where $s \in \{x, y\}$, $p(.)$ is the true probability, and c is a measure of bias in the posterior. Bayes rule is a special case of this equation with $c = 1$. In my experiment, priors are $p(X) = p(Y) = 0.5$. So, the above equation can be simplified as follows,

$$\pi(X|s) = \frac{p(s|X)^c}{p(s|X)^c + p(s|Y)^c} \tag{4}$$

Here, $c < 1$ is associated with underinference, i.e., as if the signals provide less information about the state than they actually do. This implies that the more the posterior errors, the lower the c. Alternatively, $c > 1$ corresponds to overinference, signals provide more information than they actually do.

For the second stage of the decision-making process, I use a logit function (Anderson & Holt, 1997). Here, conditional on the posterior belief, $\pi(.|s)$, an individual makes a binary choice, D, with the following probability,

$$Pr(D = X|s) = \frac{1}{1 + e^{-\beta\left(\pi[X|s] - \pi[Y|s]\right)U}} = \frac{1}{1 + e^{-\beta\left(2\pi(X|s) - 1\right)U}} \tag{5}$$

where β is a measure of response precision and U is the bonus of a correct guess (\$12). In this framework, the reasoning error is inversely related to β: the reasoning error diminishes when $\beta \to \infty$, and it increases as $\beta \to 0$. Note that there is a notable difference between this model and that of Anderson and Holt (1997). In Anderson and Holt (1997), the subjects are assumed to update their beliefs using the Bayes rule, but here the posterior belief, $\pi(.|s)$, is not necessarily Bayesian (e.g. it can be biased).

Figure 16 summarizes the behavioral model. In the first stage, the subject updates her belief according to equation (4). In the second step, conditional on the updated belief, the subject makes a binary choice according to equation (5).

Estimation: First Step

The first step of the estimation employs data from the individual condition of my experiment. In the individual condition, s is the color of a ball randomly drawn from the realized state. So, the objective probabilities $p(s|X)$ and $p(s|Y)$ can be easily computed from the content of each box. In addition, the subject's choice, D, and her posterior, $\pi(X|s)$, are directly observed in the data. This

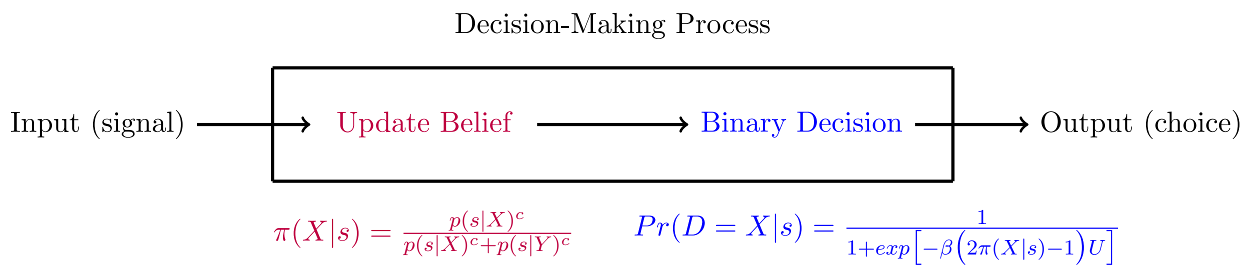


Figure 16: The behavioral model

implies that parameters c in equation (4) and β in equation (5) can be directly estimated from the data in the individual condition.[30]

The estimation results are reported in Table 4. Column (1) shows that the estimated value for parameter c is significantly lower than 1,[31] meaning that in the individual condition, subjects infer less from the signal than they should. This evidence is consistent with the fact that subjects make posterior errors in the first stage of the decision-making process. Column (2) presents the estimated value for β. The small value of this parameter speaks to the fact that subjects make reasoning errors in the second stage of the decision-making process.

Table 4: The First Step Estimation Results Using the Pooled Data of the Individual condition

	OLS (1)	Logit:True Posterior (2)	Logit:Bayes Posterior (3)
c	0.888*** (0.008)		
β		0.472*** (0.018)	0.373*** (0.012)
Observations	3171	3171	3171
R^2	0.778		
Pseudo R^2		0.519	0.647

$^{***}p < 0.01$

[30] For the parameter c, I first rearrange equation (4) as a linear regression, $\ln\left(\frac{\pi(X|s)}{\pi(Y|s)}\right) = c \ln\left(\frac{p(s|X)}{p(s|Y)}\right)$, and then use OLS for the estimation.

[31] The 95% confidence interval for c is (0.872,0.903)

Column (3) in Table 2 presents the estimated value for β conditional on the assumption that posteriors in equation (5) are Bayesian. This is the conventional assumption in the social learning experiments (Anderson & Holt, 1997; Kubler & Weizsacker, 2004). Here, the estimate for β is 0.373, significantly lower than the estimated value in the second column. This comparison suggests that the posterior error is an important factor in the individual decision-making process and not accounting for posterior errors, biased beliefs in the logit function, can lead to biased estimates for β (overestimation of the reasoning error).

Estimation: Second Step

The goal in the second step of the estimation is to use the estimates from the first step, $\hat{c} = 0.888$ and $\hat{\beta} = 0.472$, to estimate the subject's belief about the neighbor's error rate in the social condition. Here, the estimation only employs data from the social condition of my experiment.[32]

Note that the decision-making process in the social condition still follows the framework in Figure 16, with one exception: here, the subject observes the guess of a neighbor as signal. Denote the neighbor's guess by $'s' \in \{'x','y'\}$ and the neighbor's private signal by $s \in \{x, y\}$. The subject's posterior after observing the neighbor's guess can be derived as follows,

$$\pi(X|'s') = \frac{p('s'|X)^c}{p('s'|X)^c + p('s'|Y)^c} = \frac{p('s'|X)^{0.888}}{p('s'|X)^{0.888} + p('s'|Y)^{0.888}} \tag{6}$$

The parameter c in this equation is a structural parameter and is set to 0.888, the estimate from the first step estimation. However, $p('s'|X)$ and $p('s'|Y)$ in equation (6) cannot be directly computed by observing the content of boxes. These probabilities depend on the subject's belief about the behavior of the neighbor. Let's denote the subject's belief about her neighbor's error

[32] I exclude the data for the *Ball* treatment in this section. As noted earlier, the subject observes both the neighbor's guess and the ball that the neighbor has observed. So, the subject's belief about the neighbor's error rate is irrelevant in that treatment.

rates by a pair $(\tilde{\beta}, \tilde{c})$. Then, it is straightforward to derive the followings:

$$p(\text{'}x\text{'}|X) = Pr(D_n = X|x)\ p(x|X) + Pr(D_n = X|y)\ p(y|X) \tag{7}$$

$$p(\text{'}y\text{'}|X) = [1 - Pr(D_n = X|x)]\ p(x|X) + [1 - Pr(D_n = X|y)]\ p(y|X) \tag{8}$$

$$p(\text{'}x\text{'}|Y) = Pr(D_n = X|x)\ p(x|Y) + Pr(D_n = X|y)\ p(y|Y) \tag{9}$$

$$p(\text{'}y\text{'}|Y) = [1 - Pr(D_n = X|x)]\ p(x|Y) + [1 - Pr(D_n = X|y)]\ p(y|Y) \tag{10}$$

where $Pr(D_n = X|s)$, $s \in \{x, y\}$ is the subject's belief about the neighbor's choice probability:

$$Pr(D_n = X|s) = \frac{1}{1 + e^{-\tilde{\beta}\left(2\tilde{\pi}(X|s) - 1\right)U}} \tag{11}$$

and $\tilde{\pi}(X|s) = \frac{p(s|X)^{\tilde{c}}}{p(s|X)^{\tilde{c}} + p(s|Y)^{\tilde{c}}}$. Substituting equations (7)-(10) in (6), one can derive the following expressions,

$$\ln\Big(\frac{\pi(X|\text{'}x\text{'})}{1 - \pi(X|\text{'}x\text{'})}\Big) = 0.888 \times \ln\Big(\frac{Pr(D_n = X|x)\ p(x|X) + Pr(D_n = X|y)\ p(y|X)}{Pr(D_n = X|x)\ p(x|Y) + Pr(D_n = X|y)\ p(y|Y)}\Big) \tag{12}$$

$$\ln\Big(\frac{\pi(X|\text{'}y\text{'})}{1 - \pi(X|\text{'}y\text{'})}\Big) = 0.888 \times \ln\Big(\frac{[1 - Pr(D_n = X|x)]\ p(x|X) + [1 - Pr(D_n = X|y)]\ p(y|X)}{[1 - Pr(D_n = X|x)]\ p(x|Y) + [1 - Pr(D_n = X|y)]\ p(y|Y)}\Big) \tag{13}$$

where $\pi(X|.)$ is the subject's posterior after observing the neighbor's guess. To estimate the subject's belief about the neighbor's behavior, I assume $\tilde{c} = 0.888$, i.e., the subject's belief about the neighbor's posterior bias is correct. Then, I estimate $\tilde{\beta}$ by using a non-linear least square method to fit the data to equations (12)-(13). The non-linear least square estimate for $\tilde{\beta}$ is 0.038 ($s.d.$ = 0.009), which is significantly lower than the corresponding parameter for the individual reasoning error estimated in the first step, $\hat{\beta} = 0.472$ ($s.d.$ = 0.018). This result suggests that the ambiguity in the social interaction causes the subjects to assign a lower response precision to their neighbor than their own. That is, subjects think their neighbors make more errors than they actually do.