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Competition in Persuasion: An Experiment ⋆

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Abstract

We experimentally investigate a classic question, whether competition stimulates information revelation, by comparing two Bayesian persuasion models. One model has one sender (Kamenica and Gentzkow, 2011) and the other has two competing senders who reveal information sequentially and publicly (Wu, 2020). The first treatment provides strong support for Kamenica and Gentzkow (2011), where the sender uses a noisy signaling device and the receiver complies with his suggestions. In the second treatment, we find that: (1) senders reveal more information in total than the sender in the first treatment; (2) the first sender reduces the use of the noisy signaling device as compared to the sender in the first treatment; (3) the second sender exhibits a "matching" behavior pattern; (4) the receiver can make use of information from both sides and she receives higher payoffs than in the first treatment. However, our experiment also documents deviations from the theory. Competition does not improve information revelation to the extent of full information. To rationalize the behavior, we use the Quantal Response Equilibrium model to explain the features of the empirical results in our experiment.

JEL Classification: C72, C92, D83

Keywords: Bayesian Persuasion, Multiple Senders, Laboratory Experiment, Quantal Response Equilibrium

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1. Introduction

Competition among persuaders can improve information revelation in many environments. In the judicial system, a judge can know more about the case by listening to arguments between a prosecutor and a defense attorney. In politics, the president usually has advisers who hold opposing positions debating the implications of certain policies before decisions are made. In the repair of a car, the car owner would have more precise information about the condition of the car by referring to multiple mechanics. In health care, a patient can have better understanding of various diagnoses of her symptoms and receive adequate treatment by visiting more than one physician.

In these examples, a decision maker lacks knowledge of the situation, so she has to ask persuaders for advice. The persuaders do not know the true situation, but they can learn about it in many ways. We focus on a case in which persuaders can influence the learning process but cannot misrepresent what they learn. Specifically, this paper builds on a recent communication model, Bayesian persuasion (Kamenica and Gentzkow, 2011), in which a persuader (sender) is able to affect how information is generated for a decision maker (receiver).

When a sender is biased, a problem arises when he may distort the information channels in order to mislead the receiver. One solution to this information loss is for the receiver to refer to a pair of senders who have zero-sum utilities (Wu, 2020). In this way, the sender who attempts to be vague will easily be countered by the competitor and will receive a lower expected payoff. Hence, under this pressure, it is the best for him to disclose all information. This intuitive idea embodies the spirit of adversarial systems and has been supported in theoretical models (Gentzkow and Kamenica, 2017a,b; Wu, 2020). However, there has been a lack of empirical examination of this result due to intangibility of information and invisibility of interested parties' moves. To empirically investigate this problem, we bring it to the laboratory and study subjects' strategic moves under complex information environments.

There are two treatments in the experiment. Treatment 1 (one-sender treatment) is based on the canonical persuasion model as described in Kamenica and Gentzkow (2011). The one-sender treatment is composed of one sender (S) and one receiver (R). R has a task of guessing the color (blue or red) of an unknown ball. S can use certain signaling devices, which automatically send signals related to the true color, to provide R with recommendations. R observes the device and signal and then makes a guess. R intends to make the correct guess, while S only wants R to guess red. The equilibrium predicts that S will use a biased device that sends a signal of red more frequently. Treatment 2 (two-sender treatment) is based on a Bayesian persuasion game (Wu, 2020) that consists of two senders, S1 and S2, both of whom can use signaling devices. However, the senders have zero-sum utilities: S1 wants R to guess red and S2 wants R to guess blue. The addition of a competing sender prompts S1 to increase the precision of his signal because he knows that his advice may be challenged by S2. The more frequently he sends a signal he prefers, the less credibility he has, and the more possible it is that R will turn to S2's advice. Indeed, the unique equilibrium choice for S1 is full revelation. By comparing the one-sender and two-sender treatments, we can analyze the influence of competition on overall information revelation, strategic information acquisition, and decision making under various information environments.

The experimental setup yields a series of equilibrium predictions regarding information revelation and strategic behavior. First, we hypothesize that the information in the two-sender treatment should be more transparent than the one-sender treatment. Second, we expect that, in the one-sender treatment, S will use a noisy device that sends signals biased to his interest; yet, the bias is limited so that R still wants to follow his suggestions. Third, in the two-sender treatment, S1 is supposed to use the fully revealing (perfect) device. S2 is predicted to "match" S1's persuasion by using a device with the same precision level but biased in the opposite direction. R shall integrate two pieces of advice, sometimes even conflicting, to make the best decision.

The empirical findings confirm that the addition of another sender with zero-sum utility does significantly improve information revelation. We measure *informativeness* of a signal(s) by the probability that a receiver can make a correct guess given the signal(s). In the data, the informativeness of signals in the two-sender treatment is significantly higher than in the one-sender treatment, which supports our hypothesis. However, it is much lower than the fully revealing level. That means even the fiercest competition cannot totally prevent senders from withholding information. Furthermore, we have decomposed the influence of competition on information revelation into the effects of S1's behavior change and the addition of S2, and find that the increase in information mostly results from the addition of S2.

In the one-sender treatment, the subjects' behavior treatment is highly consistent with Kamenica and Gentzkow (2011): S strongly prefers the noisy device and R follows S's advice. But the messages from the two-sender treatment are mixed. On the one hand, the evidence from the two-sender treatment shows that S1 reduces the use of the noisy device, S2's behavior exhibits the "matching" pattern, and R is able to make right choices the vast majority of the time. One the other hand, there is still notable deviations from the theory — S1's choice of the perfect device is far from 100% and the noisy device is still his favorite choice. Thus, even under *potential* pressure from S2 to counteract him when he uses vague devices, S1 does not always choose to use the perfect device.

One explanation of the deviation is the following. The conformity of the first sender to the equilibrium strategy relies on that the second sender and receiver make the right choices to "punish" the first sender's non-equilibrium choices. However, both the second sender and the receiver deviate from the equilibrium predictions to some extent. We run regressions on the second sender's behavior and find that he would tend to reveal more information given that the first sender's information is more precise, but not necessarily the optimal amount of information. The receiver can choose the best response to the information *most of the time*, but not *always*. The deviations of subsequent players weaken the advantage of playing the equilibrium strategy for the first sender. In practice, the first sender actually receives equal payments from using the fully and partially revealing options in the two-sender treatment, which can explain his frequent use of the noisy detector and the substantial information loss for the receiver.

To account for the features of the data, we use the Quantal Response Equilibrium (QRE) model to further estimate. QRE is able to capture players' probabilistic choices when they miscalculate the posterior beliefs and expected payoffs under complex information environments. The estimation of the behavioral model fits the data well. In the one-sender treatment, QRE to a large degree explains the empirical distribution of players' strategies. In the two-sender treatment, the estimated distribution also qualitatively explains the behavioral pattern of all players conditional on different histories of the game. Specifically, the QRE model sheds light on how to understand the underuse of the perfect device by S1. Note that the benefit for S1 from using the noisy device relies on raising the probability of sending S1's favorable signal, whereas the cost is that it may be countered by S2's signal. When all players conform to the equilibrium strategies, the cost outweighs the benefit, which is why S1 is predicted to choose the perfect device. Nevertheless, when players make mistakes occasionally, two factors make the noisy device more desirable. First, since S2 does not always pick the best response, the probability that S1 gets effectively countered when he uses the noisy device is lower. Second, even when S1 uses the noisy device and S2 counters S1 with an opposite signal, R might not follow the suggestion from S2 as the theory predicts. Therefore, in the QRE model, the choice that gives S1 the highest expected payoff becomes the noisy device.

Because of a more complex environment, more subjects in the role of the first sender start to use uninformative detectors in the two-sender treatment. We define a sample excluding those who intentionally use this inferior option for robustness check. In Section 7.2, we analyze the comparative statics of S1's behavior and reevaluate the decomposition of the increase in informativeness with the selected sample. We also speculate about the possible changes in the theoretical results in two alternative settings, one in which two senders choose detectors *simultaneously*, and the other in which the second sender can only observe the device but not the realization.

The remainder of the paper is organized as below. In Section 2, we have a review of related literature. In Section 3, we lay out the experimental designs and theoretical hypotheses. In Section 4, we describe how we implemented our experiments. In Section 5, we present the empirical findings. In Section 6, we use QRE to explain the behavioral pattern. In Section 7, discuss in depth the deviations from theory and the alternative experimental settings. In Section 8, we conclude.

2. Literature Review

The literature on Bayesian persuasion theory starts from Kamenica and Gentzkow (2011), which is followed by a series of papers that study the case of multiple senders (Gentzkow and Kamenica, 2017a,b; Li and Norman, 2020; Wu, 2020; Au and Kawai, 2020). Kamenica and Gentzkow (2011) study a one-sender-one-receiver problem and show that by committing to an information structure, the sender can extract *maximal* benefits by manipulating the receiver's belief. Gentzkow and Kamenica (2017a,b) extend the analysis to the case of multiple senders with simultaneous moves and conclude that competition improves information transparency under certain scenarios. Wu (2020) investigates sequential persuasion and demonstrates that if there are two senders with *zero-sum* utilities, full information is supported as an equilibrium outcome. Indeed, the current experimental setup is a special case of Wu (2020) which possesses a sharp equilibrium prediction of a unique fully revealing equilibrium.

There are three current experiments that examine Bayesian persuasion. Nguyen (2017) designs an experiment that examines the one-sender-one-receiver problem in Kamenica and Gentzkow (2011). She shows that the experimental results are highly consistent with the theoretical predictions. The probabilities that senders use the predicted option and that receivers act optimally converge to above 60% and 90%, respectively. Au and Li (2018) combine Bayesian persuasion with reciprocity theory and show that the departure of data from the standard theory, that receivers' actions are not as responsive as predicted, can be explained by reciprocal concerns: receivers would view a sender as an unkind person if the sender does not provide enough information, and then they would like to punish the senders by disregarding their suggestions. Fréchette et al. (2020) examine a broader class of communication games, including Bayesian persuasion, cheap talk, and disclosure, in a unified framework. The question of interest is the overall influence of commitment and verifiability in communication. They find that receivers are responsive to senders' information, but their choices change continuously with the strength of signals, instead of being a step function of posterior beliefs.

The current experiment differs from the existing experiments in three aspects. First, we introduce multiple senders into play and explore the relationship between senders' conflicts of interest and their information revelation. Second, our experimental design is novel. On the one hand, we limit the choices for senders to simplify the setting for the subjects, with the concern that the experiment could be relatively challenging. On the other hand, unlike Nguyen (2017) and Au and Li (2018), we do not assist receivers in updating beliefs, so the subjects still need to update beliefs by themselves. Third, to the best of our knowledge, we are the first to use the QRE model to explain the behavioral patterns of subjects in an experiment on Bayesian persuasion.

Our experiment also complements the class of experiments on sender-receiver games. Battaglini (2002) studies cheap talk with two senders and a two-dimensional state space. He demonstrates that if each sender's interests are aligned with the receiver in one dimension, separately, then a fully revealing equilibrium exists where senders reveal the truth along different dimensions. In subsequent work, Lai et al. (2015) and Vespa and Wilson (2016) conduct experiments to evaluate Battaglini (2002). They provide strong evidence for the theory in simpler settings where senders' preferred dimensions are mutually independent. In more complicated settings, however, the behavior of subjects deviates from the theoretical predictions. Battaglini et al. (2019) examine whether multiple committees with heterogeneous preferences can generate more information to a legislature than in the case of one committee. However, they do not find significantly more

Detector	Probabilities of Signals
Full	If the ball is *blue*, 100% it sends a signal **Blue**; if the ball is *red*, 100% it sends a signal **Red**.
Partial	If the ball is *blue*, 80% it sends a signal **Blue**, 20% it sends a signal **Red**; if the ball is *red*, 100% it sends a signal **Red**.
None	No signal will be sent.

(a) Detectors of Sender 1

Detector	Probabilities of Signals
full	If the ball is *blue*, 100% it sends a signal **blue**; if the ball is *red*, 100% it sends a signal **red**.
partial	If the ball is *blue*, 100% it sends a signal **blue**; if the ball is *red*, 80% it sends a signal **red**. 20% it sends a signal **blue**.
none	No signal will be sent.

(b) Detectors of Sender 2

Table 1: Detectors of Senders

information from more committees. They attribute this phenomenon to the reason that more information tends to confuse the legislature and disrupt her decision making.

Sheth (2019) addresses a similar question with our paper in a disclosure game. Previous experimental studies on disclosure show that "unravelling" does not occur as theory predicts, because receivers hold relatively optimistic beliefs about non-disclosed information. Sheth (2019) intends to remedy this problem by introducing competition between senders. She finds that competition can lead to higher unravelling and higher receiver welfare, despite that it does not affect much receivers' inferences about non-disclosed information.

3. Model and Hypotheses

This section explains the theoretical models underlying the experiment. In Section 3.1, we model Treatment 1 (one-sender treatment) where there is one sender and one receiver. In Section 3.2, we model Treatment 2 (two-sender treatment) where two senders provide information. In Section 3.3, we summarize a series of hypotheses about behavior and information revelation we want to examine in the experiment.

Since it is challenging for subjects either to process information as a receiver or to understand the strategic signaling as a sender, we simplify the experimental setup so that subjects can familiarize themselves with it in limited time. As compared to the theoretical models (Kamenica and Gentzkow, 2011; Wu, 2020), the main simplification is that we restrict the choice set of each sender into three representative options: full information, partial information, and no information, instead of a continuum of information structures. The noisy options for two senders are at the same precision level but biased in the opposite directions of persuasion (Table 1).

3.1. One-Sender Treatment

		Action	
		Guesses Red	Guesses Blue
State	*Red*	100, 50	0, 0
	Blue	100, 0	0, 50

Table 2: Payoffs for Sender and Receiver

A box contains 10 balls, 3 red and 7 blue. One ball is randomly chosen. Neither the sender or the receiver observe the chosen ball. There are two players, one sender (S) and one receiver (R). Initially, S selects one detector from the *Full*, *Partial*, and *None* detectors. Each detector generates signals (**Red**, **Blue**, or *Null*) with probabilities contingent on the true state, according to the left column of Table 1. Seeing the chosen detector and signal sent, R makes a guess about the ball color (*red* or *blue*). Payoffs are determined by the true color and R's guess: S is paid 100 if R guesses red; R gets paid 50 if her guess is correct. In Table 2, the first argument of a table entry is the payoff for S, and the second is that for R. We specify the payoffs in order to equalize equilibrium payoffs for all players.

R must make a guess of the more likely color conditional on the information from S. Table 3 presents the probabilities of sending different signals and R's posterior beliefs after these signals. If S uses the *Full* detector, R should follow the signal because it perfectly matches the true color. If S uses the partial detector, signal **Blue** is still perfect while signal **Red** becomes imprecise. Yet it is optimal for R to guess *red* when she receives **Red** from the *Partial* detector because the conditional probability of being red is as high as 68%. If S chooses the *None* detector, R will take the default action of guessing blue.

In S's view, the *Full* detector guarantees his payoff 100 when the state is *red*, but it also leaves him with no chance of winning when the state is *blue*. In contrast, the *Partial* detector sends signal **Red** 44% of the time, higher than the true probability (30%) that the ball is red. Although under the *Partial* detector the strength of **Red** is affected by the error, it is sufficient to persuade the receiver into guessing *red*. Therefore, S would like to slightly reduce precision in order to increase the frequency of sending **Red**. Without doubt, the *None* detector is the worst option for S since R will always guess blue.

In summary, The unique subgame perfect equilibrium (SPE)[2] in this game requires that S chooses the

[2]Even though there is incomplete information, SPE is still a proper solution concept (Wu, 2020). After the sender commits to a

Detector	(1) Prob(**Red**)	(2) Prob(*Null*)	(3) Prob(red$\vert$**Red**)	(4) Prob(red$\vert$*Null*)	(5) S1's expected payoff
Full	0.3	-	1	-	30
Partial	0.44	-	.68	-	44
None	-	1	-	.3	0

Note: Column (1) shows the marginal probabilities of sending **Red** by detectors *Full* or *Partial*. Column (2) shows the marginal probability of sending *Null* by detector *None*. Column (3) shows the posterior probability of the ball being red after a signal **Red** from detector *Full* or *Partial*. Column (4) shows the posterior probability of the ball being red after *Null* from detector *None*. Column (5) shows S1's *ex ante* expected payoffs by using different detectors.

Table 3: Sender 1's Strategies and Expected Payoffs

Partial detector and R follows recommendations. If S deviates to the *Full* detector, R still follows his recommendations. If S deviates to the *None* detector, however, R will only guess blue.

3.2. Two-Sender Treatment

In the two-sender treatment, there is also a box containing 3 red balls and 7 blue balls, within which one ball is randomly selected and neither players observe the true color. There are two senders (S1 and S2) and one receiver (R). S1 has access to the same devices as S in the one-sender treatment (Table 1(a)). S2 moves after S1 and is able to see the detector and signal from the first period. Then, S2 chooses another detector from the *full*, *partial*, and *none* detectors, as shown in the right column of Table 1, which automatically generates another signal (**red**, **blue**, or *null*). After that, R sees both detectors and signals and makes a guess. The two senders have opposite goals. S1 gets paid if R guesses red, while S2 gets paid if R guesses blue. R, as before, aims to make the correct guess. Table 4 presents the payoffs for S1, S2, and R. In each table entry, their payoffs are listed from left to right.

Next, we solve for the SPE in this extensive form game by backward induction. In the last period, R will receive two pieces of information, update her belief, and make a guess of the more likely color. Since the ball is originally more likely to be blue, the rule of thumb for R is to follow S2's recommendation unless S1 provides a signal of higher quality. Her optimal strategy is described as follows. If the senders use either the *Full* or *full* detector, the correct guess is trivial; on the contrary, if both senders send *Null* or *null*, R should

signaling device, he cannot alter the signal generated by it. That means Bayes rule should reasonably apply to any information set irrespective of whether it is on or off equilibrium path. Then, all players maximize their expected payoffs in each continuation game, which means the equilibrium is perfect.

		Action	
		Guesses Red	Guesses Blue
State	*Red*	200, 0, 70	0, 100, 0
	Blue	200, 0, 0	0, 100, 70

Table 4: Payoffs for Sender 1, Sender 2, and Receiver

guess blue. If one sender uses the *Partial* or *partial* detector and the other uses the *None* or *none* detector, R should follow the advice from the former sender. If S1 uses the *Partial* detector that sends **Blue** or S2 uses the *partial* detector that sends **red**, the true color is indicated by the signals. The most complicated case is when S1 uses the *Partial* detector that sends **Red** and S2 uses the *partial* detector that sends **blue**. Facing conflicting signals from both flawed detectors, R should take S2's advice due to a biased prior.

In the second period, we focus on two cases where information is still incomplete after the first period: (1) S1 uses the *Partial* detector that sends signal **Red** or (2) S1 uses the *None* detector. After the history $(Partial, \textbf{Red})$, the belief about the ball being red is updated to 68%, which puts pressure on S2 to counter S1 by sending **blue**. But it is unnecessary for S2 to simply reveal the true state, because he only needs to send a signal as precise as that from S1. In this way, S2 can exploit the benefit of persuasion by using the *partial* detector. After the history $(None, Null)$, S2 has no incentive to disclose information, because R's default action has been guessing blue, and the optimal option for S2 is the *none* detector. In Table 5, Columns (1) and (2) show the posterior beliefs when information from the first period is $(Partial, \textbf{Red})$ or $(None, Null)$ and S2 uses different devices that send different signals. Column (4) show the *ex ante* payoffs S2 under different pairs of devices given that R reacts optimally. From there we can see it is optimal for S2 to always use the device at the same precision level as S1.

Anticipating S2's reactions, S1 should realize that it is not as easy to persuade R as if he was the only sender. Continuing to use the *Partial* detector allows S2 to counter him with a high success rate, which outweighs the benefit of increasing the probability of sending **Red**. Therefore, S1's first priority becomes how to maintain credibility and the *Full* detector is now his preferred choice. Column (3) of Table 5 presents S1's *ex ante* payoffs conditional on different pairs of devices used by S1 and S2.

The unique SPE is given by the strategy profile as follows. S1 chooses the *Full* detector. S2 chooses the *partial* detector when S1 chooses the *Partial* detector and sends a signal **Red**. S2 chooses the *none*

S1's Detector	S2's Detector	(1) Prob(red|**blue**)	(2) Prob(red|*null*)	(3) S1's *ex ante* payoff	(4) S2's *ex ante* payoff
Full				60	70
Partial	*full*	0	-	60	70
	partial	.3	-	48	76
	none	-	.68	88	56
None	*full*	0	-	60	70
	partial	.08	-	48	76
	none	-	.3	0	100

Note: Column (1) shows the posterior probability of being red after history (Partial, **Red**) or (*Null*, *null*) given that S2 uses detectors full or partial that generate **blue**. Column (2) shows the posterior probability of being red after history (Partial, **Red**) or (*Null*, *null*) given that S2 uses the *none* detector that generates *null*. Columns (3) and (4) show S1 and S2's *ex ante* payoffs from using different combination of detectors.

Table 5: Sender 2's Strategies and Expected Payoffs after (*Partial*, **Red**) or (*None*, *Null*)

detector when S1 chooses the *None* detector and sends a signal *Null*. In other cases, the true state has been revealed and S2's information is irrelevant. R follows S1's recommendation unless S2 provides a more precise detector.

Let us discuss two specifications of our experimental design. First, we assume that the two senders have zero-sum payoffs. It is not trivial that adding a sender can naturally lead to more information revelation. Li and Norman (2018) construct examples where adding more senders can lead to less information. The information revelation relies on the strategic interactions between those senders with conflicts of interest. It is the zero-sum assumption that guarantees full revelation as an equilibrium outcome (Wu, 2020). Second, we simplify the original theoretical model by restricting the senders' strategy spaces to include discrete points with only one noisy detector for each sender.[3] Simplifying the experiment allows us to present this complex problem to the subjects in a comprehensible way. We try to use the simplest possible setting to capture the core of our theory — that the sender himself only wants to partially reveal the information; however, the competition can stimulate him to reveal more.

[3]In theory, senders have continuous strategy spaces.

3.3. Hypotheses

Based on the patterns derived from the SPE in the previous section, we list a series of hypotheses for our experiment.

Hypothesis 1. *There is more information revealed in the two-sender treatment than in the one-sender treatment.*

As will be introduced in Section 5, we quantify information by evaluating its payoff implications to R. The higher payoff R can get with the signal, the more informative the signal is. From the above analysis, R will only receive vague information in the one-sender treatment, while R can receive full information in the two-sender treatment.

Hypothesis 2. *In the one-sender treatment, S always uses the* Partial *detector.*

As has been discussed in Section 3.1, S would like to lower the precision level to raise the rate of sending his favorable signal **Red**. Meanwhile, the bias is limited so that R still wants to follow S's suggestions.

Hypothesis 3. *In the one-sender treatment, R follows S's advice if S uses the* Full *and* Partial *detectors; if S uses the* None *detector, R guesses blue.*

When the *Full* detector is used, R has every reason to trust S. When the *Partial* detector is used, R knows there could be some error, but the signal sent by S is still more likely to be true. When the *None* detector is used, R takes the default action.

Hypothesis 4. *In the two-sender treatment, S1 always uses the* Full *detector.*

As has been discussed in Section 3.2, when S1 faces potential challenges from S2, S1 cannot benefit from using a detector biased to his own interest, because S2 can effectively counter S1's message and make him worse off. So it is the best for him to use the *Full* detector.

Hypothesis 5. *In the two-sender treatment, whenever S2's information makes a difference, S2 matches S1's choices by using the* partial *or* none *detectors, respectively.*

If S1 uses the *Full* detector or if S1 uses the *Partial* detector and sends **Blue**, S2's information has no effect on final decision making. If S1 uses the *Partial* detector and sends **Red**, S2 should use the *partial* detector so that he can effectively counter S1 with the highest probability. If S1 uses the *None* detector, S2 does not want to provide any information.

Hypothesis 6. *In the two-sender treatment, R guesses red when she receives following information: (*Full*,* ***Red****), (*Partial*,* ***Red****,* none*,* null*), (*None*,* Null*,* full*,* ***red****), (*None*,* Null*,* partial*,* ***red****); otherwise, she guesses blue.*

Due to the prior that assigns higher probability to the color being blue, R would like to trust S2 unless S1 provides more precise information. No doubt, when S1 uses the *Full* detector and sends **Red**, R will guess red. When S1 uses the *Partial* detector that sends **Red** and S2 uses the *none* detector, this is the same situation as in the one-sender treatment where R should guess red. When S2 himself sends a signal **red**, no matter from the *full* or *partial* detector, it guarantees that the true state is red.

4. Experiment Procedure

We have enrolled 197 registered undergraduate students from the University of Arizona to participate in the experiment, 92 for the one-sender treatment and 105 for the two-sender treatment. The Economic Science Laboratory (ESL) system sent invitations to students who registered in the system voluntarily one week before the experiment. The one-sender treatment lasted for 1 hour and the two-sender treatment lasted for 1.5 hours. Subjects were paid for every period, at a conversion rate of 1 USD per 100 units of experimental currency. The average payments for the one-sender treatment and two-sender treatment were 17 USD and 21 USD, respectively, including a 5 USD show-up fee. Each treatment consisted of 7 sessions. The size of each experiment session varied from 8 to 20 in the one-sender treatment and from 9 to 24 in the two-sender treatment. Each subject was only allowed to participate in one session of one treatment. The session information is shown in Table 6.

The experiments were completely computerized using Z-Tree (Fischbacher, 2007). Subjects were assigned to computers randomly at the beginning of each experiment session. Hard-copy instructions were handed out and 5-minute of instructional audio in a neutral tone was played via the loudspeaker in the lab.[4]

[4]The instructions and computer screens are displayed in the appendix.

Treatment	One-Sender							Two-Sender						
Session	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Number of Subjects	14	12	16	8	12	10	20	9	15	12	12	9	24	24

Note: Each of the two treatments consists of 7 sessions. The number of subjects ranges from 8 to 20 in the one-sender treatment and from 9 to 24 in the two-sender treatment.

Table 6: Session Information

After that, subjects were assigned a role randomly and their roles are fixed throughout the session. In the one-sender treatment, there were two roles: *Sender* and *Receiver*. In the two-sender treatment, there are two senders, *Sender 1* and *Sender 2*, who provide information, together with one receiver, who makes decisions.

Both treatments consist of 30 paying periods. At the beginning of the experiment, one trial period was provided to help subjects understand the experiment but was not counted for final payment. Within a paying period, each subject was matched with another subject (one-sender treatment) or two other subjects (two-sender treatment) randomly drawn from the pools of the other roles. It was common knowledge that the possibility of being matched with the same participant in two consecutive rounds was small. Interaction was anonymous in the sense that players could not associate any player with her actions.

In the one-sender treatment, subjects played a two-stage game. In the first stage, the sender chose a detector which generated a signal, and both the detector selected and the signal generated were observed by the receiver. In the second stage, the receiver made a guess about the true color of the ball. In the two-sender treatment, players played a three-stage game. In the first stage, Sender 1 decided which detector to use, and both the detector and its realization were observed by both Sender 2 and the receiver. In the second stage, Sender 2 chose another detector that sent another signal independently from Sender 1's signal. In the third stage, the receiver observed the detectors and the corresponding signals, and then she made a guess. At the end of each paying period, the true color of the ball, the detectors and signals, and the receiver's guess were displayed on the screen to each group of matched subjects. A historical table was also provided on the screen for subjects to review their previous actions and the associated outcomes.

One-Sender Treatment			Two-Sender Treatment				
Detector	Signal	Informativeness	Detector 1	Signal 1	Detector 2	Signal 2	Informativeness
Full	**Blue**	1	*Partial*	**Red**	*partial*	**blue**	0.7
Full	**Red**	1	*Partial*	**Red**	*none*	*null*	0.68
Partial	**Blue**	1	*None*	*Null*	*partial*	**blue**	0.92
Partial	**Red**	0.68	*None*	*Null*	*none*	*null*	0.7
None	*Null*	0.7	All other cases				1

Note: We calculate the informativeness of each combination of detectors and signals in two treatments according to Definition 1.

Table 7: Informativeness of Different Detector/Signal Combinations

5. Findings

In this section, we examine Hypotheses 1-6 in order. Section 5.1 is devoted to the examination of Hypothesis 1, Section 5.2 Hypotheses 2-3, and Section 5.3 Hypotheses 4-6.[5]

5.1. Informativeness

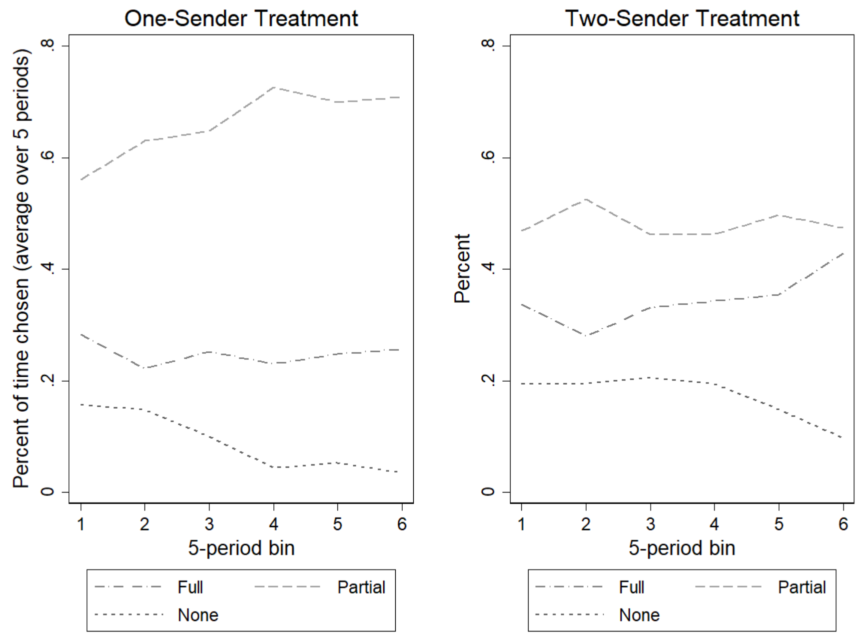
We first define the informativeness of different combinations of detectors and signals.

Definition 1. *The* informativeness *of a combination of detectors and signals is the probability that R can make the correct guess when she bases her decision on the given information. Formally, in every history h, the informativeness of the existing information equals* $\max\{Prob(red|h), Prob(blue|h)\}$.

Table 7 presents the values of informativeness different combinations of detectors and signals take on. For example, in the one-sender treatment, when S uses the *Partial* detector and sends a signal **Red**, a Bayesian R would update her belief to $Pr(red) = .68$. Hence, she would guess red and her expected correct rate is 68%. In the two-sender treatment, When S1 uses the *Partial* detector and sends a signal **Red** and S2 uses the *partial* detector and sends **blue**, the updated belief is $Pr(blue) = .7$. So R should guess blue and her chance of getting it right is 70%.

We calculate the average levels of informativeness in each session of both treatments. Using each session as an independent observation, we find that in the two-sender treatment, the information is significantly more informative than the one-sender treatment. Specifically, the informativeness of signals in the one-sender

[5] The empirical tests are t-tests, where we treat each session as one observation. The sample size is 14.



Note: In the one-sender treatment, the sender chooses the *Partial* detector with the highest frequency through 30 periods. In the two-sender treatment, the first sender still chooses the *Partial* detector with the highest frequency, but the frequency is much lower. Particularly in the last 10 periods, the frequencies of choosing the *Partial* detector and the *Full* detector are getting closer.

Figure 1: The Frequencies of the First Sender's Choices in Two Treatments

treatment is 87.9%, while that in the two-sender treatment is 95.6% (t-test, $p<0.001$, N=14). In the last 10 periods, the informativeness in the one-sender treatment is 88%, which is still lower than 95.4% in the two-sender treatment ($p<0.01$). The receiver's welfare also increases in the two-sender treatment. The average rate of the receiver's making correct guesses increases from 86% to 93% ($p<0.001$).

Therefore, Hypothesis 1 is supported by our experimental results.

Compared to the one-sender treatment, informativeness increases by a total of 7.4% in the two-sender treatment. By focusing only on information from the first sender, the informativeness of the one- and two-sender treatments is 88% and 90%, which means that the first sender only contributes 27% of the difference. It is the addition of the second sender that considerably increase the informativeness in the two-sender treatment, where the informativeness of two senders is significantly higher than that of only the first sender

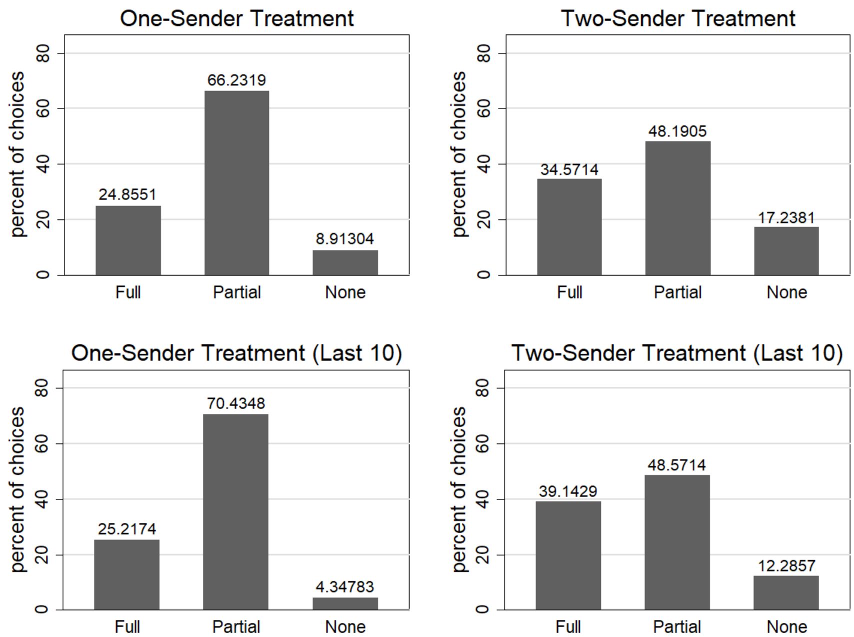


Figure 2: First Sender's Choices by Treatment in All Rounds and in the Last 10 Rounds

($p<0.001$, N=14). The contribution of the second sender accounts for 73% of the increase in informativeness. This is in part due to that more senders turn to use the uninformative detector (*None*) in the two-sender treatment. In Section 7.2, we define a sample that excludes these subjects and find that the difference in S1's informativeness across treatments becomes significantly larger.

5.2. One-Sender Treatment

5.2.1. Sender

In the one-sender treatment, S is the only sender, who is supposed to use the *Partial* detector. The experimental results, illustrated in Figures 1 and 2, provide clear support for this prediction. The leading choice of S is the *Partial* detector, whose proportion is 66% overall and reaches 70% in the last 10 rounds. This result is stable over the course of 30 periods; even in the initial 10 periods the proportion of the equilibrium choice has been above 60%. The second most used detector is the *Full* detector. Its proportion stays around 25% through 30 periods. The least used detector is the *None* detector, which only accounts for 9% and almost

Detector	Signal	Predicted Guess	Overall	L10
Full	**Blue**	blue	97.86%	100%
Full	**Red**	red	96.33%	100%
Partial	**Blue**	blue	98.1%	98.9%
Partial	**Red**	red	85.79%	83.1%
None	*Null*	blue	88.24%	80%

Note: the column "Predicted Guess" shows the optimal guesses receivers should make given different information, as predicted by theory.

Table 8: Frequency of Receivers' Making Optimal Guesses in the One-Sender Treatment

vanishes in the last 10 periods. The percentage of the *Partial* detector is significantly higher than the *Full* and *None* detectors (t-test, $p < 0.001$, N=14).

The results show that senders are willing to influence receivers' decisions by affecting the process of information acquisition, despite that full revelation is always available. Therefore, Hypothesis 2 is supported.

5.2.2. Receiver

Hypothesis 3 states that receivers should comply with senders' suggestions even if senders send noisy signals. Only when senders give no information should receivers stick to their default action, i.e., guessing blue.

As for receivers' strategies, the empirical results are consistent with the theoretical predictions. The true color is fully revealed either when S uses the *Full* detector or when S uses the *Partial* detector and sends a signal **blue**. In these cases, only 2.1% of R have made mistakes in the one-sender treatment over all rounds, and this error decreases to 0.6% in the last 10 rounds. We then look into the cases where the receiver cannot ensure the true color. As described in Table 8, when the *Partial* detector is chosen and a signal **Red** is sent, 85.79% of receivers would follow the suggestion and guess red. When no information is revealed, 88.24% of the time R guesses blue. Therefore, S's persuasion effectively affects R's decision making and R is able to make use of existing information. Based on these observations, Hypothesis 3 is supported.

Detector 1	Signal 1	Detector 2	Overall	L10
Partial	**Red**	*full*	30.81%	33.87%
		partial	**55.56%**	**51.61%**
		none	13.64%	14.52%
None	*Null*	*full*	28.73%	20.93%
		partial	38.67%	30.23%
		none	**32.6%**	**48.84%**

Note: Each row shows the frequency at which S2 chooses different detectors in the corresponding history. For example, the first row reports the frequency at which S2 chooses the *full* detector in the history (*Partial*, **Red**) in all and the L10 rounds.

Table 9: S2's Persuasion Conditional On S1's Information

5.3. Two-Sender Treatment

5.3.1. Sender 1

In the two-sender treatment, the choice of the *Partial* detector by S1 is still of the highest frequency as indicated in Figure 2. This result is not consistent with Hypothesis 4, which predicts that the *Full* detector will be used most frequently. Though there is a slight increase in the choice of the *Full* detector in the last 10 rounds, as shown in Figure 1, the percentage of the choice of *Full* still ranks the second. Moreover, the use of the *Partial* detector is significantly higher than the *Full* detector (t-test, p-value=0.05, N=14). We will discuss a plausible explanation for the underuse of the *Full* detector in Section 6.

Compared to the one-sender treatment, the percentage of S1 using the *Full* detector increases by 10% (p-value=0.14) overall and by 15% (p-value=0.12) in the last 10 periods on average. However, the change in the use of the *Full* detector is not significant. The percentage of participants using the *Partial* detector decreases by 18% (p-value=0.02) overall and 22% (p-value=0.04) in the last 10 periods. That means under pressure from a competing sender, S1 reduces his use of the noisy device. The percentage of using the *None* detector also increases slightly by 8% both overall and in the last 10 periods (p-value=0.08 for all rounds and p-value=0.22 for last 10 periods).

From above, Hypothesis 4 is overall rejected by the evidence. S1 does not choose full revelation most of the time. Nevertheless, S1 significantly reduces his use of the noisy device, which is in the same direction as predicted by the theory.

Panel A					
S2's Decision		Multinomial	Multinomial (robust se)	Multinomial (L10)	Multinomial (robust se, L10)
full	(*Partial*,**Red**)	2.563***	2.563*	5.444***	5.444**
		(0.767)	(1.347)	(3.068)	(4.471)
	Constant	0.881	0.881	0.429**	0.429
		(0.168)	(0.355)	(0.171)	(0.266)
partial	(*Partial*,**Red**)	3.433***	3.434***	5.744***	5.744**
		(0.955)	(1.52)	(2.967)	(3.93)
	Constant	1.186	1.186	0.619	0.619
		(0.210)	(0.472)	(0.218)	(0.347)
Panel B					
S2's choice		Ordered probit	Orderred probit (robust se)	Ordered probit (L10)	Ordered probit (robust se, L10)
S1 chooses B		0.32***	0.32	0.73***	0.73**
		(0.12)	(0.22)	(0.23)	(0.36)

Note: Panel A reports the marginal effects of the Multinomial Logistic for S2, where the *none* detector is the base outcome. Standard errors are in the parentheses. Panel B reports the marginal effects of the Ordered Probit for S2. The second and fourth columns report the results when standard errors are clustered at the subject level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 10: Regressions on S2's Behavior

5.3.2. Sender 2

We only focus on S2's decision making in the cases where the true color has not been revealed by S1; otherwise R can make the correct choice regardless of S2's signal. Hypothesis 5 states that S2's behavior should exhibit a "matching" pattern. That is, if the combination of S1's device and signal is ($Partial$, **Red**), S2 would use the $partial$ detector; if the combination is ($None$, $Null$), S2 would use the $none$ detector. On average, the predicted pattern is apparent in the last 10 periods.

In the case where S1 chooses the *Partial* detector and sends **Red**, the choice of S2 matches S1 55.56% of the time, which is more than full revelation (30.81%) and no revelation (13.64%). In the last 10 periods, the $full, partial$, and *none* detectors account for 33.87%, 51.61%, and 14.52%, respectively. When S1 chooses not to reveal any information, S2's choice matches S1's decision 48.84% of the time in the last 10 rounds. However, this matching choice of no revelation does not hold for the overall game. Those results are summarized in Table 9. Therefore, Hypothesis 4 is supported by the statistics in the last 10 rounds.

Panel A of Table 10 shows the multinomial logistic regressions, in which the dependent variable is S2's choice of detectors and the independent variable is binary, whether S1 chooses the *Partial* detector and send a signal **Red**, or S1 chooses the *None* detector. Only in these two cases the color of the ball remains uncertain. Four specifications of regressions are included: Multinomial regression, multinomial regression with standard robust error, multinomial regression for last 10 periods, and multinomial regression for last 10 periods with robust standard error. The relative risk ratio is reported in all four specifications. It shows that when S1 chooses the *Partial* detector and a signal **Red** is sent, S2 is more likely to choose the *full* and *partial* detectors than the *none* detector. In the last 10 periods of the game, with the robust standard error specification, the chance of S2 choosing the *partial* detector is 5.7 times of choosing the *none* detector on average, and the chance of choosing the *full* detector is 5.4 times of choosing the *none* detector on average.

Panel B of Table 10 shows the ordered probit regression result, in which the dependent variable is S2's choice of detector and the independent variable is binary, whether S1 chooses the *Partial* detector and send a signal **Red**, or S1 chooses the *None* detector. The result shows a strong positive correlation between strength of persuasion of S1 and information revelation of S2. These results provide complementary support to Hypothesis 4.

5.3.3. Receiver

From Hypothesis 6, in the two-sender treatment, the rule of thumb for R to make correct decisions is to follow S2's advice unless S1 sends a stronger signal. That is because R holds a prior belief inclined to S2's position, so there is higher pressure on S1 to provide precise information.

Even though there are many possible pieces of information R could receive, in most of the cases the true color has already been revealed and in practice R does a wonderful job of guessing colors in these situations. Then we can focus on the other 4 cases where the true color has not been revealed. As we have shown in Table 11, the vast majority of the time R can make the optimal guess; even in the most challenging case where R receives noisy and conflicting signals from both sides, R makes the optimal choice with probability 76%.

The results show that R is able to analyze complicated information and confirm Hypothesis 6.

Information	Predicted Guess	Overall	L10
(*Partial*, **Red**, *partial*, **blue**)	blue	76.6%	68.75%
(*Partial*, **Red**, *none*, *Null*)	red	85.19%	88.89%
(*None*, *Null*, *partial*, **blue**)	blue	100%	100%
(*None*, *Null*, *none*, *null*)	blue	86.04%	85.71%
When the ball is certainly red	red	$> 87\%$	$> 93\%$
When the ball is certainly blue	blue	$> 98\%$	100%

Note: The column "Predicted Guess" indicates the optimal guess receivers should make given different information. The first four rows report the frequencies that receivers make the theoretically optimal guesses in different histories. The last two rows report the minimum frequencies that receivers make the theoretically optimal guesses in all possible situations.

Table 11: Frequency of Receivers' Making Optimal Guesses in the Two-sender Treatment

6. Quantal Response Equilibrium

The previous section has documented deviations of the empirical results from the theoretical predictions. It is clear that players' behavior exhibits probabilistic, rather than deterministic, patterns. In what follows, we use the behavioral model of Quantal Response Equilibrium (QRE) to explain the statistical distribution of players' strategies.

In QRE, each player maximizes his utility subject to an error term. As McKelvey and Palfrey (1995) suggest, one source of the error is players' misperceptions of how much they will gain from playing certain strategies. In our experiment, the receiver is facing a challenge to update her belief conditional on various information, and her miscalculation is unavoidable when information is opaque. Empirically, the more uncertain the state is, the less likely she will make the best guess. Furthermore, the possibility that the receiver can make erroneous choices will seriously affect senders' choices. For instance, in the one-sender treatment, if the receiver guesses blue after a signal **Red** from the *Partial* detector, then the equilibrium strategy would be much less attractive to the sender. Also, the senders themselves may miscalculate the posterior belief of the states and the probability of sending signals, which contributes to their randomization over strategies. Therefore, QRE provides a desirable framework to study players' behavior in rational expectations of uncertainty and mistakes.

Specifically, we solve for the logit-Agent QRE (AQRE) with logistic responses, developed in McKelvey and Palfrey (1998). There is one common parameter λ for all players that captures the degree of sophisti-

Player	Choice		Predicted	Actual	Predicted (L10)	Actual (L10)
S1	*Full*		29%	25%	27%	26%
	Partial		67%	66%	70%	70%
	None		4%	9%	3%	4%
R	Condition	Guess				
	(*Full*, **Blue**)	blue	99%	98%	100%	100%
	(*Full*, **Red**)	red	99%	96%	100%	100%
	(*Partial*, **Blue**)	blue	99%	98%	100%	99%
	(*Partial*, **Red**)	red	86%	86%	86%	83%
	(*None*, *Null*)	blue	89%	88%	90%	80%

Table 12: Data and Estimates for the One-Sender Treatment

cation of players: when $\lambda = 0$, players completely randomize; when $\lambda \to \infty$, players are rational and the equilibrium converges to standard Nash Equilibrium. If λ increases with time, that means learning takes place.

In order to provide falsifiable comparative statics predictions, we make i.i.d. logit assumptions on payoff perturbations. As Haile et al. (2008) suggest, this set of assumptions imply testable restrictions.

Now we show how to calculate AQRE for Treatment 2. (The calculation for Treatment 1 is similar.) Let h_t be a history of the extensive form game up until the end of period t. For example, h_2 could be a sequence of detectors and signals (*None*, *Null*, *partial*, **blue**). For each possible history h, there is a unique posterior belief updated by Bayes rule $\mu(h)$. Let $u(\alpha|h_2), \alpha \in \{red, blue\}$, be the receiver's expected payoff from guessing α following the history h_2. We have $u(\alpha|h_2) = 70\mu(\alpha|h_2)$. Then, we set the receiver's quantal response strategy to be, for $\alpha \in \{red, blue\}$,

$$\rho(\alpha|h_2) = \frac{e^{\lambda u(\alpha|h_2)}}{\sum_{\alpha' \in \{red, blue\}} e^{\lambda u(\alpha'|h_2)}}$$

Then, Sender 2's expected payoff from picking Detector $\beta_2 \in \{full, partial, none\}$ at history h_1, provided that the receiver conforms to ρ, is denoted by $v^2(\beta_2, \rho|h_1)$. Sender 2's quantal response strategy σ_2 is calculated by

$$\sigma_2(\beta_2|h_2) = \frac{e^{\lambda v^2(\beta_2, \rho|h_2)}}{\sum_{\beta' \in \{a,b,c\}} e^{\lambda v^2(\beta', \rho|h_2)}}$$

Player	Choice		Predicted	Actual	Predicted (L10)	Actual (L10)
S1	$Full$		46%	34%	48%	39%
	$Partial$		54%	48%	52%	49%
	$None$		0%	17%	0%	12%
S2	Condition					
	($Partial$, **Red**)	$full$	35%	31%	35%	34%
		$partial$	40%	56%	41%	52%
		$none$	25%	13%	24%	15%
	($None$, $Null$)	$full$	28%	29%	28%	21%
		$partial$	32%	39%	32%	30%
		$none$	39%	32%	40%	49%
R	($Partial$, **Red**, $partial$, **blue**)	blue	76%	77%	77%	69%
	($Partial$, **Red**, $none$, $null$)	red	74%	85%	75%	89%
	($None$, $Null$, $partial$, **blue**)	blue	92%	100%	93%	100%
	($None$, $Null$, $none$, $null$)	blue	76%	86%	77%	86%

Table 13: Data and Estimates for the Two-Sender Treatment

Finally, given σ_2 and ρ, Sender 1's expected payoff from picking Detector $\beta_1 \in \{Full, Partial, None\}$ is denoted by $v^1(\beta_1, \sigma_2, \rho)$. Sender 1's mixed strategy σ_1 is calculated by

$$\sigma_1(\beta_1) = \frac{e^{\lambda v^1(\beta_1, \sigma_2, \rho)}}{\sum_{\beta' \in \{A,B,C\}} e^{\lambda v^1(\beta', \sigma_2, \rho)}}$$

Therefore, for each value of λ, we can predict the distribution of strategies. In the estimation of λ, we use the technique of the Minimum of Mean Squared Error (MMSE).[6] One choice by one player is counted as one data point in the strategy space. For example, suppose S1's predicted mixed strategy is equal to $(p_{Full}, p_{Partial}, p_{None})$, and in the data point he chooses $Full$, then the error is the Euclidean distance between $(p_{Full}, p_{Partial}, p_{None})$ and $(1,0,0)$. We find a value of λ that minimizes the average of the squared error.

Tables 12 and 13 compare the estimated QRE and the actual distribution of strategies in all periods and in the last 10 periods of the two treatments.

In Treatment 1, QRE fits the data to a high degree in either all or the last 10 periods. In QRE, the sender uses the equilibrium detector ($Partial$) the vast majority of the time, uses the $Full$ detector sometimes,

[6]We follow Brier (1950) to use the Euclidean norm as the measure of accuracy on the probability spaces.

Treatment	Period	λ	MSE	N
One-sender	$1 \sim 10$	8.9	0.34	920
	$11 \sim 20$	10.83	0.28	920
	$21 \sim 30$	10.89	0.28	920
Two-sender	$1 \sim 10$	3.8	0.41	1050
	$11 \sim 20$	4.2	0.40	1050
	$21 \sim 30$	4.3	0.36	1050

Table 14: Estimation of λ

and almost never uses the *None* detector. This is exactly what appears in the data. In the last 10 rounds, the differences of the probabilities over detectors between QRE and data are even less than 1%. On the receiver side, QRE predicts that she always makes the correct guess under complete information, and when the persuasion is noisy, she will follow the suggestion 86% of the time. When there is no information, the probability is 89%. The predictions of the receiver's choices conditional on various information are close to the empirical distribution. Except for the case where the *none* detector is used in the last 10 periods, the receiver guesses blue 80% of the time (10% lower than the empirical probability). Consider that in the last 10 periods the *None* detector is only used 4% of the time and the sample pool is relatively small, so there is naturally a higher variation in the strategic choice.

In the two-sender treatment, the QRE also shows high adherence to the data. The QRE successfully predicts that the *Partial* detector is overplayed, even though the $Full$ detector is the unique SPE strategy. The percentage using the $Full$ detector is less than but close to the *Partial* detector, and significantly higher than the *None* detector. For S2, the QRE qualitatively predicts the matching pattern. In the last 10 periods, when S1 uses the *Partial* detector and sends a signal **Red**, S2 is predicted to use the *partial* detector with probability 41%, higher than the $full$ detector (35%) and the *none* detector (24%). Similar to QRE, the data show the distribution of S1's strategy across the $full, partial$, and *none* detectors as 34%, 52%, 15%. When S1 does not give any information, the probability of S2's strategy over the $full$, $partial$, and *none* detectors in QRE, i.e. 28%, 32%, 40%, exhibits the same structure of the empirical distribution, i.e. 21%, 30%, 49%. The QRE also explains receiver's probabilistic responses. In the cases where the true state is obvious, both QRE and the data have correction rates close to 100%. In Table 13, we list results in 4 uncertain cases and in all those cases the probability in QRE is no more than 15% from the data. In the most challenging case,

Treatment	Theoretical Payoff	Empirical Payoff
One-Sender		
S	13.2	10.4
R	12.9	12.9
Two-Sender		
S1	18	16.3
S2	21	21.8
R	21	19.5

Table 15: The Theoretical and Empirical Payoffs of Players in Two Treatments (In Dollars)

when both senders give conflicting vague advice, QRE predicts 76% of R guessing blue, which is fairly close to the data, which shows 77% guessing blue.

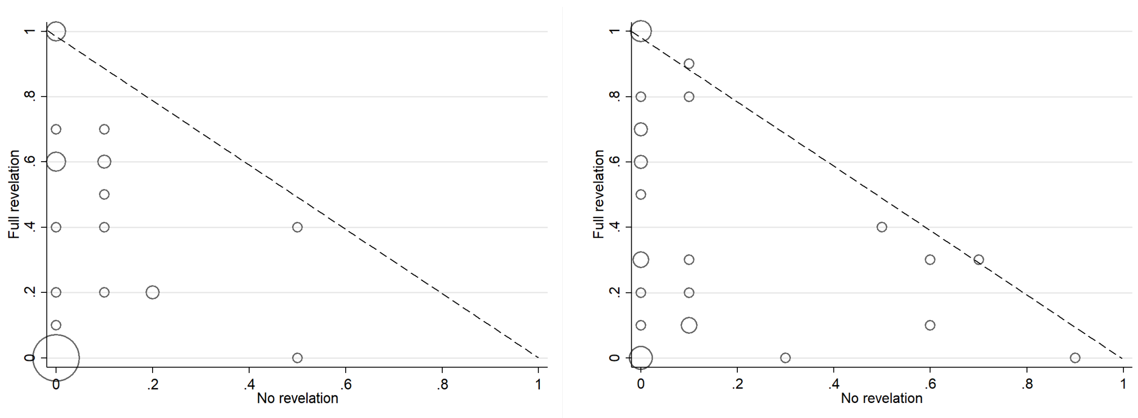
Table 14 traces the change of the estimated value of λ over the course of 30 periods in two treatments. In both treatments, λ keeps increasing. It means that the subjects went through learning processes in both experiments, and they became more sophisticated in the games after they became familiar with the contexts. Also, since the increase of λ from the first 10 periods to the second 10 periods is much larger than that between the second and last 10 periods, learning is more intense at the beginning of the experiments.

7. Discussion

7.1. Explanation for deviations

The willingness of the senders to conform to the equilibrium strategy relies on the subsequent players making the correct choices to impose punishment for his deviations. However, we find that the second sender and the receiver make the correct choices *most of the time* but not *always*.

For example, in history (*Partial*, **Red**, *partial*, **blue**), where the second sender "wins" the argument and the receiver is supposed to follow his suggestion, there is still around 30% that the receiver guesses red. The failure of the receiver to constantly make the optimal choice will not only lower the receiver's payoff herself, but also disrupt senders' choices. Taking into account the receiver's deviation, the second sender would find the optimal option conditional on (*Partial*, **Red**), the *partial* detector, less desirable. This pattern is also observed in Fréchette et al. (2020). They find that the probability with which the receiver will make the optimal choice changes continuously with the posterior beliefs, instead of being a step function.



(a) One-Sender Treatment

(b) Two-Sender Treatment

Note: Each point indicates the individual choice of one subject playing the role of the first sender. Larger circles indicate a clustering of data at that point. The x-axis indicates the frequency with which the individual chooses the *None* detector, and the y-axis the frequency with which the individual chooses the *Full* detector. The frequency of the *Partial* detector can be inferred from the figures, because the sum of the three probabilities equals 1. In sample[$*$], we exclude subjects who select the *None* detector more than 20 percent of the time.

Figure 3: Scatter Plot of Individual Choices of the First Sender in the Last 10 Periods in Two Treatments

As in Table 10, the regressions on the second sender's behavior show that competition affects the second sender: the more precise the first sender's signal is, the more precise the second sender's choice will be. But the second sender does not necessarily choose the optimal response. For example, in history (*Partial*, **Red**), the second sender is supposed to choose the *partial* detector. However, as Table 9 shows, he chooses the *full* detector with 30% and the *none* detector with 20%. The former choice makes the first sender indifferent between the *Full* and *Partial* detectors, while the latter choice makes the *Partial* detector much more attractive to the first sender. So the deviation of Sender 2 leads to more use of the *Partial* detector by Sender 1.

In summary, the deviations of subsequent players weaken the advantage of playing the equilibrium strategy for the first sender. In practice, he actually receives equal payments from using the *Full* and *Partial* detectors (Table 15), which can explain his frequent use of *Partial* and the substantial information loss for the receiver.

	Full Sample			Sample[∗]		
Treatment	One-sender		Two-sender	One-sender		Two-sender
Full	25.5%	$<$	39.1%	22.4%	$<^{**}$	41.1%
Partial	70.4%	$>^{**}$	48.6%	76.3%	$>^{**}$	56.1%
None	4.5%	$<$	12.3%	1.3%	$<^{**}$	2.9%

Note: We compare the frequencies at which the first sender chooses each detector across two treatments in the full and selected samples. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 16: The Comparison of S1's Behavior in the Last 10 Periods in Two Treatments

7.2. Selected Sample

We plot the individual choices of the first sender in both treatments in Figure 3, where each dot represents the probabilities with which a subject chooses different detectors. The figure shows that more subjects randomize between informative (*Full* and *Partial*) and uninformative options (*None*) in the two-sender treatment. We think that those subjects who intentionally use the inferior detector, *None*, may not fully understand the setup due to the complex environment. Therefore, in both treatments, We exclude those who choose the *None* detector more than twice in the last 10 periods, and define this selected sample as sample[∗] for a robustness check.

First, we decompose the contributions of S1 and S2 to the increased informativeness with sample[∗]. Unlike in the full sample, the informativeness of the first sender's signals in the two-sender treatment increases to 92.4% (p<0.05) from 88% in the one-sender treatment. Since the addition of Sender 2 further increases the informativeness from 92.4% to 96.7% (p<0.001), the effect of Sender 1's behavior change contributes 50% of the increase in informativeness.

Second, by analyzing sample[∗], we have the following three findings in regard to S1's behavior (Table 16):

1. Sender 1's behavior exhibits the same pattern as in the full sample. In the one-sender treatment, he uses the *Partial* detector the vast majority of the time, the *Full* detector sometimes, and rarely uses the *None* detector. In the two-sender treatment, he still uses the *Partial* detector the most, the *Full* detector as his second choice, and almost never the *None* detector. But the gap between the frequencies of *Full* and *Partial* decreases from 54% in the one-sender treatment to 15% in the two-sender treatment.
2. The comparisons of Sender 1's choices between treatments are more significant in sample[∗]. In the

two-sender treatment, Sender 1 uses the *Full* and *None* detectors significantly more frequently than in the one-sender treatment, while the differences are insignificant in the full sample. For the *Partial* detector, Sender 1 uses it significantly less often in the two-sender treatment in sample[$*$].

3. The gaps of the frequencies of different detectors between treatments also change. In the full sample, Sender 1 increases the frequency of using the *Full* detector by 13.6% in the two-sender treatment. In comparison, in sample[$*$], the gap widens to 18.7%. However, the gap of the frequencies of using the *None* detector reduces from 7.8% to 1.6%. Finally, the gaps in regard to the *Partial* detector are fairly close, which are around 20% both in the full sample and in sample[$*$].

7.3. Alternative Settings

We propose two variants of the original game for future work, one in which the second sender can only observe the detector but not the realization, and the other in which two senders select detectors simultaneously. An interesting finding is that these two games yield the same equilibrium outcome as the original game.

Think of the case where only the detector but not the realizations is observed. If S1 chooses the *Full* detector, information is fully revealed and the receiver would be convinced by S1's signal. If S1 chooses the *Partial* detector, S2 would react as if he observed a signal **Red** from S1; otherwise, a signal **Blue** would reveal the true state and S2's information is irrelevant. So S2 should choose the *partial* detector based on the same argument as in the original game. If S1 chooses the *None* detector, S2 will chooses the *none* detector, as the default action by the receiver is in favor of S2 without any information. Therefore, S2's behavioral pattern is essentially the same as before and it is still optimal for S1 to fully reveal the information.

Then, think of the simultaneous-move game where both senders choose their detectors at the same time (Table 17). There are two pure strategy equilibria $(Full, full)$ and $(Full, partial)$, both of which lead to full revelation of information. Using dominance we can rule out $full$ from S2's strategy space, since it is weakly dominated by $partial$. Therefore, $(Full, partial)$ is the unique prediction that survives the iterative elimination of weakly dominated strategies.

In future work, researchers can bring these two models into the laboratory and investigate whether different forms of competition can contribute to different levels of information revelation.

		S2		
		full	*partial*	*none*
	Full	30, 70	30, 70	30, 70
S1	*Partial*	30, 70	24, 76	44, 56
	None	30, 70	24, 76	0, 100

Table 17: Payoff Matrix for the Simultaneous-Move Game

8. Conclusion

In our experiment, we compare information revelation in two Bayesian persuasion games, one with one sender and the other with two competing senders. The direction of the effect of competition on information revelation is consistent with the theory: competition and information revelation are positively correlated. Yet the magnitude is far less than predicted. That means even fierce competition cannot prevent senders from withholding a considerable amount of information.

Despite some deviation, the Bayesian persuasion theory in large part explains the behavioral patterns of subjects in the laboratory. When the sender is the unique information source, he tends to adjust the information channel in order to persuade the receiver in his favorable direction. Even though the sender's information could be biased to some extent, it is still valuable for the receiver. So the receiver, with the knowledge of the sender's selfish motive, chooses to comply with his suggestions almost all the time. This is consistent with the theoretical predictions in Kamenica and Gentzkow (2011). In the presence of a competing sender, the first sender still relatively prefers a noisy information device, which violates the theoretical prediction (Wu, 2020). Nevertheless, he does decrease the use of the noisy device significantly as compared to if he were the single sender. The competing sender exhibits a "matching" pattern as predicted by theory. When the first sender's persuasion is more convincing, the second sender will tend to reveal more precise information. These results uncover an inspiring pattern: under *potential* pressure from a competing sender, the sender's intention of using noisy persuasion is hindered, and under *existing* pressure from unfavorable information, the sender will increase the use of more precise devices. As for the receiver, her decision making is still based on given information, and the vast majority of the time she is able to make the optimal choice. However, she is not perfect Bayesian, and her choices deviate from optimal actions occasionally. This deviation occurs more frequently when the signals from the senders are more opaque.

We argue that the deviation might originate from subjects' miscalculation of conditional probabilities under various information environments. The errors made by all players can accumulate when the extensive form game unravels. The possibility of the receiver making mistakes would affect the second sender's decision, and the chance of mistakes made by both the second sender and the receiver would further disturb the first sender's decision making. Therefore, we use the model of Quantal Response Equilibrium to capture subjects' probabilistic choices. The estimated distribution across different choices shows high adherence to the actual data. In the first treatment with one sender, the QRE model to a large part explains the subjects' choices. In the second treatment, the QRE estimations are consistent with the behavioral patterns of all players conditional on all histories.

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Appendices

***Appendix A**: Instruction of Treatment 1*

Welcome to today's experiment. The instructions are simple and if you follow them carefully and make certain decisions, you can earn a considerable amount of money paid to you in cash at the end of this session. The session consists of 30 periods, and you will be paid for all your decisions in each period.

At the beginning of the experiment, you will be assigned a role, either player 1 or player 2. Your role will be fixed during the entire experiment and only you know it. In each period, you will be randomly matched with players playing other roles. It is very likely that the players you play with in different periods are different.

Your earnings in the experiment are displayed in experiment currency and will be converted to dollars. Specifically, 100 units of experiment currency will be converted to $1. You will also be paid a $5 participation fee.

Experiment Procedure

A box (Box 1) contains 10 balls, 3 ***red*** balls and 7 ***blue*** balls. One ball is randomly and secretly chosen from Box 1 and put into another empty box (Box 2). No player knows the color of the ball in Box 2.

Player 1 chooses a detector that will send a signal (***B*** or ***R***) related to the color of the ball in Box 2. The signal may or may not match the actual color of the ball, and the probability of sending signals varies across detectors. After player 1 makes the choice, player 2 will be able to see the chosen detector and the sent signal. Table 1 shows the detectors player 1 can choose from.

Table 1 Player 1's Options

Options	Probability of sending signals
Detector A	If the ball is ***blue***, 100% of the time it sends a signal ***B***. If the ball is ***red***, 100% of the time it sends a signal ***R***.
Detector B	If the ball is ***blue***, 80% of the time it sends a signal ***B***; 20% of the time it sends a signal ***R***. If the ball is ***red***, 100% of the time it sends a signal ***R***.
Detector C	No signal will be sent.

Player 2 sees the detector chosen by player 1 and the signal sent by the detector. Then he/she makes a guess (***red*** or ***blue***) about the color of the ball in Box 2.

Player 2 earns 50 if his guess is correct, and 0 otherwise. Player 1 earns 100 if player 2 guesses ***red***, and 0 otherwise. Table 2 summarizes players' payoffs.

Table 2 Payoffs for Players

		Player 2's guess	
		red	***blue***
Player 1's payoff		100	0
Player 2's payoff	If the ball is ***red***	50	0
	If the ball is ***blue***	0	50

After each period, all players can review the true color of the ball, the detector chosen by player 1, the signal sent by detector, player 2's guess, and their own payoffs. Each period is independent.

Appendix B*: Instruction of Treatment 2*

Welcome to today's experiment. The instructions are simple and if you follow them carefully and make certain decisions, you can earn a considerable amount of money paid to you in cash at the end of this session. The session consists of 30 periods, and you will be paid for all your decisions in each period.

At the beginning of the experiment, you will be assigned a role, either player 1, or player 2, or player 3. Your role will be fixed during the entire experiment and only you know it. In each period, you will be randomly matched with players playing other roles. It is very likely that the players you play with in different periods are different.

Your earnings in the experiment are displayed in experiment currency and will be converted to dollars. Specifically, 100 units of experiment currency will be converted to $1. You will also be paid a $5 participation fee.

Experiment Procedure

A box (Box 1) contains 10 balls, 3 ***red*** balls and 7 ***blue*** balls. One ball is randomly and secretly chosen from Box 1 and put into another empty box (Box 2). No player knows the color of the ball in Box 2.

Player 1 chooses a detector that will send a signal (***B*** or ***R***) related to the color of the ball in Box 2. The signal may or may not match the actual color of the ball, and the probability of sending signals varies across detectors. After player 1 makes the choice, player 2 and player 3 will be able to see the chosen detector and the sent signal. Table 1 shows the detectors player 1 can choose from.

Table 1 Player 1's Options

Options	Probability of sending signals
Detector A	If the ball is ***blue***, 100% of the time it sends a signal ***B***. If the ball is ***red***, 100% of the time it sends a signal ***R***.
Detector B	If the ball is ***blue***, 80% of the time it sends a signal ***B***; 20% of the time it sends a signal ***R***. If the ball is ***red***, 100% of the time it sends a signal ***R***.
Detector C	No signal will be sent

Player 2 sees the detector chosen by player 1 and the signal sent by the detector. Then, player 2 chooses from another three detectors (different from player 1's detectors!) to send a signal (***b*** or ***r***). Similarly, the signal may or may not match the actual color of the ball, and the probability of sending signals varies across detectors. After player 2 makes the choice, player 3 will be able to see the chosen detector and the sent signal. Table 2 shows the detectors player 2 can choose from.

Table 2 Player 2's Options

Options	Probability of sending signals
Detector a	If the ball is ***blue***, 100% of the time it sends a signal ***b***. If the ball is ***red***, 100% of the time it sends a signal ***r***.
Detector b	If the ball is ***blue***, 100% of the time it sends a signal ***b***. If the ball is ***red***, 80% of the time it sends a signal ***r***; 20% of the time it sends a signal ***b***.
Detector c	No signal will be sent.

Player 3 sees the detectors chosen by player 1 and player 2 and the signals sent by both detectors. Then he/she makes a guess (***red*** or ***blue***) about the color of the ball in Box 2.

Table 3 Payoffs for Players

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Player 3's guess</td></tr>
<tr><td>red</td><td>blue</td></tr>
<tr><td colspan="2">Player 1's payoff</td><td>200</td><td>0</td></tr>
<tr><td colspan="2">Player 2's payoff</td><td>0</td><td>100</td></tr>
<tr><td rowspan="2">Player 3's payoff</td><td>If the ball is red</td><td>70</td><td>0</td></tr>
<tr><td>If the ball is blue</td><td>0</td><td>70</td></tr>
</table>

Player 1 earns 200 if player 3 guesses ***red***, and 0 otherwise. Player 2 earns 100 if player 3 guesses ***blue***, and 0 otherwise. Player 3 earns 70 if his guess is correct, and 0 otherwise. Table 3 summarizes players' payoffs.

After each period, all players can review the true color of the ball, the detectors chosen by player 1 and player 2, the signals sent by detectors, player 3's guess, and their own payoffs. Each period is independent.

***Appendix C**: Screens of the One-Sender and Two-Sender Treatments*

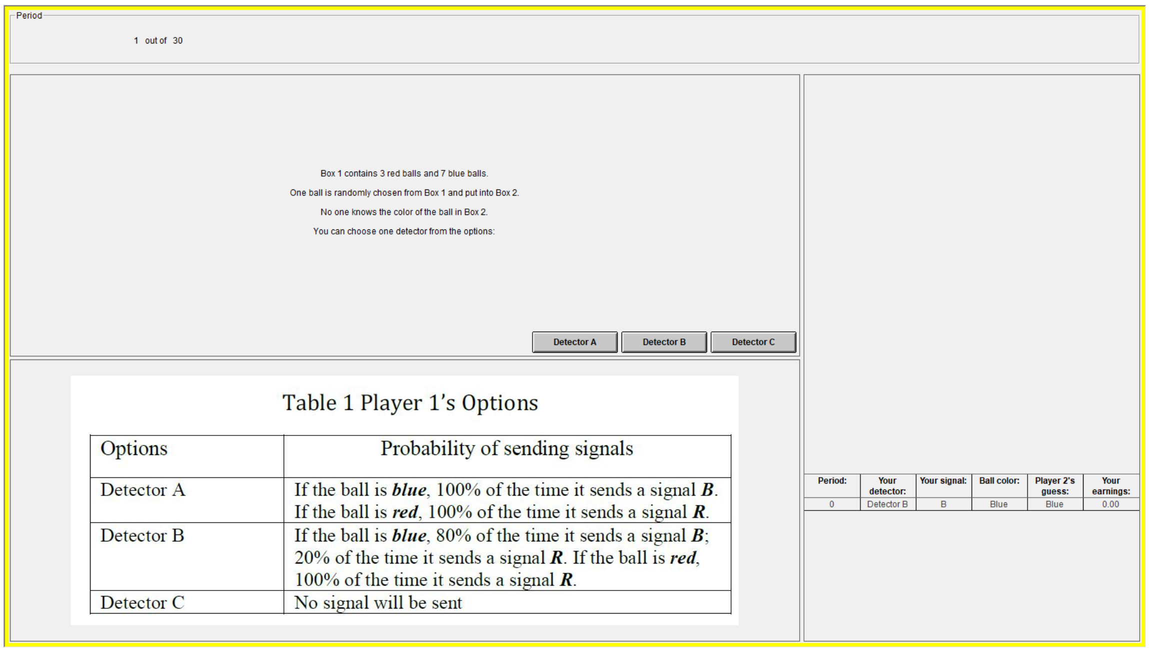

Figure 4: The Screen of Sender in the One-sender Treatment

Sender is able to see detector options, and their corresponding probabilities of sending each type of signals. Sender is able to review his/her own decisions, signals sent, his/her own payoffs, and decisions of the receiver that they are matched with in all previous rounds.

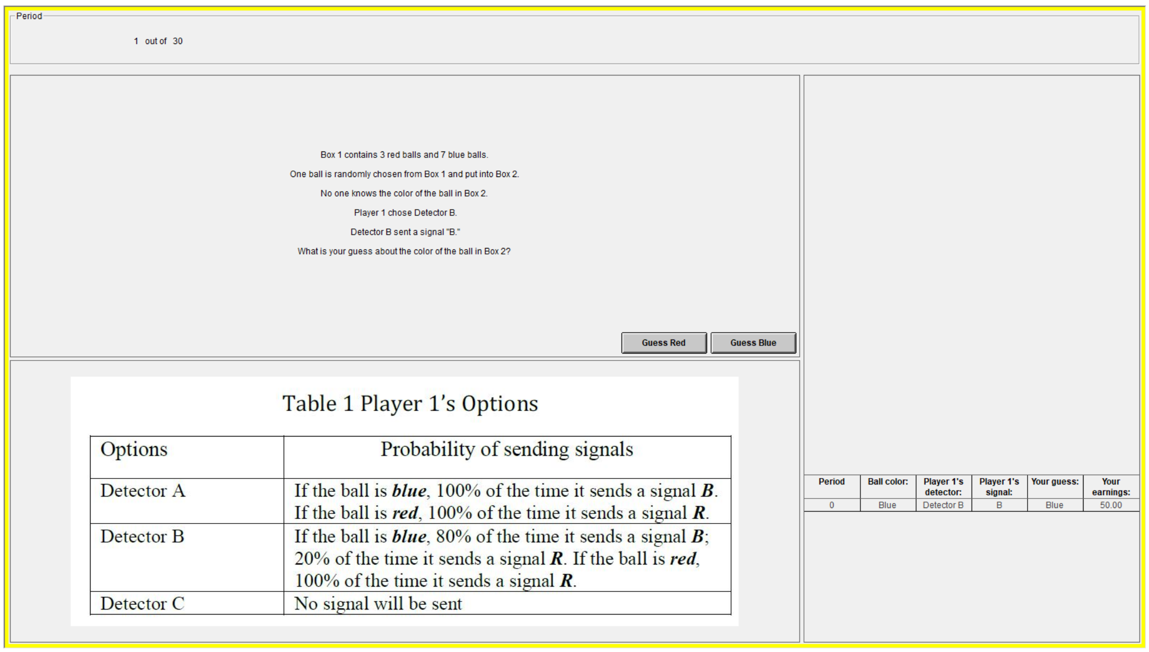

Figure 5: The Screen of Receiver in the One-sender Treatment

Receiver is able to see the detector decision of the sender, and the probabilities of sending each type of signals for each detector options. Receiver can also review his/her decisions, payoffs, and detector choice and signals sent by the sender in all the previous rounds.

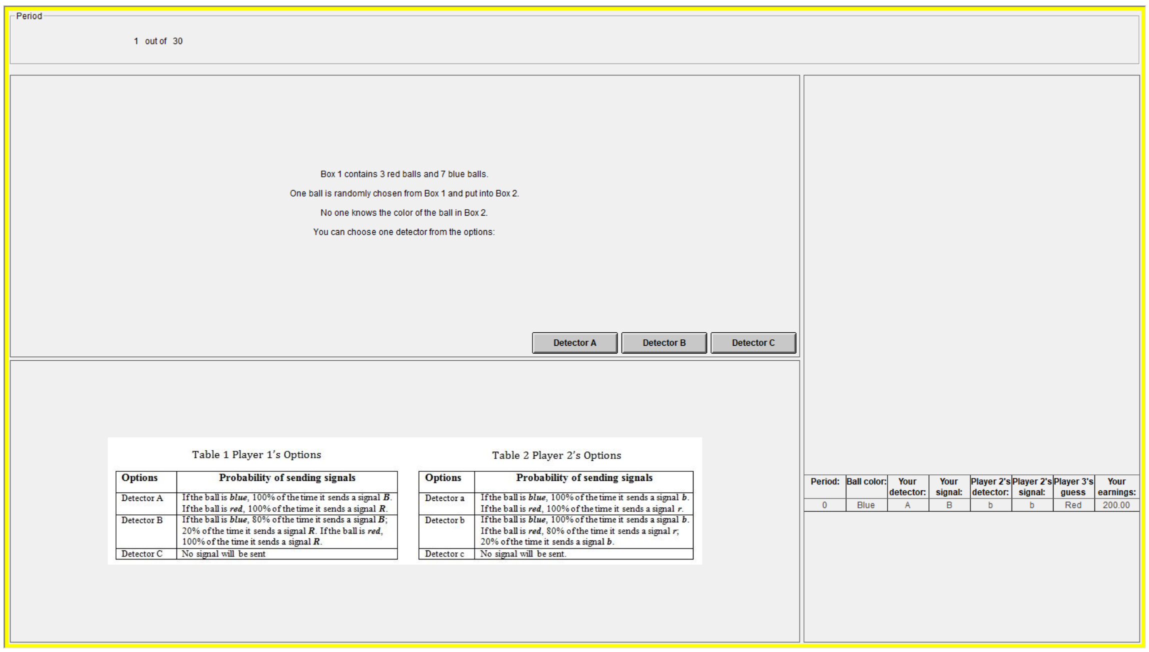

Figure 6: The Screen of Sender 1 in the Two-sender Treatment

Sender 1 is able to see detector options, and the corresponding probabilities of sending each type of signals to those options for both senders. Sender 1 is also able to review all his/her decisions, signals sent, his/her own payoffs, and the decisions of the other two players whom they are matched with in all previous rounds.

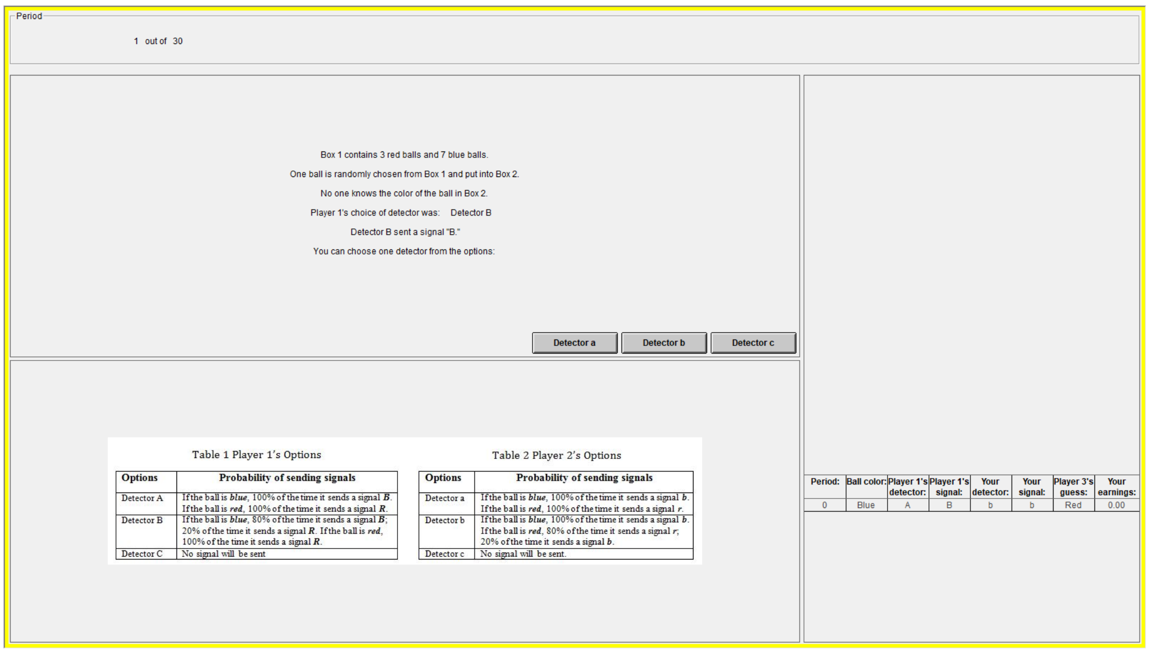

Figure 7: The Screen of Sender 2 in the Two-sender Treatment

Sender 2 is able to see the detector and signal from Sender 1. Sender 2 is also able to review all his/her decisions, signals, his/her own payoffs, and the decisions of the other two players whom they are matched with in all previous rounds.

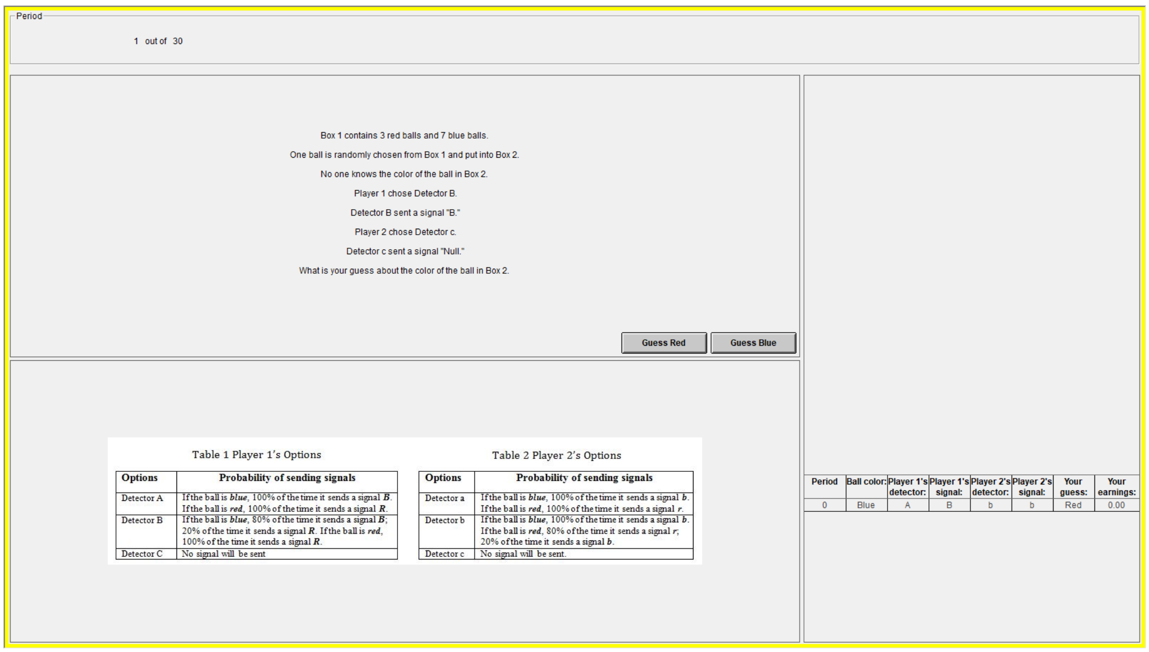

Figure 8: The Screen of Receiver in the Two-sender Treatment

Receiver is able to see both detectors chosen by both senders and signals generated by the two detectors. Receiver is also able to review all his/her previous decisions, signals sent, his/her payoffs, and the decisions of the other two players whom they are matched with in all previous rounds.