# Do we know the value of information? Heterogeneous effects in the demand for information*

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**Abstract**

This research explores the relationship between learning and willingness to pay (WTP) for new information, and whether information acquisition changes weather the strategy of another participant is implemented. The first and second order posterior beliefs were elicited. Participants shared, or not, their prior beliefs with another participant when the second order beliefs were elicited. On average, participants expect others to have the same posterior beliefs. Also, the WTP was positively related to how sensible participants were to the signals. Interestingly, participants exhibited a larger WTP for a signal realization when they implement their strategy and the other participant didn't share the same priors.

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## 1 Introduction

There is a diversity of opinions and beliefs in our society in about every topic. From politics to investment and household decisions, we engage in conversations with individuals who hold different beliefs than our own, and the decisions those people make can affect us. We also interact with people who share the same beliefs about the true state of the world. These differences in prior beliefs affect how we react to an informative signal; furthermore, these differences also affect how much we are willing to pay to get more information. This is relevant when the final decision on a common issue is delegated to another person, and we can only provide more information.

People deciding how much information to gather in the field (e.g., from customers and clients) are different from the managers who ultimately make the decisions for the organization. Also, a person could decide on a policy that affects everybody, and others could decide to present more evidence to help make a better decision. In this paper, I measured how the sensitivity of posterior probabilities to signals changes due to considering the beliefs of people with different priors who observe the same signals. I also explored how individual differences in belief updating affect their willingness to pay to observe a signal and why.

Understanding how individuals estimate the posterior beliefs of others and expect them to update becomes crucial for effective communication and decision-making. Interacting with individuals of different prior beliefs requires an understanding of how they learn. By examining the alignment or divergence between the strategies employed by participants and their expectations of others' strategies, we gain valuable insights into the mechanisms that underlie belief updating in strategic settings.

In an uncertain world, where outcomes are contingent upon random variables and the decisions of others, the ability to estimate and update first- and second-order beliefs accurately becomes paramount. Therefore, understanding how individuals form expectations and update their beliefs is essential. I study this in the context where incentives are aligned, and more information increases the expected payoffs, such as policy implementation.

Considering different posterior beliefs is relevant because a lack of consensus is pervasive. People can have different information, consider different sources of information as more accurate, or acquire new private information that makes them consider that the beliefs of others are outdated. These situations can generate different beliefs, and agents must estimate how others will update after new evidence to coordinate actions and persuade. In this study, I assume participants find the prior of others non-informative.[1] This study aims to discover how people expect others to update when they know others have different beliefs, but new common information is now available.

This paper investigates the effect of having different priors on participants' estimation of posterior beliefs and their expectations regarding the updating strategies of others. I explore how individuals anticipate others to update their beliefs based on possible samples and compare that with their own strategies. Also, participants are asked their WTP for information when a future decision is made based on their or another participant's choices. It is a standard assumption that people expect others to be Bayesian agents like themselves. In a game where incentives are aligned, this implies no difference in who makes the decision and, therefore, no differentiated information value. I found that this conclusion is inconsistent with experimental results in the context of different prior beliefs; participants were willing to pay more when they implemented their own strategies instead of someone else's.

On average, participants expect others to update their beliefs in a manner similar to their own. However, different priors lead to increased distances between the participants' strategies and their expectations of others' strategies. In the standard model, the value of new information is independent of who makes the decision when incentives are aligned. In this research, however, I show that participants exhibit a larger willingness to pay for information when they can implement their own strategy rather than relying on the strategy of another participant.

I measured the degree of conservatism and base rate neglect among participants to explore the biases potentially influencing these findings. I found that participants who display a higher degree of conservatism and base rate neglect exhibited a lower willingness to pay for information. No correlation was observed between these two biases. However, a significant correlation emerged between the biases participants displayed in their strategies and the biases they expected from others. These results are consistent with the idea that people pay more when they know they are more sensitive to new information and that they expect others to update in a similar way.

The results in this paper challenge a conventional assumption in Bayesian games and emphasize the importance of personal agency in decision-making processes. It suggests that individuals place greater value on information when they have the opportunity to act based on their own strategies rather than relying on others' strategies.

This paper contributes to our understanding of belief updating and information

[1] It can be assumed that participants already learned from others or face updated information.

value in strategic settings with differing priors. By examining the estimation of posterior beliefs and expectations of others' updating strategies, we shed light on the intricacies of decision-making processes and the factors that influence the willingness to seek and utilize information in social interactions.

The experimental results suggest nuanced impacts of common/different prior beliefs on belief updating and heterogeneity on the valuation of information. These findings contribute to a deeper understanding of the psychological and informational dynamics at play in decision-making processes, particularly in contexts involving uncertainty and diverse perspectives.

## 2 Related Literature

The literature on (non-) Bayesian updating is considerable, and the general results are that people display base rate neglect and conservatism (Benjamin, 2019).[2] I know of no paper that explores whether people expect others to display the same biases as themselves when the priors differ or are the same.

This paper innovates in the elicitation of the willingness to pay (through the BDM mechanism) in a strategic setting where the level of bias expected from another person can be used to predict the value of providing information to this person. I also analyze whether differences in prior beliefs affect the willingness to pay to receive or send an informative signal.

### 2.1 Non-Bayesian Belief Updating

It has been consistently found that participants deviate from Bayes' rule; conservatism and base rate neglect (BRN) are general features of belief updating. Benjamin (2019) presents a comprehensive analysis of the results in the laboratory. He used the model from Grether (1980, 1992) to estimate these biases. To predict the elicited posteriors in this paper, I denote with $\beta_p$ and $\beta_l$ the relative importance of the priors and the likelihood of the signal, respectively.[3]

[2] However, these biases are identifiable under different prior-likelihood combinations. For example, with homogeneous priors, only conservatives can be measured.

[3] Benjamin estimated $\beta_i^l = 0.383$ and $\beta_i^p = 0.434$ from a meta-analysis of independent experiments in settings similar to the design implemented in this study.

### 2.2 Higher-Order Believe Updating

Whether people expect others to display the same belief-updating biases as themselves is understudied. The paper, "Higher-Order Learning," from Evdokimov and Garfagnini (2022) was the first experimental effort to study how higher-order beliefs are updated. They elicited the higher-order beliefs of others' posterior beliefs in a sequential Bayesian task. These authors estimated the biases using the econometric approach of Grether (1980, 1992) (as Benjamin (2019)). They found considerable individual heterogeneity. However, the first- and higher-order beliefs parameter distributions were significantly different only at 10%,[4] and non-statistically different when the beliefs were elicited simultaneously in MTurk. Finally, they found a lack of convergence simulating data with the parameters estimated in the experiment. This was a property of Grether's quasi-Bayesian model with BRN also explored theoretically by Benjamin et al. (2019).[5] It was also found that participants with a higher cognitive ability expect others to end up agreeing more with them (Evdokimov and Garfagnini, 2023). Other studies have focused on higher-order beliefs on actions, risk preferences, and time discounting (Fedyk, 2021). Another important related work is from Agranov and Detkova (2024). They also studied expected belief updating from others and analyzed the effects of different priors, but they used statements. In that paper, there is an asymmetry in the expected belief of others after the signal, depending on participants having different priors. In this paper, I also analyze the willingness to pay to implement the strategy of another person.

It has been reported that people are blind to their own biases and frequently consider that others have more significant biases than themselves (Pronin et al., 2002; Pronin, 2008). However, the results from Evdokimov and Garfagnini (2022) show that participants in belief-updating tasks could be more prone to false consensus biases Engelmann and Strobel (2000). In the case of higher-order beliefs, people might report the same beliefs for others as for themselves, especially if the other is perceived as similar to you.

[4] The distribution of $\beta^p$ was different between the first- and second-third beliefs and $\beta^l$ was different between the first- and second-order beliefs.

[5] Intuitively, when agents base-rate-neglect, new signals move the posterior more than the Bayes rule, and the beliefs don't settle.

### 2.3 Strategic Settings

Other studies have considered higher-order beliefs in strategic settings. Szkup and Trevino (2020, n.d.) applied a game where it is payoff-relevant to estimate the actual state of the world but also to match the guess from others. They elicited participants' beliefs about their opponents' decisions after an informative signal about the game's fundamentals. This task requires calculating the expected signals observed by the opponent and knowing how those signals were updated. They found that participants are accurate in their first-order beliefs, but they deviate from the theoretical predictions in their stated beliefs about the actions of others. Another closely related experiment is the one designed by Campos-Mercade et al. (2022). They considered studying the effects of higher-order beliefs on the conservatism of employers on employees' decisions. Participants in the role of employees were sensitive to heterogeneous biases, but this came exogenously as the experimenters implemented it, and they received feedback on the decisions made by the participants in the role of employers. Because employers were classified according to their degree of conservatism in belief updating and then paired with employers, the latter had to learn the biases from employers. This setting is different from the present study since the question here is about the biases that participants have about the biases of others without getting any feedback.

### 2.4 Cognitive Ability on Belief Updating

The cognitive reflection test (CRT) test (Primi et al., 2016) is widely used and has been interpreted as a proxy for cognitive ability. It has been found that higher scores in the CRT are related to posterior beliefs closer to the Bayes rule. According to Oechssler et al. (2009), individuals who obtain high scores on the Cognitive Reflection Test (CRT) have an average reported belief closer to the Bayes rule than people with lower scores. Similar results were found by Hoppe and Kusterer (2011). Evdokimov and Garfagnini (2023) also mentioned that cognitive ability is associated with how subjects update beliefs; subjects with higher CRT scores demonstrate smaller deviations from the Bayesian benchmark when updating their first-order beliefs.

## 3 Research Questions

The study explores whether agents consider others' biases in belief updating when there are heterogeneous priors. It also explores if this affects the willingness to share information to persuade other players. More specifically, I ask:

1. How do people update their beliefs in response to new evidence, and how do they expect others to update their beliefs?
2. To what extent do people consider the biases of others when updating their beliefs?
3. How does the difference between what people learn and what they expect others to know affect information acquisition?
4. Are people more willing to pay when they expect others to have the same ability as themselves?

## 4 Contributions

This paper's main contribution is exploring experimentally how having to consider different priors affects the belief-updating process and why the value of informative signals changes depending on who makes the decision. This paper is the first to measure the effects of being in the context of different priors on the belief updating process. This is also the first time Grether's model has been used to predict the value of a signal and how this value changes depending on who is making a guess based on the signal's realization.

The higher-order updating process was explored experimentally first by Evdokimov and Garfagnini (2022) in the context of sequential learning and common priors. They found that the aggregate distribution of biases is not statistically different (at 5%) between first- and second-order beliefs. My paper explores first, as a marginal contribution, whether these results hold in a different setting; here, the updating was elicited from all possible simultaneous samples with replacement using the strategy method. Second, as a more relevant comparison, I analyze the differences in the higher-order updating under a treatment where participants had different priors. Finally, as the main contribution, I explore the consequences of the hypothesis that participants expect others to update exactly like themselves in the WTP to observe a sample; if this is true, there should not be a difference between guessing the state of the world themselves after observing a sample or letting other participants make the guess.

The delegation of decision-making and the decision to share how much information with others are affected by how people expect others to react to the signals. In this paper, I elicited the WTP to apply the strategies stated as posterior beliefs. If people expect others to use the information in the same way they would, sharing information or acquiring information to make the decision yourself should be the same when the final decision affects you and others. In a more general setting, if an agent wants to change the beliefs of others, that will depend on how they expect others to use the information observed. For example, if people expect others to be conservative, they will provide more information to change others' beliefs. Also, if the information is costly, they might be discouraged from providing information. It has been found that beliefs can determine the behavior in laboratory experiments (Schotter and Trevino, 2014), Jin et al. (2021) found that beliefs have an effect on the information provided in a signaling game.

### 4.1 Methodological contribution

This study implements the strategy method to evaluate the posterior beliefs of a single person under all possible signals. In the literature, it is common to have sequential belief updating and the direct method (participants observe an actual realization of the process and make a decision). The present setting controls for story effects and is able to compare the decision of each participant in each information condition: prior and signal.

In contrast to Evdokimov and Garfagnini (2022) within-long signal condition, participants are informed that the prior distribution of boxes from another player differs from theirs. Also, the information is presented simultaneously; every signal (sample of marbles) comes from a realization of the state of the world (box selection). The sample of N marbles is common information, and participants report first and second-order beliefs in the form of strategies.

The strategy method was implemented to explore this question without confounding the effect of different priors as an information source. Thus, participants report their strategies for all possible samples and the expected strategies of someone else. This elicitation method allows us to present the problem without deceptions and clarifies that other participants' prior probabilities are non-informative. In other studies, the beliefs were elicited using the direct method. However, there is no evidence that applying the strategy method creates a significant difference (Brandts and Charness, 2011).

## 5 Experimental Design

The main situation that the participants have to consider is the following:

### Learning Setting

There are two boxes: Yellow ($Y$) and Green ($G$). The Yellow box has three Yellow marbles and two green marbles, while the Green box has three green marbles and two yellow marbles. Therefore, the diagnosticity parameter is equal to 3/5 ($P(Y|y) = 1 - P(G|y) = \theta = 0.6$) for a single marble. One box is selected randomly with prior probability $P(Y) \in \pi = \{0.2, 0.5, 0.9\}$, and the signal consists of a random sample with replacement of four marbles ($s$) drawn from the box. The five possible samples are the number of yellow marbles drawn out of four random samples with replacement: $s \in S = \{0, 1, 2, 3, 4\}$.[6] The students had to correctly answer six understanding questions after the description of the problem before they could move on to start the experiment.

### 5.1 Experiment 1

The experiment was conducted at the University of California Santa Barbara in the LITE laboratory. I ran thirteen sessions with an average size of eleven participants per session. There were 198 participants in total, all students at UCSB.[7] The average age of the participants was 20.6 years, and 61% were female.

The experiment consists of three sections: 1) first and second-order posterior elicitation, 2) signal and strategy purchase, and 3) exit surveys. The participants were matched in pairs and belonged to the same pair during the experiment. In section one, each pair was assigned to the Common Priors (CP) or Heterogeneous Priors (HP) treatment. Using the strategy method, they had to report their own and another participant's posterior probabilities for each possible sample and prior. In section two, they report their willingness to pay to see the signal realized and make a decision according to the strategies stated in section 1. In each pair, one participant could implement the strategy of the other participant ($WTP_{-i}$), and the other participant could implement their own ($WTP_i$). The combination of these two between-subject treatments in sections one and two generated four possible groups:($CP$, $WTP_i$), ($CP$,

[6] There are $2^4$ different possible sequences, but the number of marbles of each color is sufficient to calculate the posterior probability.

[7] The first session (6 participants) had a different setting for sections 2 and 3; therefore, these participants were excluded from the analysis of the WTP and CRT.

| Section | Treatments | | | |
|---|---|---|---|---|
| 1. First and Second Order Posterior Elicitation | Common Priors $P_i(Y) - P_{-i}(Y)$ | | Heterogeneous Priors $P_i(Y) - P_{-i}(Y)$ | |
| | $90 - 90$ | | $90 - 20$ | |
| | $50 - 50$ | | $50 - 90$ | |
| | $20 - 20$ | | $20 - 50$ | |
| 2. Signal and Strategy Purchase | Own $WTP_i$ | Another's $WTP_{-i}$ | Own $WTP_i$ | Another's $WTP_{-i}$ |
| 3. Surveys | CRT and Exit Survey | | | |

Table 1. Experiment 1 design. In section 1, each pair of participants is assigned to the condition CP or HP, where they report their own and another participant's posteriors in three combinations of priors assigned to them. In section 2, one participant of the pair reports their $WTP_i$ and the other their $WTP_{-i}$. Finally, all participants go through Section 3.

$WTP_{-i}$), ($HP$, $WTP_i$), and ($HP$,$WTP_{-i}$). Finally, participants will be asked to complete a CRT and an exit survey. The total payment was revealed until the end of the experiment. The treatments and their conditions are summarized in Table 1. Each section is described in further detail below:

### Section 1: First and Second-Order Beliefs Elicitation

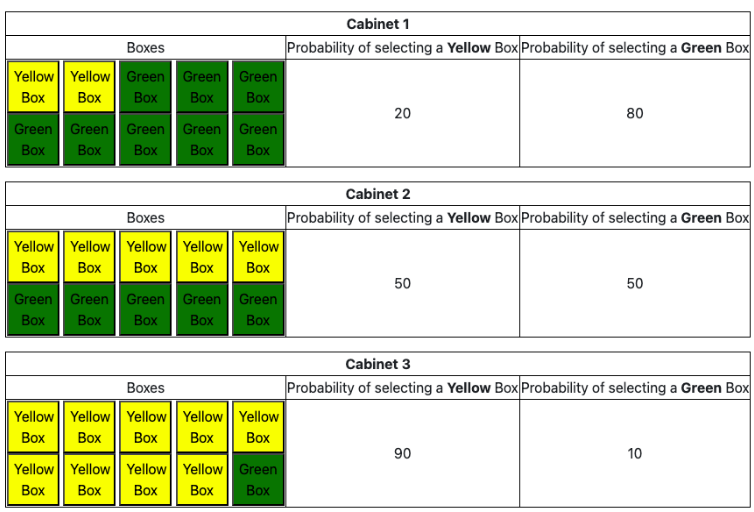



Figure 1. Screenshot of the cabinets used to explain the different priors to the participants.

Participants' beliefs for each possible sample and prior were elicited using the strategy method. Each participant ($i$) has to report the probability of the Yellow box was selected given the possible samples ($s \in S$) and stated prior ($P_i(Y) \in \pi$): $\tilde{P}_i(Y|s)$. Also, they have to report the probability stated by another participant ($j \neq i$) $\tilde{P}_{i,j}(Y|S)$ with a prior $P_j(Y)$. The probability of selecting each box for player $i$ is $P_i(Y)$, and they know the probability of selecting the Yellow box for participant $j$: $P_{-i}(Y)$. In this section there are $(|S| = 5\ samples) \times (|\pi| = 3\ priors) \times (2\ players) =$ 30 observations per participant.

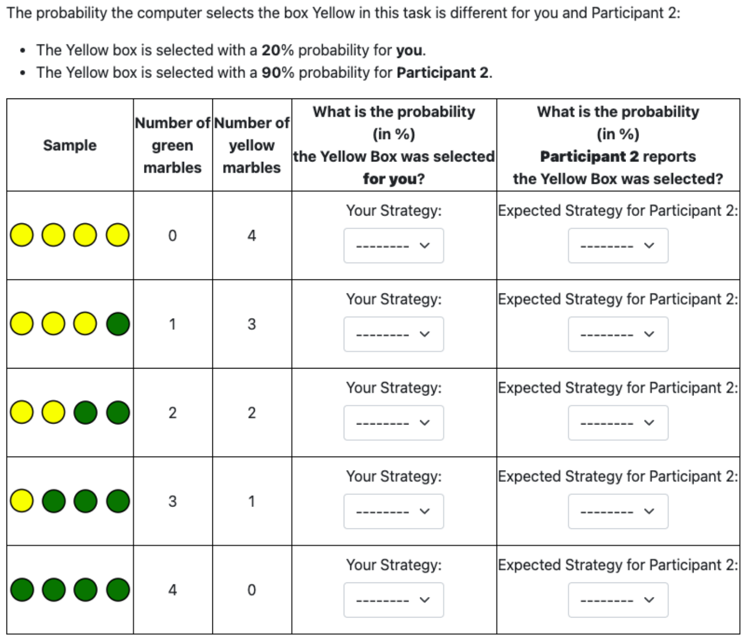
The priors were explained to the participants by presenting three different cabinets (as shown in figure 1) from where one box was randomly selected for each participant. The boxes came from the same cabinet in the common prior treatment (CP), or from different cabinets in the heterogeneous priors treatment (HP). This method allows us to ask for the posterior belief when participants have different priors without deception.

Figure 2 shows an example of the tables with the five samples where the participants reported their strategies. Each prior combination: $P_i(Y) - P_{-i}(Y)$ (see table 1) was presented in a different table. In this example from the HP treatment, participant one has a prior of 20% and participant two has a prior of 90%. Each participant was asked for their posterior probability of Box Yellow being selected ($\tilde{P}_i(Y|s)$) and the posterior probability of the other participant $\tilde{P}_{-i}(Y|s)$ in the fourth and last columns respectively. Their strategy decisions were made by selecting from a list of 101 numbers between 0 and 100 displayed when clicking on the arrow in each box. They couldn't advance until both participants filled the table.

After stating their strategies for each table, a random process working as described in the learning setting determined a sample $s$ realized for one participant. Therefore they could get paid by their estimation about another participant's strategy or by their own strategy. This practice prevents hedging when participants are reporting their second-order beliefs Blanco et al. (2010). I use the Binarized Quadratic Scoring Rule (BQSR) (Hossain and Okui, 2013; Erkal et al., 2020) to calculate the payoffs.[8] This mechanism has been used to elicit beliefs in the literature and has the theoretical property that the elicitation is incentive compatible.[9] It is explained to the participants that they must report their true beliefs to maximize their chances of getting

[8]Participants make \$3 with probability $1 - (\tilde{P}_i(Y|s) - \mathbb{1}(Y))^2$ from the implementation of their own strategy ($\tilde{P}_i(Y|s)$), and \$3 with probability $1 - (\tilde{P}_{-i}(Y|s) - \tilde{P}_j(Y|s))^2$ from their estimation of others participant's strategy ($\tilde{P}_{-i}(Y|s)$). $\tilde{P}_j(Y|s)$ refers to the actual strategy of the other participant $j \neq i$.

[9]It has been found that binary lotteries don't elicit risk-neutral behavior (Kirchkamp, Oechssler, and Andis (2021), but the BSR was more accurate than other options.


The probability the computer selects the box Yellow in this task is different for you and Participant 2:

- The Yellow box is selected with a **20%** probability for **you**.
- The Yellow box is selected with a **90%** probability for **Participant 2**.

| **Sample** | **Number of green marbles** | **Number of yellow marbles** | **What is the probability (in %) the Yellow Box was selected for you?** | **What is the probability (in %) Participant 2 reports the Yellow Box was selected?** |
|---|---|---|---|---|
| | 0 | 4 | Your Strategy: -------- | Expected Strategy for Participant 2: -------- |
| | 1 | 3 | Your Strategy: -------- | Expected Strategy for Participant 2: -------- |
| | 2 | 2 | Your Strategy: -------- | Expected Strategy for Participant 2: -------- |
| | 3 | 1 | Your Strategy: -------- | Expected Strategy for Participant 2: -------- |
| | 4 | 0 | Your Strategy: -------- | Expected Strategy for Participant 2: -------- |

Figure 2. Screenshot of the first five possible samples that participant in condition HP $(20, 90)$ has to consider. In the last two columns, they have to indicate $\tilde{P}_i(Y|s)$ and $\tilde{P}_{-i}(Y|s)$, with $s \in \{0, 1, 2, 3, 4\}$ the number of yellow marbles in sample.

up to \$9.[10] Also, the details of how they are incentivized were explained, and some examples presented. The description can be found in the appendix **??**.

There is a trade-off between complexity, incentives, and accuracy discussed by Charness et al. (2021), and there is evidence that complex descriptions bias the decision towards 50% (Danz et al., 2022).[11] Despite BQSR complexity, this elicitation method allows the implementation of an analogous incentive scheme for first and second-order beliefs, which makes the strategies stated comparable. Other mechanisms, like probability matching or the interval mechanism, cannot be asked in the same way for their own strategies and those of others. The present implementation of belief elicitation is simple and allows people to read a detailed description of the payoffs with examples.[12] The general description of truthful beliefs maximizing their chances of getting the bonus is correct. This setting maintains a simple description and an incentive-compatible mechanism.

[10]They can make \$3 in from each table.

[11]Charness et al. (2021) mentioned that, in some cases, introspection is as good as incentives. However, it is important to maintain the engagement of the participants in the laboratory and incentivize their decisions while keeping the explanation simple.

[12]The instructions can be found in the appendix.

**Section 2: Signal and Strategy Purchase**

The BDM mechanism was used to elicit participants' willingness to pay (WTP) to observe the realization $s$ and implement the strategies in section one. The learning setting is the same as the one described in section one, considering $P(Y) = 0.5$. Participants are informed that they have the opportunity to purchase a sample of four marbles that is informative of which box was selected. In a second-price auction, participants select $\tilde{V}$ from a list of 31 numbers between 0.00 and 1.50 to bid against the computer that selects a random number $x \sim U[0, 1.5]$. If $\tilde{V} \geq x$, they purchase the information for a price $x$, if the $\tilde{V} < x$, they pay nothing, and no sample is realized.[13] The number $\tilde{V}$ measures the WTP for the signal, which must equal the difference between the expected value when they receive the information and the expected value of deciding based only on the priors.

The WTP for the signal was elicited in two cases. When the participant purchase information and apply their own strategies ($\tilde{P}_i(Y|s)$); $\tilde{V}$ is denoted as $WTP_i$. When they purchase information but apply the other participant's strategy ($\tilde{P}_j(Y|s)$), $\tilde{V}$ is denoted as $WTP_{-i}$. These cases were implemented between subjects; one participant in each pair was asked for their $WTP_i$, and the other for their $WTP_{-i}$. Participants were informed that their prediction is based on the reported strategy in the first section; they were not asked to guess the color of the box after the realized sample $s$. If $\tilde{P}_i(Y|s), \tilde{P}_j(Y|s) > 0.5$, the guess would be the Yellow Box, if $\tilde{P}_i(Y|s), \tilde{P}_j(Y|s) < 0.5$, the guess would be the Green Box, and a random guess was made if $P_i(Y|s) = 0.5$ or if there was no information purchased through the BDM mechanism. The BDM mechanism was explained to the participants, and they were told that their expected payoffs increase if they report how much extra money they expect to make if the strategy in Section 1 ($\tilde{P}_i(Y|s)$ or $\tilde{P}_j(Y|s)$) is applied to the sample observed.

An extra payoff of \$3 was assigned to each participant if the guess about the box randomly selected was correct. For example, if $x = 0.55 < WTP_{-i} = 0.75$, they purchased the signal. Also, if Yellow Box was selected and the sample $s = 3$ is realized, the guess will be the Yellow Box if, for example, $\tilde{P}_j(Y|s) = 0.65$. Then, participant $i$ makes $\$3 - \$0.75 = \$2.25$ and participant $j$ makes \$3. They make no money for wrong predictions.

The BDM procedure is theoretically robust to risk neutrality.

[13] The instructions given to the participants can be read in the appendix 7.

**Section 3: CRT and Exit Survey**

Participants answered the following Cognitive Reflection Test (CRT):

- A bat and a ball cost 22 dollars in total. The bat costs 20 dollars more than the ball. How many dollars does the ball cost?
- If it takes 5 machines 5 minutes to make 5 widgets, how many minutes would it take 100 machines to make 100 widgets?
- In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how many days would it take for the patch to cover half of the lake?

They were asked for how many they, and the other participant got correctly in the CRT test. Finally, in the exit survey, participants were asked about their age, gender, if they took a probability/statistics course, and the perceived difficulty of the experiment.

Participants could make up to \$2.5 in this section. They were paid \$0.5 for each correct answer in the CRT and

Evdokimov and Garfagnini (2023) found that participants in a sequential updating task underestimate the levels of disagreement regardless of their cognitive ability (measured with a modified CRT) and learning of the state of the world. In their task, participants start with the same prior and learn about the same state of the world sequentially. This is a different setting from the present study, and I expect cognitive ability does not affect how people expect others to update. However, the possibility that cognitive ability and relative self-reported performance could impact higher-order beliefs in the present setting is explored.

# 6 Results

## 6.1 Posterior Probabilities

In figure 3 and 4, it can be observed the average posterior beliefs of the participants in Section 1 of the experiment for the HP and CP conditions, respectively. Each line corresponds to a particular prior and if the posterior is their own strategy or the prediction of another participant's strategy. With a circle shape for each point, the Bayesian benchmark is included in the graph for comparison. A different color (red, green, and blue) is used to differentiate the priors in each posterior belief (20%, 50%,

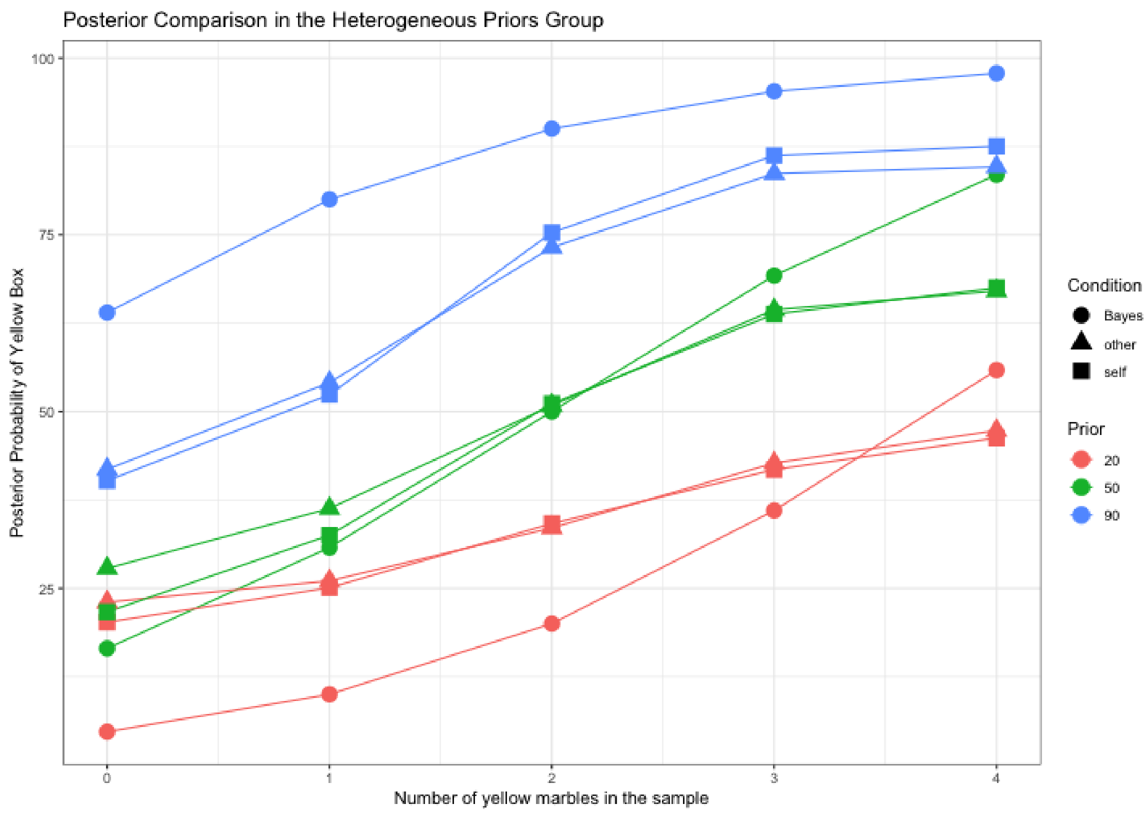



Figure 3. Mean of Posterior Beliefs in the HP condition.

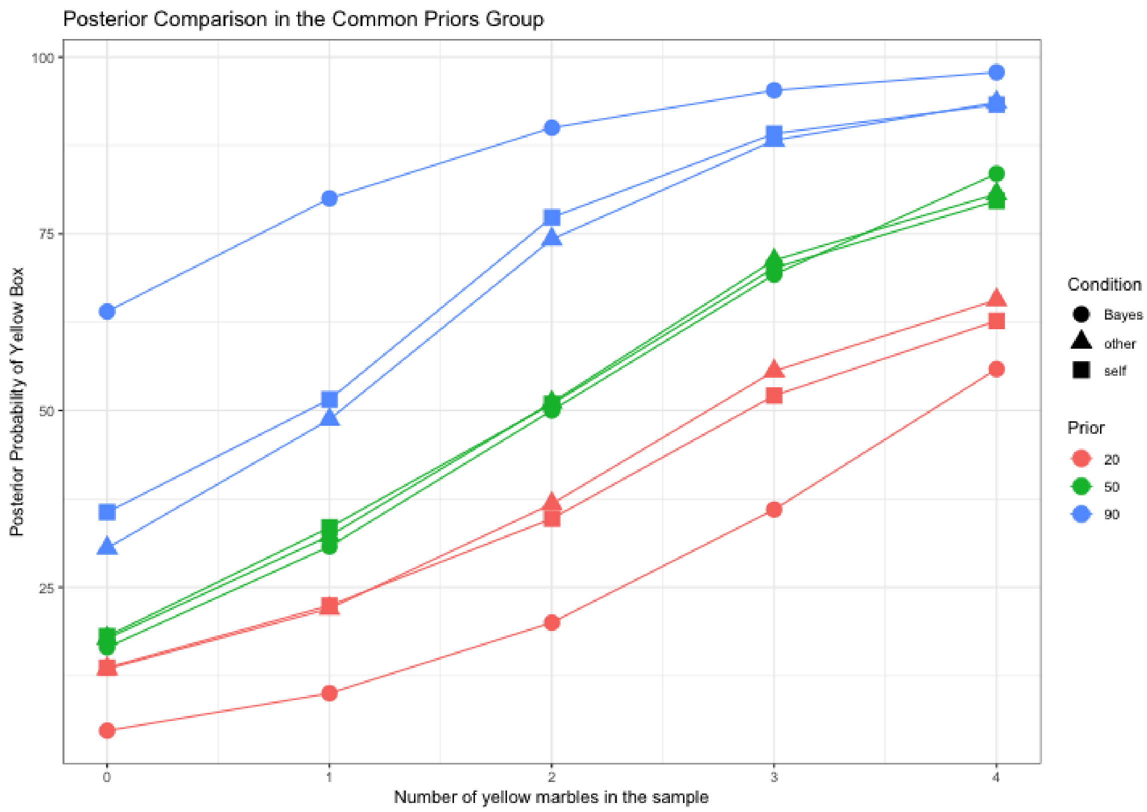



Figure 4. Mean of Posterior Beliefs in the CP condition.

or 90%, respectively). The relative position of the posteriors is predicted according to Grether's model with the estimations from Benjamin (2019) (figure 7).

Considering a prior of 90% and 50%, participants have posteriors closer to 50% relative to the Bayes rule for all signal levels (the number of yellow marbles in the sample) except for the non-informative signal of two yellow marbles in the sample. The same patterns follow with the 10% prior except for the sample with four yellow marbles. In this case, participants are over-inferring on average. This is consistent with the model's predictions based on estimations from previous studies.

The squares and triangles denote the posterior beliefs when they report their own beliefs or the beliefs of another participant. There is no important difference between these two conditions, which means that people, on average, estimate that others will behave like themselves.

When participants have to predict the behavior of another participant with the same prior, they predict others to be like themselves. However, when they have different priors, they predict, on average, the same behavior but with a larger variance. This can be observed in the box plot of the differences between first and second-order posteriors. Figure 5 and 6 show these differences for the HP and CP conditions, respectively. In the HP case, it seems that distances do not depend on the information conditions. Except for the non-informative signal of two yellow marbles and the uniform prior of 50%, where most people predicted a posterior of 50% for the other participant, which was their strategy as well. In the CP case, the vast majority of differences were zero, which means that people expect others to behave exactly like themselves. This exploratory analysis with box plots is useful, but a more specific regression to test this hypothesis was run as well.

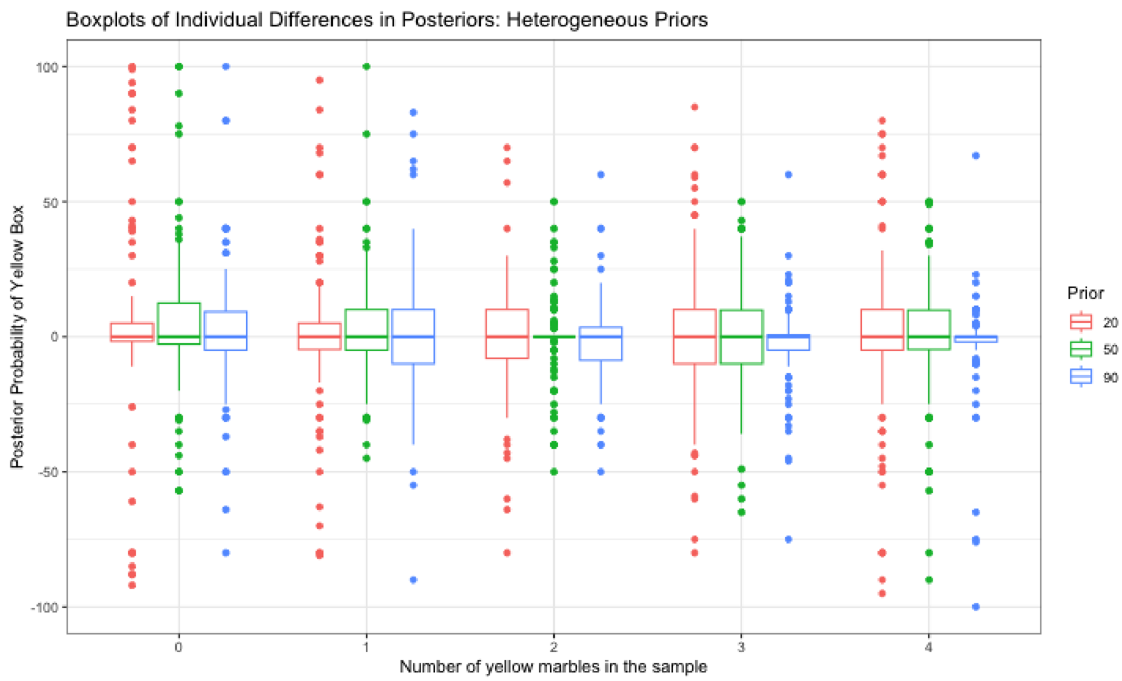



Figure 5. Boxplots of the differences between the posterior probability reported and predicted for another participant in the HP condition. These participants didn't face the same prior at the same time, but since they were asked about their strategies and others in different combinations of priors, the first and second-order beliefs can be compared directly.

The regression in table 2 shows no systematic effect on the differences between $P_i(Y|s)$ and $P_{-i}Y|s)$. For this regression, the answers were clustered at the participant level.

There is no effect on the posterior belief that this was for themselves or an expectation. The coefficient associated with the dummy variable for the prior condition (CP=1) is not significantly different from zero. This regression doesn't test if there was a difference between first and second-order posterior beliefs, but only if that

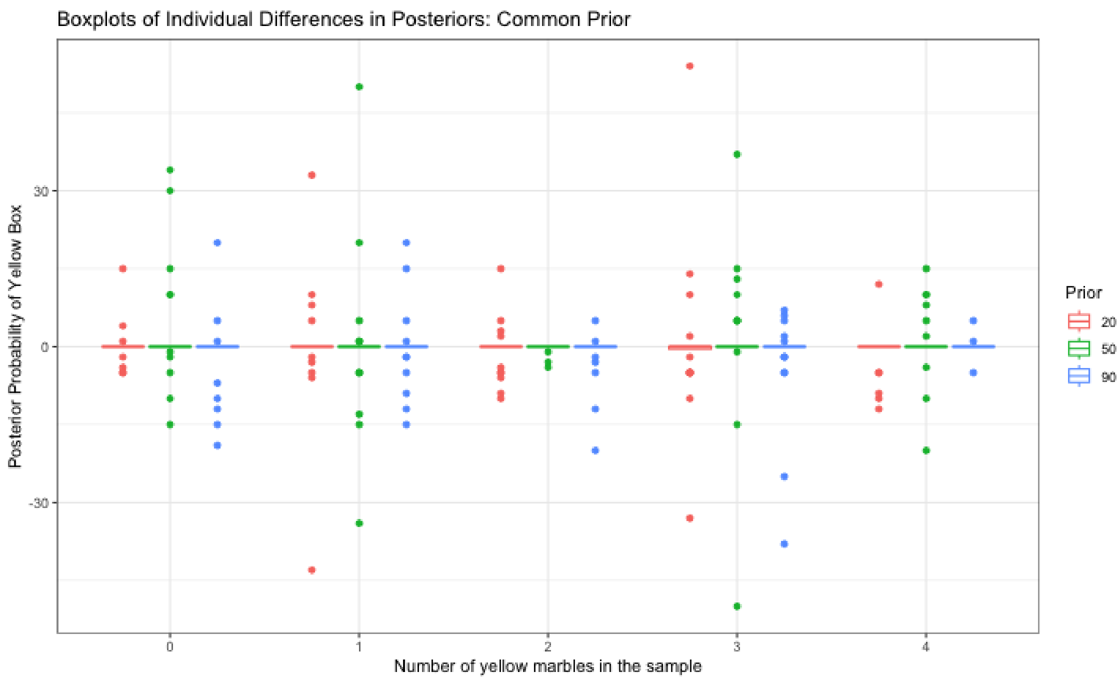



Figure 6. Boxplots of the differences between the posterior probability reported and predicted for another participant in the CP condition. They were asked for their posterior belief and that of another participant with exactly the same prior simultaneously.

difference is constant across information conditions. It is still possible that the differences in the first- and second-order beliefs follow a pattern for different priors and signals. The comparison between values of the estimated coefficients of model 2 are compared in the next section to analyze this.

Regression in table 3 takes the absolute difference as the dependent variable. For this regression, the answers were clustered at the participant level. The absolute difference $|P_i(Y|s) - P_{-i}Y|s)|$ is smaller in the CP condition.

Table 2. Regression on the Strategies Reported. This regression was clustered at the participant level.

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| Constant | 3.883 | 1.698 | 2.288 | 0.022 |
| Own Strategy | -0.528 | 0.588 | -0.898 | 0.369 |
| CP | 3.513 | 2.076 | 1.692 | 0.091 |
| Prior | 0.485 | 0.030 | 16.266 | 0 |
| No. yellow marbles | 10.301 | 0.669 | 15.399 | 0 |

Table 3. Regression on the Absolute Value of the Differences in Posterior Probabilities. This regression was clustered at the participant level.

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| Constant | 19.447 | 1.905 | 10.210 | 0 |
| CP | -11.486 | 1.236 | -9.290 | 0 |
| Prior | -0.078 | 0.019 | -4.046 | 0.0001 |
| No. yellow marbles | -0.578 | 0.283 | -2.047 | 0.041 |

### 6.2 Grether's Model

To analyze biases in higher-order belief updating, I use the logistic regression model used in the original Grether (1980) paper. I will change the notation of the model to capture the deviations from Bayes between first and second-order beliefs. The reported probability by $i$ about the expected posterior probability of $j \neq i$ is denoted by $\tilde{P}_{-i}(Y|S)$. The model for belief updating is:

$$\tilde{P}_i(Y|S) = \frac{(P_i(S|Y))^{\beta_i^l}(P_i(Y))^{\beta_i^p}}{(P_i(S|Y))^{\beta_i^l}(P_i(Y))^{\beta_i^p} + (P_i(S|G))^{\beta_i^l}(P_i(G))^{\beta_i^p}} \tag{1}$$

However, to abstract from the denominator and easily estimate the parameters in a regression, the logarithmic transformation of the posteriors is considered:

$$\frac{\tilde{P}_i(Y|S)}{\tilde{P}_i(G|S)} = \left(\frac{P_i(S|Y)}{P_i(S|G)}\right)^{\beta_i^l}\left(\frac{P_i(Y)}{P_i(G)}\right)^{\beta_i^p}$$

$$log\left(\frac{\tilde{P}_i(Y|S)}{\tilde{P}_i(G|S)}\right) = \beta_i^l log\left(\frac{P_i(S|Y)}{P_i(S|G)}\right) + \beta_i^p\left(\frac{P_i(Y)}{P_i(G)}\right)$$

The expected probability of player $i$ with respect to player $j$ is $\tilde{P}_{-i}$. When referring to first-order beliefs of $i$ the notation will be $\tilde{P}_i(B|S)$, $P_i(B)$ and $P_i(S|B)$, $B \in \{Y, G\}$. The model to adjust to the data is, therefore:

$$log\left(\frac{\tilde{P}_i(Y|S)}{\tilde{P}_i(G|S)}\right) = \beta_i^l log\left(\frac{P(S|Y)}{P(S|G)}\right) + \beta_i^p log\left(\frac{P_i(Y)}{P_i(G)}\right) \tag{2}$$

The parameter $\beta_{-i}^p$ measures the weight given to the prior probability assigned to $j \neq i$ when $i$ has to report $\tilde{P}_{-i}(Y|S)$, and $\beta_{-i}^l$ the weight given to the likelihood. Benjamin (2019) found that the parameters $\beta_i^p$ and $\beta_i^l$ (first-order beliefs) are affected by the sample size and if the information was presented simultaneously or sequentially. The present methodology implements a simultaneous and constant (N=4) sample. The estimation of both parameters will happen simultaneously.[14]

To answer the research question, it is necessary to test if $\beta_{-i}^p = \beta_i^p$ and $\beta_{-i}^l = \beta_i^l$. This corresponds with the parameters estimated in the CP and HP treatments. Figure 7 shows the estimated posterior ratios according to the model in equation 2 and the

[14] Benjamin (2019) first estimated the parameter $\beta^l$ as a function of sample size and the timing of the information and used those estimations to estimate $\beta^p$ so there was no bias since $\beta^l$ is not constant. Here, the sample has a constant size and is simultaneous, and $(\beta^l, \beta^p)$ will be estimated at the same time.

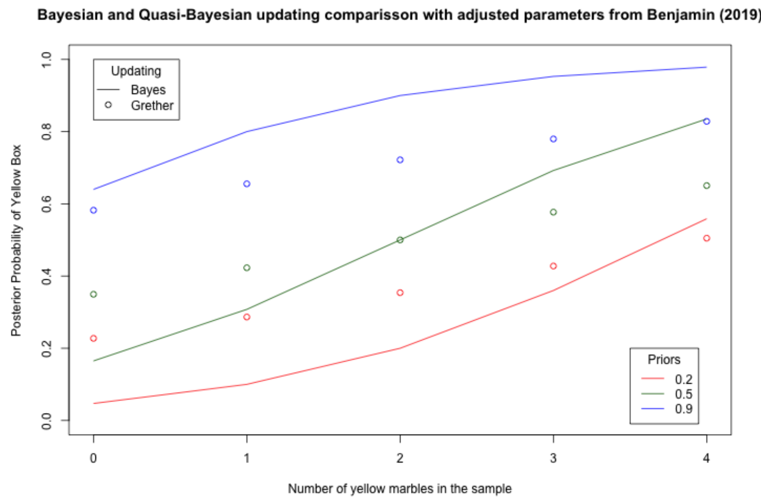



Figure 7. Posterior distribution as a function of the signal and the priors according to Grether's quasi-Bayesian model (equation 1). The parameters $\beta_i^l = 0.383$ and $\beta_i^p = 0.434$ where taken from Benjamin (2019)'s regressions for the simultaneous and incentivized experiments. These parameters, and the likelihoods and priors used in the experiments, were used to plot the dots.

parameters used in the present methodology ($\theta = 0.60$, $N = 4$). In the figure, the expected posterior for a Bayesian agent and the adjusted parameters in Benjamin (2019) for simultaneous and incentivized experiments ($\beta_i^l = 0.383$, $\beta_i^p = 0.434$ ) are shown.

### 6.2.1 Grether's Model Estimations

The regressions in table 4 evaluate if there is a systematic difference between the parameters in the quasi-Bayesian model (equation 2) for the CP and HP condition and if it was their strategy $P_i(Y|s)$ or the expected strategy for another participant $P_{-i}Y|s)$. All the parameters show a deviation from Bayes all of them are statistically different to 1. Participants have conservatism and base rate neglect. It is also apparent that the differences between the parameters for $P_i(Y|s)$ and $P_{-i}(Y|s)$ are not important.

The values of the parameters estimated in this experiment are consistent with the results from Benjamin (2019). In this case, it was not necessary to estimate $\beta^l$ first since the sample size and information provision were constant (Benjamin (2019) found that these conditions affected the value of the parameters.). Both parameters were estimated simultaneously. Also, the condition with prior 50% was evaluated for each participant, which allows for a better estimation of $\beta^l$.

Table 4. Grether's Model Regressions in the Experimental Conditions.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Log_posterior | | | |
| | Other CP | Other HP | Own CP | Own HP |
| | (1) | (2) | (3) | (4) |
| $\beta^p$ | 0.672*** | 0.586*** | 0.697*** | 0.660*** |
| | (0.085) | (0.044) | (0.085) | (0.043) |
| $\beta^l$ | 0.698*** | 0.537*** | 0.674*** | 0.621*** |
| | (0.070) | (0.037) | (0.071) | (0.036) |
| Constant | −1.144*** | −1.072*** | −1.114*** | −1.302*** |
| | (0.179) | (0.093) | (0.180) | (0.091) |
| Observations | 480 | 1,650 | 480 | 1,650 |
| Adjusted $R^2$ | 0.250 | 0.191 | 0.246 | 0.246 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 | | |

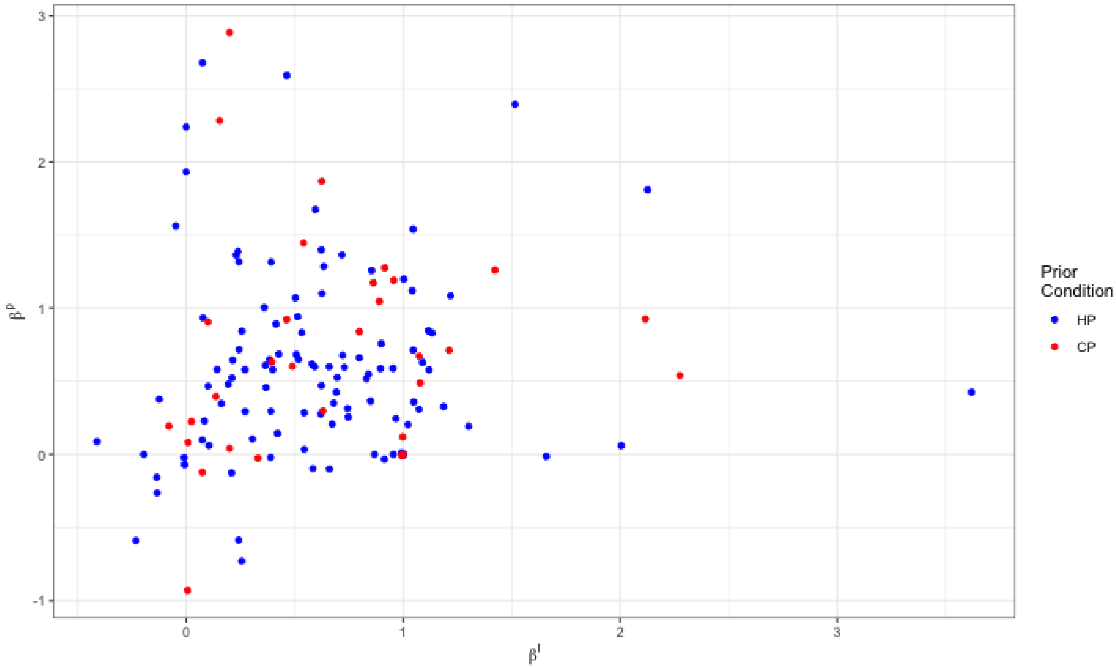



Figure 8. Grether's model calculated at the individual level. The conditions were Common (CP) or Heterogeneous Prior (HP).

#### 6.2.2 Individual Analysis

The previous aggregate analysis calculates the parameters as if they were the same for all participants. This is useful to have an idea of the average behavior. However, there could be heterogeneity in the biases that participants have. The regression in equation 2 was run for each participant to know the biases they have. Figure 8 plots the coefficients for each participant. The correlation between the coefficients was 0.05 and non-statistically significant. Therefore, we cannot classify people in one dimension with different degrees of Bayesian.[15] If the correlation were positive, it could be possible to classify people by their level of Bayesianism: they have high or low $\beta$'s. If the correlation were negative, it could be possible to classify people as conservative or BRN. However, the heterogeneity of the biases seems uniformly distributed in the unitary square. The parameters of participants in CP or HP conditions are also differentiated in figure 8 with no clear distinction between them.

[15]This is relevant when analyzing other models, like Epstein's, where the biases are one dimension deviation from the Bayes rule.

The coefficients of Grether's model were also calculated conditioned on the strategy being their own or another participant's ($\beta_i$ and $\beta_{-i}$). These correlations only include the HP condition since in the CP condition, the expectation of others answering in the same way is very strong, as seen in figure 6. [16]

Consistent with the previous analysis, the correlations were positive and significant between $\beta_i^p$ and $\beta_{-i}^p$ (0.52), and between $\beta_i^l$ and $\beta_{-i}^l$ (0.80). Also, the correlation was not significant between $\beta^p$ and $\beta^l$ independently if they are for first or second-order. These correlations were less than 0.06, far from zero, except for the correlation between $\beta_i^p$ and $\beta_i^l$ which was 0.11 but not significantly different from zero.

The correlations show a positive relationship between the biases that participants displayed and what they predicted for others. They also show a low correlation between BRN and Conservatism, which means that there is no evidence of people having a stronger BRN bias and also having a larger (or smaller) level of conservatism. The correlations inform us about the linear relationship, but analyzing the differences between the parameters can tell us if people expect others to be more biased.

Participants in this experiment might exhibit bias blind spotting (Pronin et al., 2002). This means that the biases calculated for others ($\beta_{-i}$) is larger than for themselves ($|1-\beta_i| < |1-\beta_{-i}|$). The hypothesis $\beta_i > \beta_{-i}$ can be considered since participants were generally downwards biased ($\beta_i < 1$). No significant difference was found between $\beta_i^l$ and $\beta_{-i}^l$, nor between $\beta_i^p$ and $\beta_{-i}^p$ in the CP condition, neither between $\beta_i^p$ and $\beta_{-i}^p$ in the HP condition. However, a significant difference of 0.0836 between $\beta_i^l$ and $\beta_{-i}^l$ was found with a paired t-test (p-value = 0.0212) in the HP condition. The mean for $\beta_i^l$ is larger than $\beta_{-i}^l$, consistent with a larger bias expected from others in the weight given to the likelihood of the signals.

The previous analysis of the individual parameters indicates that people expect others to be more prone to conservatism than themselves. Also, there is no relationship between BRN and Conservatism.

#### 6.2.3 Treatment Effects on $\beta$

### 6.3 WTP

Participants have a different WTP when the decision is made by themselves or by others. They are more willing to pay when the strategy implemented is theirs instead

[16] When the CP condition is included, the correlations between first and second-order beliefs are larger, and no significant correlation is found among the other coefficients. These results are included in the Appendix 8.

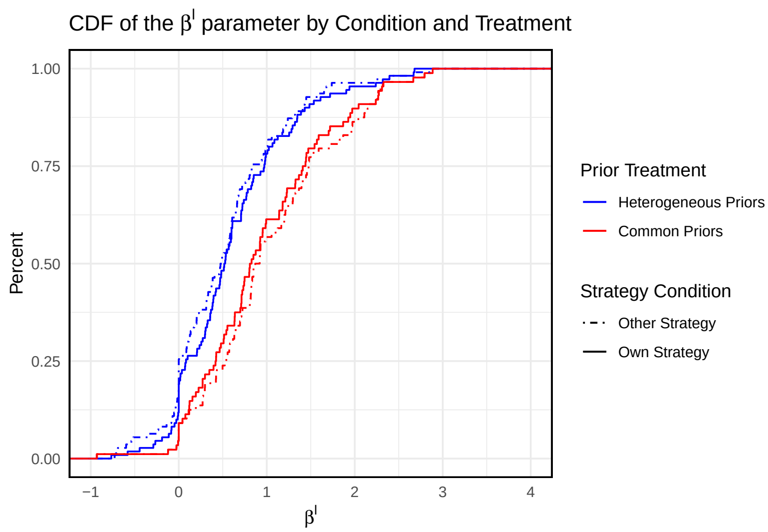



Figure 9. Distribution of $\beta^l$ by treatment and strategy condition.

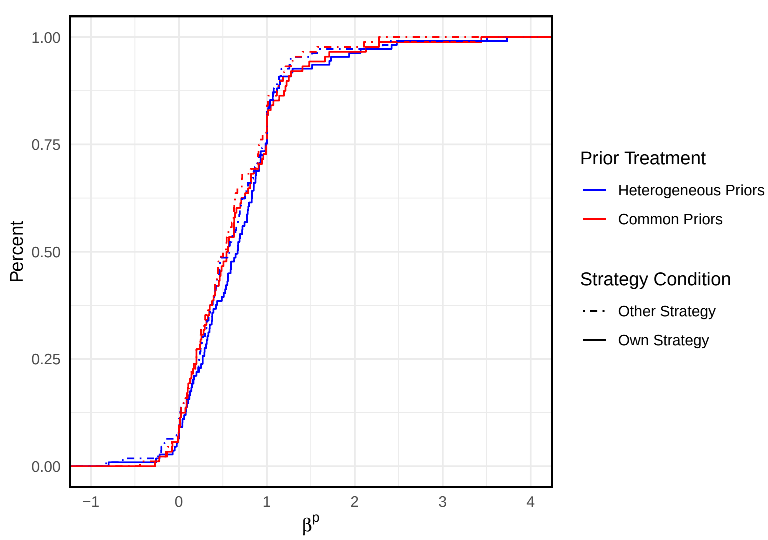



Figure 10. Distribution of $\beta^p$ by treatment and strategy condition.

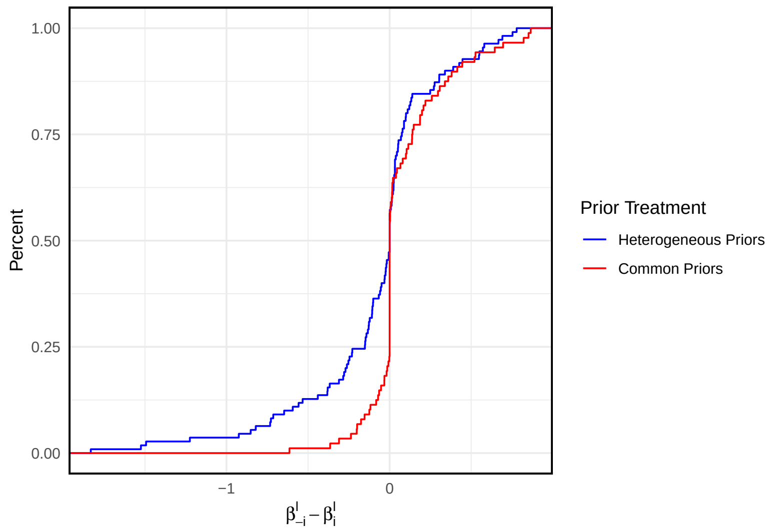



Figure 11. Differences $\beta^l$ by prior treatment. A negative number means that the participant expected a smaller weight of the signal for the other participants relative to themselves. $\beta^l_{-i}$ represents expected bias from others, $\beta^l_i$ self-bias.

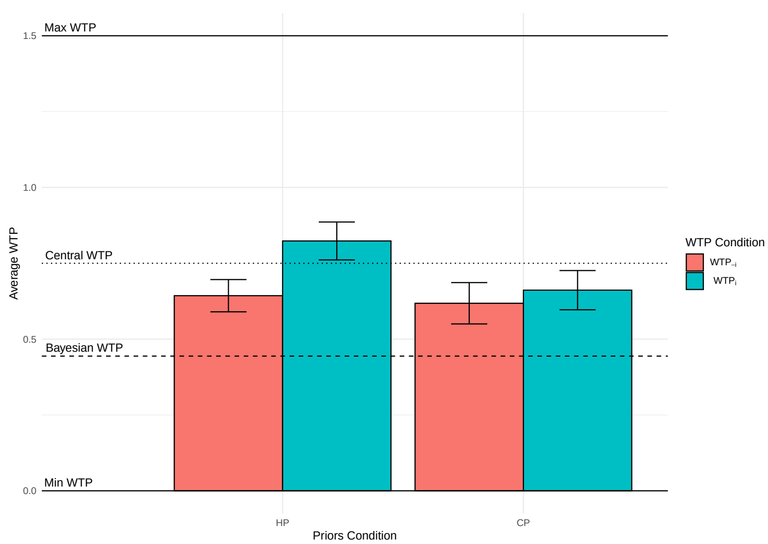



Figure 12. Average WTP by treatment.

of when the strategy implemented is by another participant. It is important to remember that they are not making the decision again; they are told that the strategies they reported in Section 1 will be implemented. In table **??**, it can be seen that the effect of implementing their own strategies is significant.

One of the hypotheses was that people who consider others to update like them would have $w_i \approx w_{-i}$. More analysis of individual differences is needed to check if individual differences can explain the WTP.

It is interesting to see that the value of the parameters estimated at the individual level is significant. The direction of those effects is also in line with the bias they measure. On one hand, a larger $\beta^p$ parameter means that participants put more weight on the priors (e.g., they BRN less). With more weight in the prior, the relative importance of new information in the posterior diminishes. This is consistent with the negative value estimated in the regression. On the other hand, a larger $\beta^l$ parameter means that participants put more weight on the likelihood of the signal (e.g., they are less conservative). With more weight in the signals, the relative importance of new information in the posterior increases. This is consistent with the positive value estimated in the regression.

In the regression in table **??**, the individual coefficients were calculated without distinguishing the higher-order beliefs. The coefficients $\beta_i^p$ and $\beta_{-i}^p$ were not significant in a separate regression. This could be related to the fact that even when they are statistically different, the correlation between them is high. A more detailed analysis of the effects of those variables is necessary.

Table 5. Regression on the WTP to apply the corresponding strategy in section 1.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | WTP | | | |
| | Own Strategy | Other Strategy | Own Strategy | Other Strategy |
| | (1) | (2) | (3) | (4) |
| $\beta_i^p$ | $-0.057$ | | | $-0.133^{*}$ |
| | (0.088) | | | (0.070) |
| $\beta_i^l$ | $0.140^{**}$ | | | 0.091 |
| | (0.059) | | | (0.063) |
| $\beta_{-i}^p$ | | $-0.104$ | $-0.137$ | |
| | | (0.076) | (0.101) | |
| $\beta_{-i}^l$ | | 0.064 | 0.081 | |
| | | (0.059) | (0.058) | |
| Constant | $0.656^{***}$ | $0.651^{***}$ | $0.747^{***}$ | $0.664^{***}$ |
| | (0.086) | (0.073) | (0.087) | (0.072) |
| Observations | 95 | 95 | 95 | 95 |
| Adjusted $R^2$ | 0.044 | 0.008 | 0.027 | 0.029 |
| *Note:* | | | | $^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01 |

Table 6. Regression on the WTP to apply the corresponding strategy in section 1.

| | *Dependent variable:* | | |
|---|---|---|---|
| | WTP | | |
| | Own Strategy | Other Strategy | Other Strategy (other wrong) |
| | (1) | (2) | (3) |
| CP condition | $-0.210^{**}$ | $-0.005$ | $-0.204$ |
| | (0.089) | (0.101) | (0.252) |
| CRT better | 0.027 | 0.049 | $-0.256$ |
| | (0.095) | (0.101) | (0.330) |
| CRT | 0.013 | $-0.072^{*}$ | $-0.016$ |
| | (0.041) | (0.041) | (0.118) |
| $\tilde{V}$ | $0.593^{***}$ | 0.269 | |
| | (0.197) | (0.232) | |
| $\tilde{V}_{wrong}$ | | | $-0.431$ |
| | | | (0.792) |
| Constant | $0.593^{***}$ | $0.651^{***}$ | $0.807^{***}$ |
| | (0.119) | (0.111) | (0.204) |
| Observations | 95 | 81 | 14 |
| Adjusted $R^2$ | 0.085 | 0.014 | $-0.180$ |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

### 6.4 CRT

The CRT test is implemented to measure relative self-reported performance. It was expected to observe that considering themselves as more intelligent than others affects the WTP for information. To avoid the experimenter's demand effects, the WTP was conducted in a between-subjects design, and the effect of the CRT can only be measured at the group level and not the differences between the $WTP_i$ and $WTP_{-i}$ at the individual level.

A 45% of the participants considered that their performance in the CRT was better than the others. The average difference between the real CRT score and what they expected for themselves was $-1.06$. This difference was statistically significant.

From the first and second regressions in table **??**, it seems that neither the relative CRT (if they expected to do better than the participant they were paired with) nor the performance in the test has an effect on the WTP for information.

## 7 Discussion

On average, people expect others to update in the same way they do. The dummy variable for participants' strategy or the expected strategy of others had no significant effect on the reported posterior belief. Also, the parameters estimated to Grether's model for first and second-order were correlated. This relationship is stronger for $\beta^l$ than for $\beta^p$, and no significant correlation is found between $\beta_i$ and $\beta_{-i}$. The only significant differences were between $\beta_i^l$ and $\beta_{-i}^l$ in the HP condition. With the present experiment settings, having different priors generates a difference only in the higher beliefs about the weight on the signal ($\beta_i^l > \beta_{-i}^l$). In general, no systematic effect of higher-order beliefs was found. However, having different priors affects the weight expected that others put on the signal; participants expected others to be more conservative.

Previous results showed no difference or weak difference between the higher-order beliefs with new information (Evdokimov and Garfagnini, 2022). However, having different prior (HP condition) increases the absolute difference between the posterior beliefs and an expectation of others being more conservative. People expect others to update similarly to themselves, and they have a significantly lower WTP when it is the strategy of others that is implemented. This can be explained because of a higher expectation of conservatism in others than in themselves, but the extent of how well this can be explained needs more attention.

Another interesting result is that participants' biases can predict the WTP to acquire information in the direction predicted by Grether's model. That means that this difference between the provision of information to others to update their beliefs is less when the biases are larger. It is relevant to mention that $\beta^p$ had a significant effect since the problem in the WTP task had a uniform distribution of the prior, in which case the level of base rate neglect is irrelevant. This phenomenon requires more attention, but it might be the case that $\beta^p$ correlates with other variables that affect the WTP for themselves.

Optimal provision of information is relevant in a context where the knowledge of the world is not perfect, and we can put some effort into finding information to make better decisions. This is the case in many settings since we don't know the world perfectly. Information provision is more relevant when the decisions of others affect our outcomes. If the incentives are aligned, it is in the agent's best interest to improve the decision of other participants. This experiment shows that the provision of information to others is hampered by people's biases.

This study analyzes the effects of predicting the updating of someone who has a different prior (HP condition). However, to identify a difference more clearly, another session with participants only being asked for their expectations of another participant can be informative. This is a between-subject design for the higher-order posteriors.

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appendix

section Appendix: Payoff Calculations Detailed (Section 1)

In every task, the computer will select a Box, generate a sample of 4 marbles, and implement your guess about the probability of the Yellow Box selected (p) to calculate your payoffs. An independent Box and sample will be selected for Participant 2, who chooses the strategy q. Remember you also have to report your guess about q, and let's call it r. These two guesses you make (p and r) determine the probability of making up to $3 in each task:

1. Guess on the box selected by the computer: p (your report divided by 100)

   For every possible sample, indicate a probability p between 0 and 1 that you believe the Yellow box was selected. If the computer selects the Yellow Box, you will make $1.50 with probability (1 - (1-p)2). If the computer selects the Green Box, you will make $1.50 with probability (1- p2). This is also shown below:

   | **Selected Box** | **Probability of winning** |
   |---|---|
   | Yellow Box | 1 - $(1-p)^2$ |
   | Green Box | 1- $p^2$ |

   Here are some examples of how the payment works:

   - If you think that the Yellow box was selected for sure, choosing p=1 gives your best chance of making $1.50. This happens because the probability of winning would be $1-(1-1)^2 = 1$, or 100%. Choosing any other number will decrease your chances of winning. For example, if you chose p = 0.5, the probability of winning would be $1-(1-0.5)^2 = 1–(0.5)^2 = 1-0.25 = 0.75$, or 75%; if you chose p = 0, the probability of winning would be $1-(1-0)^2 = 1–1 = 0$, or 0%.
   - Similarly, if you think that the Green box was selected for sure, choosing p=0 gives your best chance of winning; the probability of winning would be $1-(0)^2 = 1$, or 100%. If you chose p = 0.5, the probability of winning would be $1-(0.5)^2 = 1–0.25 = 0.75$, or 75%; if you chose p = 1, the probability of winning would be $1-(1)^2 = 1–1 = 0$, or 0%.
   - If you believe that the Yellow box was selected with a 50% chance, choosing p=0.5 gives your best chance of making $1.50; the chance of winning would be the average between the probabilities of winning given each box: $0.50*(1-(1-0.5)^2)+0.50*(1-(0.5)^2) = 0.50*(1-0.5^2)+0.50*(1-0.5^2) = 0.50*$

$0.75+0.50*0.75 = 0.75$, or 75%. Choosing any other number will decrease your chances. For example, if you chose p = 1, the probability of winning would be: $0.50*(1-(1-1)^2)+0.50*(1-(1)^2) = 0.50*(1)+0.50*(0) = 0.50$, or 50%. Similarly, if you chose p = 0, the probability of winning would be $0.50*(0)+0.50*(1) = 0.5$, or 50%.

Any number different from your belief that Yellow Box was selected will decrease your chances of winning.

2. Guess on Participant 2's guess: r (your report divided by 100)

Participant 2 will also bet on the probability that a Yellow box was selected for them by reporting the number q. You will indicate a probability r between 0 and 1, which is your guess for q. You will make $1.5 with probability:

$$(1-(q-r)^2)$$

You would wish to choose r to be as close as possible to q. Participant 2 will have the same payment scheme as you do in your first guess above. Here are some examples of how the payment works:

- If you think that Participant 2 guessed the Yellow box was selected for sure(q=1), choosing r=1 maximizes your chances of making $1.50. The probability of winning would be $1-(1-1)^2 = 1$, or 100%. Choosing any other number will decrease your chances of winning. For example, if you chose r = 0.5, the probability of winning would be $1-(1-0.5)^2 = 1-0.52 = 0.75$, or 75%; if you chose r = 0, the probability of winning would be $1–(1-0)^2 = 0$, or 0%.
- If you think that Participant 2 guessed the Yellow box was selected with a 50% probability (q=0.5), choosing r=0.5 maximizes your chances of making $1.50. The probability of winning would be $1-(0.5–0.5)^2 = 1–0 = 1$, or 100%. Choosing any other number will decrease your chances. For example, if you chose r = 1, the probability of winning would be $(1-(0.5-1)^2) = 1-0.25 = 0.75$ or 75%; if you chose r = 0, the probability of winning would be $(1-(0.5-0)^2) = 1–0.25 = 75\%$.

Any number different from your belief about Participant 2's strategy will decrease your chances of winning.

These bets were designed such that truthfully reporting your beliefs maximizes your chances of getting up to $9 in this section. Be as accurate as possible, and carefully consider the probability of the Yellow Box selected given each sample and what Participant 2 would choose.

section Appendix: Payoff Calculations Detailed (Section 2)

The computer will select the Yellow or Green Box with the same probability: 50%. That means that a random Box will be selected from Cabinet 2:

In this section, you and Participant 2 will be paid \$3 if the decision about the box selected by the computer is correct. The strategies in Section 1 will determine the decision to make considering a sample generated from the selected box:

- If the probability reported was more than 50% for the Yellow Box, the decision will be to choose the Yellow Box.
- If the probability reported was less than 50% for the Yellow Box, the decision will be to choose the Green Box.
- If the probability reported was equal to 50% for the Yellow Box, the computer will randomly choose one box for you.

Willingness to Pay to Apply Participant 2's Strategy

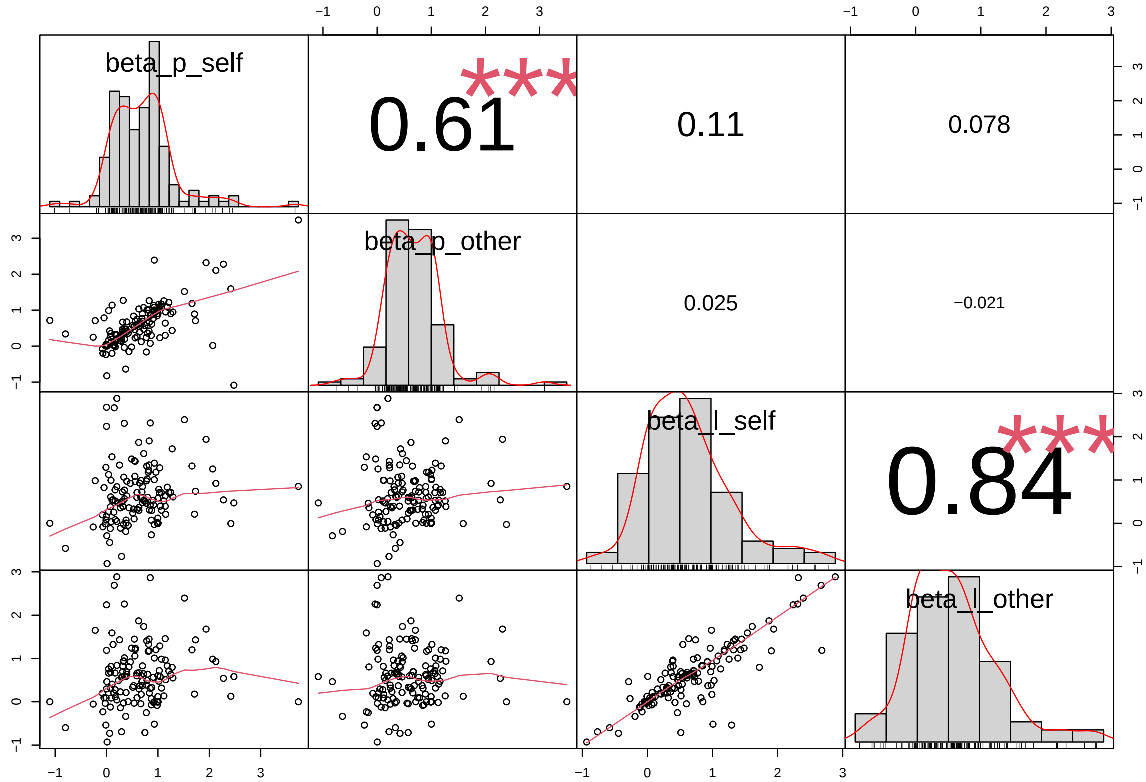
The computer will select the Yellow Box with a 50% probability and generate a sample of 4 marbles. However, in this section, you will not observe the sample for free. You have to decide how much you are willing to pay so that Participant 2's strategy reported in Section 1 can be applied to the sample generated from the Selected Box. Notice that a sample can be informative of the actual box selected.

How is your purchase determined? You will participate in an auction against the computer to purchase the right to observe the sample generated. You have to make a bet that represents your willingness to pay.

An amount of \$X between \$0.00 and \$1.50 will be randomly chosen by the computer. \$X can take any value between \$0.00 and \$1.50 with the same probability. Then two cases can occur concerning your bet:

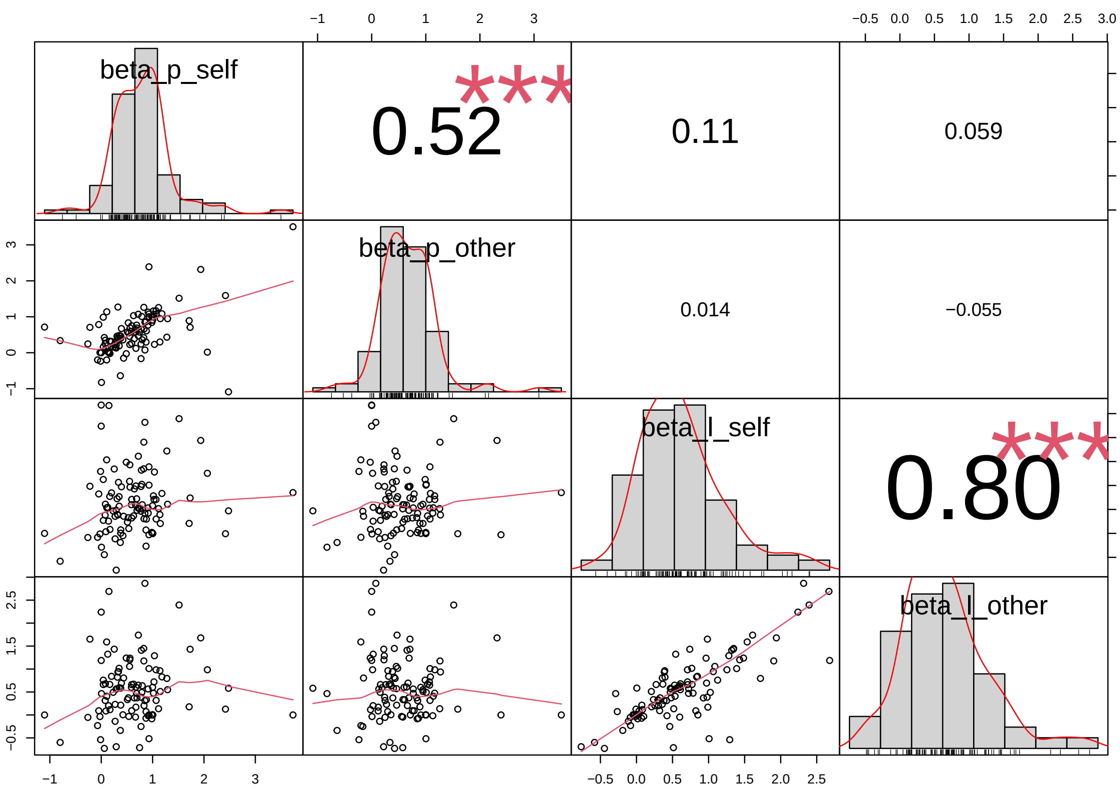
If your willingness to pay is larger or equal to \$X, you will pay \$X to observe the sample. Notice that \$X cannot be larger than your bet in this case. If your willingness to pay is smaller than \$X, you pay nothing, and no sample is shown. Notice that if the sample does not increase your chances of selecting the correct box and making \$3, you should bet \$0.00. And if the sample increases your chances, you should increase your bet. You will increase your expected payoffs if you report how much extra money you expect to make if Participant 2's strategy in Section 1 is applied to the sample observed.

Remember that you and Participant 2 will be paid \$3 if Participant 2's decision about the box selected by the computer is correct.




Appendix Figure C1. correlation of the coefficients from Grether's model estimated individually. This includes HP and CP groups.

# 8 Appendix: Individual Coefficients




Appendix Figure C2. correlation of the coefficients from Grether's model estimated individually. This includes only the HP.