Overcommunication and Bounded Rationality in Strategic Information Transmission Games: An Experimental Investigation*

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Abstract

Since Crawford and Sobel (1982), the theory of strategic information transmission has found a wide range of applications and has become increasingly important in the literature. In this paper we conduct laboratory experiments to test this theory. Our experimental results strongly support the basic insight of the theory, namely, that less information is transmitted when preferences of the sender and the receiver diverge. Moreover, the average payoffs for the senders, the receivers, and the overall subject population are very close to those predicted by the most informative equilibrium. However, the evidence shows that subjects consistently overcommunicate in that the senders' messages are more informative about the true states of the world and that the receivers rely more on the senders' messages in choosing actions, compared with what the theory allows in the most informative equilibrium. These findings are robust to certain variations of payoff parameters and noisy signals. In addition, we do not find any clear learning effect in our data. To understand the overcommunication phenomenon, we use two popular approaches of bounded rationality: behavior type analysis and quantal response equilibrium, to analyze subjects' behavior in our experiment data.

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1 Introduction

In many real world situations decision makers have to rely on others for information needed to make good decisions, who often have preferences different from the decision makers' and hence may act strategically in communicating their information to the decision makers. Following the seminal work of Crawford and Sobel (1982), the literature on strategic information transmission has grown rapidly, with a wide range of applications in economics and many related fields such as political science (e.g., congress committee decisions), finance (e.g., stock analysts), and organization theory (e.g., managers versus subordinates or consultants). Given its increasing importance in the literature, it is natural to ask whether and to what extent the theoretical insights of Crawford and Sobel and the subsequent works hold out empirically. However, aside from the standard limitations of field data (e.g., no controlled environments, too much noise), this theory is very difficult to test by field data, because its key variables (e.g., communication, preference differences) are inherently unobservable. Experiments are well suited to test the theory by providing controlled environments and by allowing experimenters choose the variables unobservable in field data (e.g., preference differences).

In this paper, we conduct laboratory experiments to test the theory of strategic information transmission. We are interested in whether and to what extent the main insights of the theory are supported by experimental data. In the model of Crawford and Sobel (1982), one player (the sender) communicates his private information about the state of the world to a decision maker (the receiver). They show that messages are partitions of the state space in all equilibria. Moreover, in the most informative equilibrium, less information can be transmitted as the preference difference between the two players increases. With non-trivial preference differences, little information can be communicated even in the most informative equilibrium, that is, the finest partition in equilibrium is quite coarse.[1] We design a relatively simple game of strategic information transmission with discrete states, messages and actions. The most informative equilibrium of this game ranges from the completely informative equilibrium (truth-telling by the sender and fully-trusting by the receiver), to partially informative equilibria, to the completely uninformative equilibrium ("babbling" equilibrium), as the preference difference between the sender and the receiver increases. We run a series of experiments with varying preference differences, and find evidence that strongly supports the theoretical comparative statics predictions. Specifically, the experimental results clearly show that as the preference difference increases, less information is transmitted from the senders and utilized by the receivers, in the sense that correlations between states and messages, between messages and actions, and between states and actions all

[1] In the canonical example in which the state is uniformly distributed on $[0, 1]$ and utility functions are quadratic, there can be at most two partitions (less than or greater than $1/4$) when the preference difference between the two players is only $1/8$.

decrease in preference difference. Moreover, the average payoffs for the senders, the receivers, and the overall subject population are very close to the equilibrium payoffs predicted by the theory. These findings suggest that the subjects not only understand the game and behave strategically (and hence become less "trusting" when their partner's preference is more different from theirs), but also seem to be playing according to the most informative equilibrium.

A closer look at the subjects' behavior in the data, however, clearly rejects the conclusion that the subjects as a whole play according to equilibrium. In fact, the data show that there is a robust tendency for the subject population to communicate more than what the theory allows in the most informative equilibrium. In the case of large preference differences, correlations between states and messages, between messages and actions, and between states and actions are all significantly positive, while the theory predicts that they should all be zero. Regression results on individual subject data further confirm that messages, states and actions are all positively correlated with each other, rejecting strongly the babbling equilibrium hypothesis. We then examine distributions of states conditional on messages, distributions of actions conditional on messages, and distributions of actions conditional on states. In all cases, the experimental data clearly show that these conditional distributions (frequencies) are not consistent with theory predictions: messages are informative about the states, and actions rely on messages and hence are correlated with states. For example, in our game with the state space of $\{1, 3, 5, 7, 9\}$, in the case of large preference difference in which the babbling equilibrium is the unique equilibrium of the game, for the message of 5, the empirical distribution of states is: $s = 1$ (43.75%), $s = 3$ (16.25%), $s = 5$ (28.75%), $s = 7$ (6.25%), $s = 9$ (5.00%), with an average state of 3.25. Compared with the uniform distribution with an expected state of 5 predicted by the theory, this empirical distribution contains a substantial amount of information about the true state of the world.

To test the robustness of these results, we run experiments with modified designs. It turns out that the experimental results from the baseline sessions are very robust to variations of parameter values that change the subjects' payoff sensitivity and to variations of message space the senders are allowed to use. Furthermore, we run experiments in which the senders are only given noisy signals about the true states of the world. The results show that the noisiness of signals does not have noticeable effects on experimental outcomes, suggesting that the overcommunication phenomenon is not due to a simple "trusting-the-expert" mentality by the subjects. We also investigate the possible effects of subjects learning on the experimental results. Regression analysis on payoffs and correlations using data from a session of experiment with 31 rounds of play find no clear time trend and no convergence to equilibrium predictions, suggesting that there is no clear learning effect at least up to 31 rounds in the experiments.

These findings raise two questions. First, why are the average payoffs so close to the equilibrium predictions while at the same time subjects' individual behavior is clearly different from equilibrium strategies? Second, what are the possible explanations for the subjects' behavior? In particular, what are the reasons behind the overcommunication phenomenon? Two approaches of bounded rationality, behavior type analysis and quantal response equilibrium, are commonly used in the existing literature to explain non-equilibrium phenomena in experimental data. To understand the overcommunication phenomenon in our experiment, we apply both approaches to analyze our data.

The behavior type analysis approach is developed by a number of scholars, e.g., Nagel (1995), Stahl and Wilson (1995), Ho, Camerer and Weigelt (1998), and Costa-Gomes, Crawford and Broseta (2001, 2002). They demonstrate that subjects in their experiments (in particular, "beauty contest" games) consistently behave in a specific bounded rational way: subjects of different levels of sophistication have the non-equilibrium belief that other subjects are one level lower than themselves in sophistication and best response to that belief.[2] To apply this approach in communication games, Crawford (2003) cites earlier experiment evidence (e.g., Blume, DeJong, Kim and Sprinkle, 2001) and argues that the system of subject types should be anchored on the "truster" type of senders and the "believer" type of receivers.[3] In our data, there are indeed senders who always tell the truth (the truster type) and receivers who always believe the senders (the believer type). So we follow Crawford (2003) to define the system of behavior types for our game.[4] We then follow the classification methodology of Costa-Gomes *et al* (2001, 2002) to classify subjects whose actions can be consistently identified as fitting into one of the behavior types. About 75% of the subjects in our experiments can be classified. We calculate the expected payoffs and correlations generated by the distribution of behavior types combined with some random noise. The results match the actual data quite well. This suggests the following interpretation of our experimental results. Subjects of lower levels of sophistication overcommunicate, resulting in more communication than what the theory predicts. However, since the subjects are randomly paired, a sender of a certain type can be matched with possibly many types of receivers in a given round. Some of these matches are equilibrium-alike, others ("mismatches") give rise to outcomes quite different from equilibrium. Combined with some noise, these mismatches tend to offset the payoff gains and losses (relative to the equilibrium predictions), leading to average payoffs close

[2] See Crawford (1997) and Camerer (2002) for comprehensive surveys and further references.

[3] In other games it is standard to specify the lowest level of sophistication to behave completely randomly (choosing every available strategy with equal probability). However, complete randomization is the sender's equilibrium strategy in the babbling equilibrium of communication games (which always exists). Thus, the system of behavior types in communication games cannot be anchored on complete randomization. Similarly, it is not straightforward to apply the cognitive hierarchy theory of Camerer, Ho, and Chong (2002) to communication games.

[4] The next level of sophistication is for the senders to send messages identical to their most preferred actions to best response to the believer type receivers (the liar type of senders), and for the receivers to best response to the liar senders by taking actions equal to messages minus the preference differences (the inverter type of receivers. The system of behavior types can be constructed in this iterative way.

to the equilibrium predictions.

An alternative approach to bounded rationality is the "quantal response equilibrium" proposed by McKelvey and Palfrey (1995, 1998), in which players have correct beliefs about their opponents but do not maximize their payoffs perfectly given the beliefs. One advantage of this approach is that it explicitly takes into account noisy behavior of subjects. One advantage of this approach is that QRE explicitly takes into account noisy behavior by subjects. To apply this approach to our experiment data, we follow McKelvey and Palfrey (1998) to solve for the logit-agent quantal response equilibrium (logit-AQRE) for our game, and do the maximum likelihood estimation using our data. The results suggest that the logit-AQRE explains the communication patterns in our experimental data pretty well.

In the existing literature there are very few experimental works testing the theory of strategic information transmission. Closest to our paper is Dickhaut, McCabe and Mukherji (1995), who pioneered direct experimental testing of the theory of strategic information transmission. Their experimental results also confirm the comparative statics predictions of the theory. Our experimental design is similar to theirs, but differ in several aspects. First, our experimental design allows sharper tests of the theory. Dickhaut, *et al*, use a game in which both the state space and the action space are $\{1, 2, 3, 4\}$. In this game the receiver is often indifferent between two actions, which makes outcomes of different equilibria not sharply distinguishable.[5] Moreover, we control for repeated game effects while Dickhaut, *et al*, let each pair of subjects play three rounds of the game in sessions with 4 pairs of subjects. Despite the differences in design, it is comforting that their findings are broadly confirmed in our experiments. However, we go beyond confirming the comparative statics predictions of the theory. We find similarities between average payoffs and equilibrium-predicted payoffs, and more importantly, the overcommunication phenomenon. We establish the robustness of these findings along several dimensions. Lastly, we analyze the possible reasons behind the non-equilibrium behavior of subjects and what results in payoffs being so close to the equilibrium predicted payoffs.

Blume, DeJong, Kim and Sprinkle (1998, 2001) also conduct a series of experiments on strategic information transmission games. Their experimental results clearly indicate an over-communication tendency by the subjects, see, e.g., Tables V-VII of Blume *et al* (2001). They also do a quite thorough investigation into whether such non-equilibrium phenomenon is consistent with several different solution concepts. However, their experimental design does not directly correspond to the game of Crawford and Sobel (1982). Moreover, since they are mainly interested in the evolution of meanings of messages, subjects interacted with each other many times and

[5] For example, in the babbling equilibrium the receiver is supposed to choose either 2 or 3 and the sender should purely randomize among 1, 2, 3 or 4. If the receiver's tie-breaking leans toward matching the sender (i.e., choosing 2 for message 2, and 3 for message 3), this babbling equilibrium is indistinguishable with the completely informative equilibrium 50% of time.

summary history about other subject pairs was revealed at the end of each period. Our focus and experimental design are different from theirs.

There is a very active literature, both theoretical and experimental, on pre-game communication when players try to communicate to their opponents their intentions to play the game in a particular way, e.g., see Farrell and Rabin (1996).[6] Due to space limit, we will not discuss the relationships between such pre-game communication and strategic information transmission (where players communicate their private information to their opponents). Crawford (1988) offers an excellent overview of the theoretical connections and distinctions between these two types of cheap talk games as well as the related experimental literature.

Several theoretical models, e.g., Eyster and Rabin (2000), Ottaviani and Squintani (2002), and Crawford (2003), predict that under certain conditions players communicate their private information more than the standard Bayesian Nash equilibrium allows. We will discuss the relations of these papers with our study in Section 7.

The rest of the paper is organized as follows. Section 2 presents the theoretical model and its predictions, and Section 3 discusses our experiment design. Then we present the experimental results of the baseline sessions in Section 4 and the results of robustness tests in Section 5. In Section 6 we examine possible learning effects. The next two sections use two approaches of bounded rationality to interpret our data. Section 7 analyzes the data using the behavior type analysis approach mentioned above, and Section 8 applies quantal response equilibrium to the data. Concluding remarks are contained in Section 9.

2 Theoretical Model and Predictions

In our experiments, subjects are paired to play the following specific game of strategic information transmission. One player in each pair is the sender and the other is the receiver. The sender is informed about the state of the world, which is a number uniformly drawn from the state space $S = \{1, 3, 5, 7, 9\}$. The receiver knows the distribution of s, but not its realization. The sender then chooses to send a message to the receiver, where the feasible message space is any subset of $M = \{1, 3, 5, 7, 9\}$. After receiving a message from the sender, the receiver chooses an action from the action space of $A = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$. The true state of the world and the receiver's action determine the two players' payoffs in points according to the following pre-specified formula

$$
\begin{aligned}
u_R &= 110 - 10 \cdot |s - a|^k \\
u_S &= 110 - 10 \cdot |s + d - a|^k
\end{aligned}
$$

[6] Palfrey and Rosenthal (1991) study a model in which players have private information about their costs of contributing to a public project and also can announce their intentions (whether to contribute) before the contribution stage. They obtain mixed experimental results regarding communication in the cheap talk stage.

where u_R and u_S are the payoffs for the receiver and the sender, respectively, s is the true state of the world, a is the receiver's action, d is the preference difference between the sender and the receiver, and k is a positive parameter. Thus, the receiver's ideal action is to match the true state of the world, while the sender's is the true state of the world plus d.

In games of strategic information transmission, it is well known that there exists a babbling equilibrium in which the sender always sends a purely uninformative message (message not correlated with his information about the true state of the world) and the receiver always ignores the sender's message and makes decisions based on her own prior knowledge about the state of the world. In the babbling equilibrium, no information is transmitted from the informed sender to the receiver. Naturally the focus of research is on the most informative equilibrium, that is, how much information can be possibly transmitted in any equilibrium. Informativeness can be measured by the correlation between actions and the true states of the world. The correlation is zero in the babbling equilibrium, and takes the maximum value of one if actions perfectly match the states of the world. In addition, the informativeness of the sender's messages can be measured by the correlation between the true states of the world and the messages he sends; and how "trusting" the receiver is can be measured by the correlation between the messages she receives and the actions she takes.

In the game used in our experiments, as the preference difference varies, the most informative equilibria can be characterized as follows.

Proposition 1 *For $k \geq 1$, the most informative equilibria of the game (for different d's) are*

(i) the **separating (completely informative) equilibrium** *if $d \leq 1$, in which for every state of the world s, the sender always tells the truth ($m(s) = s$), and the receiver always chooses the action according to the (truthful) message ($a(m) = m$);*

(ii) the **partial pooling equilibrium** *if $1 < d \leq 1.5$, in which the sender sends a same message for states 1 and 3, and another message for states 5, 7, and 9 ($m(s = 1) = m(s = 3) = \{13\}; m(s = 5) = m(s = 7) = m(s = 9) = \{579\}$),[7] and the receiver chooses 2 or 7 according to $a(m = \{13\}) = 2$ and $a(m = \{579\}) = 7$;*

(iii) the **partial pooling equilibrium** *if $1.5 < d \leq 2.5$, in which the sender chooses $m(s = 1) = 1$ and pools for states 3, 5, 7, and 9 ($m(s = 3) = m(s = 5) = m(s = 7) = m(s = 9) = \{3579\}$, while the receiver chooses 1 if $m = 1$ ($a(m = 1) = 1$) and 6 otherwise ($a(m = \{3579\}) = 6$);*

(iv) the **babbling equilibrium** *if $d > 2.5$, in which the sender pools for states 1, 3, 5, 7, and 9(for all s, $m(s) = \{13579\}$), and the receiver always chooses 5 (for all m, $a(m) = 5$).*

[7] $\{13\}$ means pooling of states 1 and 3, $\{579\}$ means pooling of states 5, 7, and 9, etc.

Our experiments have four treatments with $d_1 = 0.5$, $d_2 = 1.2$, $d_3 = 2$, and $d_4 = 4$, corresponding to the four cases in Proposition 1. We choose a value of 1.4 for parameter k in our baseline sessions, so that payoffs are sensitive to the choices subjects make (the receiver's payoffs range from 110 to -73.79 and the sender's earning can range from 110 to - 214.23 when $d = 4$), but not too high that subjects may suffer from a loss in one round too large to recover in the experiment (for example, for $k = 2$ and $d = 4$, the sender could get payoffs of -1330 in one round). Besides, it is not desirable for one or few abnormal rounds to have too large an impact on the payoffs and to potentially affect subjects' behavior in latter rounds. In our experiments with $k = 1.4$ and $d = 4$, subjects sometimes got negative point payoffs in some rounds but all recovered their losses and got positive total payoffs by the end of the experiments. For robustness analysis, we also conduct experiments with different values of k, which will be discussed later in Section 5.

The properties of the most informative equilibria are presented in Table 1 below.

Table 1: Properties of the Most Informative Equilibria

d	Equilibrium Messages	Equil. Actions	Senders' Payoffs	Receivers' Payoffs	Overall Payoffs†	Corr. (S,M)‡	Corr. (M,A)	Corr. (S,A)
0.5	{1},{3},{5},{7},{9}	1,3,5,7,9	106.21 (0.00)	110.00 (0.00)	108.11 (1.89)	1.000	1.000	1.000
1.2	{13},{579}	2, 7	89.52 (18.06)	95.44 (10.33)	92.48 (15.01)	0.750	0.866	0.866
2	{1},{3579}	1, 6	72.37 (31.77)	87.38 (19.88)	79.88 (27.54)	0.500	0.707	0.707
4	{13579}	5	29.46 (66.32)	71.59 (27.26)	50.52 (54.90)	0.000	0.000	0.000

Notes: Numbers inside the parenthesis are the standard deviations of the corresponding payoffs.
† This is the average of the sender's and receiver's payoffs. This measure is useful because our experiments randomly assign a subject's role as the sender or receiver at the beginning of each round.
‡ When calculating the correlations involving messages, we interpret the messages as mixing across the possible states. In other words, {13} would be mixing between 1 and 3, and so on.

The main insight of Crawford and Sobel is clearly shown in Table 1. As the preference difference d between the sender and the receiver increases, less information can be transmitted in the most informative equilibrium. Specifically, as d increases, the sender's message becomes less informative as he pools more. As a result, as d increases from 0.5, to 1.2, to 2, and to 4, the correlation between the true state and the sender's message decreases from 1, to 0.75, to 0.5, all the way down to 0. Correspondingly, as d increases, the receiver trusts the sender less as her actions are less correlated with his messages. For $d = 0.5, 1.2, 2, 4$, the correlation between the sender's messages and the receiver's actions decreases from 1, to 0.866, to 0.707, all the way down to 0. Consequently, as a measure of how much information is reflected in the receiver's decisions, the correlation between actions and the true states decreases as d increases.[8] Accordingly, both

[8]Note that the correlation between messages and actions is identical to the correlation between states and

the sender's and the receiver's payoffs decrease in d, with the sender's payoff suffering a much greater reduction than the receiver's as d increases from 0.5 to 4. The following hypotheses summarize the theoretical predictions of the model.

Hypothesis 1 *As the preferences of the sender and the receiver diverge, less information is transmitted by the sender and utilized by the receiver: the correlations between states and messages, between messages and actions, and between states and actions all decrease.*

Hypothesis 2 *As the preferences of the sender and the receiver diverge, both the sender's and the receiver's payoffs decrease.*

3 Experiment Design

The experiment was conducted in the California Social Science Experimental Laboratory (CASSEL) located at UCLA, and programmed with the software z-Tree (Fischbacher, 1999). Typically, sessions lasted from 1.5 to 2.5 hours, and subjects were predominantly UCLA undergraduate students, with few graduate students. As is standard, subjects interacted with each other only through computer terminals during the experiments. Subjects are paid a \$5 show-up fee plus whatever they earn from playing the games; their dollar earnings are converted from point payoffs using a pre-specified exchange rate.[9]

In each experiment session, $2N$ subjects were matched into N pairs. Pairing was done in such a way that two subjects would play against each other at most once; and this is made known and clear to all subjects to avoid problems of repeated interactions.[10] In each round, within each pair one player was randomly chosen to be the sender and the other to be the receiver. For each pair, the computer program generated a number uniformly from $\{1, 3, 5, 7, 9\}$, and revealed the number to the sender. After knowing this number, the sender chose a message to send to the receiver. Besides one of the five possible states, the sender was also allowed to randomize over the state space. For example, the sender could instruct the computer to send "3 or 5 or 7", and the computer program would generate a number uniformly from the set the sender specified and

actions. Since we treat pooling of states as an explicit mixing of these states (done by the computer program), the distribution of the realized messages is the same as the distribution of states. For example, when $d = 1.2$, the sender will mix between 1 and 3 equally for states $s = 1$ and $s = 3$ (each with probability of $\frac{1}{5} \cdot \frac{1}{2} + \frac{1}{5} \cdot \frac{1}{2} = 0.2$), leading to the realized message of $m = 1$ or $m = 3$ each with a probability of 0.2. Moreover, the receiver will take an action of 2 when seeing messages 1 or 3, which corresponds to states 1 or 3. Therefore, the correlation of actions with states is the same with messages.

[9]Excluding the \$5 show-up fee, average dollar earning ranges from about \$10.30 to \$32.11 from the lowest payoff session to the highest payoff session.

[10]The Appendix contains a sample of instructions for one of the sessions.

sent it to the receiver. Once the receiver got the sender's message, she chooses an action from $\{1, 2, 3, 4, 5, 6, 7, 8, 9\}$. The even numbers were included in the action space so that the receiver could make better decisions if she tried to maximize her expect payoff and her beliefs led to the expected state being one of the even numbers (e.g., the state being either 1 or 3 with equal probabilities). Payoff functions and parameters were publicly announced to the subjects, while possible values of payoffs are presented in tables to the subjects so they do not have to do the calculations. For example, when the true state of the world is 7, the sender's and the receiver's payoffs in points for the four treatments $d = 0.5, 1.2, 2, 4$, are as shown in Table 2.

Table 2: Payoffs When True State s = 7 (k=1.4)

Actions	action 1	action 2	action 3	action 4	action 5	action 6	action 7	action 8	action 9
member B	-12.86	14.82	40.36	63.44	83.61	100.00	110.00	100.00	83.61
A (d=0.5)	-27.43	1.23	27.87	52.23	73.93	92.36	106.21	106.21	92.36
A (d=1.2)	-48.59	-18.63	9.44	35.43	59.04	79.84	97.09	108.95	102.68
A (d= 2)	-73.79	-42.45	-12.86	14.82	40.36	63.44	83.61	100.00	110.00
A (d= 4)	-141.19	-106.74	-73.79	-42.45	-12.86	14.82	40.36	63.44	83.61

Notes: The sender is called "member A", and the receiver "member B" in the experiments. The receiver's payoff depends on the state and her action, and is invariant to d.

In the experiments, the tables of payoffs as functions of the true state of the world and the receiver's action were presented to the subjects as shown in the following screen shots. The preference difference d was shown in a box in the upper right corner of each player's screen (in the example, $d = 4$). The payoff table was presented on the left side of the screen for each player. The first column was titled "Secret number", which represents the state of the world in the experiments. Subjects needed to click on the button of a number in the first column to view the payoffs for both players (which depend on member B's actions) if the true value of the secret number was that number. In the example, member A clicked on buttons of "1", "3", "5", and not (yet) on "7" or "9", while member B clicked all the buttons except "7". On the right side of member A's screen, member A could find the true value of the secret number ("5" in this example) and was asked to choose a message in the box below. In this example, member A chose "5 or 7 or 9", which meant that the computer program would generate a number from among the three with equal probability. The number turned out to be "9" in this case, which the computer sent to member B. The right side box of member B's screen told her that member A sent a message "The number I received is 9", where she was also reminded that "This message could come from a random draw".[11] Member B was then asked to choose an action from the

[11] We restrict the language protocol to "The number I received is" to ensure that both subjects communicate in a common language. We do not deal with issues of evolution of meanings of messages that Blume, DeJong, Kim and Sprinkle (1998, 2001) study.

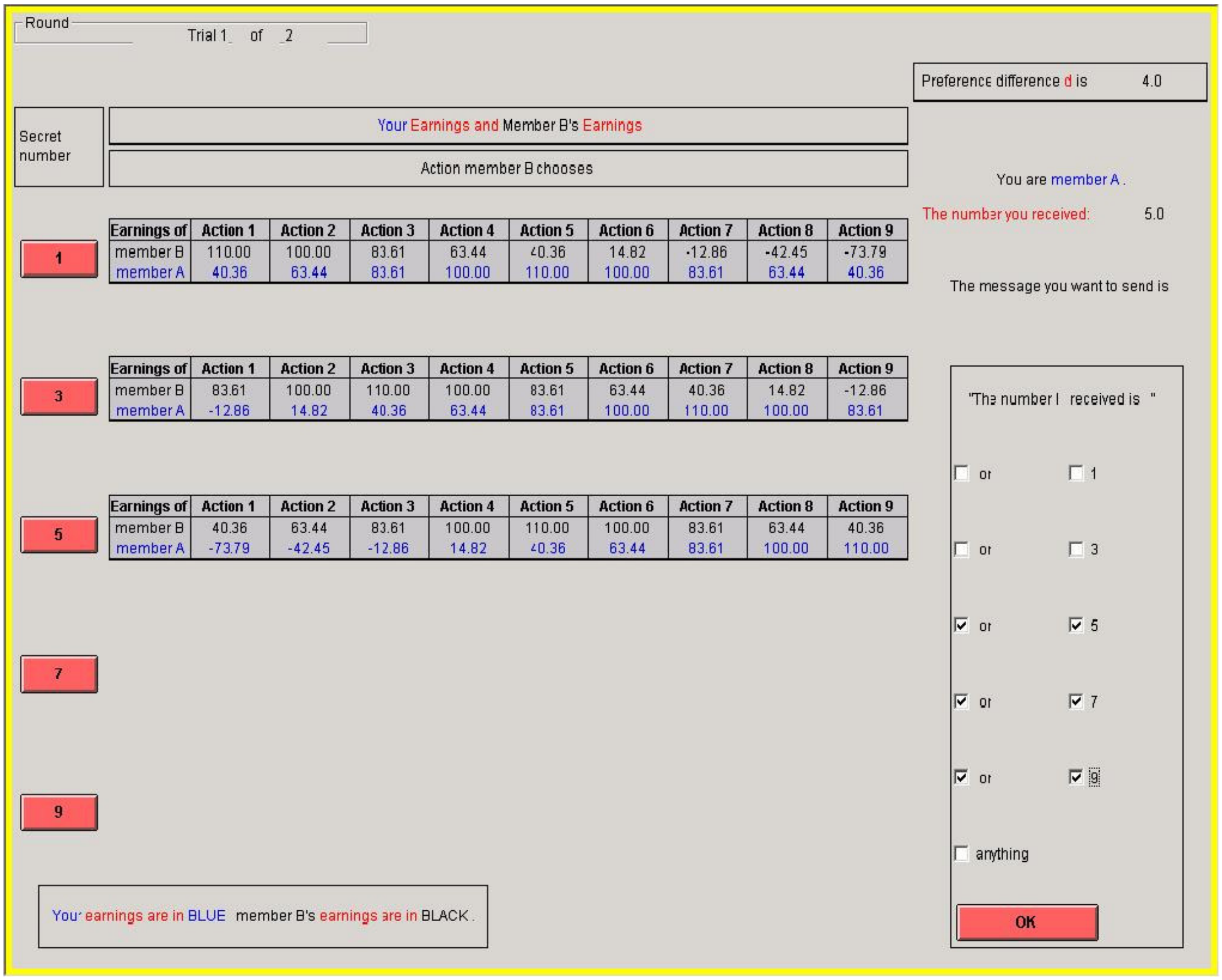

Figure 1: Sender's (Member A's) Screen.

action space. At the end of each round, a summary table revealed all the relevant information to both players, including the true state of the world, the sender's message, the receiver's action, and each player's payoff.

We ran three sessions using our base design with the payoff parameter k set at 1.4. Session 1 was conducted with 28 subjects and a total of 21 rounds, five rounds each for $d = 0.5, 1.2, 2$ and six rounds for $d = 4$, resulting in 70 observations for each of the first three cases and 84 for the last. Session 2 was run with 32 subjects and a total of 31 rounds, all with $d = 4$, resulting in 496 observations. Session 3 was run with 32 subjects and a total of 20 rounds, all with $d = 2$, resulting in 320 observations. The results from these three sessions turned out to be very close, so we grouped them together as a single sample.

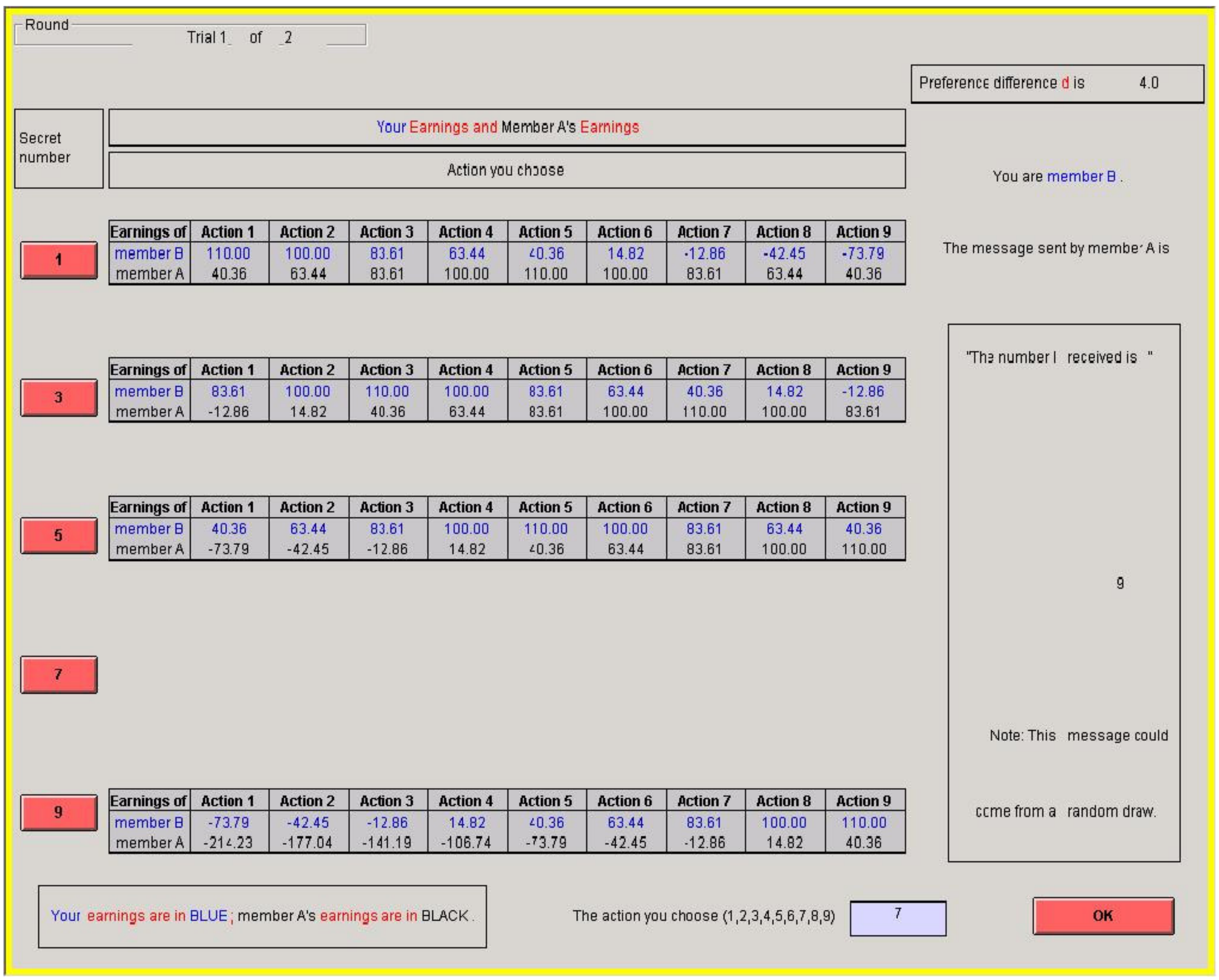

Figure 2: Receiver's (Member B's) Screen.

4 Experimental Results

In this section we present the experimental results of the three baseline sessions.

Result 1 *The experimental outcomes are strongly supportive of Hypothesis 1: less information is transmitted by the sender and utilized by the receiver as preferences between the sender and the receiver diverge. Specifically, the correlations between states and messages, between messages and actions, and between states and actions all decrease as* d *increases.*

Table 3 presents the correlations calculated from our experimental data.

Table 3: Actual Information Transmission

Number of Observations	k	d	Corr. (S,M)	Corr. (M,A)	Corr. (S,A)
70	1.4	0.5	0.916	0.965	0.876
70	1.4	1.2	0.896	0.924	0.830
390	1.4	2	0.734	0.794	0.618
580	1.4	4	0.391	0.542	0.207

As d increases from 0.5 to 4, the senders' messages become less and less informative, measured by the correlation between states and messages. While not very different for the cases $d = 0.5$ and $d = 1.2$, the correlation between states and messages decreases significantly when $d = 2$ ($corr.(S, M) = 0.734$) and drops much farther when $d = 4$ ($corr.(S, M) = 0.391$). The receivers show a similar pattern, with the correlation between messages and actions decreasing from 0.965, to 0.924, to 0.794, and then to 0.542 as d increases from 0.5, to 1.2, to 2, and then to 4. As a measure of how much information is actually used in the receivers' actions, the correlation between states and actions also exhibits a clear comparative static pattern predicted by theory: it decreases from 0.876, to 0.830, to 0.618, and then to 0.207 as d increases from 0.5, to 1.2, to 2, and then to 4. Therefore, our experimental outcomes are strongly supportive of the theoretical prediction of Hypothesis 1. This indicates that subjects in our experiments as a whole understand the basic strategic aspects of the game and are responsive to incentives presented in the experiment design.

Result 2 *The experimental outcomes are strongly supportive of Hypothesis 2: both the senders' and the receivers' average payoffs decrease as the preference difference increases. Moreover, the average payoffs for the senders, the receivers, and the subject population are very close to those predicted by the most informative equilibrium.*

We calculate the average payoffs for the senders, the receivers, and the whole subject population, for each value of preference difference $d = 0.5, 1.2, 2, 4$. Table 4 presents the results, as well as the equilibrium predicted payoffs (from Table 1) for comparison. It is clear from Table 4 that the actual payoffs exhibit strong monotonic patterns as preferences between the senders and the receivers diverge, just as theory predicts. In particular, as d increases from 0.5, to 1.2, to 2, and then to 4, the average payoff for the senders decreases from 99.08, to 88.76, to 75.03, and then to 36.89; the average payoff for the receivers decreases from 101.79, to 93.54, to 83.69, and then to 65.84; and accordingly the average payoff for the subject population decreases from 100.44, to 91.15, to 79.36, and then to 51.37. These results lend strong support for the comparative static prediction of the Crawford and Sobel (1982).

Table 4: Theoretical vs. Actual Payoffs

# of obs.	d	Senders' Payoffs Predicted (s.d.)	Senders' Payoffs Actual (s.d.)	Receivers' Payoffs Predicted (s.d.)	Receivers' Payoffs Actual (s.d.)	Average Predicted (s.d.)	Average Actual (s.d.)
70	0.5	106.21	99.08*	110.00	101.79**	108.11	100.44*
		(0.00)	(24.16)	(0.00)	(25.82)	(1.89)	(24.95)
70	1.2	89.52	88.76	95.44	93.54	92.48	91.15
		(18.06)	(18.10)	(10.33)	(19.97)	(15.01)	(19.14)
390	2	72.37	75.03	87.38	83.69*	79.88	79.36
		(31.77)	(37.28)	(19.88)	(32.69)	(27.54)	(35.30)
580	4	29.46	36.89**	71.59	65.84**	50.52	51.37
		(66.32)	(68.38)	(27.26)	(42.72)	(54.90)	(58.80)

* T-test shows actual payoffs differ from equilibrium payoffs significantly at the 5-percent level of confidence.

** T-test shows actual payoffs differ from equilibrium payoffs significantly at the 1-percent level of confidence.

Another finding from Table 4 is that the actual payoffs are very close to their corresponding payoffs predicted by the most informative equilibrium, given how noisy experimental data usually are. For $d = 0.5$, the most informative equilibrium is the separating (completely informative) outcome in which both the sender and the receiver get deterministic payoffs. In this case one expects that some subjects in the experiments make errors sometimes or just want to try other strategies (e.g., trying to learn), thus leading to somewhat lower payoffs. From Table 4, the senders and the receivers on average get 7.13 and 8.21 points less, respectively, than their equilibrium payoffs when $d = 0.5$. For the cases of $d = 1.2$ and $d = 2$, actual payoffs and equilibrium payoffs are very close for both the senders and the receivers and for the population average. In fact, in most instances, they are almost identical, e.g., 89.52 (equilibrium) and 88.76(actual), 95.44 (equilibrium) and 93.54 (actual), 79.88 (equilibrium) and 79.36 (actual). For $d = 4$, the actual payoffs for the senders and the receivers are still quite close to the corresponding equilibrium payoffs, but not as close as in the cases of $d = 1.2$ and $d = 2$. The actual average population payoff (51.37) for $d = 4$ is very close to the equilibrium payoff (50.52), since the senders' gain relative to equilibrium ($36.89 - 29.46 = 7.43$ points) is largely offset by the receivers' loss relative to equilibrium ($71.59 - 65.84 = 5.75$). Note also that even the standard deviations calculated from our experimental data come very close to those predicted by the theory, with the case of $d = 0.5$ being the obvious exception. Finally, we perform t-statistic tests to determine whether actual payoffs differ from equilibrium payoffs in a statistically significant way. For the cases of $d = 1.2$ and $d = 2$, actual payoffs are not statistically different from the corresponding equilibrium payoffs at the 5-percent level of confidence, except for the receivers' average payoff when $d = 2$. Since the sample size is large for $d = 4$, it is easy to get significant values of the t-statistics and reject the null hypothesis that the actual payoff *equals* the equilibrium payoff.[12] However, even when the t-test is significant, all it says is that statistically the actual payoff is not equal to the equilibrium payoff. The differences between theoretical and actual payoffs in those cases are still small given how noisy experimental data usually are. In sum, the evidence in Table 4 indicates that the actual payoffs in our experiments are very close to those predicted by theory.

Does this mean that subjects play according to the most informative equilibrium? The results on payoffs suggest a positive answer. However, after examining the data in more detail, we find that this is not the case.

Result 3 *Subjects behave differently from the equilibrium strategies predicted by theory. In particular, except for the full revelation case, the senders tend to communicate information and the receivers tend to "trust" the senders more than the most informative equilibrium.*

To understand this result, let us first look at the following table (Table 5) which compares correlations from the actual experimental data (from Table 3) and theoretical correlations in the most informative equilibrium (from Table 1).

Again, the full revelation case ($d = 0.5$) is special since the theoretical correlations are all equal to one. As expected, the actual correlations are smaller than but close to one. What is interesting is that in all other cases ($d = 1.2, 2, 4$), the correlations between states and messages from the experiments are all significantly greater than those predicted by theory. In particular, for $d = 4$, the actual correlation is almost 0.4 while the theoretical correlation is zero. This clearly suggests that the senders communicate more information about the true states of the world in their messages than the theory allows in the most informative equilibrium. Similarly, in all three cases $d = 1.2, 2, 4$, the correlations between messages and actions from the experiments

[12] Despite of the large sample size, the average population payoff is still not significantly different from the equilibrium payoff. Also, note that observations in our data are not independent, so significance can be overstated.

Table 5: Theoretical vs. Actual Information Transmission

Number of Observations	d	Correlation(S,M) Predicted	Correlation(S,M) Actual	Correlation(M,A) Predicted	Correlation(M,A) Actual	Correlation(S,A) Predicted	Correlation(S,A) Actual
70	0.5	1.000	0.916	1.000	0.965	1.000	0.876
70	1.2	0.750	0.896	0.866	0.924	0.866	0.830
390	2	0.500	0.734	0.707	0.794	0.707	0.618
580	4	0.000	0.391	0.000	0.542	0.000	0.207

are all greater than those predicted by theory, especially when $d = 4$ (the actual correlation is 0.542, compared to zero for the theoretical correlation). At least in the case of a large preference difference ($d = 4$), the evidence strongly suggests that the receivers tend to trust the senders much more than theory allows. Compared with equilibrium strategies, both senders and receivers in our experiments show an overcommunication tendency for cases with large preference differences.[13]

Surprisingly, the overcommunication tendency by both senders and receivers does not necessarily imply that information actually used in the decisions is than the theory predictions. Table 5 shows that the correlation between states and actions from the experiments is actually lower than that predicted by theory in all cases except $d = 4$. In particular, despite the fact that both senders and receivers overcommunicate when $d = 1.2$ and $d = 2$, the actual correlations between states and actions are lower than the equilibrium predictions: 0.830 (actual) versus 0.866 (equilibrium) for $d = 1.2$, and 0.618 (actual) versus 0.707 (equilibrium) for $d = 2$. For the case of $d = 4$, even though the actual correlation between states and actions (0.207) is still significantly greater than the equilibrium correlation of zero, its magnitude is much smaller compared with the strong overcommunication tendency of senders and receivers.

To further investigate these correlations, we perform statistical tests to see if the actual correlations are significantly different from the predicted ones. Consider a linear regression $Y = a + bX + \epsilon$. Then

$$b = \frac{s_Y}{s_X} \cdot Corr(X, Y)$$

where s_X, s_Y are the sample standard deviation of X and Y, and $Corr(X, Y)$ is the sample correlation between X and Y. To test the null hypothesis $H_0 : Corr(X, Y) = \sigma_{XY}$, where σ_{XY} is the correlation between X and Y predicted by theory, we can regress

$$(Y - r_{XY} \cdot X) = \alpha + \beta X + \epsilon$$

[13]Note that since senders and receivers communicate more than what is allowed in the most informative equilibrium, their behavior is even further away from the less informative equilibria of the game.

where

$$r_{XY} = \frac{s_Y}{s_X} \cdot \sigma_{XY}$$

The t-test on β would tell us if β is statistically different from zero, or equivalently, if $Corr(X, Y)$ (the actual correlation between X and Y) is statistically different from σ_{XY} (the theoretical correlation). We run the regressions with (Y, X) being one of the three pairs (Message, State), (Action, Message) and (Action, State). The results of these regressions are presented in Table 6. Consistent with our casual observation above, for the correlation between states and messages, we find the t-test significant for all but the case of $d = 0.5$ (where the actual correlation is 0.916), indicating that the actual correlations $0.896(d = 1.2), 0.734(d = 2)$, and $0.391(d = 4)$ are statistically higher than the predicted ones, 0.75, 0.5, and 0, respectively. Also, for the correlation between messages and actions, the t-test is significant for $d = 2$ (0.794 vs. 0.707) and $d = 4$ (0.542 vs. 0), but not significant for $d = 0.5$ (0.924 vs. 0.866) and $d = 1.2$ (0.965 vs. 1). Interestingly, for the correlation between states and actions, the t-test is significant for $d = 0.5$, as well as $d = 2, 4$, but not for $d = 1.2$. In fact, the β's are negative for all but the case of $d = 4$, meaning that actual correlations are lower than the predicted ones and indicating some mismatch given the overcommunication tendency shown in the other correlations. However, the correlations of the aggregate data cannot reveal what kind of mismatch there is. To gain insights about this question, we need to look into the finer details of the experimental data.

As a first step, we examine the frequencies of actions taken by the receivers conditional on the true states of the world. For this and the other conditional frequencies discussed later, we focus on the observations for the case of $d = 4$, because the actual correlations in this case differ from equilibrium predictions the most and also because we have the most observations for this case. For $d = 4$, the only equilibrium is the babbling equilibrium, in which the receiver should choose action 5 regardless of the messages she receives and hence regardless of the true states of the world. The experimental results are presented in Table 7. For simplicity, we group actions into three groups: "actions 1 to 3", "actions 4 to 6", and "actions 7 to 9". For the 580 observations we have on $d = 4$, the frequencies of the five states ($s = 1, 3, 5, 7, 9$) are very close to uniform. Several observations can be made of Table 7. First, for each of the 5 states, only about half of the time actions 4 to 6 are chosen. That is, only about half of the observations can be considered broadly consistent with equilibrium. Secondly, as the state becomes larger, the frequency weights switch from the small actions to the large actions. Specifically, as the state increases, while the frequencies of actions 4 to 6 remain more or less constant, the frequencies of small actions 1 to 3 decreases ($s = 7$ poses a minor exception)[14] and the frequencies of large actions 7 to 9 increases. Comparing states 1 and 9, the frequency of small actions 1 to 3 decreases from almost

[14]This is because some receivers simply subtract 4 from 7, resulting in many 3's. See Section 6 for further explanations.

Table 6: Regression Tests for Correlations

Correlations {Regression}	d	N	Predicted Corr.	Actual Corr.	α (s.e.)	β (s.e.)	R^2	F (p-value)
	0.5	70	1.000	0.916	0.489	-0.085	0.04	2.963
					(0.272)	(0.049)		(0.090)
Corr(S,M)	1.2	70	0.750	0.896	1.949**	0.137**	0.10	7.403
					(0.292)	(0.050)		(0.008)
$\{(M - r_{SM} \cdot S)$	2	390	0.500	0.734	2.308**	0.230**	0.11	45.958
$= \alpha + \beta S + \epsilon\}^{\dagger}$					(0.184)	(0.034)		(0.000)
	4	580	0.000	0.391	5.466**	0.347**	0.15	104.483
					(0.193)	(0.034)		(0.000)
	0.5	70	1.000	0.965	0.303	-0.033	0.02	1.197
					(0.173)	(0.030)		(0.278)
Corr(M,A)	1.2	70	0.866	0.924	-0.508	0.060	0.02	1.574
					(0.322)	(0.048)		(0.214)
$\{(A - r_{MA} \cdot M)$	2	390	0.707	0.794	0.912**	0.081**	0.02	7.928
$= \alpha + \beta M + \epsilon\}$					(0.180)	(0.029)		(0.005)
	4	580	0.000	0.542	2.138**	0.481**	0.29	240.771
					(0.236)	(0.031)		(0.000)
	0.5	70	1.000	0.876	0.797*	-0.121*	0.06	4.480
					(0.316)	(0.057)		(0.038)
Corr(S,A)	1.2	70	0.866	0.830	1.341**	-0.035	0.00	0.283
					(0.379)	(0.065)		(0.596)
$\{(A - r_{SA} \cdot S)$	2	390	0.707	0.618	2.464**	-0.081*	0.01	4.938
$= \alpha + \beta S + \epsilon\}$					(0.198)	(0.037)		(0.027)
	4	580	0.000	0.207	4.786**	0.163**	0.04	25.879
					(0.182)	(0.032)		(0.000)

† $r_{SM} = \frac{s_M}{s_S} \cdot \sigma_{SM}$, where s_M, s_S are the standard deviations of Message M and State S, respectively, and σ_{SM} is the theoretical correlation between M and S. Similarly, $r_{MA} = \frac{s_A}{s_M} \cdot \sigma_{MA}$ and $r_{SA} = \frac{s_A}{s_S} \cdot \sigma_{SA}$.

$*$ T-test shows significant difference from zero at the 5-percent level of confidence.

$**$ T-test shows significant difference from zero at the 1-percent level of confidence.

30% to just 10%, while the frequency of large actions 7 to 9 increases from below 20% to about 43%. Thirdly, the average action clearly exhibits an increasing trend as the state becomes larger. These observations strengthen the claim that the experimental outcomes are not consistent with the babbling equilibrium predictions.

Table 7: Frequencies of Actions Conditional on States (d=4)

State	# of obs.	Actions 1,2,3 (%)	Actions 4,5,6 (%)	Actions 7,8,9 (%)	Average Action	$\chi^2(8)$ Statistics (p-value†)
1	115	34 (29.75%)	59 (51.30%)	22 (19.13%)	4.670	19.48 (0.012)
3	122	24 (19.67%)	58 (47.54%)	40 (32.79%)	5.516	28.38 (0.000)
5	118	16 (13.56%)	61 (51.69%)	41 (34.75%)	5.746	38.76 (0.000)
7	113	19 (16.81%)	47 (41.59%)	47 (41.59%)	5.973	46.10 (0.000)
9	112	12 (10.71%)	52 (46.43%)	48 (42.86%)	6.071	48.29 (0.000)

† The confidence level (p-value) is reported for the χ^2 test against the null hypothesis that Action 5 is the intended equilibrium play while all other actions are errors made with equal probability. To do so, we adjust the error probabilities so that the predicted frequency of Action 5 equals the actual frequency observed.

For a more formal analysis, we perform χ^2 tests to see if the empirical distribution of actions conditional on each state is consistent with the theory. If the theory prediction is interpreted literally, namely, the distribution of actions should be the degenerate one with all the probability mass on action 5, the test is trivially rejected by our data. We use a stronger test by postulating that subjects "tremble hands" while choosing the equilibrium strategy and that the observed choices of action 5 are all equilibrium plays while all other actions result from erroneous plays with equal probabilities. Since action 5 is observed less than 50% of the time, our test is very strong in that it allows noisy plays more than 50% of the time. The last column of Table 7 presents the χ^2 test results. For every state $s = 1, 3, 5, 7, 9$, the test results strongly reject the null hypothesis of equilibrium play with errors at the 2-percent level of confidence. In other words, with very high probabilities the observed frequencies of actions conditional on each state are not consistent with the babbling equilibrium hypothesis, even if a large amount of errors are allowed.

To analyze more closely the senders' behavior, we compute the frequencies of the true states conditional on the senders' messages, which are presented in Table 8. The empirical frequencies of states conditional on messages indicate how informative each message ($s = 1, 3, 5, 7, 9$) is about

Table 8: Frequencies of States Conditional on Messages (d=4)

Message	# of obs.	State 1 (%)	State 3 (%)	State 5 (%)	State 7 (%)	State 9 (%)	Average State	$\chi^2(4)$ Statistics (p-value†)
1	31	19 (61.29%)	4 (12.90%)	2 (6.45%)	3 (9.68%)	3 (9.68%)	2.871	33.35 (0.000)
3	53	14 (26.42%)	21 (39.62%)	6 (11.32%)	8 (15.09%)	4 (7.55%)	3.755	18.04 (0.001)
5	80	35 (43.75%)	13 (16.25%)	23 (28.75%)	5 (6.25%)	4 (5.00%)	3.250	42.75 (0.000)
7	84	22 (26.19%)	25 (29.76%)	15 (17.86%)	14 (16.67%)	8 (9.52%)	4.071	10.88 (0.028)
9	332	25 (7.53%)	59 (17.77%)	72 (21.69%)	83 (25.00%)	93 (28.01%)	5.964	41.92 (0.000)

† The confidence level (p-value) is reported for the χ^2 test against the null (babbling equilibrium) hypothesis that messages are completely uninformative so that all states are possible with equal probability conditional on each message.

the true state of the world. In the babbling equilibrium, the sender's message should be completely uninformative, namely, the distribution of states conditional on any message should still be uniform over $\{1, 3, 5, 7, 9\}$, so that the receiver cannot draw any inference from the messages she receives. In the 580 observations with $d = 4$, the frequencies of messages are very skewed: message 1 was sent only 31 times while message 9 was sent 332 times. The fact that messages are concentrated on 9 does not itself reject the hypothesis that messages are uninformative, since senders in different states could all pool at a same message. However, the frequencies of states conditional on messages clearly rejects the hypothesis that messages are uninformative. For message 1, with more than 60% probability the state is one, and with more than 80% probability the state is less than or equal to 5. If a receiver is shown Table 8, her optimal action upon receiving a message of 1 is to choose the average state conditional on message 1, which is 2.87, far from the equilibrium action 5. Similar patterns are observed for messages 3 and 5, where the frequency weights are predominantly placed on small states 1, 3, and 5, and the conditional average state is much smaller than the equilibrium prediction of 5.[15] The conditional frequencies of states is closest to the uniform distribution for message 7, except that the frequency weights are surprisingly still skewed towards small states,[16] leading to a conditional average state of only about 4. On the other hand, the conditional frequencies of states for message 9 are clearly skewed

[15]Interestingly, the average state when the message is 5 is lower than that when the message is 3. This is because some receivers simply subtract 4 from 5, resulting in a probability of 43.75% that Action 1 is chosen when the message is 5. See Section 6 for further explanations.

[16]This can be attributed to the fact that some receivers would subtract 4 from 7, resulting in a probability of 29.76% that Action 3 is taken when the message is 7.

towards large states 5, 7, and 9, resulting in a conditional average state of almost 6. To sum up, the evidence here strongly indicates that the senders' messages are informative about the true states of the world, and that they overcommunicate compared with the theoretical prediction.

The last column of Table 8 presents the results of χ^2 tests for each message $s = 1, 3, 5, 7, 9$. The null hypothesis (babbling equilibrium) is that the senders' messages are uninformative so that conditional on messages the states are uniformly distributed. The test results strongly reject the uniform distribution of state hypothesis at the 0.1-percent level of confidence for all messages except for $m = 7$, in which case the null hypothesis is rejected at the 3-percent level of confidence. Clearly, messages are informative about the states, hence the senders overcommunicate compared with the babbling equilibrium prediction.

Table 9: Frequencies of Actions Conditional on Messages (d=4)

Message	# of obs.	Actions 1,2,3 (%)	Actions 4,5,6 (%)	Actions 7,8,9 (%)	Average Action	$\chi^2(8)$ Statistics (p-value†)
1	31	20 (64.52%)	11 (35.48%)	0 (0.00%)	2.774	44.13 (0.000)
3	53	22 (41.51%)	25 (47.17%)	6 (11.32%)	4.094	28.90 (0.000)
5	80	23 (28.75%)	49 (61.25%)	8 (10.00%)	4.288	20.07 (0.010)
7	84	31 (36.90%)	36 (42.86%)	17 (20.27%)	4.786	81.83 (0.000)
9	332	9 (2.71%)	156 (46.99%)	167 (50.30%)	6.611	257.13 (0.000)

† The confidence level (p-value) is reported for the χ^2 test against the null hypothesis that Action 5 is the intended equilibrium play while all other actions are errors made with equal probability. To do so, we adjust the error probabilities so that the predicted frequency of Action 5 is equal to the actual frequency observed.

The receivers' overcommunication tendency can be seen from Table 9, which presents the frequencies of actions conditional on messages. Again, in the babbling equilibrium, the receiver should choose action 5 regardless of the message she receives. This is clearly not the case in our experiments. Actions 4 to 6 are taken less than 50% of the time except for message 5. Receivers are far more likely to take small actions 1 to 3 for small messages 1 or 3 than large messages 5, 7, and (especially) 9, and are also far more likely to take large actions 7 to 9 for large messages 7 or 9 than small messages 1,3, and 5. The average action exhibits a clear monotonic trend as the message increases.

Again, we perform χ^2 tests to see if the receivers ignore the messages sent by the senders. We use the stronger test as before by postulating that receivers play the equilibrium strategy with errors of equal probabilities and that the observed choices of action 5 are all equilibrium plays. From the results in the last column of Table 9, the babbling equilibrium hypothesis is rejected at the 1-percent level of confidence for all messages. The evidence clearly indicates that receivers's actions vary with the senders' messages, hence they "over-trust" the senders compared with the babbling equilibrium prediction.

5 Robustness Analysis

To test how robust the results from our baseline sessions are, we ran two sessions of experiments with somewhat different designs but with equilibrium predictions essentially identical to the base design. By changing the experimental design while holding the theoretical predictions fixed, we can test whether the experimental results are sensitive to the design details.

For the first robustness test, we ran one session with the payoff parameter k set at 1.2, so that payoffs are less sensitive to the difference between action and state compared with the baseline sessions where k is 1.4. Moreover, we used a different design when subjects choose messages such as "1 or 3". Specifically, instead of doing the mixing automatically for the senders in the baseline sessions, senders must send a unique message "1 or 3". We ran the session with 32 subjects and a total 31 rounds, 5 rounds of $d = 0.5$, 13 rounds of $d = 1.2$, 5 rounds of $d = 2$, and 8 rounds of $d = 4$.

Table 10 produces the payoff comparisons between equilibrium predictions and actual experimental outcomes for the first robustness test session with $k = 1.2$ and the modified message space. As in the baseline sessions (Table 4), the average payoffs for the senders, the receivers, and the subject population are close to those predicted by the most informative equilibrium. Even the standard deviations are very close in most cases. Results of t-statistic tests indicate that actual payoffs and equilibrium payoffs are statistically indistinguishable for $d = 4$. Even if statistically significant, the actual and theoretical payoff differences in other cases are small relative to the absolute magnitude of the payoffs.[17] This evidence indicates that the experimental results of our baseline sessions are robust to this kind of variation of the payoff parameter k and message space.

The correlations between states and messages, between messages and actions, and between states and actions for this robustness test session are presented in Table 11.[18] Clearly Hypothesis

[17]Somewhat different from Table 4 for the baseline sessions, actual payoffs here are statistically different from equilibrium payoffs for smaller d's. The main reason for this can be that standard deviations are smaller when $k = 1.2$ than when $k = 1.4$. Moreover, there are much more observations for $d = 1.2$ in this robustness test session than in the baseline sessions.

[18]In the 496 observations, 157 involve mixed messages such as "7 or 9". In computing the correlations between states and messages and between messages and actions, we use a computer program to do the randomization

Table 10: Theoretical vs. Actual Payoffs for Robustness Test 1

# of			Senders' Payoffs		Receivers' Payoffs		Average	
obs.	k	d	Predicted (s.d.)	Actual (s.d.)	Predicted (s.d.)	Actual (s.d.)	Predicted (s.d.)	Actual (s.d.)
80	1.2	0.5	105.65	101.71^{**}	110.00	104.71^{**}	107.82	103.21^{**}
			(0.00)	(11.01)	(0.00)	(12.11)	(2.18)	(11.63)
208	1.2	1.2	92.46	94.87^{**}	96.81	100.35^{**}	94.64	97.61^{**}
			(13.94)	(11.92)	(8.78)	(11.59)	(11.85)	(12.06)
80	1.2	2	80.13	85.81^{*}	91.05	94.92^{*}	85.59	90.37^{*}
			(22.02)	(21.78)	(15.48)	(15.16)	(19.80)	(19.25)
128	1.2	4	53.43	49.82	79.70	80.48	66.56	65.15
			(43.33)	(42.02)	(20.18)	(27.99)	(36.26)	(38.80)

$*$ T-test shows actual payoffs differ from equilibrium payoffs significantly at the 5-percent level of confidence.
$**$ T-test shows actual payoffs differ from equilibrium payoffs significantly at the 1-percent level of confidence.

1 is supported in this case, as all correlations decrease as the preference difference increases. As in the baseline sessions, here both senders and receivers exhibit a strong overcommunication tendency for relatively large preference differences, since the actual correlations between states and messages and between messages and actions are both greater than their counterparts in the most informative equilibrium. In particular, when $d = 4$, the correlation between states and messages is 0.391 and the correlation between messages and actions is 0.642, while the equilibrium prediction is zero for both correlations. Also, the correlation between states and actions is 0.312, indicating that substantial information is actually used in the receivers' decisions. Comparing Table 11 with Table 5 also reveals that the correlations are quite close in the two cases, especially for the correlation between states and messages, which differs only in the third or fourth digit (not shown) for $d = 0.5, 1.2,$and 4. Therefore, the evidence from the first robustness test shows that the main results of the baseline sessions are robust for a smaller k and a somewhat different message space.

For the second robustness test, we ran another session in which the payoff parameter k is further lowered to 1, making payoffs even less sensitive to the difference between action and state. The message space is the same as the previous robustness session. An additional modification introduced in this session is that we gave senders noisy signals instead of perfect ones. Specifically, at the beginning of each round, senders were not perfectly informed about the true state of the world, but were given a noisy signal. With 90% chance the signal equaled the true state of the world, and with 10% chance the signal was randomly drawn by the computer program

and record the realizations as the messages for correlation calculations. This gives us a basis to compare these correlations with those of the baseline sessions.

Table 11: Theoretical vs. Actual Information Transmission for Robustness Test 1

# of obs.	k	d	Correlation(S,M) Predicted	Correlation(S,M) Actual	Correlation(M,A) Predicted	Correlation(M,A) Actual	Correlation(S,A) Predicted	Correlation(S,A) Actual
80	1.2	0.5	1.000	0.916	1.000	0.955	1.000	0.923
208	1.2	1.2	0.750	0.897	0.866	0.912	0.866	0.895
80	1.2	2	0.500	0.837	0.707	0.850	0.707	0.755
128	1.2	4	0.000	0.391	0.000	0.642	0.000	0.312

uniformly from $\{1, 3, 5, 7, 9\}$. The reason for introducing noisy signals is the following: One possible explanation for overcommunication is that the receivers tend to trust the senders "too much" because they believe that the senders are more "powerful" due to their knowledge about the state of the world (in applications the senders are usually experts of some sort). If this is a force behind overcommunication, one expects its effect will diminish with noisy signals since the senders are less knowledgable and hence less powerful. We ran the session with 48 subjects and a total 20 rounds, 5 rounds for each of the four cases $d = 0.5, 1.2, 2, 4$.

Table 12 presents the payoff comparisons between equilibrium predictions and actual experimental outcomes for the second robustness test session with $k = 1.0$ and noisy signals. Note that the equilibrium predicted payoffs are quite different from those in the baseline sessions (Table 4) when preference difference is large ($d = 2, 4$). Also note that with noisy signals, the equilibrium predicted payoffs have substantial variances even in the perfectly separating equilibrium when $d = 0.5$. Again, just like in the baseline sessions, Table 12 clearly shows that the average payoffs for the senders, the receivers, and the subject population match very well with those predicted by the most informative equilibrium. This claim can be strongly supported by the results of t-tests. Except for $d = 0.5$, the actual payoffs are not different from the equilibrium predictions at the 5-percent level of confidence in all but one case (the senders' payoffs when $d = 2$). In many of these cases the difference between actual and theoretical payoffs is within one point. The fact that signals are noisy (and hence the senders may not be perceived as authoritative as in the case of perfect signals) does not seem to have any effect on the experimental outcomes.

Let us now examine information transmission in the second robustness test. Table 13 presents the correlations between signals and messages, messages and actions, and between signals and actions.[19] Since the senders only get the signals but do not observe the states, we use the correlations with respect to signals, for they reflect more closely how much information is communicated than correlations with respect to states. The equilibrium predictions about the correlations with

[19]As in the first robustness test, we use simulations to treat messages such as "7 or 9" in calculating the correlations regarding messages.

Table 12: Theoretical vs. Actual Payoffs for Robustness Test 2 (Prob. of Correct Signal = 0.9)

# of obs.	k	d	Senders' Payoffs Predicted (s.d.)	Senders' Payoffs Actual (s.d.)	Receivers' Payoffs Predicted (s.d.)	Receivers' Payoffs Actual (s.d.)	Average Predicted (s.d.)	Average Actual (s.d.)
120	1.0	0.5	102.20	96.83**	106.80	100.08**	104.50	98.46**
			(11.14)	(16.19)	(12.24)	(17.70)	(11.93)	(17.01)
120	1.0	1.2	93.10	94.07	96.16	95.50	94.63	94.78
			(13.36)	(12.86)	(11.33)	(14.19)	(12.48)	(13.54)
120	1.0	2	85.12	90.25**	92.72	93.75	88.92	92.00
			(16.16)	(19.07)	(13.47)	(16.71)	(15.35)	(17.98)
120	1.0	4	70.00	68.00	86.00	86.50	78.00	77.25
			(28.28)	(30.06)	(14.97)	(21.41)	(24.00)	(27.64)

* T-test shows actual payoffs differ from equilibrium payoffs significantly at the 5-percent level of confidence.
** T-test shows actual payoffs differ from equilibrium payoffs significantly at the 1-percent level of confidence.

respect to signals are exactly the same as before, making comparisons with the previous results easier. The correlations for $d = 0.5$ look a bit lower than before, perhaps because some subjects were still learning about the game in the first few rounds (in which $d = 0.5$ was used) and the game is somewhat more complicated than in the other designs due to the noisy signals. However, the results in this session are still consistent with those in the baseline sessions. For $d = 1.2, 2, 4$, correlations all decrease in d, confirming Hypothesis 1. Moreover, both senders and receivers overcommunicate as the correlations between signals and messages and between messages and actions are greater than those in the most informative equilibrium. In fact, the correlations for $d = 1.2, 2, 4$ in Table 13 are reasonably close to those in Table 5, without any clear dominance pattern. Therefore, we conclude that noisy signals do not seem to have any effect on the experimental outcomes. It suggests that the "trusting the expert" explanation of overcommunication does not play an important role.

Table 13: Theoretical vs. Actual Information Transmission for Robustness Test 2

# of obs.	Prob. of	k	d	Correlation(Sig,M) Predicted	Correlation(Sig,M) Actual	Correlation(M,A) Predicted	Correlation(M,A) Actual	Correlation(Sig,A) Predicted	Correlation(Sig,A) Actual
120	0.9	1.0	0.5	1.000	0.868	1.000	0.924	1.000	0.870
120	0.9	1.0	1.2	0.750	0.887	0.866	0.904	0.866	0.832
120	0.9	1.0	2	0.500	0.858	0.707	0.862	0.707	0.769
120	0.9	1.0	4	0.000	0.354	0.000	0.457	0.000	0.259

6 Learning Effects

Another possible explanation for subjects' overcommunication tendency observed in our experiments is learning. The game used in our experiments is not a trivial one for people without game theory training, so it may take a while for subjects to learn to play the equilibrium strategies.[20] To examine this learning hypothesis, we ran a session using our base design (Session 2 as described in the end of Section 3) in which 32 subjects played 31 rounds of the game with preference difference $d = 4$. By holding the design (including preference difference) fixed throughout the session, we can compare outcomes in early rounds with those in later rounds to see if subjects behave differently after gaining experience playing the game. We focus on the case of $d = 4$ to test the learning effect for two reasons. One reason is that among the four difference preferences, deviations from equilibrium predictions are the largest for $d = 4$. Hence, if learning leads to convergence to equilibrium, then its effect will be strongest for $d = 4$. Another reason we focus on $d = 4$ is that in this case subjects should have the strongest incentives to learn to play the equilibrium strategies, because it is most costly for subjects to be outguessed by their opponent. In trying to increase the subjects' incentives to learn, we use a generous exchange rate of points to dollars ($1=50 points) in this session. The session lasted less than 2.5 hours, the highest payoff was $45.1 and the lowest was $12.7 (excluding the $5 show-up fee).

Table 14: Theoretical vs. Actual Payoffs: Learning Effect

Rounds	k	d	Senders' Payoffs		Receivers' Payoffs		Average	
			Predicted	Actual	Predicted	Actual	Predicted	Actual
1–5	1.4	4	29.46 (66.32)	39.74 (67.91)	71.59 (27.26)	67.76 (39.92)	50.52 (54.90)	53.75 (57.28)
6–10	1.4	4	29.46 (66.32)	41.79 (67.57)	71.59 (27.26)	59.57 (45.64)	50.52 (54.90)	50.68 (58.16)
11–15	1.4	4	29.46 (66.32)	33.90 (70.46)	71.59 (27.26)	69.91 (35.27)	50.52 (54.90)	51.90 (58.41)
16–20	1.4	4	29.46 (66.32)	31.73 (70.62)	71.59 (27.26)	67.94 (44.08)	50.52 (54.90)	49.84 (61.43)
21–25	1.4	4	29.46 (66.32)	35.82 (61.40)	71.59 (27.26)	68.05 (38.23)	50.52 (54.90)	51.94 (53.49)
26–31	1.4	4	29.46 (66.32)	42.50 (68.05)	71.59 (27.26)	61.60 (45.48)	50.52 (54.90)	52.05 (58.51)

Table 14 presents the average payoffs of this session in groups of 5 rounds (the last 6 rounds are grouped together). The senders' average payoff does not show any sign of convergence to equilibrium: it is 39.74 in the first 5 rounds, decreases to 31.73 for rounds 16-20, and then increases to 42.50 for rounds 26-31, while the equilibrium prediction is 29.46. Neither is the receivers' average payoff converging to equilibrium. In fact, the 5 round average decreases from 67.76 in the first 5 rounds to 61.60 in rounds 26-31, further away from the equilibrium prediction

[20] In all of our experiments, subjects play several practice rounds before they play the real rounds to learn about the experimental design.

of 71.59. The population average payoff is close to the equilibrium prediction, but shows no time trend. Overall, the evidence on average payoffs does not indicate any significant learning effect.

Table 15: Payoff Regressions Testing for Learning Effects

Dependent Variable	Sender' Payoff	Receiver' Payoff	Overall Payoff
α	42.503**	61.598**	52.051**
(s.e.)	(6.914)	(4.262)	(4.182)
d_1	-2.762	6.163	1.700
(s.e.)	(10.256)	(6.321)	(6.203)
d_2	-0.717	-2.028	-1.373
(s.e.)	(10.256)	(6.321)	(6.203)
d_3	-8.607	8.314	-0.147
(s.e.)	(10.256)	(6.321)	(6.203)
d_4	-10.770	6.339	-2.216
(s.e.)	(10.256)	(6.321)	(6.203)
d_5	-6.686	6.455	-0.115
(s.e.)	(10.256)	(6.321)	(6.203)
R^2	0.004	0.008	0.000
# of obs.	496	496	992
F statistics	0.356	0.829	0.086
(p-value)	(0.878)	(0.530)	(0.995)

Notes: For each dependent variable (sender's payoff, receiver's payoff, overall payoff), the regression specification is

$$Y_i = \alpha + d_1 D_{i(1-5)} + d_2 D_{i(6-10)} + d_3 D_{i(11-15)} + d_4 D_{i(16-20)} + d_5 D_{i(21-25)} + \epsilon_i$$

$*$ Significant at the 5-percent level of confidence.
$**$ Significant at the 1-percent level of confidence.

To further verify the claim that payoffs do not exhibit clear learning effect, we run the following regressions:

$$Y_i = \alpha + d_1 D_{i(1-5)} + d_2 D_{i(6-10)} + d_3 D_{i(11-15)} + d_4 D_{i(16-20)} + d_5 D_{i(21-25)} + \epsilon_i$$

where the dependent variable Y is the sender's payoff, the receiver's payoff, and the overall payoff, respectively; and the dependent variables are a constant and dummy variables indicating the groups of rounds (rounds 1-5, 6-10, 11-15, 16-20, 21-25). If the parameter for a dummy variable, say d_1, is found significant, then it means that the payoffs in rounds 1-5 are significantly different from those in rounds 26-31. The regression results are reported in Table 15. For all three regressions, none of the dummy variables are even remotely significant. Furthermore, the F-statistics for the regressions are very small, meaning that the evidence overwhelmingly supports the null hypothesis that all other groups of rounds are no different from the last 6 rounds. Thus, the evidence on payoffs strongly indicates that there is no clear learning effect in our data.

Examining the table of correlations also reveals the same picture. From Table 16, one can see that none of the three correlations exhibit a clear time trend, let alone convergence to equilibrium. For example, the correlation between states and messages and the correlation between messages and actions both are greater in the last 6 rounds than in the first 5 rounds after some ups and downs in between.

Table 16: Theoretical vs. Actual Information Transmission: Learning Effect

Rounds	k	d	Correlation(S,M)		Correlation(M,A)		Correlation(S,A)	
			Predicted	Actual	Predicted	Actual	Predicted	Actual
1–5	1.4	4	0.000	0.244	0.000	0.500	0.000	0.139
6–10	1.4	4	0.000	0.351	0.000	0.530	0.000	0.091
11–15	1.4	4	0.000	0.434	0.000	0.449	0.000	0.329
16–20	1.4	4	0.000	0.470	0.000	0.566	0.000	0.175
21–25	1.4	4	0.000	0.439	0.000	0.627	0.000	0.245
26–31	1.4	4	0.000	0.344	0.000	0.557	0.000	0.133

To test rigorously any learning effect in the correlations, we run the following three regressions:

$$Y_i = \alpha + \beta X_i + d_1 D_{i(1-5)} X_i + d_2 D_{i(6-10)} X_i + d_3 D_{i(11-15)} X_i + d_4 D_{i(16-20)} X_i + d_5 D_{i(21-25)} X_i + \epsilon_i$$

where (Y, X) is one of the three pairs (Message, State), (Action, Message) and (Action, State). Also included as dependent variables in the regressions are the product terms of dummy variables and X. Since the parameter β is proportional to the correlation between (Y, X) for rounds 26-31, a non-significant β will support the babbling equilibrium prediction. On the other hand, if the parameter for a dummy variable, say d_1, is found to be significant, it means that the correlation between (Y, X) in rounds 1-5 are significantly different from that in rounds 26-31. Table 17 reports the regression results.

The first thing to note from Table 17 is that β is significant in all three regressions, indicating that all three correlations are significantly different from zero—the babbling equilibrium prediction for rounds 26-31. Moreover, all the parameters d_1 to d_5 are not significant in all three regressions, except for d_1 in the regression of message on state. Aside from the exception, the results show that the correlations are not significantly different across rounds, suggesting no clear learning effect. In fact, the F-tests of $d_i = 0$ for all i are not significant, except for $(X, Y) =$ (Message, State) since its d_1 is significant.[21] Note that the sign of d_1 in the regression of message

[21]The F tests of $\beta = 0$ and $d_i = 0$ for all i are all significant, because β is significant in all regressions.

Table 17: Correlation Regressions Testing for Learning Effect

Regression	Message on State[♭]	Action on Message[†]	Action on State[‡]
α	5.556**	2.387**	4.958**
(s.e.)	(0.208)	(0.245)	(0.189)
β	0.380**	0.461**	0.159**
(s.e.)	(0.053)	(0.038)	(0.048)
d_1	-0.191**	0.009	-0.049
(s.e.)	(0.063)	(0.037)	(0.057)
d_2	-0.051	0.023	0.002
(s.e.)	(0.062)	(0.035)	(0.056)
d_3	-0.058	-0.062	-0.057
(s.e.)	(0.061)	(0.035)	(0.056)
d_4	-0.046	-0.027	-0.056
(s.e.)	(0.061)	(0.035)	(0.055)
d_5	0.006	0.001	0.013
(s.e.)	(0.060)	(0.034)	(0.054)
# of obs.	496	496	496
R^2	0.163	0.295	0.040
F statistics	15.852	34.034	3.415
(p-value)	(0.000)	(0.000)	(0.003)
F statistics $d_i = 0\ \forall i$	2.825	1.343	0.770
(p-value)	(0.016)	(0.245)	(0.572)

♭ $M_i = \alpha + \beta S_i + d_1 D_{i(1-5)} S_i + d_2 D_{i(6-10)} S_i + d_3 D_{i(11-15)} S_i + d_4 D_{i(16-20)} S_i + d_5 D_{i(21-25)} S_i + \epsilon_i$

†$A_i = \alpha + \beta M_i + d_1 D_{i(1-5)} M_i + d_2 D_{i(6-10)} M_i + d_3 D_{i(11-15)} M_i + d_4 D_{i(16-20)} M_i + d_5 D_{i(21-25)} M_i + \epsilon_i$

‡$A_i = \alpha + \beta S_i + d_1 D_{i(1-5)} S_i + d_2 D_{i(6-10)} S_i + d_3 D_{i(11-15)} S_i + d_4 D_{i(16-20)} S_i + d_5 D_{i(21-25)} S_i + \epsilon_i$

* Significant at the 5-percent level of confidence.

** Significant at the 1-percent level of confidence.

on state is negative, meaning that the correlation between message and state is smaller in rounds 1-5 than in rounds 26-31. So even if there is a time trend in the correlation between messages and states, it is moving further away from equilibrium. Therefore, the results of the correlation regressions indicate that there is no clear learning effect.

To conclude this section, we do not find any clear time trend in our data that can suggest learning plays a significant role in the experimental outcomes. Of course, this is not to say that learning definitely will not lead to convergence to equilibrium. There are 31 rounds in this session of our experiment, and there does not appear to be any significant time trend. It is possible that it takes much longer for subjects to learn and eventually learning results in convergence to equilibrium. But we have to leave it to future research to investigate this possibility. It is interesting to note that, in contrast to our result here, Blume *et al* (2001) report evidence indicating significant learning effects: senders became more "sophisticated" (e.g., revealing their types less often) and receivers became less gullible. Because Blume *et al* are interested in the evolution of messages, their experimental design facilitates possible subject learning much more than ours. In their experiments, there were 60 rounds of play and subjects were randomly paired with 6 opponents and thus interacted with an opponent about 10 periods. Moreover, summary history about other subject pairs was revealed to all subjects at the end of each period. In our experiments, opportunities for subjects to learn are more limited since they played 31 rounds, interacted with any other subject only once, and only knew the outcomes of the games they played in.

7 Bounded Rationality: Behavior Type Analysis

Our experimental results show that on the aggregate level subjects understand the basic strategic elements of the game (hence the comparative statics hypotheses 1 and 2 are strongly confirmed), but both senders and receivers tend to overcommunicate relative to what theory allows in the most informative equilibrium. So the following questions naturally arise. What accounts for the non-equilibrium behavior? Why are the actual average payoffs so close to the equilibrium predictions? In order to answer these questions, we need to examine the subjects' individual behavior to figure out what kinds of non-equilibrium behavior the subjects exhibit. In this section, we apply one approach of bounded rationality, behavior type analysis, to our experiment data to understand the overcommunication phenomenon. To identify behavior patterns, we need a non-trivial number of plays of the same game for each subject. For this reason, we use the data from Session 2 of the base design, in which there are 31 rounds of play with preference difference $d = 4$. With 31 rounds of play, each subject on average plays 15-16 rounds as the sender and 15-16 rounds as the receiver.

Using earlier experiment evidence (e.g., Blume, DeJong, Kim and Sprinkle, 2001) on communication games, Crawford (2003) defines the system of behavior types that is anchored on the "truster" type of senders and the "believer" type of receivers. We follow Crawford (2003) to define the system of behavior types for our game with $d = 4$. The definitions are listed in Table 18. A sender of the lowest level of sophistication, type L0 or the truster type, simply sends the truthful message all the time. In response to the type L0 sender, the type L0 or the believer type receiver completely trusts the sender and always chooses the action identical to the sender's message. The next level sender, type L1 or liar type, believes that the receiver is of the L0 type, and hence incorporates his policy bias ($d = 4$) into his messages. In response to the type L1 sender, the type L1 or the inverted type receiver will choose action 1 for a message of 5, action 3 for a message of 7, and action 7 for a message 9 (since it is equally likely from an L1 sender in states 5, 7, 9). Messages 1 and 3 would be "out-of-equilibrium" for an L1 sender; we assign the belief of state 1 for the L1 receiver. An L2 sender best responses to an L1 receiver and will always send a message of 9 regardless of the true state.[22] An L2 receiver best responses to an L2 sender and hence will always choose action 5. In equilibrium the sender should randomize and hence any message will be consistent, so it is not meaningful to identify an equilibrium type sender. On the other hand, an equilibrium type receiver will always choose action 5 regardless of the message she receives, which coincides with the L2 type. Finally, a sophisticated type sender maximizes his payoffs given the empirical distribution of the receivers' behavior, while a sophisticated type receiver best responses to the empirical distribution of the senders' behavior. Their optimal strategies are given in the last row of Table 18.

Table 18: Type Classification Definition(d=4)

Type	Sender's Message (given S)					Receiver's Action (given M)				
Name	S=1	S=3	S=5	S=7	S=9	M=1	M=3	M=5	M=7	M=9
L0	1	3	5	7	9	1	3	5	7	9
L1	5	7	9	9	9	1	1	1	3	7
L2	9	9	9	9	9	5	5	5	5	5
Eq	any	any	any	any	any	5	5	5	5	5
Sop	7	9	9	9	9	2	3	3	4	6

We then follow the classification methodology of Costa-Gomes *et al* (2001, 2002) to classify subjects whose actions can be consistently identified as fitting into one of the behavior types. In applying the type definitions to classify the 32 subjects, we allow for errors of plus or minus

[22] In state 1, an L2 sender is indifferent between sending a message of 7 and a message of 9 to an L1 receiver, and we break the tie towards 9. The results are not significantly affected by this tie-breaking choice.

1.[23] Then we count how many times a subject's choices are consistent with one of the types as a sender and as a receiver separately. Subjects are classified into a particular type if their behavior is consistent with that type for more than 60% of the time (e.g., at least 10 out of 16 times). If a subject is consistent with more than one type by the 60% rule, we classify him or her as the type he or she is most consistent with. If there is a tie between two or more types, we classify that subject to the lowest type of sophistication.[24] Table 19 presents the classification results for the senders.

Table 19: Type Classifications Results: Senders

Type	Count	Subject Number (% of consistency)
L0	2	18(80%), 22(90.9%)
L1	8	1(83.3%), 2(66.7%), 12(71.4%), 14(69.2%), 16(60%), 23(76.9%), 29(63.2%), 32(64.7%)
L2	10	3(78.9%), 4(100%), 6(100%), 9(62.5%), 11(85.7%), 17(86.7%), 20(82.4%), 25(81.3%), 27(72.2%), 31(64.7%)
Sop	4	5(94.4%), 8(88.2%), 19(100%), 30(100%)
N/A	8	7, 10, 13, 15, 21, 24, 26, 28

Among the 32 subjects, 24 can be classified as one of the behavior types. Two can be classified as the L0 type, 8 the L1 type, 10 the L2 type, and 4 the sophisticated type.

The classification results for the receivers is presented in Table 20. Among the 32 subjects, 26 can be classified as one of the behavior types. Three can be classified as the L0 type, 3 the L1 type, 11 the L2 or Equilibrium type, and 9 the sophisticated type.

The fact that about 75% of the subject population fits into the behavior types seems to indicate that this approach of bounded rationality is reasonably successful in describing the behavior of a majority of subjects. Moreover, it is interesting to note that some subjects, such as 18 and 22, are highly consistent as the truster type L0 senders and believer type L0 receivers; and quite a many subjects are highly consistent as either the liar type L1 senders or the inverter type L1 receivers.[25] This suggests roughly the following interpretation of our data. Those subjects of

[23] Note that this has no effect on classification of the senders, since their messages differ from each other by 2.

[24] There are three subjects (20, 29, 31) who are tied for two or more types as senders and five subjects (5, 8, 15, 19, 24) who are tied for two or more types as receivers. Using alternative tie-breaking rules does not have much effect on the analysis below.

[25] Examining these low type subjects' individual behavior, we do not find indication of learning over time, that is, they do not become more rational over time. This is quite remarkable for the L0 types, since the potential gain from becoming more rational is rather significant. By our calculation, given the empirical distribution of the

Table 20: Type Classifications Results: Receivers

Type	Count	Subject Number (% of consistency)
L0	3	18(62.5%), 22(95%), 25(66.7%)
L1	3	5(69.2%), 8(92.9%), 19(86.7%)
L2/Eq	11	1(68.4%), 4(100%), 6(77.8%), 9(80%), 12(82.4%), 15(70.6%), 21(66.7%), 24(88.2%), 27(61.5%), 30(80%), 32(100%)
Sop	9	2(78.9%), 7(62.5%), 10(60%), 11(70.6%), 14(77.8%), 17(81.3%), 23(72.2%), 26(73.3%), 28(71.4%)
N/A	6	3, 13, 16, 20, 29, 31

lower levels of sophistication overcommunicate, resulting in the greater-than-equilibrium amount of information transmitted from the senders to the receivers. However, since the subjects are randomly paired, types of senders and types of receivers are sometimes matched "correctly" to produce equilibrium-like outcomes (e.g., an L2 sender and an L2 receiver), but some other times matched "incorrectly" according to the equilibrium. In different matches, the receivers get more than their equilibrium payoffs in some cases (e.g., an L0 receiver versus an L0 sender), but in other cases get less than their equilibrium payoffs (e.g., a L0 receiver versus a L1 sender). Combined with some noise, these mismatches tend to offset the payoff gains and losses (relative to the equilibrium predictions), leading to average payoffs close to the equilibrium predictions.

To make the above interpretation more concrete, we calculate the payoffs and correlations implied by the distribution of types, and compare it with the actual ones. To proceed, however, we must specify behavior patterns for the subjects who cannot be classified by our criterion. There is no a prior guidance of how re-classification should be done, since unclassified subjects by definition do not show strong behavior patterns. We consider two scenarios as illustrative examples. In the first scenario, we suppose these subjects on average act like L0 types and L1 types half of the time each (and hence cannot be classified by our 60% consistency requirement). In the second scenario, we suppose they on average act like L0 types half of the time and act in a completely random way in the other half of the time. In each scenario, we use the type distributions to calculate the implied sender's and receiver's expected payoffs and the implied correlations between states, messages, and actions. Table 21 reports the results as well as the actual data and the equilibrium predictions for comparison.

From Table 21, we can see that the first scenario with unclassified subjects as half L0 types

receivers' actions, the expected payoffs for the sender's types are 22.77, 46.06, 48.68 and 50.28, for L0, L1, L2, and Sophisticated types, respectively. Given the empirical distribution of the senders' messages, the expected payoffs for the receiver's types are 58.16, 71.85, 71.59 and 76.56, for L0, L1, L2, and Sophisticated types, respectively.

Table 21: Estimation Results of Nash Equilibrium, Type Analysis and AQRE ($d = 4$)

	Actual	Nash	Type Scenario 1	Type Scenario 2	Crawford Equilibrium	QRE ($\lambda = 2.0042$)
Senders' u_S	37.37	29.46	40.54	35.82	50.24	23.53
Receivers' u_R	65.67	71.59	72.86	67.85	79.75	66.27
Corr(S,M)	0.376	0.000	0.531	0.388	0.630	0.328
Corr(M,A)	0.534	0.000	0.631	0.517	0.829	0.403
Corr(S,A)	0.183	0.000	0.361	0.222	0.608	0.180

and half L1 types overestimates communication (all three correlations are greater than those of actual data) and the senders' and receivers' expected payoffs. On the other hand, the second scenario (that all unclassified subjects are supposed to act randomly half of the time and act according to L0 types) does a very good job matching up with the actual data in terms of both correlations and expected payoffs. This shows that at least with some reasonable adjustments the behavior type analysis can explain our experimental data quite well, predicting both the degree of overcommunication and the players' expected payoffs. Having said that, we offer a word of caution. The main issue is that subjects of higher levels of sophistication in our games are not very distinguishable from each other, for example, L2 and sophisticated senders only differ in state 1, while L2 and equilibrium senders and receivers are not distinguishable at all (Table 18). Moreover, several subjects are tied with two or three higher types on both the sender and receiver sides. Even though the tie-breaking rule does not have important effects on our result, it is possible that the type classification may not be robust in other somewhat different environments. Thus, the results from the behavior type analysis in this section are not conclusive. Models and experimental designs that allow sharper distinction of subject types are needed for further investigation.

A related, but slightly different way to interpret our experiment data is to explain the data as some *equilibrium* in a model in which some subjects are rational and others are of some behavior types. Crawford (2003) studies a cheap talk model with a zero-sum underlying game in which players can be rational or the L0 and L1 types (i.e., truster and liar senders, believer and inverter receivers). In equilibrium, rational type players best response to their opponents, taking into account that their opponents can be one of the three types. He characterizes the equilibrium of the game and shows how it changes as the initial type distribution changes. Even though the underlying game in our study is quite different from that in Crawford (2003), it is easy to apply his method here, because subjects of L2 and Equilibrium types in our games are not very distinguishable from the sophisticated types (Table 18). As a result, in the classification quite a many subjects classified as L2 types are equally (or very close to be) consistent with sophisticated types. More precisely, if L2 type is ruled out, 8 out of 10 L2 type senders in Table 19 can be re-classified as sophisticated type, and 5 out of 11 L2 type receivers in Table 20 can be re-classified as sophisticated type. Reclassifying those unclassified subjects so that they on average act like L0 type half of the time and L1 type in the other half of the time, we arrive at a type distribution roughly as follows: the senders are L0, L1 and sophisticated with proportions $(20\%, 40\%, 40\%)$, and the receivers are L0, L1 and sophisticated with proportions $(30\%, 30\%, 40\%)$. With these type distributions, it can be verified that in equilibrium the sophisticated type sender sends a message 7 when the state is 1, and 9 in all other states, which coincides with the behavior of the sophisticated sender who best responses to the empirical distribution of the receivers' actions (Table 18). In equilibrium, the sophisticated type receiver will choose 1 in state 1, choose 3 in states 3, 5, 7, and choose 7 in state 9. Compared with the behavior of the sophisticated receiver who best responses to the empirical distribution of the senders' actions (Table 18), the theoretically sophisticated receiver's strategy is very close but not identical in states 1, 7, 9. We compute the correlations and expected payoffs in this equilibrium. The results are in Table 21, under the column titled "Crawford Equilibrium". Evidently, the Crawford equilibrium substantially overestimates communication and expected payoffs. The reason for the overestimation by the Crawford equilibrium and by the non-equilibrium type simulation of scenario 1 above (with half L0 types and half L1 types for unclassified subjects) is the same. In our experiment data, there is much noise in subjects' behavior, which is not taken into account by either interpretation. The second scenario (with half L0 types and half complete randomization) matches the data very well, because it introduces complete randomness into the subject population.

8 Bounded Rationality: Quantal Response Equilibrium

An alternative explanation for non-equilibrium behavior in experimental data is the concept of Quantal Response Equilibrium (QRE) introduced in McKelvey and Palfrey (1995, 1998). In Quantal Response Equilibrium, players have correct beliefs about their opponents' behavior, but they either make mistakes while trying to maximizing their payoffs or their preferences over different strategies are stochastic. Unlike the rational approach and the behavior type analysis, QRE explicitly takes into account noisy behavior of subjects. McKelvey and Palfrey (1995, 1998) demonstrate that QRE can be very useful in organizing and interpreting experimental data for a variety of experiments. In this section we apply the concept of QRE to our experiment data to shed light on the overcommunication phenomenon.

Specifically, following McKelvey and Palfrey (1998), we solve for the logit agent quantal response equilibrium (logit-AQRE) for our game.[26] Let $u(a,s)$ and $v(a,s)$ be the utilities of the sender and receiver, respectively, when the state is s and the receiver chooses an action a. Then in the logit-AQRE with a parameter λ, the sender in state s sends a message $m \in \{1,3,5,7,9\}$ with probability $p_{sm} = Pr(m|s)$:

$$p_{sm} = \frac{e^{\lambda \overline{u_s}(m)}}{\sum_{j=1,3,}^{5,7,9} e^{\lambda \overline{u_s}(j,)}}$$

where $\overline{u_s}(m) = \sum_{a=1}^{9} q_{ma} u(a,s)$ is the sender's expected payoff from sending a message m in state s; the receiver chooses an action a upon receiving a message m with probability $q_{ma} = Pr(a|m)$:

$$q_{ma} = \frac{e^{\lambda \overline{v_m}(a)}}{\sum_{j=1}^{9} e^{\lambda \overline{v_m}(j)}}$$

where $\overline{v_m}(a) = \sum_{s=1,3}^{5,7,9} r(s|m) v(a,s)$ is the receiver's expected payoff from choosing an action a upon the receipt of message m and $r(s|m) = p_{sm} / \sum_{i=1}^{9} p_{im}$ is her posterior belief about the states.

Hence, $\mathbf{P} = (p_{sm})_{5\times5}$ and $\mathbf{Q} = (q_{ma})_{5\times9}$ represent the sender's and receiver's mixed strategies, respectively, in the logit-AQRE. For any given λ, to solve for the seventy variables from the system of seventy equations, we iterate by starting with an initial $\mathbf{P}_0$ and obtaining the new $\mathbf{Q}_1$ and $\mathbf{P}_1$ using the above equations. We perform this procedure iteratively until $\mathbf{P}$ and $\mathbf{Q}$ converge to a fixed point. We then calculate the likelihood for this λ and obtain the maximum likelihood estimator by maximizing the likelihood function.[27]

Similar to the issue of choosing the right anchor for the behavior type analysis, choosing a proper initial point $\mathbf{P}_0$ is important in applying the logit-AQRE to strategic information transmission games. In these games, since the sender's strategies (namely, their messages) do not directly affect payoffs (thus the term "cheap talk"), there are many payoff-equivalent equilibria but with different equilibrium strategies. For example, in the $d = 4$ case, while babbling is the only equilibrium outcome, there are in fact many babbling equilibria, in each of which the sender sends a particular message in all states. So if we choose a complete random strategy for the sender as the initial $\mathbf{P}_0$, the iteration process quickly settles on a babbling equilibrium. To avoid this problem, we use the truth-telling strategy for the senders as the initial $\mathbf{P}_0$ (i.e., identity matrix).

For the ease of comparison, the result of the logit-AQRE estimation is displayed in the last column of Table 21. As shown in Table 21, the maximum likelihood estimator of λ is 2.0042. In the estimated AQRE, the correlation between state and action is very close to the actual data,

[26]For details of the solution concept and its applications, see McKelvey and Palfrey (1998).

[27]We use the golden section method in the estimation since λ is one dimension and $L(\lambda)$ is unimodal according to our grid search.

the correlations between state and message and between message and action are fairly close to the actual data. Hence the logit-AQRE provides a good interpretation for the communication patterns in our experimental data. In terms of payoffs, the receiver's expected payoff in the estimated AQRE is very close to that of actual data, while the sender's is somewhat lower. This may suggest that the logit-AQRE incorporates all kinds of noisy actions, while subjects in the data do not make mistakes (especially the very bad mistakes) to the extent the logit-AQRE postulates.[28]

9 Conclusion

In this paper we conduct laboratory experiments to test the theory of strategic information transmission originated by Crawford and Sobel (1982). Our main findings are the following. First, our experimental results strongly support the basic insight of the theory, namely, less information is transmitted when preferences of the sender and the receiver diverge. Secondly, the evidence shows that subjects consistently overcommunicate in that the senders' messages are more informative about the true states of the world and the receivers utilize the senders' messages more in choosing actions, compared with what the theory allows in the most informative equilibrium. Thirdly, these results are robust to certain variations of payoff parameters and noisy signals, and are robust to subjects' learning. Fourthly, we use both the behavior type analysis and quantal response equilibrium to analyze subjects' behavior in our experiment data. Both approaches have some success in interpreting our data. In particular, with each of the two approaches, we generate the kinds of correlations (overcommunication) and average payoffs (close to equilibrium payoffs) observed in the experimental data.

While we have some success in explaining our experimental results (in particular, overcommunication and near equilibrium payoffs) using the two bounded rationality approaches, the test may not be very "powerful" in the sense that for large preference differences, messages and actions tend to cluster toward the highest state (state 9), as the sender's bias is in one direction. In future work, it is desirable to develop models such that biases are symmetric so that clustering does not arise. Questions about what the underlying motives for the L0 types are naturally arise. Subjects 18 and 22 are highly consistent as L0 senders and L0 receivers in that they send truthful messages and choose actions blindly following the messages. Are they driven by social preferences (e.g., trust)? Where do their beliefs come from? These questions all await for further investigation.

[28] To be sure, the QRE requires that players make worse mistakes less often. In our game, the sender suffers more than the receiver in their respective worst payoff cases: when the state is 1 and the action is 9, the loss to the sender is 214.23 and the loss to the receiver is 73.79. So this may explain why the sender's expected payoff is under-estimated by the logit-AQRE.

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CASSEL
CALIFORNIA SOCIAL SCIENCE EXPERIMENTAL LABORATORY
2400 Public Policy Building

Date: 07/16/03
Description: 32 Player, 1 Sessions – 31 Rounds plus 2 Practice Rounds
Experimenter: Hongbin Cai and Tao-yi Joseph Wang
Script Reader: please point to the relevant part of the screen when you are reading the script where there are *Italicized* font style and try to emphasize on the parts that are in **Bold** font style.

DECISION MAKING EXPERIMENT INSTRUCTIONS (CS)

Welcome

You are about to participate in an experiment on decision-making, and you will be paid for your participation in cash, privately at the end of the experiment. What you earn depends partly on your decisions, partly on the decisions of others, and partly on chance. Please turn off all pagers and cellular phones now. Please close any programs that you have opened on the computer.

The entire experiment will take place through computer terminals, and all interaction between you will take place through the computers. It is important that you not talk or in any way try to communicate with other participants during the experiment unless specified by the experimenter.

We will start with a brief instruction period. During the instruction period you will be given a description of the main features of the experiment and will be shown how to use the computers. If you have any questions during this period, raise your hand and your question will be answered so everyone can hear.

General Instructions

Open your envelope, and read the record sheet inside. You will use this sheet later to record your final earnings. Your computer number is the number following "SSEL" written on your monitor. Write your name and computer number on the sheet. Keep your sheet in a safe place; you will need it at the end of the session to receive your payment.

[Wait for everyone to write down their computer number.]

At this time, please pull out the dividers that separate you from your neighbors. During the course of this experiment, please refrain from talking with your neighbors.

[Show SCREEN 1]

Please double click on the zLeaf Icon. This will bring you to the zLeaf welcome screen.
Are there any questions?

[Show SCREEN 2] *[Check the Client's table and make sure all (32 clients) have login.]*
[Shuffle the other subjects several times.]
[Load 03-07-16-00.param.CS_32.ztt, etc.]

The experiment you are participating in consists of a number of rounds. At the end of the final round, you will be asked to fill out a questionnaire and get paid the total amount you have accumulated during the course of the session in addition to the $5 show-up fee. Everybody will be paid in private after showing the record sheet. You are under no obligation to tell others how much you earned.

During the experiment all the earnings are denominated in FRANCS. Your dollar earnings at the end of the experiment are determined by the FRANCS/$ exchange rate posted on the board in the front and back of the room. This exchange rate is equal to 0.02 $ / FRANCS. Therefore, 50 FRANCS are equivalent to $1.

Practice Rounds

We will begin the experiment now. The experiment consists of 2 practice rounds and 31 real rounds. In the real rounds, two participants are matched into a pair. You will not be matched with the same people from previous rounds throughout the entire experiment. Thus, the matching is done in such a way that the decisions you make in one round can hardly affect the decisions of people you will be matched with in later rounds.

First, we are going do to the practice rounds**. During the practice rounds do not hit any keys until you are told to do so.** You are not paid for the practice rounds; it is just for you to familiarize yourself with the experiment and the computer program.

[Show SCREEN 3] *[Start Treatment: 03-07-16-00.param.CS_32.ztt]*

At the beginning of each round, you will be randomly joined with another participant to form a pair. One participant in each pair is randomly chosen to be member A, and the other member B. From your computer screen, you will find your role (member A or member B) in the pair, and the preference difference between member A and member B, the meaning of which will be made clear later.

[Show SCREEN 4]

This is the same screen, but for member B. Note that throughout the experiment, the preference difference is always 4.

[Show SCREEN 5]

In each round, the computer program generates a secret number that is randomly drawn from the set {1,3,5,7,9} for every pair. The computer will send the secret number to Member A. After receiving the number, member A will send a message to member B, and then member B will choose an action. Both member A and B's earnings depend on the value of the secret number and member B's action.

[Show SCREEN 6]

In particular, member B's earnings will be 110 minus 10 times the distance between the secret number and the action chosen by member B to the power 1.4. Member A's earnings will be 110 minus 10 times the distance between "the secret number plus a preference difference" and the action chosen by member B to the power 1.4. You do not need to worry about this calculation since the computer will do it for you.

[Show SCREEN 7]

The graph in front shows the possible earnings when the secret number is 3. The red line shows the earnings of member B given different action he or she chooses; the blue line shows the earnings of member A given different action B chooses. Note that member B's earnings are the highest when the action is 3, coinciding with the secret number (3). Member A's earnings are the highest when the action is 7, which is the secret number (3) plus the preference difference (4). The peak of member A's earnings (7) and the peak of member B's earnings (3) has a difference of 4, which is the preference difference, d.

[Show SCREEN 8]

In this graph, the secret number is 1. Hence, member B gets the highest earnings when the action is 1, and member A gets the highest earnings when the action is 5, which is 1 plus the preference difference, 4.

[Show SCREEN 9]

On your screen, you will see the table of all possible earnings. For the example show in front, the preference difference d is 4, the secret number and the action chosen are both 1, then member B's earnings are 110, and member A's earnings are 40.36, reflecting member B's peak in the previous graph. If the action is 5, member B's earnings are now 40.36, and member A's earnings are 100, reflecting member A's peak in the previous graph. Are there any questions?

After reading the information on your screen, press the red button saying, "Press to Start." Then, member A will receive the secret number, which is indicated at the top right of the screen. The possible earnings for every scenario are presented at the left.

[Show SCREEN 10]

If you are member A, you can click on the red buttons indicating the possible values of the secret number to view the earnings you and member B might get if that were the true value. The table of possible earnings given different actions chosen by member B shows up. Note that your earnings are shown in **BLUE** and the other member's earnings are shown in **BLACK**.

[Show SCREEN 11]

You may click on different buttons to see earnings in other scenarios. You may take your time and click as many times as you want, but remember that other participants are waiting.

[Show SCREEN 12]

In the example projected in the screen, the preference difference is 4, and the number member A received is 5. Hence, member A's earnings is 110 (the highest) if Action 9 were chosen by member B, while member B's earnings is 110 (the highest) if Action 5 were chosen by member B.

[Show SCREEN 13]
Member A will now send a message to member B. The message box is at the right side of the screen. You can choose to check any of the checkboxes and form a message indicating the value or range of the number received.

If you would like to mix between two or more values, simply check all of the values you want to mix between. Just remember to check the "or" box in front of them to confirm. **If you choose more than one value, the computer will randomly choose one of the values with equal probability and send it to member B.** For example, on the screen shown here, member A chooses the message, "The number I received is 5 or 7 or 9." Hence, the computer will then randomly choose a number from {5, 7, 9}, and send it to member B. Note that you may also choose to send a message saying, "anything," without checking any other boxes. This is the same as choosing "1 or 3 or 5 or 7 or 9," and the computer will send to member B a randomly drawn number from {1, 3, 5, 7, 9}. Select any message you would like to send, and click "OK."

[Show SCREEN 14] *[Wait for all senders to finish their choices.]*

Has everyone as member A finished his/her message? Is there any question about the message sending process?

Now it is member B's turn to choose an action. Just like the previous screen, the message sent by member A is at the right side of the screen, and possible earnings are at the left. You can click on possible values of the secret number to view the earnings you and member A might get if that were the true value. Remember that your earnings are in **BLUE**, and the other member's earnings are in **BLACK**.

[Show SCREEN 15]

Note that if member A sent a message that consists of more than one values, the computer will randomly pick one of them and display it on your screen. Hence, seeing a "3" on your screen could mean that member A sent out "The number I received is 3" or that member A sent out a mixed message with 3 as one possible value. For example, it could be that member A sent out "anything," and the computer draw "3" out of the pool {1, 3, 5, 7, 9}. For another example, as is projected on the screen, although member A previously chosen the message "5 or 7 or 9," member B receives the number "9," which is randomly drawn from 5, 7, and 9. Member B now will choose an action among 1, 2, 3, 4, 5, 6, 7, 8, and 9. Type in the action you choose and click "OK" to conclude this round.

[Show SCREEN 16] *[Wait for all receivers to finish their choices.]*

At the end of the round, the secret number is revealed, and your earnings are determined accordingly. A summary of this round indicates your role, the value of the secret number, the number member A received, the message member A actually sent, the message B received, the action chosen by member B, and your earnings both in this round and cumulated in the entire session. Since this is just a practice round, your cumulated earnings are still zero. Are there any questions?

[Show SCREEN 17]

Click "OK" and proceed to the other practice rounds. In this practice round, you will get a chance to play the other role. I.e. if you were member A in the previous round, you will now be member B, and vice versa. You may send or choose any message or action in this practice round.

Real Rounds

We will now start the real rounds. You will now play 31 (or 21) rounds, each round paired with a different participant.

Remember: You will not be matched with the same people from previous rounds throughout the entire experiment. Hence, your decisions in one round can hardly affect the decisions of the people you will play with in future rounds. **This is not a practice; you will be paid!**

Click "ok" to proceed to the real rounds. Please continue to make your choices.

Farewell

This is the end of the experiment. On your screen you will see a dialog box indicating your FRANCS earnings for this session.

[Start Questionnaire: 03-07-16-00.questionnaire.CS.ztq]

Please fill in your first name, last name, major, which year you are in, gender and ethnicity background. Then, press "OK". You will be paid accordingly.

The experiment has ended. On your screen you will see a dialog box indicating your total earnings for the entire experiment. Please make sure you record the dollar payoff in your record sheet.

Take this sheet to the counter for payment. This sheet will be matched to our computer printout of results for payment. Your payments will be rounded up to the nearest quarter. Thank you for your participation.