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Team vs. Individual, Hypothesis Testing vs. Model Selection, and the Minimax Model

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Abstract

We report results of an experiment comparing team and individual behavior in a two-player zero-sum game, and assess the predictive power of the minimax model. Based on hypothesis testing, the play of teams is consistent with the minimax hypothesis in the first half of the experiment, but the play of teams in the second half, and that of individuals in both halves are not. Based on model selection, the aggregated behavior of teams in the first half is best fitted by a belief-based learning model, whereas that of teams in the second half and that of individuals in both halves are best fitted by the minimax model. At the decision-maker level, the minimax model is best for about half of the teams and individuals.

Keywords: Minimax, team decision-making, model selection, learning

JEL Classification: C72, C92

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1 Introduction

Two-player zero-sum games are an important class of non-cooperative games. In addition to the historical reason that the original research on game theory focused on this context, these games provide solid theoretical predictions under the assumption of rational play. In every two-player zero-sum games, the minimax strategy coincides with the maximin strategy. Furthermore, the strategy profile that consists of minimax (maximin) strategies coincides with the Nash equilibrium of the game. In this sense, game theory makes a confident prediction in this class of games. However, earlier experiments using two-player zero-sum games with unique mixed strategy equilibria found that subjects typically do not play near the minimax prediction, especially at the decision-maker level (O'Neill, 1987; Brown and Rosenthal, 1990; Rapoport and Boebel, 1992; Ochs, 1995; Mookherjee and Sopher, 1997; Binmore et al., 2001; Shachat, 2002; Rosenthal et al., 2003; Geng et al., 2015; Van Essen and Wooders, 2015).

Given a substantial deviation of behavior from the minimax prediction, one of the next important issues is whether subject behavior approaches it as the experiment progresses. We might retain some confidence in the minimax model as a good predictor for subject behavior if deviation from the minimax is concentrated in the early rounds of the experiment. Some papers have addressed this question, but they have revealed no such tendency. Typically, a substantial deviation from the minimax was established in the early rounds of experiments, and maintained persistently thereafter.[1] One possibility for these results is that they are a consequence of the insufficiency of repetition, although subjects can play minimax with sufficient experiences of the game. Another is that they are a consequence of the lack of ability of subjects to learn and approach the minimax.

This paper presents an examination of the behavior of common-purpose

[1]See Brown and Rosenthal (1990), Ochs (1995), Mookherjee and Sopher (1997), Rosenthal et al. (2003), and Van Essen and Wooders (2015). Palacios-Huerta and Volij (2008) found that professional soccer players playing two-player zero-sum games behave consistently with the minimax prediction. Wooders (2010), after re-examining their data, reported that professionals tend to follow nonstationary mixtures, with action frequencies that are negatively correlated between the first and second halves of the experiment.

freely-discussing two-person teams that have been known to be able to behave consistently with the minimax, and assesses the predictive power of the minimax model over time. Okano (2013) revealed that when teams play a well-known 4×4 O'Neill (1987) game against each other, the choice frequencies conform closely to those implied by the minimax hypothesis, even at the decision-maker level. Furthermore, Okano (2016) re-examined the data by splitting the data into halves, which revealed that teams behave consistently with the minimax both in the first and second halves of the experiment. To observe the movement of behavior over time, this paper presents a study of a slightly more complex 5×5 game developed by Rapoport and Boebel (1992). It requires subjects to engage in a cognitively more demanding task than the O'Neill game. Therefore, we expect that this game gives a more reasonable chance of divergence from the minimax. We also conducted an experiment with single individuals for comparison with the behavior of teams.

We evaluate the predictive power of the minimax model in two ways: hypothesis testing and model selection. Hypothesis testing provides an objective method to either accept or reject a null hypothesis that no difference exists between two or more variables. Because the minimax theory gives an exact prediction, e.g., the relative frequencies of choices are *exactly equal to* the minimax strategy, it must be the null hypothesis. We can claim that the subjects do not follow the minimax if the null hypothesis is rejected. If the null hypothesis is not rejected, however, we cannot say that the subjects follow the minimax, but that the behavior of subjects is *consistent with* the minimax hypothesis in the sense that no compelling evidence exists that subjects do not follow the minimax, although they might follow a logic other than the minimax. Therefore, hypothesis testing addresses the question of whether the minimax is incorrect or the research is inconclusive.

We find, using overall round data, that the relative frequencies of actions depart from the minimax prediction for both teams and individuals. When we partition the data into the first and second half, however, the relative frequencies of actions by teams in the first half are reasonably close to those implied by the minimax prediction, although those of teams in the second half, and those of individuals in both halves are not. These observations suggest that, although teams play consistently with the minimax prediction for the early rounds of experiment, they gradually depart from it as the experiment progresses, whereas individuals do not follow the minimax play in the course of the experiment.

Model selection is a statistical method by which we select the best fit model to the data from a set of two or more competing models. For several reasons, model selection is important to evaluate the performance of the minimax model in this context, though previous research did not pay attention to it so much. First, even if we have found, based on hypothesis testing, that the minimax is incorrect (such as the cases for teams in the second half and individuals in both halves in our experiment), it does not mean that the minimax is very wrong. The possibility exists that the minimax fits the data better than other competing models. Model selection therefore addresses the question of how close the minimax is to the experimental data over the other models.[2] Secondly, even if we have found that the relative frequencies of choices are close to the minimax prediction (such as the case for teams in the first half in our experiment), the possibility exists that subjects follow a model other than the minimax. For example, Brown (1951) and Robinson (1951) showed that, in every two-player zero-sum games, if both players follow an adaptive learning model called fictitious play, then the relative frequencies of choices converge to the mixed-strategy Nash equilibrium of the game. This implies that consistency of the choice frequencies with the minimax is also supported by an adaptive learning model. Model selection can clarify whether the data are best fitted by the minimax or by the other models. Thirdly, related to the general criticisms of hypothesis testing, the conclusion is affected by which value of significance levels we choose. Although we adhere strictly to adoption of the 5 percent significance level in Section 3, selection of the significance level is basically arbitrary. If we adopt, for example, the 10 percent significance level, then the results of teams in the first half are

[2]This point is also emphasized by O'Neill (1991) and by Rapoport and Boebel (1992).

somewhat weakened because the p-values of three tests presented in Table 4 lie between 0.05 and 0.10 (see the fourth column in Table 4). Model selection is one method to complement the findings from hypothesis testing.[3]

Rapoport and Boebel (1992) recognized the importance of model selection. As rivals of the minimax model, they considered equiprobable model that predicts random play with equal probability, and win-weighted model in which the probability of choosing each strategy is proportional to that strategy's number of win opportunities. They found that the minimax model mostly outperforms these two models. This paper presents consideration of the experience-weighted attraction learning model (Camerer and Ho, 1999; Camerer et al., 2002; Ho et al., 2008), reinforcement learning model (Arthur, 1991, 1993; Roth and Erev, 1995; Erev and Roth, 1998), belief-based learning model (Cheung and Friedman, 1997; Fudenberg and Levine, 1998), and quantal response equilibrium (McKelvey and Palfrey, 1995) as rivals of the minimax model. Each is a prominent model known as a good predictor of the experimental data.

Using overall round data, we find that aggregated data are best fitted by the minimax model for both teams and individuals. When we partition the data into halves, aggregated data of teams in the first half are best fitted by the belief-based learning model, whereas those of teams in the second half and those of individuals in both halves are best fitted by the minimax model. At the decision-maker level, the minimax model is best for more than or equal to half of subjects for both teams and individuals. Teams for which the best fit model is the minimax in the first half are more likely to continue to play in the same manner in the second half than individuals are. Furthermore, we detect several differences in learning parameters of experience-weighted attraction learning model between teams and individuals.

Aside from the literature on experiments on two-player zero-sum games, the present paper contributes to the literature on team decision-making. In much of economic theory, game theory, and most experimental investigations

[3] Weakliem (2016) presents general arguments related to criticisms of conventional hypothesis testing and the importance of model selection as an alternative method.

of these theories, no distinction exists between decisions by teams and those by individuals. In many real life situations, however, decisions are often made by teams or groups in which two or more individuals are freely interacting. Households, firms, and governments, which are important objects of analysis in economics, are typically not individuals, but groups of people. On the background of practical relevance, a growing body of literature compares individual decision-making to team decision-making in various strategic environments.

Most studies have demonstrated that teams are more self-interested, and strategically more sophisticated than individuals.[4] For example, teams make and accept smaller transfers in the ultimatum game (Bornstein and Yaniv, 1998), send or return smaller amounts in the trust game (Cox, 2002; Kugler et al., 2007), exit the game earlier in the centipede game (Bornstein et al., 2004), act more strategically in the signaling game (Cooper and Kagel, 2005), better anticipate the game dynamics in the beauty contest game (Kocher and Sutter, 2005; Sutter, 2005; Kocher et al., 2006), choose smaller transfers in the dictator game (Luhan et al., 2009)[5], are better at coordinating on efficient outcomes in the coordination game (Feri et al., 2010), play a Nash equilibrium strategy more often in various normal-form games (Sutter et al., 2013), and contribute less in the public goods game (Huber et al., 2017).[6]

Our analysis can detect driving forces underlying the differences in the behaviors of teams and individuals. In our experiment, teams and individuals can access information on their own choice, the opponent's choice, the outcome of the game up to then, and the current amount of money. They need to process this information to reach better decisions (i.e., exploit the opponent). Not only in economics, but also in social psychology, teams are known to have higher

[4]Here, we briefly review the literature. Bornstein (2008), Charness and Sutter (2012), and Kugler et al. (2012) provide more thorough reviews.

[5]Cason and Mui (1997) found that team decision-making in the dictator game is likely to be dominated by the more other-regarding member.

[6]Auerswald et al. (2016) and Cox and Stoddard (2016) found that teams contribute more than individuals in public goods games. Kagel and McGee (2016) reported that, in a finitely repeated prisoner's dilemma game, teams choose less cooperation than individuals in the first super-game. Then, they change the behavior to more cooperation in the subsequent super-games.

abilities for processing available information than individuals have (Chalos and Pickard, 1985; Blinder and Morgan, 2005). These findings lead us to predict that teams and individuals follow different learning processes in the experiments.

An effective mode of addressing the question of whether and how learning processes by teams and individuals differ is to apply a behavioral learning model to the experimental data, examine model fits, and compare estimates of the parameters. Although learning is important for virtually every area of economics, little is known about the differences in learning processes used by teams and individuals. We are aware of two studies that have addressed this issue. Kocher and Sutter (2005) applied EWA, belief-based, and reinforcement learning model to team and individual decisions in the beauty contest game, and examined model fits. Feri et al. (2010) applied the EWA learning model to team and individual decisions in various coordination games, and compared their coefficients. We are the first to provide evidence for the difference in learning between teams and individuals in two-player zero-sum games.

The paper is organized as follows. Section 2 describes the experimental design that enables us to examine the behavior of teams and individuals in a two-player zero-sum game. Section 3 presents the results of hypothesis-testing for the minimax model. Section 4 presents model selection. We first present details of competing models, and then clarify the best fit model for teams and individuals. Section 5 provides some discussion and concluding remarks.

2 Experimental Design

There are two treatments in our experiment. In the team treatment, subjects were assigned to a two-person team. Each team interacted with another team. Subjects were seated with their teammate at one computer terminal, were allowed to discuss matters freely face-to-face, and were required to reach a single decision in each round. No decision rule was imposed. They were requested to speak softly and were strictly forbidden to speak to members of other teams. The minimum distance from the next team (computer terminal) was about three

Table 1: Payoff Matrix

		Player Y				
		C	L	F	I	O
Player X	C	W	L	L	L	L
	L	L	L	W	W	W
	F	L	W	L	L	W
	I	L	W	L	W	L
	O	L	W	W	L	L

Notes: W and L in cells denote a win and a loss for player X, respectively. Player Y's payoffs are the reverse of X's.

meters. In the individual treatment, subjects were mutually isolated and were not allowed to communicate.

Subjects repeatedly played a 5×5 two-player zero-sum game developed by Rapoport and Boebel (1992). Decision-makers (teams/individuals) were assigned randomly to one of two player roles: X or Y. Players X and Y chose one of five pure strategies denoted by the letters C, L, F, I, and O. That choice determines the winner. The payoff matrix is displayed in Table 1. W and L in each cell denote a win and a loss for player X, respectively. The game has a unique mixed strategy equilibrium in which both players choose C, L, F, I, and O with probabilities 3/8, 2/8, 1/8, 1/8, and 1/8, respectively. Subjects were matched anonymously with a fixed opponent, with whom they played 120 game rounds.

We kept the per-subject monetary incentives constant across teams and individuals. At the beginning of play, each team (individual) was given 7200 yen (3600 yen).[7] In each round, when teams (individuals) assigned player X won the game, they received 200 yen (100 yen) from the opponent. When teams (individuals) assigned player Y won the game, they received 120 yen (60 yen) from the opponent. Earnings of teams were divided equally between team members. Because player X (Y) should win 37.5 percent (62.5 percent) of the time when both players choose the action according to the equilibrium, the expected payoffs were zero for both players. In addition to the earnings from the experiment, subjects were paid 1400 yen as a show-up fee.

[7] 1 US dollar was about 80 yen at the time the experiments were conducted.

The experiment was conducted in February 2011 and February 2012 at Osaka University. Subjects were recruited through campus-wide advertisements. The experiment consisted of eight sessions (six for the team treatment, and two for the individual treatment), with 12 to 24 subjects for each session. In total, 152 undergraduate and graduate students participated in this experiment. No subject participated in more than one experimental session. Of these, 112 subjects participated in the team treatment. Consequently, we have 56 teams (28 pairs). The remaining 40 subjects (20 pairs) participated in the individual treatment.

Experimental sessions lasted about two hours, and proceeded as follows.[8] At the beginning of the session, participants received written instructions, which were read aloud. Participants were offered the opportunity to ask private questions. After reading the instructions, participants picked a card with a seat number. For all participants in the team treatment, another participant was assigned to the same seat, who is the participant's teammate. Therefore, the assignment to the team was at random. Before the play for real money, subjects had an opportunity to review the experiment contents for five minutes. From this time on, in the team treatment, subjects were allowed to discuss experiment-related matters freely with the teammate. Immediately after the experiment, subjects received a payment in cash.

The experiment was programmed and conducted using z-Tree software (Fischbacher, 2007). At the top of the screen display, the number and remaining time of the current round were shown. Subjects were requested to come up with a decision within 30 seconds. A red sign would appear on the screen and ask them to reach a decision immediately if they did not enter their decision after 30 seconds. At the middle-left, the payoff matrix was displayed. On the screen of player X, the payoff matrix in Table 1 was displayed. On the screen of player Y, the row and column players in Table 1 were switched, and W and L were reversed. At the middle-right of the screen, the current money total was displayed, with five buttons labeled C, L, F, I, and O. Subjects chose their action by clicking one of these buttons. At the bottom, history information was shown,

[8] See Supplementary Appendix C and D for the details of instructions.

Table 2: Relative Frequencies of Choices in Team Treatment

		Player Y					Marginal
		C	L	F	I	O	Frequencies
Player X	C	0.148 (0.141)	0.104 (0.094)	0.055 (0.047)	0.035 (0.047)	0.036 (0.047)	0.379 (0.375)
	L	0.086 (0.094)	0.063 (0.063)	0.037 (0.031)	0.034 (0.031)	0.025 (0.031)	0.245 (0.250)
	F	0.052 (0.047)	0.043 (0.031)	0.017 (0.016)	0.014 (0.016)	0.015 (0.016)	0.140 (0.125)
	I	0.038 (0.047)	0.033 (0.031)	0.018 (0.016)	0.014 (0.016)	0.015 (0.016)	0.118 (0.125)
	O	0.037 (0.047)	0.032 (0.031)	0.019 (0.016)	0.015 (0.016)	0.016 (0.016)	0.119 (0.125)
Marginal Frequencies		0.360 (0.375)	0.275 (0.250)	0.145 (0.125)	0.113 (0.125)	0.107 (0.125)	

Notes: Numbers in parentheses represent the relative frequencies predicted under the minimax hypothesis.

which included the round number, one's own and the opponent's choice, and the outcome of the game. After subjects chose an action, the outcome was displayed, which included the current money total, one's own and the opponent's choice, and the outcome of the game for that round.

3 Hypothesis Testing for Minimax Model

This section presents results of hypothesis testing for the minimax prediction. Throughout this section, we adopt the 5 percent significance level for classification of the minimax hypothesis as accepted or rejected.

3.1 Overall Round Data

First, we describe the results obtained using data during all 120 rounds. Tables 2 and 3 show the aggregate-level relative frequencies of action profiles (interior of

Table 3: Relative Frequencies of Choices in Individual Treatment

		Player Y C	L	F	I	O	Marginal Frequencies
	C	0.137 (0.141)	0.105 (0.094)	0.048 (0.047)	0.036 (0.047)	0.042 (0.047)	0.368 (0.375)
	L	0.092 (0.094)	0.070 (0.063)	0.036 (0.031)	0.034 (0.031)	0.029 (0.031)	0.261 (0.250)
Player X	F	0.046 (0.047)	0.032 (0.031)	0.010 (0.016)	0.009 (0.016)	0.013 (0.016)	0.111 (0.125)
	I	0.041 (0.047)	0.025 (0.031)	0.015 (0.016)	0.010 (0.016)	0.011 (0.016)	0.103 (0.125)
	O	0.065 (0.047)	0.040 (0.031)	0.021 (0.016)	0.016 (0.016)	0.015 (0.016)	0.157 (0.125)
Marginal Frequencies		0.382 (0.375)	0.272 (0.250)	0.131 (0.125)	0.105 (0.125)	0.110 (0.125)	

Notes: Numbers in parentheses represent the relative frequencies predicted under the minimax hypothesis.

the box) and choices for player roles (right and bottom of the table) in the team and individual treatments, respectively. In parentheses below these numbers, the corresponding relative frequencies expected under the minimax hypothesis are listed. In both treatments, the relative frequencies show a rough adherence to the minimax prediction, as previous experiments also revealed.

Table 4 presents results of hypothesis testing for the minimax prediction. Each column corresponds to a different round interval (overall, first half, and second half) and a different type of decision-maker (team and individual).[9] Panel I in Table 4 presents the results of statistical tests using the aggregated data. The first two rows are p-values of chi-square goodness-of-fit tests of the marginal frequencies for players X and Y to the minimax hypothesis, whereas the third row shows p-values of chi-square goodness-of-fit tests of the action profiles to

[9]Readers interested in these findings in more detail are directed to the tables presented in Supplementary Appendix A.

Table 4: Summary of Statistical Test Results

Rounds:	1-120		1-60		61-120	
Treatment:	Team	Indiv.	Team	Indiv.	Team	Indiv.
			I. Aggregate Level			
P-values from chi-square goodness-of-fit test:						
Player X	0.060	0.000	0.115	0.000	0.045	0.001
Player Y	0.000	0.002	0.061	0.001	0.000	0.150
Action Profile	0.000	0.000	0.006	0.000	0.000	0.014
			II. Decision-Maker and Pair Level			
Percentage of rejections at the 5 percent:						
Player X	17.9%	20.0%	3.6%	15.0%	10.7%	15.0%
Player Y	28.6%	25.0%	14.3%	20.0%	17.9%	15.0%
Action Profile	39.3%	15.0%	7.1%	25.0%	21.4%	20.0%
			III. Joint Level			
P-values from chi-square joint test:						
Player X	0.015	0.001	0.878	0.095	0.105	0.002
Player Y	0.000	0.000	0.066	0.001	0.000	0.002
Action Profile	0.000	0.004	0.072	0.008	0.000	0.012
P-values from Kolmogorov-Smirnov test:						
	0.000	0.000	0.635	0.053	0.003	0.024

Notes: Columns correspond to different round intervals (overall, first half, second half), and different types of decision-maker (team and individual). Rows show results for respective tests. Panel I presents p-values from the chi-square goodness-of-fit tests of aggregated marginal frequencies of players X and Y, and aggregated action profiles to the minimax prediction. Panel II presents percentages of decision-makers and pairs for which we can reject the null hypothesis at the 5 percent level for the same chi-square test as in Panel I. Panel III presents results of statistical tests in which the null hypothesis is that all decision makers play minimax. The first three rows show p-values from the chi-square joint tests for player X, player Y, and action profiles, respectively. The last row shows p-values obtained from Kolmogorov-Smirnov tests using p-values from chi-square goodness-of-fit tests at the decision-maker level to the uniform distribution on $[0, 1]$.

the joint probability distribution implied by the minimax hypothesis.[10] For overall round data (the second and third columns), the minimax hypothesis is mostly rejected in both treatments. We cannot reject it only for player X in the team treatment.

Panel II in Table 4 presents results of chi-square tests at the individual decision-maker level and pair level, rather than the aggregated data. Instead of reporting p-values, we present the percentage of decision-makers and pairs for which we reject the null hypothesis at the 5 percent level. For the test of action profiles, we aggregate choices F, I, and O into a single choice to increase the credibility of the chi-square test.[11] If all decision-makers follow the minimax strategy, then we expect that 5 percent of decision-makers exhibit the rejection of these tests at the 5 percent level. For overall round data, we have more rejections in both treatments than theory predicts. Furthermore, for tests of player Y and action profiles, a greater fraction of teams exhibit the violation from minimax than individuals.

Panel III in Table 4 presents examination of the joint hypothesis that *all* decision-makers follow the minimax strategy. The first three rows show p-values from the chi-square joint test. The test statistic is simply the sum of all test statistics of the chi-square test at the decision-maker level.[12] The null hypothesis is rejected for player X, player Y, and action profiles in both treatments.

Under the minimax prediction, while the choice frequencies of each decision-maker should adhere to the equilibrium proportion, they should also be scat-

[10] Under the null hypothesis, the test statistic is distributed asymptotically as $\chi^2(4)$ for the test of marginal frequencies, and $\chi^2(24)$ for the test of action profiles.

[11] At the decision-maker level, we have only 60 observations in each half, which lacks the credibility of the statistical test. For example, the expected frequency of FF play is 0.9375 ($= \frac{1}{8} \times \frac{1}{8} \times 60$) with 60 observations under the minimax prediction. According to Gibbons and Chakraborti (2003), when using the chi-square test, we should have data with which the expected frequency exceeds 1.5 in each category. Otherwise, we should combine two or more categories into a single one. We decided to combine F, I, and O into a single choice, because they are strategically equivalent. With this manipulation, the minimum expected frequency is LL play, which is 3.75 ($= \frac{2}{8} \times \frac{2}{8} \times 60$) with 60 observations. Under the null hypothesis, the test statistic is distributed asymptotically as $\chi^2(8)$.

[12] Under the null hypothesis that all decision-makers follow the minimax strategy, the test statistic is distributed asymptotically as $\chi^2(4 \times n/2)$ for players X and Y, and $\chi^2(8 \times n/2)$ for action profiles where n is the number of decision-makers in the treatment.

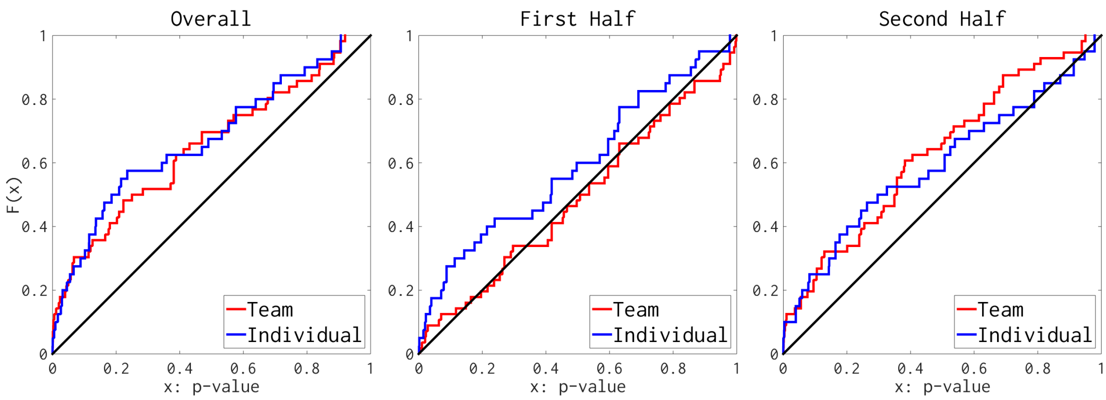

Figure 1: Empirical Cumulative Distribution Functions for Observed p-values from Chi-square Goodness-of-Fit Tests at the Decision-Maker Level.

tered adequately around the equilibrium proportion because playing a mixed strategy indicates that each action is a *random draw* from the multinomial distribution. This implies that p-values from the chi-square tests at the decision-maker level should be distributed as the uniform distribution $U[0, 1]$ under the hypothesis that all decision-makers follow the minimax strategy. Figure 1 portrays empirical cumulative distribution functions (CDF) for observed p-values. The CDF of the uniform distribution is represented by the 45 degree line in the figure. For overall round data (on the left side of Figure 1), the empirical CDF are skewed upwardly in both treatments, indicating that there are a lot of small p-values. The last row of Panel III in Table 4 shows p-values of a one-tailed Kolmogorov-Smirnov test of these p-values to $U[0, 1]$. The null hypothesis is rejected in both treatments, indicating that the plays of all teams and individuals are scattered excessively around the equilibrium proportion.

In summary, a substantial deviation from the minimax play exists in the choice frequencies in terms of the aggregated, decision-maker, and joint levels for both treatments. Furthermore, no prominent difference is apparent between teams and individuals. These results contrast to those reported by Okano (2013; 2016), who confirmed more consistency with the theory by teams than by individuals in 4×4 games. This result might derive from adopting a 5×5 game in our experiment in which greater complexity of the game lead subjects (even teams) to diverge from minimax play.

3.2 Half Data

In this subsection, we simply split data into the first and second 60 rounds, and apply the same analysis as in the previous subsection. The fourth and fifth columns in Table 4 present results of statistical tests using data of the first 60 rounds. In the team treatment, we cannot reject the null hypotheses that aggregated marginal frequencies for players X and Y are the same as those under the minimax play, although we reject it for the test on action profiles (Panel I). In the individual treatment, we reject the same null hypotheses in all cases. For the decision-maker level data (Panel II), in the team treatment, we observe the near numbers of rejection to those we expect at the 5 percent level under the null hypothesis. It is rejected for 3.6% of player X and 7.1% of action profiles, although the rejection rate is somewhat higher for player Y (14.3%). The individual treatment shows more rejections than the team treatment, and more than theory predicts. The chi-square joint tests for player X, player Y, and action profiles do not reject the joint null hypothesis in the team treatment (the first three rows of panel III). In the individual treatment, the same tests reject the null hypothesis for player Y, and action profiles, although the test for player X cannot reject it. The visual comparison shown in Figure 1 reveals the conformity of the empirical CDF of observed p-values of teams to the CDF for $U[0, 1]$, whereas those of individuals are slightly skewed upwardly. The one-tailed Kolmogorov-Smirnov test shows that we cannot reject the null hypothesis that observed p-values are drawn from $U[0, 1]$ for both teams and individuals.

The sixth and seventh columns in Table 4 show results of statistical tests obtained using data in the second half. At the aggregate level, decision-maker level, and joint level, the choice frequencies of teams and individuals are far from the minimax prediction. The exceptions are the chi-square joint test for player X in the team treatment ($p = 0.105$), and the chi-square test of aggregated marginal frequencies for player Y in the individual treatment ($p = 0.150$).

In summary, regarding choice frequencies, teams behave consistently with the minimax prediction in the first half in most cases. In the second half, how-

Table 5: Runs Test

Rounds:	1-120		1-60		61-120	
Treatment:	Team	Indiv.	Team	Indiv.	Team	Indiv.
C	5.4%	10.0%	5.4%	5.0%	0.0%	10.0%
L	5.4%	10.0%	1.8%	7.5%	5.4%	5.0%
F	3.6%	7.5%	3.6%	2.5%	0.0%	0.0%
I	1.8%	10.0%	0.0%	2.6%	0.0%	5.0%
O	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Notes: Columns correspond to different round intervals (overall, first half, second half), and different types of decision-maker (team and individual). Rows present percentage of decision makers that we can reject the serial independence hypothesis at the 5 percent level for each choice.

ever, they play far from the minimax prediction. Therefore, as the experiment progresses, team behavior departs from minimax play, rather than converges to it. In this sense, the minimax model is successful in predicting the short-run behavior of teams, but not the long-run behavior. In the individual treatment, subjects choose actions that are inconsistent with the minimax prediction in both halves, as observed in previous experiments.

3.3 Serial Independence Hypothesis

Another implication of minimax play is that subject's choices are serially independent. Table 5 shows results of runs test for respective choices. The first row, for example, presents the percentage of decision-makers for which we reject the serial independence hypothesis at the 5 percent level for the sequence of C and non-C choices.[13] For both teams and individuals, our subjects do not exhibit serial correlation to the degree found in earlier experiments. We observe fewer or nearly equal numbers of rejections to those we expect at the 5 percent level under the null hypothesis, although individuals sometimes exhibit more rejections than theory predicts (especially when applying tests to overall round data).

[13]One team and one individual did not choose I in the first half. Because we cannot apply runs test to these data, we excluded those.

4 Model Selection

This section provides results of model selection by which we select the model that best predicts the subject behavior across five models including the minimax model. Alternative models are experience-weighted attraction learning model (EWA), reinforcement learning model (RL), belief-based learning model (BL), and quantal response equilibrium (QRE).

We use maximum likelihood estimation. Players are indexed by $i \in \{1, \cdots, n\}$. Let $s_i(t) \in \{C, L, F, I, O\}$ be player i's strategy in round $t \in \{1, \ldots, T\}$, and $P_i^j(t)$ be player i's probability of choosing $j \in \{C, L, F, I, O\}$ in round t that the model predicts. Then, the log-likelihood function for the aggregate level is

$$LL = \sum_{i=1}^{n} \sum_{t=1}^{T} \log \Big(\sum_{j \in \{C,L,F,I,O\}} I(j, s_i(t)) P_i^j(t) \Big),$$

and that for the decision-maker level is

$$LL_i = \sum_{t=1}^{T} \log \Big(\sum_{j \in \{C,L,F,I,O\}} I(j, s_i(t)) P_i^j(t) \Big),$$

where $I(j, s_i(t))$ is the indicator function, taking the value one if $j = s_i(t)$, and zero otherwise.

Five models we examine have different numbers of parameters to be estimated.[14] Basically, a model with too many parameters becomes sensitive, meaning that it can fit the observed data very well, but can be too closely tailored to it. The estimates of such a model become unstable. Therefore, it generalizes poorly for the other random samples from the population. Conversely, a model with too few parameters becomes rigid, indicating that it causes high bias and poor prediction, although the estimates of such models become stable. Penalized-likelihood information criteria are used widely for model selection. Across those, we use the Akaike information criterion (AIC) and Bayesian information

[14]The minimax model has no parameter to be estimated. Under the minimax model, $P_i^C(t) = 3/8$, $P_i^L(t) = 2/8$, and $P_i^F(t) = P_i^I(t) = P_i^O(t) = 1/8$, for all i and t.

criterion (BIC). AIC is given as $-2LL^* + 2k$ and BIC is given as $-2LL^* + k\log(M)$, where LL^* is the maximized log-likelihood, k is the number of parameters, and M is the number of observations. The model with the smallest information criterion is preferred.

4.1 Three Learning Models

The central feature of all three learning models (RL, BL, and EWA) is a set of variables known as "attraction," which are updated each round. Let $A_i^j(t)$ be player i's attraction to strategy j in round t. The attractions in round t determine the choice probabilities in round $t+1$. We use the following logistic function,

$$P_i^j(t+1) = \frac{\exp(\lambda A_i^j(t))}{\sum_{m\in\{C,L,F,I,O\}} \exp(\lambda A_i^m(t))},$$

where λ represents the sensitivity of players to differences among attractions.[15][16] It is a free parameter to be estimated. When $\lambda = 0$, a player chooses all strategies with equal probability. As λ gets larger, a player chooses a strategy with the highest attraction with greater probability. Three learning models differ in the way in which attractions are updated each round, which we describe next.

4.1.1 Reinforcement Learning Model

The RL model incorporates the basic idea that strategies that have earned greater payoffs in the past are more likely to be played in the future, which is known as the *law of effect* in psychology. Letting $\pi_i(j, s_{-i}(t))$ be player i's payoff in round t when i chooses j and the opponent chooses $s_{-i}(t)$, the updating rule for each attraction is

$$A_i^j(t) = \phi A_i^j(t-1) + I(j, s_i(t))\pi_i(j, s_{-i}(t)).$$

[15] Arthur (1991; 1993), Roth and Erev (1995), and Erev and Roth (1998) used the probabilistic choice rule given by $P_i^j(t+1) = A_i^j(t)/\sum_m A_i^m(t)$. Cheung and Friedman (1997) used the probit function. Which of these forms fits better has not been established (Dhami, 2016).

[16] Cheung and Friedman (1997) included the term of the player's own idiosyncratic tendency to favor a strategy when attractions of two strategies have the same value.

Because of indicator function, attraction to a strategy is reinforced only if that strategy was actually chosen in that round. Parameter ϕ represents the depreciation rate of the previous attractions, taking account of forgetting, limited memory, or a rapidly changing environment. When $\phi = 0$, a player remembers only the most recent payoff. When $\phi = 1$, a player remembers all past payoffs and weights them equally in the current decision. For the RL model, we have two parameters (λ and ϕ) to be estimated.[17][18]

4.1.2 Belief-Based Learning Model

In the BL model, players form their beliefs about what the opponent will do. Beliefs are calculated from the opponent's play in the past. Given these beliefs, players then choose actions that have higher expected payoffs. Although there are many ways of forming beliefs, we consider a general weighted fictitious play model (Cheung and Friedman, 1997). The updating rules for each attraction are

$$\begin{aligned} A_i^j(t) &= \frac{\phi N(t-1) A_i^j(t-1) + \pi_i(j, s_{-i}(t))}{N(t)}, \text{ and} \\ N(t) &= \phi N(t-1) + 1. \end{aligned}$$

Parameter $N(t)$ represents an "experience" variable. To see how $N(t)$ works, set $N(0) = 0$ for simplicity. When $\phi = 0$, then $N(t) = 1$, and $A_i^j(t) = \pi_i(j, s_{-i}(t))$. This arrangement indicates that, each round, each attraction is the payoff that was, or would have been, received in the previous round, given the opponent choice $s_{-i}(t)$. In this case, the BL model assumes that a player (tends to) choose the strategy that is the best response to the opponent choice in the previous round. This model is sometimes called a Cournot learning model. When $\phi = 1$, then

[17] In addition to the forgetting parameter ϕ, Roth and Erev (1995) introduced two additional parameters into the basic RL model. One is a cutoff parameter. Whenever, in the basic model, the probability with which a strategy is played falls below some small "cutoff" probability, that strategy will never be played. Another is an experimentation parameter, which captures the idea that not only are choices which were successful in the past more likely to be played in the future, but *similar* choices will be played more often as well.

[18] Mookherjee and Sopher (1997) considered another kind of RL model so that attractions are average payoffs in the past, rather than cumulative ones.

$N(t) = t$, which is simply the number of plays. Furthermore, we obtain

$$A_i^j(t) = \frac{\pi_i(j, s_{-i}(1)) + \pi_i(j, s_{-i}(2)) + \cdots + \pi_i(j, s_{-i}(t))}{t},$$

which is the average payoff that was, or would have been received by that strategy up to the current round, given the opponent choices ($s_{-i}(1)$, $s_{-i}(2)$, ..., $s_{-i}(t)$). In this case, the BL model assumes that a player (tends to) choose the strategy that is best response to the accumulated mixed strategy of the opponent up to then, indicating fictitious play (Brown, 1951; Robinson, 1951). $N(0)$ is interrupted as a pregame experience, and is a parameter to be estimated. For the BL model, we have three parameters (λ, ϕ, and $N(0)$) to be estimated.

4.1.3 Experience-Weighted Attraction Learning Model

The EWA model combines the RL and BL models. Attractions are updated according to either the payoff the strategy actually earned, or some fraction of the payoff an unchosen strategy would have earned. The updating rules for respective attractions are

$$\begin{aligned} A_i^j(t) &= \frac{\phi N(t-1) A_i^j(t-1) + [\delta + (1-\delta) I(j, s_i(t))] \pi_i(j, s_{-i}(t))}{N(t)}, \text{ and} \\ N(t) &= \phi(1-\kappa) N(t-1) + 1. \end{aligned}$$

The parameter δ represents the relative weight given to the foregone payoff. One might interpret it as a form of regret over foregone payoffs. When $\delta = 0$, only the actual payoffs matter, which is the key feature of the RL model. When $\delta = 1$, both the actual and foregone payoffs equally matter, which the BL model requires. The EWA model takes the middle ground. The parameter κ determines the growth rate of attractions. When $\kappa = 1$, then $N(t) = 1$. Consequently, attractions accumulate past actual and hypothetical payoffs, indicating that they can grow and grow as time passes. When $\kappa = 0$, then attractions are the weighted averages of those payoffs, indicating that they cannot grow beyond the payoff bounds.

When $\delta = 0$, $N(0) = 1$, and $\kappa = 1$, then the updating rules are reduced to those of the RL model. When $\delta = 1$, and $\kappa = 0$, then the updating rules are reduced to those of the BL model. For the EWA model, we have five parameters (λ, ϕ, κ, $N(0)$, and δ) to be estimated.

For estimation in the RL, BL, and EWA models, we imposed restrictions on the parameters that

$$\lambda \in [0, \infty), \ \phi, \kappa, \delta \in [0, 1], \text{ and } N(0) \in \left[0, \frac{1}{1-(1-\kappa)\phi}\right],$$

to ensure model identification.[19] Furthermore, we estimated initial attractions (common to all players) from the actual data in the first round, as suggested by Ho et al. (2008).[20]

4.2 Quantal Response Equilibrium

QRE is a parameterized family of a static equilibrium model in which each player's utility is subject to random error. Formally, let $q = (q_C, q_L, q_F, q_I, q_O)$ and $r = (r_C, r_L, r_F, r_I, r_O)$ be mixed strategies for players X and Y, respectively. Let $\pi_X(j, r)$ be the player X's expected payoff of choosing the pure strategy

[19]For each of model parameters to fall within the restricted range, we apply an appropriate transformation. For example, we estimate q_1 without restriction such that $\lambda = \exp(q_1)$, which ensures that $\lambda \in [0, \infty)$. Similarly, we estimate q_2, q_3, q_4, and q_5 without restriction such that $\phi = 1/[1+\exp(q_2)]$, $\kappa = 1/[1+\exp(q_3)]$, $\delta = 1/[1+\exp(q_4)]$, and $N(0) = [1/(1-(1-\kappa)\phi)]/[1+\exp(q_5)]$ to restrict each parameter to fall within the restricted range.

[20]For estimation of the initial attractions in the RL and EWA models, we adopt the following procedure. Let f^j be the relative frequency of strategy j in the first round. Then, we can obtain initial attractions from the equations

$$\frac{\exp(\lambda A_i^j(0))}{\sum_{m\in\{C,L,F,I,O\}} \exp(\lambda A_i^m(0))} = f^j, \ j \in \{C, L, F, I, O\}.$$

The initial attractions are solvable, as a function of λ, as

$$A_i^j(0) - \frac{1}{5}\sum_j A_i^j(0) = \frac{1}{\lambda}\log(\tilde{f^j}),$$

where $\tilde{f^j} = f^j/(\prod_m f^m)^{1/5}$. For identification, we set the initial attraction with the lowest relative frequency to be zero, and solve for the other attractions as a function of λ and $\tilde{f^j}$.

The estimation of initial attractions for the BL model differs from the RL and EWA models. In the BL model, initial attractions are the same as the expected payoff given initial beliefs. Therefore, we estimated the initial beliefs that maximize the likelihood given the relative frequency in the first round, with λ being one for identification. Then, we can calculate the expected payoffs from these initial beliefs rescaled with $1/\lambda$. Then they are used as initial attractions.

$j \in \{C, L, F, I, O\}$ when player Y chooses r. We define the function $\hat{\pi}_X(j, r)$ as

$$\hat{\pi}_X(j, r) = \pi_X(j, r) + \epsilon_{Xj},$$

where ϵ_{Xj} is a random payoff disturbance for strategy j of player X. QRE assumes that each player chooses a strategy j such that $\hat{\pi}_X(j, r) \geq \hat{\pi}_X(m, r)$ for all $m \in \{C, L, F, I, O\}$. If $\{\epsilon_{Xj}\}$ are distributed independently with an extreme value distribution with variance parameter $1/\lambda$, then the choice probabilities of player X are given as

$$q_j = \frac{\exp(\lambda \pi_X(j, r))}{\sum_{m \in \{C,L,F,I,O\}} \exp(\lambda \pi_X(m, r))}.$$

Similarly, let $\pi_Y(j, q)$ be the player Y's expected payoff of choosing j when player X chooses q. Then, similar calculations yield the choice probabilities of player Y, as follows:

$$r_j = \frac{\exp(\lambda \pi_Y(j, q))}{\sum_{m \in \{C,L,F,I,O\}} \exp(\lambda \pi_Y(m, q))}.$$

For any fixed value of λ, a logistic QRE is a mixed strategy pair $(q^*(\lambda), r^*(\lambda))$ satisfying

$$q_j^*(\lambda) = \frac{\exp(\lambda \pi_X(j, r^*(\lambda)))}{\sum_{m \in \{C,L,F,I,O\}} \exp(\lambda \pi_X(m, r^*(\lambda)))}, \text{ and } r_j^*(\lambda) = \frac{\exp(\lambda \pi_Y(j, q^*(\lambda)))}{\sum_{m \in \{C,L,F,I,O\}} \exp(\lambda \pi_Y(m, q^*(\lambda)))}.$$

When $\lambda = 0$, each player chooses all strategies with equal probability. As λ goes to infinity, the variance of the shocks goes to zero, with behavior approaching a Nash equilibrium. For QRE, λ is the only parameter to be estimated. Note that λ is common across players X and Y. Therefore, in our estimation, we first estimated λ^* in the pair. Then, we obtained each player's log-likelihood by setting $P_i^j(t) = q_j^*(\lambda^*)$ for all t for player X, and $P_i^j(t) = r_j^*(\lambda^*)$ for all t for player Y.

Table 6: Model Fits at the Aggregate Level (Rounds 1-120)

		Team			Individual		
Player	Model	LL^*	AIC	BIC	LL^*	AIC	BIC
X	EWA	−5000.0	**10010.1**	10040.7	−3614.5	7239.0	7268.0
	RL	−5151.0	10306.0	10318.3	−3683.0	7370.0	7381.5
	BL	−5016.0	10038.0	10056.4	−3779.6	7565.2	7582.6
	QRE	−5017.5	10037.0	10043.2	−3586.0	7174.0	7179.7
	MM	−5017.5	10035.0	**10035.0**	−3586.0	**7172.0**	**7172.0**
Y	EWA	−5074.4	10158.8	10189.4	−3545.1	7100.3	7129.2
	RL	−5197.6	10399.3	10411.5	−3586.2	7176.4	7188.0
	BL	−5073.5	10153.0	10171.3	−3765.5	7537.0	7554.4
	QRE	−5017.5	10037.1	10043.2	−3532.4	7066.8	7072.6
	MM	−5017.5	**10035.1**	**10035.1**	−3532.4	**7064.8**	**7064.8**

Notes: LL^* is maximized log-likelihood. AIC is given as $-2LL^* + 2k$, and BIC is given as $-2LL^* + k\log(M)$, where k is the number of parameters, and M is the number of observations. Best fits are shown in bold typeface.

4.3 Results

4.3.1 Overall Round Data

Table 6 presents maximized log-likelihoods and information criteria at the aggregate level for each player role in each treatment. Numbers with the minimum information criterion are presented in bold typeface. Because we pool the data across subjects with the same player role in the same treatment, this analysis assumes that all these subjects follow the model with the same parameters (i.e., homogeneous single-representative agent model).

Model selection reveals that the minimax model (MM) actually performs well. The minimax model is best for player Y in the team treatment and both players in the individual treatment, according to both AIC and BIC. For player X in the team treatment, the EWA model is best according to AIC, whereas the minimax model is best according to BIC.

We next proceed to the analysis at the decision-maker level, allowing heterogeneity in learning across subjects.[21] Table 7 shows the percentages of the

[21] Several papers have found considerable heterogeneity in parameters of the learning models across subjects (Cheung and Friedman, 1997; Ho et al., 2008; Dittrich et al., 2012), indicating that subjects follow different learning dynamics.

Table 7: Percentage of the Best Fit Model at the Decision-Maker Level (Rounds 1-120)

		Model				
Criterion	Treatment	EWA	RL	BL	QRE	MM
AIC	Team	8.9%	10.7%	26.8%	1.8%	51.8%
	Individual	35.0%	7.5%	2.5%	5.0%	50.0%
BIC	Team	1.8%	10.7%	10.7%	0.0%	76.8%
	Individual	5.0%	7.5%	7.5%	0.0%	80.0%

best fit models. According to BIC, which prefers simpler models than AIC, the behavior of 76.8 percent of teams and 80.0 percent of individuals is best fitted by the minimax model.[22] For the remaining subjects, the adaptive learning models (EWA, RL, and BL) are selected for both teams and individuals. QRE is never selected. Because our primary concern is how well the minimax model fits to the experimental data, and to argue conservatively, in what follows, we focus only on the results according to AIC.

Even according to AIC, the minimax model performs well for predicting the decision-maker level behavior, irrespective of the type of decision-maker. The minimax model is best for about half of subjects in both treatments (51.8% in the team treatment, and 50.0% in the individual treatment). Combined with the results of hypothesis testing in section 3.1, we have deeper insight into the performance of the minimax model. Recall that, by examining the overall round data, a substantial deviation exists in the choice frequencies of the minimax prediction both in the team and individual treatments at both the aggregate and decision-maker levels. This indicates that the minimax hypothesis is not correct. However, model selection reveals that the minimax model still fits the experimental data well over the alternative models considered here.

The learning models (EWA, RL, and BL) are mostly selected for the remaining subjects, but the composition is fairly different between teams and individuals. The share of the EWA model is the lowest across three learning models in the

[22]Because $e^2 \approx 7.4$, BIC penalizes complex models more strongly than AIC does, given data with a sample size of no less than 8.

team treatment, whereas most subjects are classified into the EWA model in the individual treatment. The shares of the three learning models are significantly different (chi-square test, $p = 0.000$). This result leads us to expect that the weights on the foregone payoffs in the EWA model might differ between teams and individuals. Teams tend to assign weight on foregone payoffs near one or zero, whereas individuals tend to put it in the middle way on [0,1], as confirmed in Section 4.5.

4.3.2 Half Data

Here, we split the data into the first and second half, and apply model selection separately for each half.[23] Table 8 presents the respective results of model selection at the aggregate level in the first and second half. The best fit model is changed over time in the team treatment. The BL model is best in the first half, whereas the minimax model is best in the second half for both players according to both AIC and BIC. In the individual treatment, the minimax model is best for both players in both halves with the exception that QRE is selected for player X in the first half according to AIC. Recall that, in section 3.2, the relative frequencies of choices for players X and Y are close to those by the minimax model in the first half of the team treatment. Model selection reveals that this is a result in which teams have exhibited behavior that is best fitted by the BL model, not the minimax model. In the second half of the team treatment, and in both halves of the individual treatment, the minimax model is best, although the relative frequencies of choices are far from those by minimax play.

We examine more deeply the performance of the BL model in the first half of the team treatment. Since the Cournot learning model ($\phi = 0$) and fictitious play ($\phi = 1$) are nested within the BL model, we can compare the performance of the BL model against those models, using the likelihood ratio test. Test statistic LR is given as $2(LL^*_u - LL^*_r)$, where LL^*_u and LL^*_r represent the maximized

[23]Some studies have divided the data into some successive time blocks, and have examined the model fits to evaluate the effect of the subject's experience on the performance of the model (McKelvey and Palfrey, 1995; Erev and Roth, 1998).

Table 8: Model Fits at the Aggregate Level for Each Half

			Team			Individual		
Rounds	Player	Model	LL^*	AIC	BIC	LL^*	AIC	BIC
1-60	X	EWA	−2441.8	4893.5	4920.7	−1800.8	3611.5	3637.0
		RL	−2499.7	5003.3	5014.2	−1834.3	3672.6	3682.8
		BL	−2443.5	**4892.9**	**4909.2**	−1877.2	3760.5	3775.7
		QRE	−2476.2	4954.4	4959.9	−1786.3	**3574.7**	3579.8
		MM	−2476.2	4952.4	4952.4	−1787.8	3575.7	**3575.7**
	Y	EWA	−2510.6	5031.2	5058.4	−1749.4	3508.8	3534.3
		RL	−2546.8	5097.7	5108.5	−1781.8	3567.6	3577.7
		BL	−2496.1	**4998.1**	**5014.4**	−1862.2	3730.5	3745.8
		QRE	−2507.9	5017.7	5023.1	−1743.6	3489.2	3494.3
		MM	−2507.9	5015.7	5015.7	−1743.1	**3486.1**	**3486.1**
61-120	X	EWA	−2566.4	5142.8	5170.0	−1821.5	3652.9	3678.4
		RL	−2578.1	5160.1	5171.0	−1844.8	3693.6	3703.8
		BL	−2572.2	5150.4	5166.7	−1838.9	3683.8	3699.0
		QRE	−2541.3	5084.6	5090.0	−1798.1	3598.3	3603.4
		MM	−2541.3	**5082.6**	**5082.6**	−1798.1	**3596.3**	**3596.3**
	Y	EWA	−2518.2	5046.4	5073.5	−1794.1	3598.2	3623.7
		RL	−2528.3	5060.6	5071.4	−1825.8	3655.7	3665.9
		BL	−2535.7	5077.4	5093.7	−1792.8	3591.6	3606.8
		QRE	−2509.7	5021.4	5026.8	−1789.3	3580.7	3585.8
		MM	−2509.7	**5019.4**	**5019.4**	−1789.3	**3578.7**	**3578.7**

Notes: For explanations, see notes to Table 6.

log-likelihoods from the unrestricted (BL model) and restricted models (either Cournot model or fictitious play), respectively. Under the null hypothesis (that the restricted model is true), LR has a $\chi^2(1)$ distribution.

Table 9 shows parameter estimates in the first half of the team treatment, and results of the likelihood ratio test. The estimated ϕ is equal to or nearly one for each player. Actually, the likelihood ratio test does not reject the null hypothesis that fictitious play is the true model for player X. However, in spite of ϕ being near one (0.973), the null hypothesis is rejected for player Y, in favor of the BL model. The Cournot model is clearly rejected for both players.

Table 10 provides the percentages of the best fit model at the decision-maker level in the first and second half, respectively. As in overall round data, according to BIC, the minimax model is best for about 80 percent of teams and individuals. Therefore, to evaluate the predictive power of the minimax model

Table 9: Parameter Estimates of BL models, and Likelihood Ratio Tests in the First Half of the Team Treatment

Player	Model	ϕ	λ	$N(0)$	LL^*	LR	p-value
X	BL	1.000	0.011	18.704	-2443.5		
	Cournot Model	*0.000*	0.000	0.214	-2686.7	486.461	0.000
	Fictitious Play	*1.000*	0.011	18.704	-2443.5	0.000	1.000
Y	BL	0.973	0.016	30.951	-2496.1		
	Cournot Model	*0.000*	0.001	0.191	-2683.4	374.633	0.000
	Fictitious Play	*1.000*	0.014	20.726	-2499.9	7.751	0.005

Notes: LL^* is maximized log-likelihood. LR is given as $2(LL^*_u - LL^*_r)$, where LL^*_u and LL^*_r represent the maximized log-likelihoods from the unrestricted (BL model) and restricted models (either Cournot model or fictitious play), respectively. Numbers in italic face are fixed.

Table 10: Percentage of the Best Fit Model at the Decision-Maker Level for Each Half

			Model				
Criterion	Rounds	Treatment	EWA	RL	BL	QRE	MM
AIC	1-60	Team	5.4%	17.9%	25.0%	1.8%	50.0%
		Individual	20.0%	7.5%	7.5%	5.0%	60.0%
	61-120	Team	3.6%	17.9%	7.1%	5.4%	66.1%
		Individual	0.0%	20.0%	20.0%	0.0%	60.0%
BIC	1-60	Team	0.0%	10.7%	10.7%	0.0%	78.6%
		Individual	5.0%	5.0%	7.5%	0.0%	82.5%
	61-120	Team	0.0%	12.5%	1.8%	3.6%	82.1%
		Individual	0.0%	10.0%	7.5%	5.0%	77.5%

conservatively, we again present only the results according to AIC.

Even according to AIC, the minimax model again performs well for both halves of both treatments. It is best for more than or exactly half of subjects. Across those, the share in the first half of the team treatment is the lowest (50.0 percent). Then, it increases in the second half, from 50.0 to 66.1 percent. This increase is not significant at the 5 percent level (chi-square test, $p = 0.085$). In the individual treatment, the minimax model is selected for 60.0 percent of subjects in both halves.

The remaining subjects are mostly classified into three learning models. The share of learning models in the first half is similar to that of overall round data. In the team treatment, the share of the EWA model is the lowest of the three learning models, and that of the BL model is the highest. In the individual treatment, many subjects are classified into the EWA model. The shares of three learning models are significantly different between treatments (chi-square test, $p = 0.007$). At the decision-maker level, we cannot clearly observe that BL performs well in the team treatment, although we have weaker evidence that the share of MM is relatively lower, and that of BL is relatively higher.

The mode of change in the share of three learning models between halves for teams differs greatly from individuals. In the team treatment, only the share of the BL model decreases considerably, which is significant (chi-square test, $p = 0.010$), although the share of three learning models is not significantly different between halves (chi-square test, $p = 0.207$). In the individual treatment, all subjects are classified into either the RL or BL model in the second half. The EWA model is never selected. The share of the three learning models are significantly different between halves (chi-square test, $p = 0.002$).

Finally, we address how each subject changes the behavior over time. The best fit model is changed between halves for 53.6 percent of teams and 67.5 percent of individuals. Therefore, changing behavior over time is commonly observed. Tables 11 and 12 present the empirical transition probability with which subjects for whom the best fit model changes from the model in the

Table 11: Empirical Transition Probability in Team Treatment

		Second Half				
		EWA	RL	BL	QRE	MM
		0.036	0.179	0.071	0.054	0.661
		(2/56)	(10/56)	(4/56)	(3/56)	(37/56)
First	EWA	0.000	0.667	0.000	0.000	0.333
Half	0.054 (3/56)	(0/3)	(2/3)	(0/3)	(0/3)	(1/3)
	RL	0.000	0.200	0.100	0.100	0.600
	0.179 (10/56)	(0/10)	(2/10)	(1/10)	(1/10)	(6/10)
	BL	0.071	0.214	0.143	0.071	0.500
	0.250 (14/56)	(1/14)	(3/14)	(2/14)	(1/14)	(7/14)
	QRE	0.000	0.000	0.000	0.000	1.000
	0.018 (1/56)	(0/1)	(0/1)	(0/1)	(0/1)	(1/1)
	MM	0.036	0.107	0.036	0.036	0.786
	0.500 (28/56)	(1/28)	(3/28)	(1/28)	(1/28)	(22/28)

Notes: Each cell shows the percentage of subjects with the best model change from the model in the corresponding row in the first half to that in the corresponding column in the second half among the total subjects for whom the best model is that in the corresponding row. Percentages below the model name represent percentages with which the model is selected as the best model in each half.

Table 12: Empirical Transition Probability in Individual Treatment

		Second Half				
		EWA	RL	BL	QRE	MM
		0.000	0.200	0.200	0.000	0.600
		(0/40)	(8/40)	(8/40)	(0/40)	(24/40)
First	EWA	0.000	0.250	0.125	0.000	0.625
Half	0.200 (8/40)	(0/8)	(2/8)	(1/8)	(0/8)	(5/8)
	RL	0.000	0.000	0.000	0.000	1.000
	0.075 (3/40)	(0/3)	(0/3)	(0/3)	(0/3)	(3/3)
	BL	0.000	0.000	0.333	0.000	0.667
	0.075 (3/40)	(0/3)	(0/3)	(1/3)	(0/3)	(2/3)
	QRE	0.000	0.000	0.000	0.000	1.000
	0.050 (2/40)	(0/2)	(0/2)	(0/2)	(0/2)	(2/2)
	MM	0.000	0.250	0.250	0.000	0.500
	0.600 (24/40)	(0/24)	(6/24)	(6/24)	(0/24)	(12/24)

Notes: For explanations, see notes to Table 11.

corresponding row to the one in the corresponding column out of total subjects for whom the best fit model is the one in the corresponding row (the percentages of the same row sum to one). The percentages below the model name represent the one with which the model is selected as the best fit model, as presented in Table 10.

In the team treatment, except the EWA model, more than or equal to half of teams change the best fit model from the corresponding one to the minimax model. Of 28 teams with a best fit model that is non-minimax in the first half, 15 teams (53.6 percent) changed the best fit model to the minimax. This phenomenon is also found in the individual treatment. Of 16, it is 12 individuals (75.0 percent). These percentages were not significantly different between treatments (chi-square test, $p = 0.160$). The important difference is that 78.6 percent of teams for which the best model is the minimax model in the first half keep the behavior invariant in the second half, although it is 50.0 percent in the individual treatment, which is significantly different (chi-square test, $p = 0.031$). This result shows that once teams behave in the way that the minimax fits well, they are more likely to continue to play in the same way even if time progresses, than individuals do.

4.4 Performance of Competing Models

Some readers might wonder at our results that the minimax performs well in most cases because competing models (EWA, RL, BL, and QRE) are known to be a good predictor for the experimental data. Here, it is worth filling a gap separating the results of earlier research and our own.

First, related to three learning models, we will clarify, by reviewing previous research closely, that our results are not so different from previously reported results. Camerer and Ho (1999) found that EWA generally performs well, examining various experimental data gathered by other researchers. Moreover, they found that the BL model, as well as EWA, fits well to the data in Mookherjee and Sopher's (1997) two-player zero-sum games.[24] They considered the RL, BL, and random choice models as rivals of EWA, but not Nash equilibrium. Therefore, they did not evaluate the relative performances of EWA and MM. When we particularly focus on the three learning models (EWA, RE, and BL) in our analysis, Tables 6 and 8 reveal that EWA and BL show better performance. Therefore, our results are consistent with theirs.

Erev and Roth (1998) examined the performance of their RL models using 12 experimental datasets of games with unique mixed strategy equilibria gathered by them and other researchers. Their results show that RL models generally outperform Nash equilibrium. However, a closer examination of their results reveals that when we particularly focus on complex games such as O'Neill's (1987) 4×4 game and Rapoport and Boebel's (1992) 5×5 game, Nash equilibrium often outperforms their RL models.[25]

Feltovich (2000) examined the performance of the RL and BL models using data from asymmetric-information game experiment and the data from other experiments, and found that the RL model generally outperforms the BL model, and that both the RL and BL models perform better than Nash equilibrium. However, he also found through re-examination of the data in Mookherjee and Sopher's (1997) 6×6 two-player zero-sum game, that Nash equilibrium outperforms the RL and BL models with some criteria.[26] In summary, considering the evidence for two-player zero-sum games with many strategies (such as 4×4, 5×5, and 6×6), performance of Nash equilibrium (minimax) exceeding that of adaptive learning models is commonly observed.

Related to QRE, it is noteworthy that maximized log-likelihoods for QRE in Table 6 are equal to those for MM. Actually, the estimates of λ for QRE are very large values in our estimation. Because QRE has a parameter to be estimated and because MM does not, both AIC and BIC for QRE become larger than those for MM, leading the result that QRE is not selected as the best fit model.

[24] Table I in Camerer and Ho (1999) presents this result.

[25] See Tables 1 and 2 in Erev and Roth (1998). In simpler 2×2 games, RL models generally perform well.

[26] Tables VII and VIII in Feltovich (2000) illustrate that point.

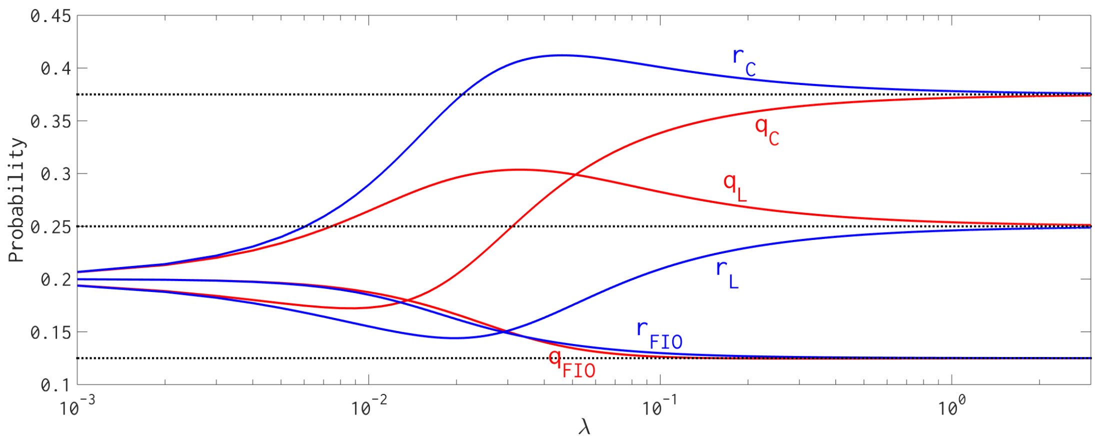

Figure 2: Quantal Response Equilibrium as a Function of λ.

Figure 2 portrays a QRE graph as a function of λ. The q_j and r_j ($j \in \{C, L, FIO\}$) represent probabilities with which players X and Y choose strategy j in QRE, respectively.[27] Figure shows that $q_C < r_C$, and $q_L > r_L$ for any $\lambda > 0$. In other words, QRE predicts that (for any intermediate error level) player X always chooses C less often than player Y, and that player X always chooses L more often than player Y. However, Tables 2 and 3 show that our data violate it in both treatments, indicating that QRE predicts in the wrong direction the way in which subjects deviate from the equilibrium. Then, the λ that maximize the likelihood must be arbitrarily large because the difference between q_C and r_C, and that between q_L and r_L are zero under the equilibrium, which is the closest to the observed data.[28] The same problem occurred in both halves of the team treatment and in the second half of the individual treatment. In the first half of the individual treatment, the experimental data satisfy $q_C < r_C$ and $q_L > r_L$, and QRE is selected for player X according to AIC. At the decision-maker level, we encountered the same problem for about 70 percent of pairs in both treatments.

Finally, for a robustness check to examine the extent to which our results can be generalized, we apply model selection to the data reported by Palacios-

[27]Because F, I, and O are strategically equivalent, QRE predicts that the probabilities with which each player chooses those strategies are the same.

[28]In the individual treatment, player X chooses C more often than player Y, as QRE predicts, although it fails to predict correctly the way of deviation for L. In this case, it is case-by-case whether we can obtain reasonable estimate of λ. Then, we were unable to do so for our case.

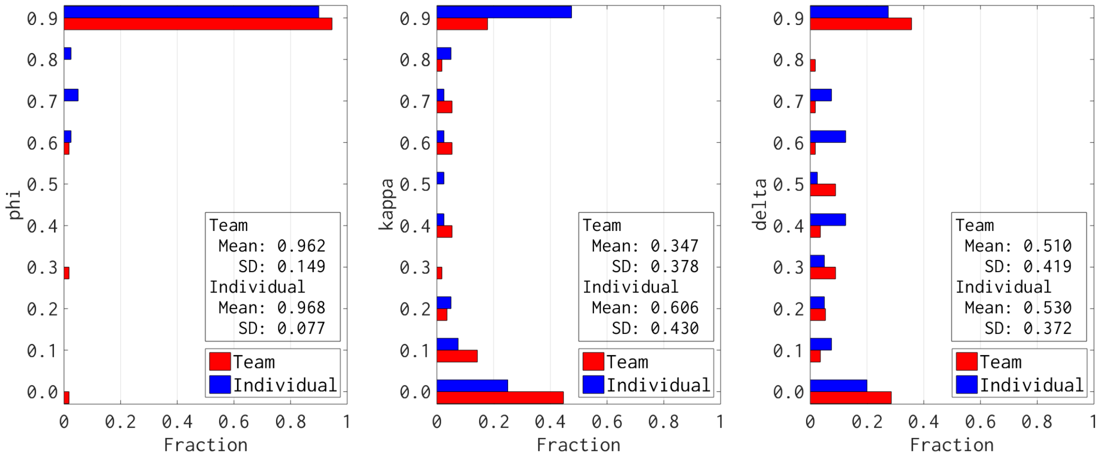

Figure 3: Distributions of EWA Parameters (Rounds 1–120).

Huerta and Volij (2008), which are presented in Supplementary Appendix B. We used their data in which professional soccer players and their college students played O'Neill's (1987) 4×4 game. Again, we find that the minimax model mostly performs well for predicting their behavior at both the aggregate and decision-maker level with some exceptions.[29] Furthermore, the estimate of λ for QRE often becomes arbitrarily large for the reason presented above.

4.5 Comparison of EWA Parameters

Although our primary objective is investigation of the best fit models across five models, it is worth comparing EWA parameter estimates between teams and individuals, and clarifying how they use available information, under the assumption that all teams and individuals follow the EWA model. Figure 3 depicts the distributions of key parameters (ϕ, κ, and δ) in the EWA model at the decision-maker level using overall round data.

Figure 3 reveals that ϕ concentrated on the value near one in both treatments. The values are not significantly different between treatments (Wilcoxon rank-sum test, $p = 0.144$). This result indicates that both teams and individuals tend to treat the entire history as equally important. This may caused by our

[29]The aggregated behavior of professionals in the second half is mostly best fitted by QRE.

experimental design in which the screen display includes all history information up to the current round, which avoids subjects from forgetting the past events.

The mean value of κ is smaller for teams than for individuals. Figure 3 shows that distributions of κ have bimodal peaks for both treatments, but it tends to concentrate near zero for teams, and near one for individuals. The values are significantly different between treatments (Wilcoxon rank-sum test, $p = 0.006$) This result indicates that teams tend to respond to the (weighted) average payoffs, whereas individuals tend to respond to the cumulative payoffs.

The values of δ are similar between teams and individuals. The values are not significantly different (Wilcoxon rank-sum test, $p = 0.574$). Figure 3 shows that the distributions of δ also have bimodal peaks concentrating near either zero or one for both treatments, but their tendency is stronger for teams than for individuals. The fraction of teams with δ being either more than 0.9 or fewer than 0.1 are 64.3 percent, whereas it is 47.5 percent for individuals. The squared ranks test rejects the null hypothesis that two distributions have equal variance ($p = 0.009$). This result indicates that teams either tend to extremely take the hypothetical payoffs into account, or tend not to care about those at all.[30] This result is consistent with the finding of model selection that (when we particularly examine three learning models) teams tend to be classified into either the RL or BL model, whereas individuals tend to be classified into the EWA model, as presented in Table 7.

Figures 4 and 5 depict the distributions of estimated parameters in the first and second halves, respectively. As in overall round data, ϕ concentrated on the values near one in both halves of both treatments, indicating that both teams and

[30]This result might be explained by group polarization, which is a well-known phenomenon in social psychology (see, for example, Brown, 1986) by which group discussion leads the group decision to more extreme points in the same direction as the initial tendencies of a member's individual preference. A main source for group polarization is the persuasive argument theory by which, during discussion, a member is exposed to persuasive arguments that were not available before the discussion. A person then changes his position in favor of that direction (Burnstein, and Vinokur, 1973; Burnstein, Vinokur, and Trope, 1973). If subjects in a group find it persuasive that they should care only about the realized payoff, then that team is more likely to behave according to the RL model (δ tends to be near zero). If subjects in a group find it persuasive that they should care about the foregone payoff as well as the realized payoff, then that team is more likely to be a BL learner (δ tends to be near one).

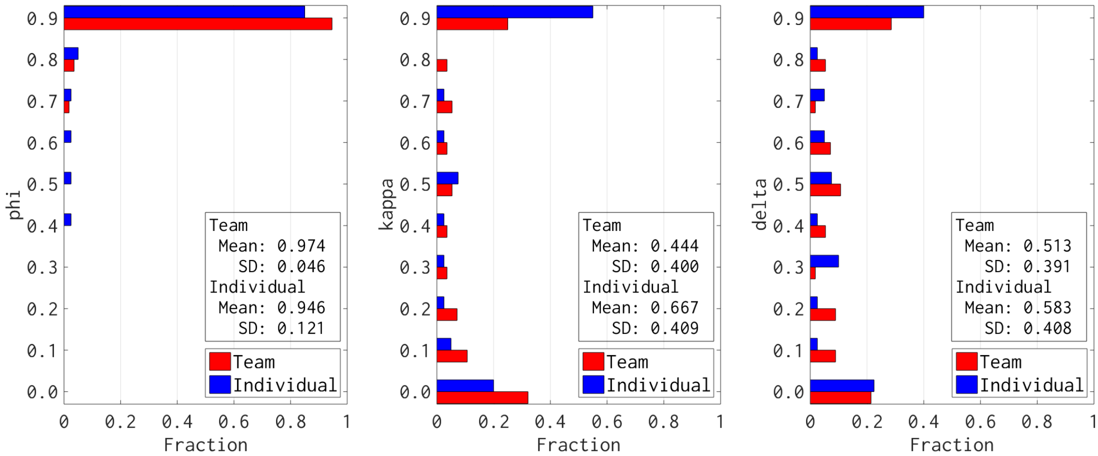

Figure 4: Distributions of EWA Parameters (Rounds 1–60).

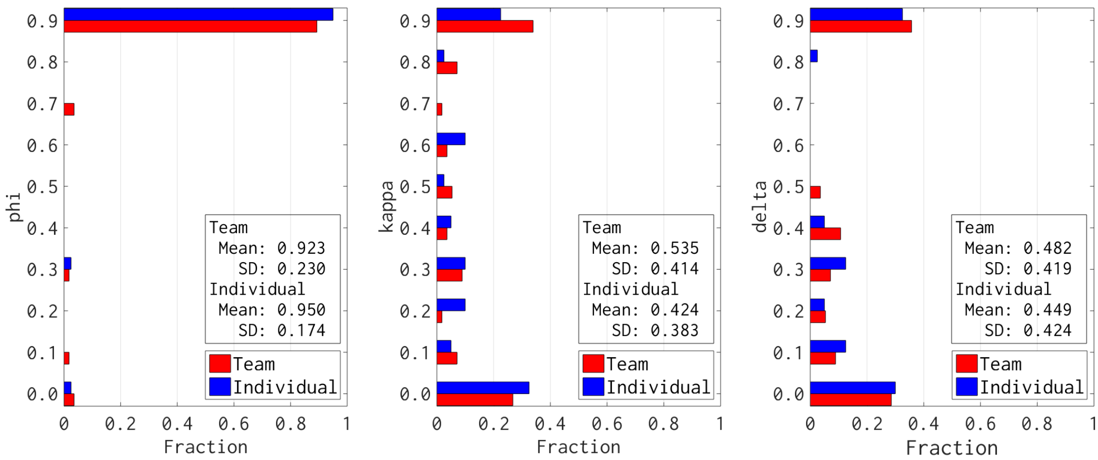

Figure 5: Distributions of EWA Parameters (Rounds 61–120).

individuals only slightly discount past events. The values are not significantly different between treatments in both halves (Wilcoxon rank-sum test, $p = 0.991$ in the first half, and $p = 0.297$ in the second half).

In the first half, the distributions of κ have similar characteristics to the overall round data for both treatments. They have bimodal peaks, but tend to concentrate near zero for teams, and to concentrate near one for individuals. The values are significantly different between treatments (Wilcoxon rank-sum test, $p = 0.007$). However, this tendency is not apparent in the second half. The values are not significantly different between treatments ($p = 0.166$). This result indicates that tendency of teams to respond to the average payoffs and that of individuals to respond to the cumulative payoffs only hold in the early rounds of the experiment.

The distributions of δ again have bimodal peaks in both halves of both treatments. However, as opposed to overall round data, we cannot observe polarization by teams that δ concentrates on either zero or one. The variance of distributions are not significantly different between treatments in both halves (squared ranks test, $p = 0.588$ in the first half, and $p = 0.788$ in the second half). Furthermore, we cannot clarify by this analysis why the aggregated data of teams in the first half is best fitted by the BL model. In the first half, the mean value of δ is smaller for teams, and not significantly different from that of individuals (Wilcoxon rank-sum test, $p = 0.341$). In addition, the fraction of teams with δ being higher than 0.9 is lower than that of individuals with the same category.

5 Discussion and Conclusion

To evaluate the performance of the minimax model over time, we conducted an experiment in which teams and individuals play a two-player zero-sum game with a unique mixed strategy equilibrium. Based on the relative frequencies of choices, teams play near the minimax prediction in the first half of the experiment. However, adherence to minimax play does not last in the second half. We must conclude that the minimax model is successful in predicting the short-run behavior of teams, but not long-run behavior. The play of individuals is far from the minimax prediction throughout the course of the experiment, as previous experiments have found.

Model selection provides further evidence for the performance of the minimax model. The aggregated behavior of teams in the first half is best fitted by a belief-based learning model, not the minimax model. Therefore, although the relative frequencies of teams in the first half are close to the minimax prediction, the minimax model is not the best predictor, given the team's history of play. The minimax model is best in predicting the behavior of teams in the second half and that of individuals in both halves. Therefore, although the relative frequencies of teams in the second half and those of individuals in both halves are far from the minimax prediction, the minimax model is still close to the experimental data over the alternative models.

How can we interpret these observations? The belief-based learning model imposes a greater degree of rationality and ability of information processing. Players must know the underlying game structure and track the entire past history of the opponent's choice (unless they are not Cournot learners). They must calculate the hypothetical payoffs from the opponent's play that each strategy would have earned to form their beliefs. Then they (tend to) choose the action with the highest expected payoff with greater probability. Given that teams are known to be strategically sophisticated and to have higher abilities of processing available information, teams can engage in performing belief learners in the first half of the experiment, but individuals cannot.

Given that the relative frequencies are far from the minimax prediction, good performance of the minimax model in the second half of teams and both halves of individuals should be interrupted by poor performance (mis-prediction) of the competing models, rather than giving rise to the interpretation such that subjects know how to play minimax. Related to teams, tracking the entire past history becomes a greater information load as time progresses. This might lead teams to give up tracking all such information, and to play without ample consideration of past events in the second half. Then, learning models fail to predict team behavior correctly, and the minimax becomes a relatively good performer. Individuals, in the first place, might not have sufficient ability to process the available information, which leads them to choose the actions that are not correlated so much to the past events. Consequently, the minimax model performs relatively better, although the choice frequencies of individuals are not close to the minimax prediction. If these interpretations have a point, the important message is that we should still strive to develop behavioral models of learning and equilibrium that predict the behavior of subjects well in complex two-player zero-sum games such as those in our experiment.

At the decision-maker level, the minimax model is best for most teams and individuals in both halves. This result is consistent with model selection at the aggregate level in the second half of teams and in both halves of individuals. However, this is not consistent with good performance of the BL model in the first half of teams, although we have weaker evidence that the fraction of the minimax model as best is relatively lower, and that of belief-based learning model as best is relatively higher. This inconsistency must be addressed in future research.

Comparison of the parameter estimates of the EWA model clarified how teams learn differently from or similarly to individuals in several respects. The important findings of this analysis are the following: (1) both teams and individuals treat the entire past history as equally important, (2) teams tend to respond to the average past payoffs, while individuals tend to respond to the cumulative past payoffs (using overall round and first half data), (3) teams either tend to extremely take the hypothetical payoffs into account, or tend not to care about those at all (using overall round data), and (4) learning parameters in the second half are mutually similar. We cannot clarify by these analyses why the aggregated data of teams in the first half are best fitted by the BL model. That point must be addressed in future research.

From a methodological perspective, we use the method of model selection, as well as hypothesis testing, to evaluate the performance of the minimax model. As noted before, model selection can address questions of how close the minimax is to the experimental data, whereas hypothesis testing addresses the question of whether the minimax is incorrect or not. These questions are equally important. We have no reason to discuss it based only on either one of the two.

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Supplementary Appendix to "Team vs. Individual, Hypothesis Testing vs. Model Selection, and the Minimax Model"

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Contents

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A Additional Tables

This section provides additional tables. Tables from A1 to A6 show the relative frequencies of choices, number of runs, and the results of statistical tests in the team and individual treatments with different round intervals (overall round, first half, and second half). Symbols ** and * denote the rejection of the chi-square goodness-of-fit test of the frequencies for a given choice to the minimax prediction at the 5% and 10% levels, respectively. The test statistic is distributed asymptotically with $\chi^2(1)$ under the minimax hypothesis. Symbols ♯♯ and ♯ represent the rejection of the chi-square goodness-of-fit test of the frequencies for all choices (C, L, F, I, and O) to the minimax prediction at the 5% and 10% levels, respectively. The test statistic is distributed asymptotically with $\chi^2(4)$ under the minimax hypothesis. Columns "Number of Runs" show the total number of runs in the sequence of the corresponding choice and choices other than that choice (e.g., in the sequence of C and Non-C choices). Let R_j be the number of runs for $j \in \{C, L, F, I, O\}$, and N_j and N_{nj} be the number of j and Non-j choices. Under the null hypothesis of serial independence, the probability that there are exactly R_j runs conditional on N_j and N_{nj} occurrences is given as

$$f(R_j|N_j, N_{nj}) = \begin{cases} 2\binom{N_j-1}{(R_j/2)-1}\binom{N_{nj}-1}{(R_j/2)-1} \Big/ \binom{N_j+N_{nj}}{N_j}, & \text{if } R_j \text{ is even,} \\ \left(\binom{N_j-1}{(R_j-1)/2}\binom{N_{nj}-1}{(R_j-3)/2} + \binom{N_j-1}{(R_j-3)/2}\binom{N_{nj}-1}{(R_j-1)/2}\right) \Big/ \binom{N_j+N_{nj}}{N_j}, & \text{if } R_j \text{ is odd.} \end{cases}$$

The serial independence hypothesis is rejected at the 5% level if $F(R_j|N_j, N_{nj}) < 0.025$ or if $F(R_j - 1|N_j, N_{nj}) > 0.975$, where $F(R_j|N_j, N_{nj}) = \sum_{i=1}^{R_j} f(R_j|N_j, N_{nj})$. Symbols ‡ and † denote the rejection of runs test for a given choice at the 5% and 10% levels, respectively.

Tables from A7 to A12 show the relative frequencies of action profiles, with results of chi-square tests with F, I, and O combined. Symbols ♯♯ and ♯ denote the rejection of the chi-square test of the frequencies for action profiles to the minimax prediction at the 5% and 10% levels, respectively. The test statistic is distributed asymptotically with $\chi^2(8)$ under the minimax hypothesis.

Table A1: Team Treatment (Rounds 1-120)

		Relative Frequencies					χ^2	Number of Runs				
Pair	Player	*C*	*L*	*F*	*I*	*O*	Test	*C*	*L*	*F*	*I*	*O*
1	*X*	0.400	0.275	0.125	0.142	0.058**		64	52	27	33	15
	Y	0.425	0.158**	0.183*	0.133	0.100	♯	70†	37	40	31	25
2	*X*	0.358	0.233	0.150	0.117	0.142		55	45	33	25	31
	Y	0.233**	0.233	0.233**	0.167	0.133	♯♯	42	42	43	37	27
3	*X*	0.317	0.292	0.125	0.100	0.167		52	54	27	21	39
	Y	0.325	0.217	0.183*	0.183*	0.092	♯	54	47	29‡	34	19
4	*X*	0.417	0.208	0.142	0.133	0.100		51	31‡	33	23†	23
	Y	0.367	0.308	0.083	0.142	0.100		46‡	56	17	29	23
5	*X*	0.325	0.333**	0.125	0.133	0.083		54	45†	30	25	21
	Y	0.275**	0.333**	0.142	0.108	0.142		53	47	31	25	25
6	*X*	0.325	0.317*	0.092	0.083	0.183*	♯	59	55	23	17	37
	Y	0.300*	0.325*	0.100	0.150	0.125		53	60	24	33	31
7	*X*	0.383	0.250	0.158	0.075*	0.133		63	47	33	15	29
	Y	0.408	0.325*	0.117	0.042**	0.108	♯♯	60	62†	29	11	25
8	*X*	0.317	0.283	0.125	0.133	0.142		53	47	29	31	33
	Y	0.333	0.292	0.183*	0.100	0.092		46	55	38	25	19
9	*X*	0.442	0.242	0.150	0.083	0.083		53	43	33	15†	19
	Y	0.342	0.267	0.150	0.108	0.133		45†	49	31	21	29
10	*X*	0.433	0.225	0.092	0.117	0.133		67	41	23	25	31
	Y	0.450*	0.183*	0.133	0.083	0.150		58	34	29	19	31
11	*X*	0.350	0.275	0.125	0.142	0.108		60	42	31	29	25
	Y	0.292*	0.308	0.233**	0.075*	0.092	♯♯	44	47	49	19	22
12	*X*	0.358	0.217	0.150	0.158	0.117		53	33‡	31	37	27
	Y	0.458*	0.267	0.108	0.067*	0.100		59	46	21	17	20
13	*X*	0.400	0.217	0.133	0.117	0.133		65	49†	31	27	31
	Y	0.325	0.275	0.167	0.108	0.125		50	52	39	27	29
14	*X*	0.342	0.267	0.158	0.108	0.125		53	42	33	23	24
	Y	0.308	0.233	0.158	0.150	0.150		54	45	33	30	29
15	*X*	0.442	0.292	0.125	0.100	0.042**	♯♯	63	50	30	25	11
	Y	0.417	0.358**	0.108	0.017**	0.100	♯♯	58	66†	25	5	23
16	*X*	0.242**	0.275	0.217**	0.167	0.100	♯♯	41	55	41	35	23
	Y	0.250**	0.275	0.233**	0.125	0.117	♯♯	49	53	48	24	29
17	*X*	0.400	0.242	0.117	0.142	0.100		55	45	25	33	23
	Y	0.433	0.267	0.117	0.100	0.083		56	39†	24	23	21
18	*X*	0.375	0.275	0.133	0.100	0.117		54	48	31	25	25
	Y	0.450*	0.308	0.083	0.083	0.075*	♯	63	63‡	21	21	19
19	*X*	0.350	0.275	0.142	0.067*	0.167		51	51	31	15	31
	Y	0.450*	0.233	0.133	0.100	0.083		61	43	32	25	18
20	*X*	0.400	0.225	0.150	0.117	0.108		47‡	41	35	25	25
	Y	0.350	0.183*	0.192**	0.150	0.125		67‡	39	32†	31	24

Table A1: Continued

Pair	Player	Relative Frequencies *C*	*L*	*F*	*I*	*O*	χ^2 Test	Number of Runs *C*	*L*	*F*	*I*	*O*
21	*X*	0.542**	0.167**	0.175*	0.058**	0.058**	♯♯	52	38	31	15	15
	Y	0.375	0.317*	0.117	0.108	0.083		51	50	21†	24	19
22	*X*	0.458*	0.200	0.150	0.083	0.108		61	39	31	21	25
	Y	0.483**	0.283	0.125	0.075*	0.033**	♯♯	65	51	29	19	9
23	*X*	0.358	0.225	0.092	0.158	0.167		64	47	23	36	35
	Y	0.350	0.283	0.133	0.175*	0.058**		59	54	31	42‡	15
24	*X*	0.458*	0.208	0.125	0.117	0.092		57	33†	23	25	19
	Y	0.333	0.367**	0.133	0.108	0.058**	♯♯	60	63	31	22	13
25	*X*	0.300*	0.192	0.158	0.192**	0.158	♯♯	55	41	34	38	33
	Y	0.325	0.308	0.117	0.142	0.108		52	48	25	27	27
26	*X*	0.367	0.217	0.117	0.117	0.183*		56	43	27	28	35
	Y	0.375	0.300	0.125	0.083	0.117		55	44	20‡	17	23
27	*X*	0.425	0.208	0.142	0.108	0.117		61	43	33	25	27
	Y	0.267**	0.208	0.175*	0.150	0.200**	♯♯	46	45	35	27	42
28	*X*	0.333	0.217	0.225**	0.125	0.100	♯♯	51	45	49	29	25
	Y	0.375	0.292	0.100	0.117	0.117		57	49	23	27	25
All	*X*	0.379	0.245	0.140**	0.118	0.119	♯					
	Y	0.360*	0.275**	0.145**	0.113**	0.107**	♯♯					

Notes: Symbols ** and * denote the rejection of the chi-square goodness-of-fit test of the frequencies for a given choice to the minimax prediction at the 5% and 10% significance levels, respectively. Symbols ♯♯ and ♯ denote the rejection of the chi-square goodness-of-fit test of the frequencies for all choices (*C*, *L*, *F*, *I*, and *O*) to the minimax prediction at the 5% and 10% significance levels, respectively. Symbols ‡ and † denote the rejection of runs test for a given choice at the 5% and 10% significance levels, respectively.

Table A2: Team Treatment (Rounds 1-60)

		Relative Frequencies					χ^2	Number of Runs				
Pair	Player	C	L	F	I	O	Test	C	L	F	I	O
1	X	0.367	0.283	0.133	0.150	0.067		30	26	15	19	9
	Y	0.417	0.150*	0.183	0.150	0.100		38‡	19	18	17	13
2	X	0.367	0.233	0.150	0.117	0.133		29	21	19	13	15
	Y	0.283	0.133**	0.233**	0.200*	0.150	♯♯	23	15	23	21	13
3	X	0.367	0.300	0.100	0.067	0.167		24	27	13	9	20
	Y	0.367	0.133**	0.250**	0.133	0.117	♯♯	24	17	18†	15	11
4	X	0.433	0.183	0.167	0.117	0.100		28	17	18	11	11
	Y	0.367	0.267	0.033**	0.183	0.150		25	24	5	19	18
5	X	0.317	0.383**	0.100	0.133	0.067		26	23	12	13	9
	Y	0.267*	0.267	0.150	0.117	0.200*		24	20	15	15	17
6	X	0.350	0.300	0.083	0.083	0.183		31	27	11	10	20
	Y	0.367	0.267	0.133	0.133	0.100		34	27	16	17	13
7	X	0.417	0.217	0.117	0.117	0.133		34	18	15	11	13
	Y	0.350	0.367**	0.117	0.067	0.100		31	33	15	9	11
8	X	0.333	0.267	0.133	0.150	0.117		27	25	15	17	15
	Y	0.283	0.300	0.183	0.133	0.100		18‡	29	20	17	13
9	X	0.483*	0.200	0.133	0.083	0.100		27	19	15	9	11
	Y	0.367	0.217	0.117	0.117	0.183		25	20	13	12	19
10	X	0.450	0.200	0.100	0.133	0.117		39‡	21	13	13	13
	Y	0.383	0.217	0.133	0.100	0.167		26	20	15	11	17
11	X	0.367	0.350*	0.117	0.117	0.050*		30	22†	15	11	7
	Y	0.383	0.233	0.200*	0.083	0.100		22†	19	22	11	13
12	X	0.383	0.233	0.150	0.167	0.067		28	17†	14	21	9
	Y	0.433	0.250	0.133	0.083	0.100		25	20	10‡	11	9
13	X	0.367	0.250	0.117	0.133	0.133		32	27	15	16	15
	Y	0.317	0.233	0.183	0.117	0.150		25	23	21	15	17
14	X	0.367	0.233	0.150	0.050*	0.200*		28	21	15	7	18
	Y	0.333	0.267	0.183	0.067	0.150		28	26	17	9	13
15	X	0.417	0.317	0.100	0.100	0.067		28	20†	13	13	9
	Y	0.483*	0.367**	0.050*	0.000**	0.100	♯♯	31	31	7	n.a.	11
16	X	0.317	0.267	0.167	0.150	0.100		27	28	18	17	13
	Y	0.283	0.333	0.200*	0.117	0.067		23	31	21	13	9
17	X	0.400	0.317	0.083	0.100	0.100		29	29	11	13	13
	Y	0.400	0.317	0.067	0.117	0.100		26	21	9	14	13
18	X	0.417	0.283	0.117	0.083	0.100		27	25	15	11	13
	Y	0.450	0.317	0.067	0.100	0.067		29	33†	9	13	9
19	X	0.333	0.317	0.150	0.067	0.133		25	27	17	9	13
	Y	0.400	0.250	0.167	0.117	0.067		30	21	20	15	7
20	X	0.350	0.250	0.167	0.100	0.133		24	24	21	13	17
	Y	0.317	0.183	0.217**	0.167	0.117		33†	21	18	17	12

Table A2: Continued

Pair	Player	Relative Frequencies *C*	*L*	*F*	*I*	*O*	χ^2 Test	Number of Runs *C*	*L*	*F*	*I*	*O*
21	*X*	0.533**	0.183	0.150	0.050*	0.083	♯	26	20	15	7	11
	Y	0.400	0.317	0.067	0.100	0.117		26	26	7	11	13
22	*X*	0.450	0.250	0.150	0.067	0.083		30	23	14	9	11
	Y	0.517**	0.283	0.083	0.067	0.050*	♯	33	27	11	9	7
23	*X*	0.417	0.250	0.033**	0.167	0.133		34	24	5	21	13
	Y	0.433	0.233	0.117	0.150	0.067		34	22	15	19	9
24	*X*	0.433	0.250	0.150	0.067	0.100		26	18†	13	9	11
	Y	0.317	0.400**	0.167	0.083	0.033**	♯♯	32	33	21	10	5
25	*X*	0.350	0.217	0.133	0.133	0.167		31	21	14	16	15
	Y	0.350	0.283	0.133	0.133	0.100		24	22	15	13	13
26	*X*	0.383	0.200	0.150	0.067	0.200*		30	20	17	9	17
	Y	0.367	0.267	0.133	0.117	0.117		29	20	10‡	11	11
27	*X*	0.450	0.217	0.117	0.100	0.117		30	23	15	12	15
	Y	0.300	0.283	0.133	0.117	0.167		26	32‡	15	13	19
28	*X*	0.283	0.233	0.267**	0.117	0.100	♯♯	24	27	29	14	13
	Y	0.350	0.267	0.133	0.117	0.133		26	24	15	15	13
All	*X*	0.389	0.257	0.132	0.107**	0.116						
	Y	0.367	0.264	0.142**	0.114	0.113	♯					

Notes: For explanations, see notes to Table A1.

Table A3: Team Treatment (Rounds 61-120)

Pair	Player	Relative Frequencies C	L	F	I	O	χ^2 Test	Number of Runs C	L	F	I	O
1	X	0.433	0.267	0.117	0.133	0.050*		34	27	13	14	7
	Y	0.433	0.167	0.183	0.117	0.100		33	19	23	15	13
2	X	0.350	0.233	0.150	0.117	0.150		26	24	15	13	17
	Y	0.183**	0.333	0.233**	0.133	0.117	♯♯	19	27	21	17	15
3	X	0.267*	0.283	0.150	0.133	0.167		28	28	15	13	19
	Y	0.283	0.300	0.117	0.233**	0.067	♯	31†	31	11	19	9
4	X	0.400	0.233	0.117	0.150	0.100		24	15‡	15	13	12
	Y	0.367	0.350*	0.133	0.100	0.050*		22†	33	13	11	6
5	X	0.333	0.283	0.150	0.133	0.100		29	23	19	13	13
	Y	0.283	0.400**	0.133	0.100	0.083	♯	29	27	17	11	9
6	X	0.300	0.333	0.100	0.083	0.183		28	29	13	8	17
	Y	0.233**	0.383**	0.067	0.167	0.150	♯♯	19	33	9	17	19
7	X	0.350	0.283	0.200*	0.033**	0.133		30	30	19	5	17
	Y	0.467	0.283	0.117	0.017**	0.117		29	29	15	3	15
8	X	0.300	0.300	0.117	0.117	0.167		26	22	15	15	19
	Y	0.383	0.283	0.183	0.067	0.083		28	26	19	9	7†
9	X	0.400	0.283	0.167	0.083	0.067		27	25	19	7†	9
	Y	0.317	0.317	0.183	0.100	0.083		21	29	19	10	10
10	X	0.417	0.250	0.083	0.100	0.150		28	21	11	13	18
	Y	0.517**	0.150*	0.133	0.067	0.133		33	15	15	9	15
11	X	0.333	0.200	0.133	0.167	0.167		30	20	17	19	19
	Y	0.200**	0.383**	0.267**	0.067	0.083	♯♯	23	29	28	9	10
12	X	0.333	0.200	0.150	0.150	0.167		26	17	17	17	18
	Y	0.483*	0.283	0.083	0.050*	0.100		35	26	11	7	12
13	X	0.433	0.183	0.150	0.100	0.133		34	23	16	11	17
	Y	0.333	0.317	0.150	0.100	0.100		25	29	19	13	13
14	X	0.317	0.300	0.167	0.167	0.050*		26	22	19	17	7
	Y	0.283	0.200	0.133	0.233**	0.150	♯	27	19	16	22	17
15	X	0.467	0.267	0.150	0.100	0.017**		36	31‡	18	13	3
	Y	0.350	0.350*	0.167	0.033**	0.100		27	36‡	18	5	13
16	X	0.167**	0.283	0.267**	0.183	0.100	♯♯	15	28	23	18	11
	Y	0.217**	0.217	0.267**	0.133	0.167	♯♯	26†	23	27	12	21
17	X	0.400	0.167	0.150	0.183	0.100		26	17	14	21	11
	Y	0.467	0.217	0.167	0.083	0.067		31	19	15	9	9
18	X	0.333	0.267	0.150	0.117	0.133		28	24	17	15	13
	Y	0.450	0.300	0.100	0.067	0.083		34	30	13	9	11
19	X	0.367	0.233	0.133	0.067	0.200*		26	25	15	7	18
	Y	0.500**	0.217	0.100	0.083	0.100		31	22	13	11	12
20	X	0.450	0.200	0.133	0.133	0.083		23†	17	15	13	9
	Y	0.383	0.183	0.167	0.133	0.133		35	19	15	15	13

Table A3: Continued

Pair	Player	Relative Frequencies C	L	F	I	O	χ^2 Test	Number of Runs C	L	F	I	O
21	X	0.550**	0.150*	0.200*	0.067	0.033**	♯♯	26	19	16	9	5
	Y	0.350	0.317	0.167	0.117	0.050*		25	24	15	14	7
22	X	0.467	0.150*	0.150	0.100	0.133		32	16	17	13	15
	Y	0.450	0.283	0.167	0.083	0.017**	♯	33	25	19	11	3
23	X	0.300	0.200	0.150	0.150	0.200*		30	23	19	16	23
	Y	0.267*	0.333	0.150	0.200*	0.050*	♯	25	32	17	24	7
24	X	0.483*	0.167	0.100	0.167	0.083		32	16	11	17	9
	Y	0.350	0.333	0.100	0.133	0.083		28	31	11	12	9
25	X	0.250**	0.167	0.183	0.250**	0.150	♯♯	24	21	21	22	19
	Y	0.300	0.333	0.100	0.150	0.117		28	26	11	15	15
26	X	0.350	0.233	0.083	0.167	0.167		27	23	11	20	18
	Y	0.383	0.333	0.117	0.050*	0.117		26	24	11	7	13
27	X	0.400	0.200	0.167	0.117	0.117		32	20	19	13	13
	Y	0.233**	0.133**	0.217**	0.183	0.233**	♯♯	21	14	21	15	24
28	X	0.383	0.200	0.183	0.133	0.100		28	19	20	15	13
	Y	0.400	0.317	0.067	0.117	0.100		32	26	9	13	13
All	X	0.369	0.233	0.148**	0.129	0.121	♯♯					
	Y	0.352*	0.286**	0.149**	0.111*	0.101**	♯♯					

Notes: For explanations, see notes to Table A1.

Table A4: Individual Treatment (Rounds 1-120)

		Relative Frequencies					χ^2	Number of Runs				
Pair	Player	C	L	F	I	O	Test	C	L	F	I	O
1	X	0.350	0.292	0.067*	0.058**	0.233**	♯♯	59	55	17	15	49
	Y	0.275**	0.292	0.158	0.175*	0.100	♯	48	53	37	40	25
2	X	0.383	0.250	0.075*	0.083	0.208**	♯♯	61	55‡	19	19	45
	Y	0.317	0.267	0.175*	0.142	0.100		57	52	37	35	24
3	X	0.367	0.217	0.167	0.125	0.125		63	45	41‡	29	29
	Y	0.475**	0.150**	0.158	0.117	0.100	♯♯	53	32	32	29	23
4	X	0.375	0.208	0.150	0.117	0.150		53	35	31	17‡	33
	Y	0.375	0.283	0.100	0.108	0.133		42‡	49	21	22	29
5	X	0.350	0.275	0.092	0.150	0.133		49	49	21	31	25
	Y	0.317	0.367**	0.150	0.042**	0.125	♯♯	58	56	29	11	27
6	X	0.367	0.217	0.200**	0.092	0.125		58	45	42	23	31
	Y	0.425	0.208	0.158	0.083	0.125		64	43	34	19	29
7	X	0.383	0.250	0.092	0.150	0.125		52	51	20	29	27
	Y	0.400	0.267	0.125	0.100	0.108		40‡	40†	27	23	21
8	X	0.333	0.267	0.083	0.125	0.192**		42‡	43	19	30	41
	Y	0.350	0.325*	0.158	0.075*	0.092		48	54	31	11‡	19
9	X	0.308	0.342**	0.100	0.117	0.133		52	56	21	23	29
	Y	0.442	0.233	0.092	0.108	0.125		54	37	23	24	25
10	X	0.417	0.208	0.075*	0.083	0.217**	♯♯	54	42	13‡	19	41
	Y	0.408	0.217	0.167	0.108	0.100		61	36	37	16‡	21
11	X	0.400	0.217	0.108	0.075*	0.200**	♯	48†	32‡	23	17	39
	Y	0.358	0.283	0.133	0.108	0.117		55	47	29	23	27
12	X	0.375	0.333**	0.092	0.067*	0.133		63	67‡	21	17	25
	Y	0.292*	0.425**	0.117	0.042**	0.125	♯♯	45	59	25	11	25
13	X	0.375	0.300	0.108	0.125	0.092		46‡	48	23	27	19
	Y	0.333	0.200	0.200**	0.125	0.142		52	42	37	27	31
14	X	0.425	0.308	0.083	0.042**	0.142	♯♯	58	39‡	19	11	32
	Y	0.500**	0.192	0.133	0.125	0.050**	♯♯	51†	37	27	25	13
15	X	0.333	0.208	0.158	0.108	0.192**		63†	41	31	25	39
	Y	0.458*	0.308	0.067*	0.092	0.075*	♯♯	62	56	17	23	17
16	X	0.392	0.217	0.158	0.092	0.142		52	40	35	21	29
	Y	0.333	0.267	0.133	0.125	0.142		53	48	30	23	33
17	X	0.417	0.267	0.075*	0.117	0.125		55	49	17	23	27
	Y	0.383	0.267	0.175*	0.075*	0.100		61	51	37	17	23
18	X	0.367	0.250	0.092	0.117	0.175*		53	47	23	19‡	31
	Y	0.375	0.317*	0.058**	0.117	0.133		48†	48	15	21†	25
19	X	0.300*	0.283	0.125	0.108	0.183*		44	42	23	27	35
	Y	0.358	0.308	0.042**	0.150	0.142	♯	61	53	8‡	33	28
20	X	0.342	0.317*	0.117	0.108	0.117		49	53	23	21	27
	Y	0.458*	0.258	0.117	0.092	0.075*		69	48	25	20	19
All	X	0.368	0.261	0.111**	0.103**	0.157**	♯♯					
	Y	0.382	0.272**	0.131	0.105**	0.110**	♯♯					

Notes: For explanations, see notes to Table A1.

Table A5: Individual Treatment (Rounds 1-60)

		Relative Frequencies					χ^2	Number of Runs				
Pair	Player	*C*	*L*	*F*	*I*	*O*	Test	*C*	*L*	*F*	*I*	*O*
1	*X*	0.350	0.317	0.100	0.067	0.167		30	30	13	9	21
	Y	0.283	0.300	0.150	0.150	0.117		21	29	17	17	15
2	*X*	0.383	0.233	0.117	0.117	0.150		32	27	15	13	18
	Y	0.367	0.200	0.200*	0.117	0.117		32	20	21	15	15
3	*X*	0.333	0.217	0.183	0.133	0.133		32	19	22	15	15
	Y	0.450	0.183	0.183	0.050*	0.133		24	18	17	7	15
4	*X*	0.317	0.250	0.150	0.133	0.150		25	17‡	15	11†	17
	Y	0.367	0.300	0.067	0.117	0.150		24	25	7	13	14
5	*X*	0.333	0.300	0.100	0.200*	0.067		22	25	13	20	9
	Y	0.250**	0.433**	0.167	0.017**	0.133	♯♯	24	30	17	3	15
6	*X*	0.367	0.200	0.183	0.083	0.167		27	22	18	11	21
	Y	0.400	0.183	0.217**	0.100	0.100		32	21	23	10	13
7	*X*	0.300	0.283	0.150	0.167	0.100		21	27	15	17	13
	Y	0.467	0.217	0.117	0.100	0.100		23†	17	13	11	11
8	*X*	0.383	0.250	0.083	0.117	0.167		19‡	25	11	14	18
	Y	0.433	0.333	0.167	0.017**	0.050*	♯♯	26	26	15	3	7
9	*X*	0.350	0.333	0.083	0.117	0.117		27	27	9	11	15
	Y	0.500**	0.200	0.050*	0.083	0.167		18‡	15†	7	9	14
10	*X*	0.467	0.200	0.067	0.083	0.183		23†	21	7	11	19
	Y	0.467	0.117**	0.150	0.183	0.083	♯	32	11	17	12‡	9
11	*X*	0.400	0.267	0.100	0.067	0.167		24	16‡	11	7	21
	Y	0.350	0.267	0.167	0.100	0.117		25	19	19	11	15
12	*X*	0.333	0.400**	0.067	0.050*	0.150	♯♯	29	37†	7	7	13
	Y	0.367	0.317	0.133	0.067	0.117		24	26	13	9	11
13	*X*	0.383	0.300	0.100	0.100	0.117		23	24	10	11	11
	Y	0.467	0.183	0.133	0.100	0.117		32	21	17	11	12
14	*X*	0.367	0.450**	0.083	0.000**	0.100	♯♯	22†	22‡	9	n.a.	13
	Y	0.533**	0.167	0.167	0.083	0.050*	♯♯	25	17	17	9	7
15	*X*	0.367	0.267	0.117	0.083	0.167		32	26	15	11	21
	Y	0.450	0.317	0.083	0.117	0.033**		33	31	11	15	5
16	*X*	0.433	0.217	0.167	0.017**	0.167	♯	26	21	18	3	17
	Y	0.317	0.283	0.167	0.067	0.167		25	24	19	7	18
17	*X*	0.400	0.250	0.117	0.100	0.133		25	21	13	13	13
	Y	0.400	0.300	0.150	0.067	0.083		27	27	15	9	9
18	*X*	0.350	0.217	0.083	0.083	0.267**	♯♯	24	18	11	7†	23
	Y	0.333	0.283	0.083	0.100	0.200*		25	27	11	11	17
19	*X*	0.317	0.317	0.067	0.083	0.217**	♯	22	22	7	11	21
	Y	0.367	0.383**	0.050*	0.133	0.067	♯	29	29	4‡	14	7
20	*X*	0.267*	0.333	0.117	0.150	0.133		19	27	13	13	17
	Y	0.533**	0.283	0.117	0.033**	0.033**	♯♯	30	22	13	5	5
All	*X*	0.360	0.280**	0.112	0.098**	0.151**	♯♯					
	Y	0.405**	0.263	0.136	0.090**	0.107*	♯♯					

Notes: For explanations, see notes to Table A1.

Table A6: Individual Treatment (Rounds 61-120)

		Relative Frequencies					χ^2	Number of Runs				
Pair	Player	C	L	F	I	O	Test	C	L	F	I	O
1	X	0.350	0.267	0.033**	0.050*	0.300**	♯♯	29	25	5	7	29
	Y	0.267*	0.283	0.167	0.200*	0.083		28	24	21	23	11
2	X	0.383	0.267	0.033**	0.050*	0.267**	♯♯	29	29	5	7	27
	Y	0.267*	0.333	0.150	0.167	0.083		25	32	17	21	10
3	X	0.400	0.217	0.150	0.117	0.117		32	27‡	19	14	15
	Y	0.500**	0.117**	0.133	0.183	0.067	♯♯	30	15	16	23	9
4	X	0.433	0.167	0.150	0.100	0.150		29	19	17	7‡	17
	Y	0.383	0.267	0.133	0.100	0.117		19‡	25	14	10	15
5	X	0.367	0.250	0.083	0.100	0.200*		28	24	9	11	17
	Y	0.383	0.300	0.133	0.067	0.117		34	27	13	9	12
6	X	0.367	0.233	0.217**	0.100	0.083		31	23	25	13	11
	Y	0.450	0.233	0.100	0.067	0.150		32	23	12	9	17
7	X	0.467	0.217	0.033**	0.133	0.150		31	25	5	13	15
	Y	0.333	0.317	0.133	0.100	0.117		17‡	23	15	13	11
8	X	0.283	0.283	0.083	0.133	0.217**		24	19†	9	16	23
	Y	0.267*	0.317	0.150	0.133	0.133		23	29	17	9‡	13
9	X	0.267*	0.350*	0.117	0.117	0.150		25	29	13	13	15
	Y	0.383	0.267	0.133	0.133	0.083		37‡	23	17	15	11
10	X	0.367	0.217	0.083	0.083	0.250**	♯	32	22	7†	9	23
	Y	0.350	0.317	0.183	0.033**	0.117		29	25	21	5	13
11	X	0.400	0.167	0.117	0.083	0.233**	♯	25	16	13	10	19
	Y	0.367	0.300	0.100	0.117	0.117		31	28	11	12	13
12	X	0.417	0.267	0.117	0.083	0.117		35	31‡	15	11	13
	Y	0.217**	0.533**	0.100	0.017**	0.133	♯♯	22	34	13	3	15
13	X	0.367	0.300	0.117	0.150	0.067		23	25	13	17	9
	Y	0.200**	0.217	0.267**	0.150	0.167	♯♯	20	22	21	17	19
14	X	0.483*	0.167	0.083	0.083	0.183		37	17	11	11	19
	Y	0.467	0.217	0.100	0.167	0.050*		27	21	11	17	7
15	X	0.300	0.150*	0.200*	0.133	0.217**	♯♯	31	15	17	15	19
	Y	0.467	0.300	0.050*	0.067	0.117		30	26	7	9	13
16	X	0.350	0.217	0.150	0.167	0.117		27	20	17	19	12
	Y	0.350	0.250	0.100	0.183	0.117		28	25	12	17	15
17	X	0.433	0.283	0.033**	0.133	0.117		31	29	5	11†	15
	Y	0.367	0.233	0.200*	0.083	0.117		34	24	23	9	15
18	X	0.383	0.283	0.100	0.150	0.083		30	29	12	13	9
	Y	0.417	0.350*	0.033**	0.133	0.067	♯	23†	21†	5	11†	9
19	X	0.283	0.250	0.183	0.133	0.150		22	20	17	17	15
	Y	0.350	0.233	0.033**	0.167	0.217**	♯	33	24	5	19	22
20	X	0.417	0.300	0.117	0.067	0.100		31	27	11	9	11
	Y	0.383	0.233	0.117	0.150	0.117		40‡	27	13	16	15
All	X	0.376	0.243	0.110	0.108*	0.163**	♯♯					
	Y	0.358	0.281**	0.126	0.121	0.114						

Notes: For explanations, see notes to Table A1.

Table A7: Relative Frequencies of Action Profiles in the Team Treatment (Rounds 1-120)

Pair	Action Profile C,C	C,L	C,FIO	L,C	L,L	L,FIO	FIO,C	FIO,L	FIO,FIO	χ^2 Test
1	0.242	0.058	0.100	0.092	0.008	0.175	0.092	0.092	0.142	♯♯
2	0.133	0.058	0.167	0.042	0.067	0.125	0.058	0.108	0.242	♯♯
3	0.125	0.075	0.117	0.125	0.042	0.125	0.075	0.100	0.217	
4	0.200	0.158	0.058	0.050	0.058	0.100	0.117	0.092	0.167	♯♯
5	0.125	0.067	0.133	0.075	0.142	0.117	0.075	0.125	0.142	♯♯
6	0.133	0.117	0.075	0.083	0.058	0.175	0.083	0.150	0.125	♯♯
7	0.117	0.175	0.092	0.117	0.067	0.067	0.175	0.083	0.108	♯
8	0.108	0.100	0.108	0.083	0.067	0.133	0.142	0.125	0.133	
9	0.175	0.100	0.167	0.067	0.033	0.142	0.100	0.133	0.083	♯
10	0.158	0.083	0.192	0.125	0.017	0.083	0.167	0.083	0.092	
11	0.117	0.100	0.133	0.083	0.092	0.100	0.092	0.117	0.167	
12	0.142	0.117	0.100	0.075	0.083	0.058	0.242	0.067	0.117	♯
13	0.133	0.117	0.150	0.042	0.083	0.092	0.150	0.075	0.158	
14	0.117	0.075	0.150	0.092	0.050	0.125	0.100	0.108	0.183	
15	0.142	0.167	0.133	0.142	0.083	0.067	0.133	0.108	0.025	♯♯
16	0.092	0.067	0.083	0.042	0.092	0.142	0.117	0.117	0.250	♯♯
17	0.175	0.142	0.083	0.108	0.050	0.083	0.150	0.075	0.133	
18	0.192	0.100	0.083	0.117	0.075	0.083	0.142	0.133	0.075	
19	0.175	0.058	0.117	0.125	0.058	0.092	0.150	0.117	0.108	
20	0.108	0.058	0.233	0.067	0.067	0.092	0.175	0.058	0.142	♯
21	0.167	0.192	0.183	0.100	0.033	0.033	0.108	0.092	0.092	♯♯
22	0.233	0.150	0.075	0.100	0.033	0.067	0.150	0.100	0.092	♯♯
23	0.108	0.125	0.125	0.117	0.033	0.075	0.125	0.125	0.167	
24	0.200	0.125	0.133	0.050	0.083	0.075	0.083	0.158	0.092	♯♯
25	0.100	0.083	0.117	0.042	0.083	0.067	0.183	0.142	0.183	
26	0.150	0.100	0.117	0.092	0.083	0.042	0.133	0.117	0.167	
27	0.150	0.083	0.192	0.067	0.050	0.092	0.050	0.075	0.242	♯♯
28	0.125	0.067	0.142	0.083	0.075	0.058	0.167	0.150	0.133	
All	0.148	0.104	0.127	0.086	0.063	0.096	0.126	0.108	0.142	♯♯

Symbols ♯♯ and ♯ denote the rejection of the chi-square test of the frequencies for action profiles to the minimax prediction at the 5% and 10% significance levels, respectively.

Table A8: Relative Frequencies of Action Profiles in the Team Treatment (Rounds 1-60)

	Action Profile									χ^2
Pair	C,C	C,L	C,FIO	L,C	L,L	L,FIO	FIO,C	FIO,L	FIO,FIO	Test
1	0.217	0.050	0.100	0.083	0.017	0.183	0.117	0.083	0.150	
2	0.183	0.000	0.183	0.050	0.050	0.133	0.050	0.083	0.267	♯♯
3	0.183	0.050	0.133	0.117	0.033	0.150	0.067	0.050	0.217	
4	0.250	0.117	0.067	0.033	0.050	0.100	0.083	0.100	0.200	
5	0.117	0.050	0.150	0.067	0.150	0.167	0.083	0.067	0.150	♯
6	0.167	0.117	0.067	0.067	0.033	0.200	0.133	0.117	0.100	
7	0.117	0.233	0.067	0.083	0.050	0.083	0.150	0.083	0.133	♯
8	0.133	0.083	0.117	0.033	0.100	0.133	0.117	0.117	0.167	
9	0.200	0.100	0.183	0.050	0.033	0.117	0.117	0.083	0.117	
10	0.133	0.100	0.217	0.083	0.017	0.100	0.167	0.100	0.083	
11	0.133	0.067	0.167	0.150	0.083	0.117	0.100	0.083	0.100	
12	0.117	0.117	0.150	0.083	0.100	0.050	0.233	0.033	0.117	
13	0.133	0.100	0.133	0.033	0.083	0.133	0.150	0.050	0.183	
14	0.150	0.083	0.133	0.083	0.050	0.100	0.100	0.133	0.167	
15	0.200	0.150	0.067	0.150	0.117	0.050	0.133	0.100	0.033	♯♯
16	0.133	0.100	0.083	0.033	0.100	0.133	0.117	0.133	0.167	
17	0.167	0.167	0.067	0.100	0.100	0.117	0.133	0.050	0.100	
18	0.183	0.133	0.100	0.150	0.067	0.067	0.117	0.117	0.067	
19	0.150	0.067	0.117	0.117	0.083	0.117	0.133	0.100	0.117	
20	0.117	0.050	0.183	0.083	0.067	0.100	0.117	0.067	0.217	
21	0.200	0.183	0.150	0.083	0.050	0.050	0.117	0.083	0.083	
22	0.250	0.133	0.067	0.117	0.033	0.100	0.150	0.117	0.033	♯
23	0.150	0.150	0.117	0.150	0.000	0.100	0.133	0.083	0.117	
24	0.217	0.117	0.100	0.050	0.117	0.083	0.050	0.167	0.100	♯
25	0.133	0.083	0.133	0.067	0.083	0.067	0.150	0.117	0.167	
26	0.150	0.100	0.133	0.067	0.050	0.083	0.150	0.117	0.150	
27	0.167	0.150	0.133	0.083	0.050	0.083	0.050	0.083	0.200	
28	0.067	0.050	0.167	0.100	0.067	0.067	0.183	0.150	0.150	
All	0.161	0.104	0.124	0.085	0.065	0.107	0.121	0.095	0.138	♯♯

Notes: For explanations, see notes to Table A7.

Table A9: Relative Frequencies of Action Profiles in the Team Treatment (Rounds 61-120)

	Action Profile									χ^2
Pair	C, C	C, L	C, FIO	L, C	L, L	L, FIO	FIO, C	FIO, L	FIO, FIO	Test
1	0.267	0.067	0.100	0.100	0.000	0.167	0.067	0.100	0.133	♯♯
2	0.083	0.117	0.150	0.033	0.083	0.117	0.067	0.133	0.217	
3	0.067	0.100	0.100	0.133	0.050	0.100	0.083	0.150	0.217	
4	0.150	0.200	0.050	0.067	0.067	0.100	0.150	0.083	0.133	
5	0.133	0.083	0.117	0.083	0.133	0.067	0.067	0.183	0.133	
6	0.100	0.117	0.083	0.100	0.083	0.150	0.033	0.183	0.150	♯
7	0.117	0.117	0.117	0.150	0.083	0.050	0.200	0.083	0.083	
8	0.083	0.117	0.100	0.133	0.033	0.133	0.167	0.133	0.100	
9	0.150	0.100	0.150	0.083	0.033	0.167	0.083	0.183	0.050	♯
10	0.183	0.067	0.167	0.167	0.017	0.067	0.167	0.067	0.100	
11	0.100	0.133	0.100	0.017	0.100	0.083	0.083	0.150	0.233	♯
12	0.167	0.117	0.050	0.067	0.067	0.067	0.250	0.100	0.117	
13	0.133	0.133	0.167	0.050	0.083	0.050	0.150	0.100	0.133	
14	0.083	0.067	0.167	0.100	0.050	0.150	0.100	0.083	0.200	
15	0.083	0.183	0.200	0.133	0.050	0.083	0.133	0.117	0.017	♯♯
16	0.050	0.033	0.083	0.050	0.083	0.150	0.117	0.100	0.333	♯♯
17	0.183	0.117	0.100	0.117	0.000	0.050	0.167	0.100	0.167	
18	0.200	0.067	0.067	0.083	0.083	0.100	0.167	0.150	0.083	
19	0.200	0.050	0.117	0.133	0.033	0.067	0.167	0.133	0.100	
20	0.100	0.067	0.283	0.050	0.067	0.083	0.233	0.050	0.067	♯♯
21	0.133	0.200	0.217	0.117	0.017	0.017	0.100	0.100	0.100	♯♯
22	0.217	0.167	0.083	0.083	0.033	0.033	0.150	0.083	0.150	
23	0.067	0.100	0.133	0.083	0.067	0.050	0.117	0.167	0.217	
24	0.183	0.133	0.167	0.050	0.050	0.067	0.117	0.150	0.083	
25	0.067	0.083	0.100	0.017	0.083	0.067	0.217	0.167	0.200	♯
26	0.150	0.100	0.100	0.117	0.117	0.000	0.117	0.117	0.183	
27	0.133	0.017	0.250	0.050	0.050	0.100	0.050	0.067	0.283	♯♯
28	0.183	0.083	0.117	0.067	0.083	0.050	0.150	0.150	0.117	
All	0.135	0.105	0.130	0.087	0.061	0.085	0.131	0.121	0.146	♯♯

Notes: For explanations, see notes to Table A7.

Table A10: Relative Frequencies of Action Profiles in the Individual Treatment (Rounds 1-120)

	Action Profile									χ^2
Pair	C, C	C, L	C, FIO	L, C	L, L	L, FIO	FIO, C	FIO, L	FIO, FIO	Test
1	0.083	0.125	0.142	0.067	0.092	0.133	0.125	0.075	0.158	
2	0.133	0.117	0.133	0.058	0.067	0.125	0.125	0.083	0.158	
3	0.167	0.067	0.133	0.083	0.025	0.108	0.225	0.058	0.133	
4	0.167	0.100	0.108	0.058	0.058	0.092	0.150	0.125	0.142	
5	0.100	0.167	0.083	0.075	0.075	0.125	0.142	0.125	0.108	♯
6	0.150	0.058	0.158	0.092	0.050	0.075	0.183	0.100	0.133	
7	0.158	0.083	0.142	0.067	0.083	0.100	0.175	0.100	0.092	
8	0.142	0.133	0.058	0.083	0.058	0.125	0.125	0.133	0.142	
9	0.133	0.083	0.092	0.175	0.075	0.092	0.133	0.075	0.142	
10	0.183	0.075	0.158	0.050	0.033	0.125	0.175	0.108	0.092	
11	0.175	0.117	0.108	0.058	0.083	0.075	0.125	0.083	0.175	
12	0.092	0.142	0.142	0.117	0.125	0.092	0.083	0.158	0.050	♯♯
13	0.158	0.083	0.133	0.100	0.050	0.150	0.075	0.067	0.183	
14	0.192	0.100	0.133	0.167	0.042	0.100	0.142	0.050	0.075	♯♯
15	0.108	0.125	0.100	0.108	0.067	0.033	0.242	0.117	0.100	♯♯
16	0.117	0.108	0.167	0.058	0.050	0.108	0.158	0.108	0.125	
17	0.142	0.108	0.167	0.108	0.075	0.083	0.133	0.083	0.100	
18	0.133	0.100	0.133	0.083	0.100	0.067	0.158	0.117	0.108	
19	0.075	0.117	0.108	0.092	0.117	0.075	0.192	0.075	0.150	♯
20	0.125	0.092	0.125	0.142	0.067	0.108	0.192	0.100	0.050	
All	0.137	0.105	0.126	0.092	0.070	0.100	0.153	0.097	0.121	♯♯

Notes: For explanations, see notes to Table A7.

Table A11: Relative Frequencies of Action Profiles in the Individual Treatment (Rounds 1-60)

	Action Profile									χ^2
Pair	C, C	C, L	C, FIO	L, C	L, L	L, FIO	FIO, C	FIO, L	FIO, FIO	Test
1	0.100	0.117	0.133	0.083	0.083	0.150	0.100	0.100	0.133	
2	0.100	0.100	0.183	0.100	0.017	0.117	0.167	0.083	0.133	
3	0.133	0.083	0.117	0.117	0.033	0.067	0.200	0.067	0.183	
4	0.100	0.133	0.083	0.067	0.083	0.100	0.200	0.083	0.150	
5	0.050	0.183	0.100	0.050	0.117	0.133	0.150	0.133	0.083	♯♯
6	0.150	0.067	0.150	0.067	0.033	0.100	0.183	0.083	0.167	
7	0.100	0.033	0.167	0.083	0.083	0.117	0.283	0.100	0.033	♯♯
8	0.183	0.150	0.050	0.083	0.017	0.150	0.167	0.167	0.033	♯♯
9	0.183	0.050	0.117	0.167	0.083	0.083	0.150	0.067	0.100	
10	0.233	0.050	0.183	0.067	0.000	0.133	0.167	0.067	0.100	
11	0.183	0.133	0.083	0.050	0.083	0.133	0.117	0.050	0.167	
12	0.083	0.100	0.150	0.167	0.100	0.133	0.117	0.117	0.033	
13	0.200	0.100	0.083	0.167	0.017	0.117	0.100	0.067	0.150	
14	0.200	0.067	0.100	0.233	0.050	0.167	0.100	0.050	0.033	♯♯
15	0.100	0.133	0.133	0.167	0.067	0.033	0.183	0.117	0.067	
16	0.150	0.150	0.133	0.033	0.050	0.133	0.133	0.083	0.133	
17	0.167	0.117	0.117	0.083	0.100	0.067	0.150	0.083	0.117	
18	0.083	0.100	0.167	0.067	0.083	0.067	0.183	0.100	0.150	
19	0.067	0.167	0.083	0.100	0.133	0.083	0.200	0.083	0.083	♯
20	0.117	0.100	0.050	0.167	0.083	0.083	0.250	0.100	0.050	♯♯
All	0.134	0.107	0.119	0.106	0.066	0.108	0.165	0.090	0.105	♯♯

Notes: For explanations, see notes to Table A7.

Table A12: Relative Frequencies of Action Profiles in the Individual Treatment (Rounds 61-120)

	Action Profile									χ^2
Pair	C, C	C, L	C, FIO	L, C	L, L	L, FIO	FIO, C	FIO, L	FIO, FIO	Test
1	0.067	0.133	0.150	0.050	0.100	0.117	0.150	0.050	0.183	
2	0.167	0.133	0.083	0.017	0.117	0.133	0.083	0.083	0.183	
3	0.200	0.050	0.150	0.050	0.017	0.150	0.250	0.050	0.083	♯♯
4	0.233	0.067	0.133	0.050	0.033	0.083	0.100	0.167	0.133	
5	0.150	0.150	0.067	0.100	0.033	0.117	0.133	0.117	0.133	
6	0.150	0.050	0.167	0.117	0.067	0.050	0.183	0.117	0.100	
7	0.217	0.133	0.117	0.050	0.083	0.083	0.067	0.100	0.150	
8	0.100	0.117	0.067	0.083	0.100	0.100	0.083	0.100	0.250	
9	0.083	0.117	0.067	0.183	0.067	0.100	0.117	0.083	0.183	
10	0.133	0.100	0.133	0.033	0.067	0.117	0.183	0.150	0.083	
11	0.167	0.100	0.133	0.067	0.083	0.017	0.133	0.117	0.183	
12	0.100	0.183	0.133	0.067	0.150	0.050	0.050	0.200	0.067	♯♯
13	0.117	0.067	0.183	0.033	0.083	0.183	0.050	0.067	0.217	♯♯
14	0.183	0.133	0.167	0.100	0.033	0.033	0.183	0.050	0.117	
15	0.117	0.117	0.067	0.050	0.067	0.033	0.300	0.117	0.133	♯♯
16	0.083	0.067	0.200	0.083	0.050	0.083	0.183	0.133	0.117	
17	0.117	0.100	0.217	0.133	0.050	0.100	0.117	0.083	0.083	
18	0.183	0.100	0.100	0.100	0.117	0.067	0.133	0.133	0.067	
19	0.083	0.067	0.133	0.083	0.100	0.067	0.183	0.067	0.217	
20	0.133	0.083	0.200	0.117	0.050	0.133	0.133	0.100	0.050	
All	0.139	0.103	0.133	0.078	0.073	0.091	0.141	0.104	0.137	

Notes: For explanations, see notes to Table A7.

B Robustness Check: Model Selection to Data from Professional vs. Student Behavior Experiment

This section presents results of model selection applied to the data gathered by Palacios-Huerta and Volij (2008) in which professional soccer players and college students play two-player zero-sum games. The main purpose of this re-examination is a robustness check. Using data from the other experiment determines the extent to which our results of model selection are generalizable. Particularly, we are interested in how often the minimax model is selected as the best fit model in the similar but different strategic environment where different types of decision makers play.

Palacios-Huerta and Volij (2008) (henceforth PH-V) recruited professional soccer players and college students, and compared their behaviors in two games with unique mixed strategy equilibria: "penalty kick" game they introduced and the well-known O'Neill (1987) game. They found that the play of professional soccer players conforms closely to the behavior under the minimax prediction, although that of college students does not. Wooders (2010) re-examined the PH-V data and found that the play of professionals is inconsistent with the minimax hypothesis in several respects. A main finding was that, when the data are partitioned into halves, the choice frequencies are far from those implied by the minimax hypothesis at more than the expected rate for professionals, just as those of the college students. Professionals tend to follow nonstationary mixtures, with action frequencies that are negatively correlated between the first and second halves of the experiment.

This section applies model selection to PH-V data where subjects play the O'Neill game. The payoff matrix of O'Neill game is shown in Table A13. A win was worth 1 Euro. The game has a unique mixed strategy equilibrium in which both players choose J, 1, 2, and 3 with probabilities of 0.4, 0,2, 0.2, and 0.2, respectively. This experiment examined 40 professional soccer players who were paired with a fixed opponent. They played 200 rounds of the game.

Table A13: O'Neill Game

		Column Player			
		J	1	2	3
	J	*W*	*L*	*L*	*L*
Row	1	*L*	*L*	*W*	*W*
Player	2	*L*	*W*	*L*	*W*
	3	*L*	*W*	*W*	*L*

Notes: *W* and *L* indicate a win and a loss for row player, respectively. Column player's payoffs are the reverse of row's.

Similarly, 40 college students formed 20 fixed pairs, and played 200 rounds of the game.

There are several reasons to use PH-V data with O'Neill game for robustness check. First, it is important to use data gathered by other experimenters because they are unaffected by our purpose of analysis. We can avoid the danger of unconsciously promoting our desiring behavior both in making details of experimental design and during the experimental session. Second, the O'Neill game is a similar but different strategic environment to the game in Rapoport and Boebel (1992) (RB game, hereafter). The shared features are that the payoff matrix includes only two outcomes. Moreover, in equilibrium, the game is symmetric with respect to the mixed strategies of the row and column players. The different feature is that O'Neill game is a 4×4 game rather than a 5×5 game. Third, PH-V data include behaviors which are both consistent (overall round data for professionals) and inconsistent (half data for professionals, and overall and half data for college students) with the minimax prediction based on hypothesis testing. We can see the contrast of the results between model selection and hypothesis testing. Fourth, details of the experimental procedures used in the PH-V experiment differ from ours in several respects. The PH-V experiment was not computerized. Subjects in the same pair sat opposite each other at a table. Each subject held four cards, and chose one of these at each hand. The game was presented without the help of a matrix. Subjects learned the rules through practice. We can assess the degree to which the results of model selection are robust to these differences.

Table A14: Model Fits at the Aggregate Level with Professionals and College Students in PH-V Experiment

Rounds	Player	Model	Professional LL^*	Professional AIC	Professional BIC	Student LL^*	Student AIC	Student BIC
1-200	Row Player	EWA	−5330.5	10671.0	10702.5	−5363.9	10737.8	10769.2
		RL	−5405.3	10814.6	10827.2	−5393.6	10791.2	10803.8
		BL	−5336.2	10678.3	10697.2	−5354.3	10714.7	10733.6
		QRE	−5332.2	10666.4	10672.7	−5351.6	10705.2	10711.5
		MM	−5332.2	**10664.4**	**10664.4**	−5351.6	**10703.2**	**10703.2**
	Column Player	EWA	−5377.6	10765.2	10796.6	−5386.5	10783.1	10814.5
		RL	−5388.6	10781.3	10793.9	−5386.8	10777.6	10790.2
		BL	−5439.4	10884.8	10903.7	−5387.4	10780.7	10799.6
		QRE	−5335.6	10673.3	10679.6	−5364.8	10731.5	10737.8
		MM	−5335.6	**10671.3**	**10671.3**	−5364.8	**10729.5**	**10729.5**
1-100	Row Player	EWA	−2631.7	5273.3	5301.3	−2670.1	5350.3	5378.3
		RL	−2676.0	5356.0	5367.2	−2688.8	5381.6	5392.8
		BL	−2636.0	5277.9	5294.7	−2662.2	5330.4	5347.2
		QRE	−2635.9	5273.9	5279.5	−2660.5	5322.9	5328.5
		MM	−2635.9	**5271.9**	**5271.9**	−2660.2	**5320.4**	**5320.4**
	Column Player	EWA	−2739.9	5489.9	5517.9	−2664.7	5339.4	5367.4
		RL	−2744.4	5492.9	5504.1	−2664.7	5333.5	5344.7
		BL	−2745.1	5496.1	5513.0	−2772.0	5550.0	5566.8
		QRE	−2721.2	5444.4	5450.0	−2643.0	5288.1	5293.7
		MM	−2721.2	**5442.4**	**5442.4**	−2643.6	**5287.1**	**5287.1**
101-200	Row Player	EWA	−2725.9	5461.8	5489.8	−2770.5	5550.9	5578.9
		RL	−2764.1	5532.1	5543.3	−2770.5	5544.9	5556.1
		BL	−2769.1	5544.1	5560.9	−2770.6	5547.2	5564.0
		QRE	−2694.2	**5390.5**	5396.1	−2691.4	5384.8	5390.4
		MM	−2696.2	5392.5	**5392.5**	−2691.4	**5382.8**	**5382.8**
	Column Player	EWA	−2660.9	5331.9	5359.9	−2704.0	**5418.1**	5446.1
		RL	−2740.4	5484.8	5496.0	−2731.3	5466.6	5477.8
		BL	−2736.1	5478.1	5494.9	−2732.6	5471.1	5487.9
		QRE	−2609.9	**5221.9**	**5227.5**	−2721.2	5444.4	5450.0
		MM	−2614.5	5228.9	5228.9	−2721.2	5442.4	**5442.4**

Notes: LL^* is maximized log-likelihood. AIC is given as $-2LL^* + 2k$, and BIC is given as $-2LL^* + k\log(M)$, where k is the number of parameters, and M is the number of observations. Best fits are denoted using bold typeface.

Table A14 shows results of model selection with aggregated data. The minimax model mostly performs well for predicting the behaviors of both professionals and college students. Using overall round data and first half data, the minimax model is best for both professionals and college students according to both AIC and BIC. In the second half, however, the other models are often preferred. For professionals, QRE is best for both players according to AIC, and for column player, even according to BIC. For college students, EWA is best for column player according to AIC.

Combined with the results obtained by Palacios-Huerta and Volij (2008), for overall round data, the minimax model is highly successful in predicting the behavior of professionals. When we partition the data into halves, however, we obtain different conclusions. Although Wooders (2010) found that the choice frequencies of professionals in the first half is far from those implied by the minimax prediction, their behavior is still best fitted by the minimax model over the other competing models. Furthermore, in the second half, the minimax model performs poorly in the sense that, in addition to the fact that the choice frequencies of professionals are far from those implied by the minimax prediction, QRE outperforms the minimax model.

It is interesting to compare the results of teams and professionals from the perspective of model selection. The choice frequencies of teams from the first half data in our experiment and those of professionals from overall round data in PH-V experiment conform closely to those implied by the minimax prediction. However, their behavior differs in learning process because teams exhibit the behavior that is best fitted by the BL model, whereas professionals exhibit the behavior that is best fitted by the minimax model.

Next, we assess results of model selection at the decision-maker level in Table A15. The minimax model performs overwhelmingly well. Even according to AIC, the behavior of 75.0–80.0 percent of professionals and students is best fitted by the minimax model. According to BIC, its value becomes more than 90 percent. The learning models (EWA, RL, and BL) perform poorly compared

Table A15: The Percentage of the Best Fit Model at the Decision-Maker Level with Professionals and College Students in PH-V Experiment

			Model				
Criterion	Rounds	Treatment	EWA	RL	BL	QRE	MM
AIC	1-200	Professional	0.0%	10.0%	2.5%	7.5%	80.0%
		Student	0.0%	12.5%	0.0%	12.5%	75.0%
	1-100	Professional	0.0%	12.5%	2.5%	5.0%	80.0%
		Student	0.0%	7.5%	2.5%	10.0%	80.0%
	101-200	Professional	0.0%	2.5%	2.5%	17.5%	77.5%
		Student	0.0%	12.5%	2.5%	10.0%	75.0%
BIC	1-200	Professional	0.0%	2.5%	0.0%	2.5%	95.0%
		Student	0.0%	0.0%	0.0%	2.5%	97.5%
	1-100	Professional	0.0%	5.0%	0.0%	0.0%	95.0%
		Student	0.0%	2.5%	0.0%	2.5%	95.0%
	101-200	Professional	0.0%	2.5%	2.5%	2.5%	92.5%
		Student	0.0%	2.5%	0.0%	0.0%	97.5%

to our results. They are selected as the best fit models for less than or equal to 15 percent for all time intervals, perhaps because of the difference of the game played and/or the experimental design. First, the O'Neill game is simpler than RB game. As a result, subjects in RB game faced a cognitively more demanding task than those in O'Neill game, which led subjects in RB game to play more adaptively than subjects in O'Neill game. Second, in the PH-V experiment, subjects played the game face-to-face. This design might prevent subjects from calculating the optimal behavior from the previous information to avoid facial expressions that might reveal a move. Conversely, our experiment was computerized, and teams and individuals were isolated from each other. This allowed them to consider past outcomes deeply. Third, in our experiment, all information (the own choice, the opponent choice, and outcome of the game) up to the current round was displayed in the screen display. Subjects could access those information easily, perhaps facilitating adaptive play.

C Translated Instructions for the Team Treatment

Today, we're going to ask you make a simple decision. You will receive the rewards gained from the decisions as well as a participation reward of ¥1,400. Please read the guidelines below carefully before participating in the experiment. Do not talk or give signals to each other while reading the directions. We may ask you to leave if you do so. You cannot leave the room during the experiment unless it's an emergency. Please turn off your cellphones during the experiment. The use of writing implements during the experiment is prohibited.

The Experiment Description

First, you will pair up with another participant. You and your teammate will discuss and make a decision as a team. Teams will be formed as follows. First, you will draw a card with a seat number, and take a seat according to the number. There will be another participant who will be assigned to the same seat. That participant is your teammate. When making a decision, the two of you will freely speak about this experiment. Then, one of you will select the choices the team has made at the computer. Either one of you can operate the computer.

Take a look at a paper with the sign. On the document is either an X or Y. It represents the player role of your team. Teams assigned X are known as "Player X" and teams assigned Y will be "Player Y". The roles of Player (X or Y) do not change during the experiment. Teams assigned X will stay as Player X, and teams assigned Y will remain as Player Y until the experiment ends. Furthermore, depending on your letters X or Y, the experiment location will be different. Players will move to their experiment areas after reading this guideline.

You will be divided into pairs of two teams to play a simple game. A computer automatically chooses the pairs. Each pair comprises a team of Player X and a team of Player Y. Because Player X and Player Y are in different locations, your pair will not be in the same space. Your pair will not change during the experiment.

The rules of the game you play are as follows. Each team will receive ¥7,200 at the beginning of the experiment. In every round, each team will choose a letter from "C", "L", "F", "I", or "O". Winning and losing depends on the choice of Players X and Y.

Player X \ Player Y	C	L	F	I	O
C	Win	Loss	Loss	Loss	Loss
L	Loss	Loss	Win	Win	Win
F	Loss	Win	Loss	Loss	Win
I	Loss	Win	Loss	Win	Loss
O	Loss	Win	Win	Loss	Loss

Player X Win-Loss Standing

The table above shows the standings for Player X. The letters "C", "L", "F", "I", and "O" on the left side indicate Player X's choice while the letters on top indicate Player Y's choice. Wins and losses in the table represent the win or loss of Player X.

Player Y \ Player X	C	L	F	I	O
C	Loss	Win	Win	Win	Win
L	Win	Win	Loss	Loss	Loss
F	Win	Loss	Win	Win	Loss
I	Win	Loss	Win	Loss	Win
O	Win	Loss	Loss	Win	Win

Player Y Win-Loss Standing

The table above shows the standings for Player Y. The letters "C", "L", "F", "I", and "O" on the left side indicate Player Y's choice while the letters on top indicate Player X's choice. Wins and losses in the table represent win or loss of Player Y. Note that the win of Player X is the loss of Player Y and the loss of Player X is the win of Player Y.

For instance, if Player X and Player Y choose C, then Player X wins and Player Y loses. If Player X chooses C and Player Y chooses L, then Player X loses and Player Y wins.

If Player X wins, then Player X will receive ¥200 from Player Y, meaning that the money total of Player X will increase ¥200, and that of Player Y will decrease ¥200. If Player Y wins, then Player Y will receive ¥120 from Player X, meaning that the money total of Player Y will increase ¥120, and that of Player X will decrease ¥120.

You are going to play 120 rounds of this game. If either team run out of money, then that is game over for that pair. The money you have at the end of the experiment will be your reward. The reward will be divided in half for you and your teammate. If your team has ¥6,000 at the end of the game, then each member will receive a reward of ¥4,400 composed of a ¥3,000 reward and the ¥1,400 participation reward. For the pairs of teams with a team that ran out of money, the members of the losing team will receive a reward of ¥1,400 composed of a ¥0 reward and the ¥1,400 participation reward. The members of the winning team will receive the reward of ¥8,600 composed of half the ¥14,400 reward and the ¥1,400 participation reward.

If you have any questions, raise your hand quietly. A staff member will answer your questions privately.

Computer Display Descriptions and the Experimental Procedures

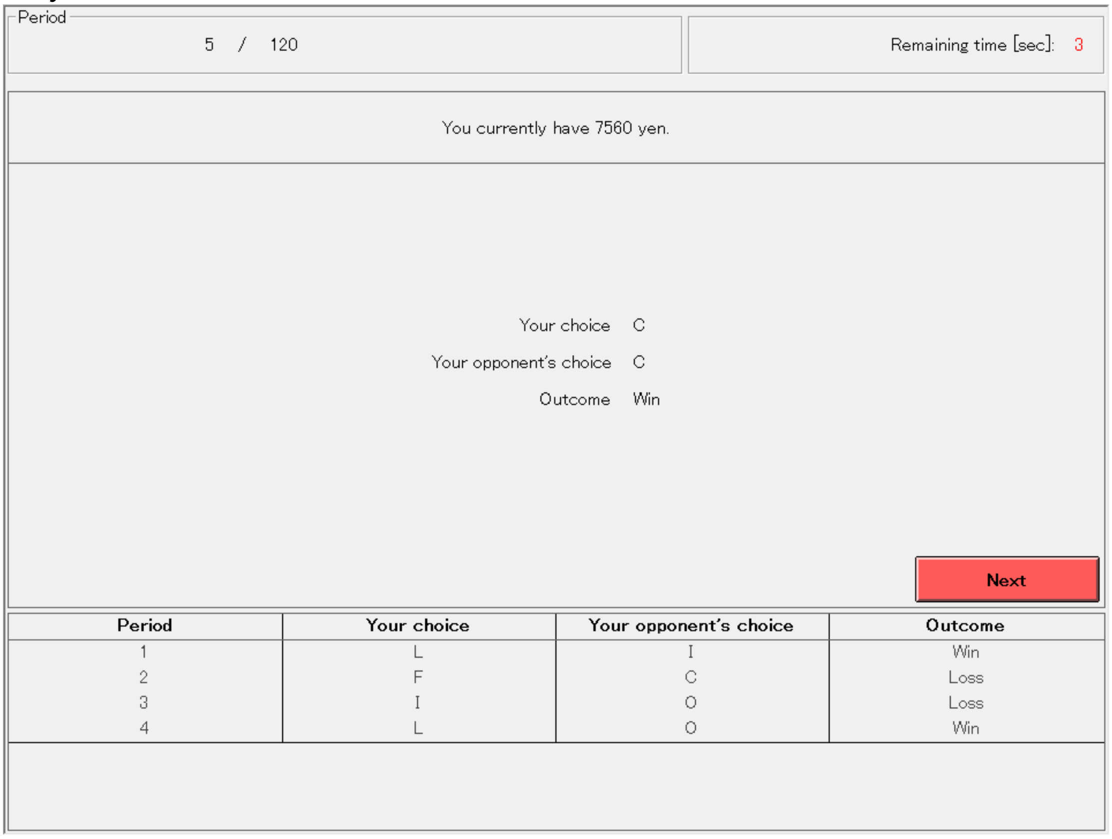
Player X Selection Screen

The screen above will be displayed on Player X's selection screen. On the top left is the current number of rounds. This display shows that this is the 5th round. In the middle left is the Player X standing. Wins and losses represent the wins and losses of Player X. On the bottom is the history that displays the round number, your choice, your opponent's choice and the outcome. On the upper middle right is your current money total. Right below that is the selection screen. You can choose and click either one of "C", "L", "F", "I", or "O". Once all teams finish choosing an action, the outcome will be displayed.

Player Y Selection Screen

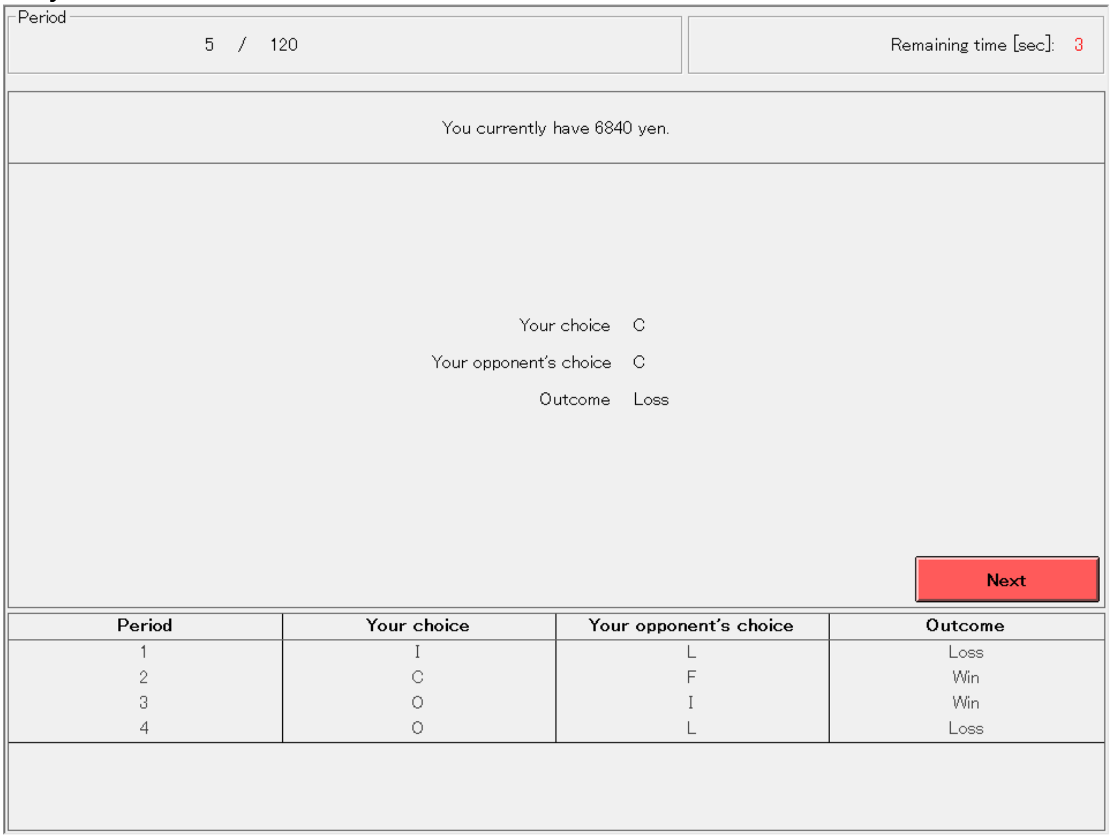
The screen above will be displayed on Player Y's selection screen. The screen display is the same as player X's display. In the middle left is the Player Y standing. Wins and losses represent the wins and losses of Player Y. You can choose and click either one of "C", "L", "F", "I", or "O". Once all teams finish choosing an action, the outcome will be displayed.

Player X Outcome Screen



The screen above is Player X's outcome screen. Similarly to the selection screen, it shows the current round on the top left, and the history on the bottom. It shows your current money total on the upper middle of the display and your choice, your opponent's choice, and the outcome below. Once you have checked the outcome screen, click Next.

Player Y Outcome Screen



The screen above is Player Y's outcome screen. The screen display is the same as Player X's display. Once you have checked the outcome screen, click Next.

If you have any questions, raise your hand quietly. A staff member will answer your questions privately.

Below is the description of the experimental procedures.

Experimental Procedures

1. We will begin by assigning seats. Follow the staff directions and take a card. Please take a seat according to the number indicated on the card.
2. Once you take a seat, there will be 5 minutes for you to think over the experiment. Discuss the experiment freely with your teammate.
3. 5 minutes later, the experiment will begin with the announcement, "The experiment starts now. Please look at the display."

Notes

- Please discuss quietly so that the other teams cannot hear you. Inappropriate behaviors such as loud conversations or speaking to other teams may result in a ¥0 reward.

If you have any questions, raise your hand quietly. A staff member will answer your questions privately.

D Translated Instructions for the Individual Treatment

Today, we're going to ask you make a simple decision. You will receive the rewards gained from the decisions as well as a participation reward of ¥1,400. Please read the guidelines below carefully before participating in the experiment. Do not talk or give signals to each other while reading the directions. We may ask you to leave if you do so. You cannot leave the room during the experiment unless it's an emergency. Please turn off your cellphones during the experiment. The use of writing implements during the experiment is prohibited.

The Experiment Description

First, take a look at a paper with the sign. On the document is either an X or Y. It represents your player role. Persons assigned X are known as "Player X" and persons assigned Y will be "Player Y". The roles of Player (X or Y) do not change during the experiment. Persons assigned X will stay as Player X, and persons assigned Y will remain as Player Y until the experiment ends. Furthermore, depending on your letters X or Y, the experiment location will be different. Players will move to their experiment areas after reading this guideline.

You will be divided into pairs of two persons to play a simple game. A computer automatically chooses the pairs. Each pair comprises a person of Player X and a person of Player Y. Because Player X and Player Y are in different locations, your pair will not be in the same space. Your pair will not change during the experiment.

The rules of the game you play are as follows. Each of you will receive ¥3,600 at the beginning of the experiment. In every round, each of you will choose a letter from "C", "L", "F", "I", or "O". Winning and losing depends on the choice of Players X and Y.

Player Y

		C	L	F	I	O
	C	Win	Loss	Loss	Loss	Loss
Player	L	Loss	Loss	Win	Win	Win
X	F	Loss	Win	Loss	Loss	Win
	I	Loss	Win	Loss	Win	Loss
	O	Loss	Win	Win	Loss	Loss

Player X Win-Loss Standing

The table above shows the standings for Player X. The letters "C", "L", "F", "I", and "O" on the left side indicate Player X's choice while the letters on top indicate Player Y's choice. Wins and losses in the table represent the win or loss of Player X.

Player X

		C	L	F	I	O
	C	Loss	Win	Win	Win	Win
Player	L	Win	Win	Loss	Loss	Loss
Y	F	Win	Loss	Win	Win	Loss
	I	Win	Loss	Win	Loss	Win
	O	Win	Loss	Loss	Win	Win

Player Y Win-Loss Standing

The table above shows the standings for Player Y. The letters "C", "L", "F", "I", and "O" on the left side indicate Player Y's choice while the letters on top indicate Player X's choice. Wins and losses in the table represent win or loss of Player Y. Note that the win of Player X is the loss of Player Y and the loss of Player X is the win of Player Y.

For instance, if Player X and Player Y choose C, then Player X wins and Player Y loses. If Player X chooses C and Player Y chooses L, then Player X loses and Player Y wins.

If Player X wins, then Player X will receive ¥100 from Player Y, meaning that the money total of Player X will increase ¥100, and that of Player Y will decrease ¥100. If Player Y wins, then Player Y will receive ¥60 from Player X, meaning that the money total of Player Y will increase ¥60, and that of Player X will decrease ¥60.

You are going to play 120 rounds of this game. If either person run out of money, then that is game over for that pair. The money you have at the end of the experiment will be your reward. If you have ¥3,000 at the end of the game, then you will receive a reward of ¥4,400 composed of a ¥3,000 reward and the ¥1,400 participation reward. For the pairs with a person that ran out of money, the losing person will receive a reward of ¥1,400 composed of a ¥0 reward and the ¥1,400 participation reward. The winning person will receive the reward of ¥8,600 composed of ¥7,200 reward and the ¥1,400 participation reward.

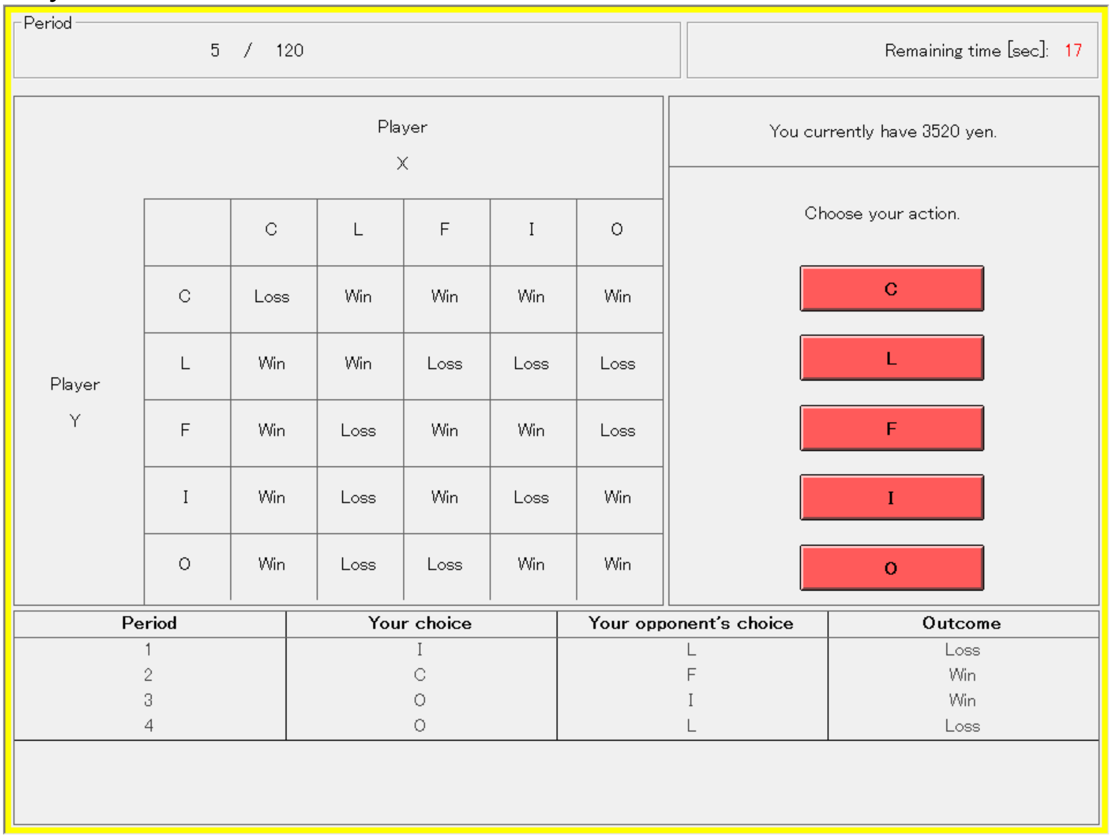
If you have any questions, raise your hand quietly. A staff member will answer your questions privately.

Computer Display Descriptions and the Experimental Procedures

Player X Selection Screen

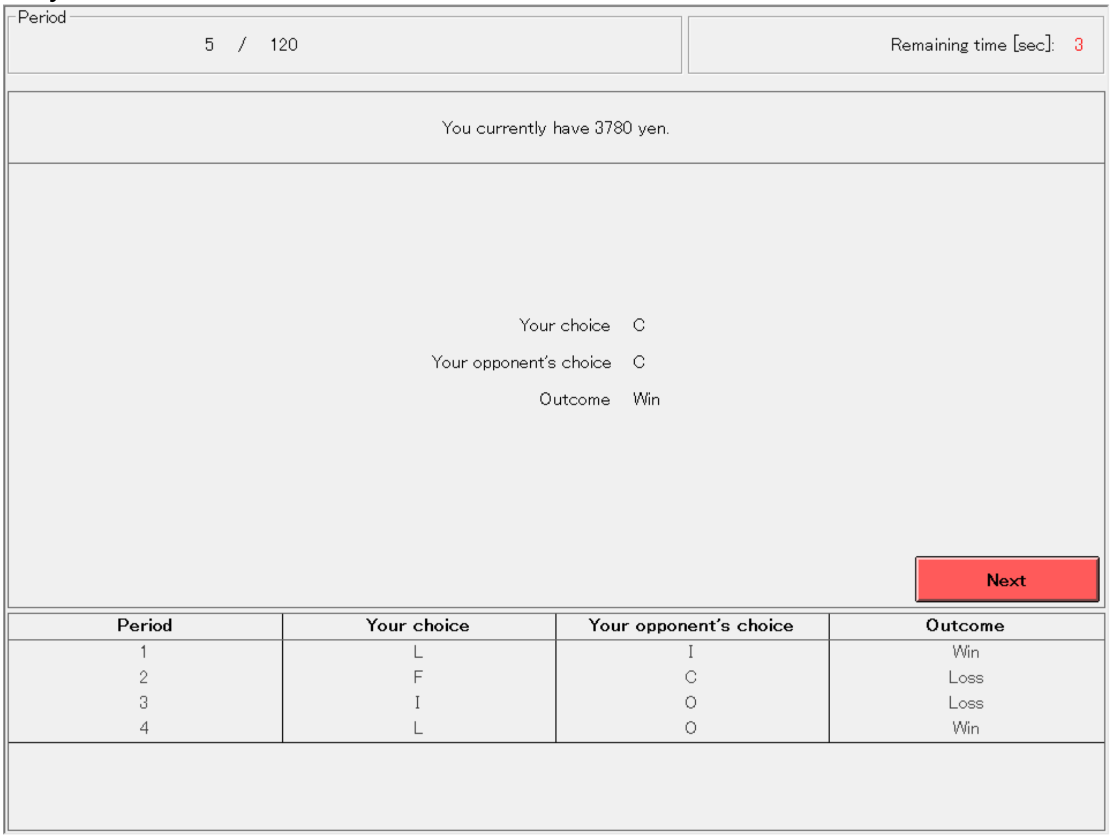
The screen above will be displayed on Player X's selection screen. On the top left is the current number of rounds. This display shows that this is the 5th round. In the middle left is the Player X standing. Wins and losses represent the wins and losses of Player X. On the bottom is the history that displays the round number, your choice, your opponent's choice and the outcome. On the upper middle right is your current money total. Right below that is the selection screen. You can choose and click either one of "C", "L", "F", "I", or "O". Once all of you finish choosing an action, the outcome will be displayed.

Player Y Selection Screen



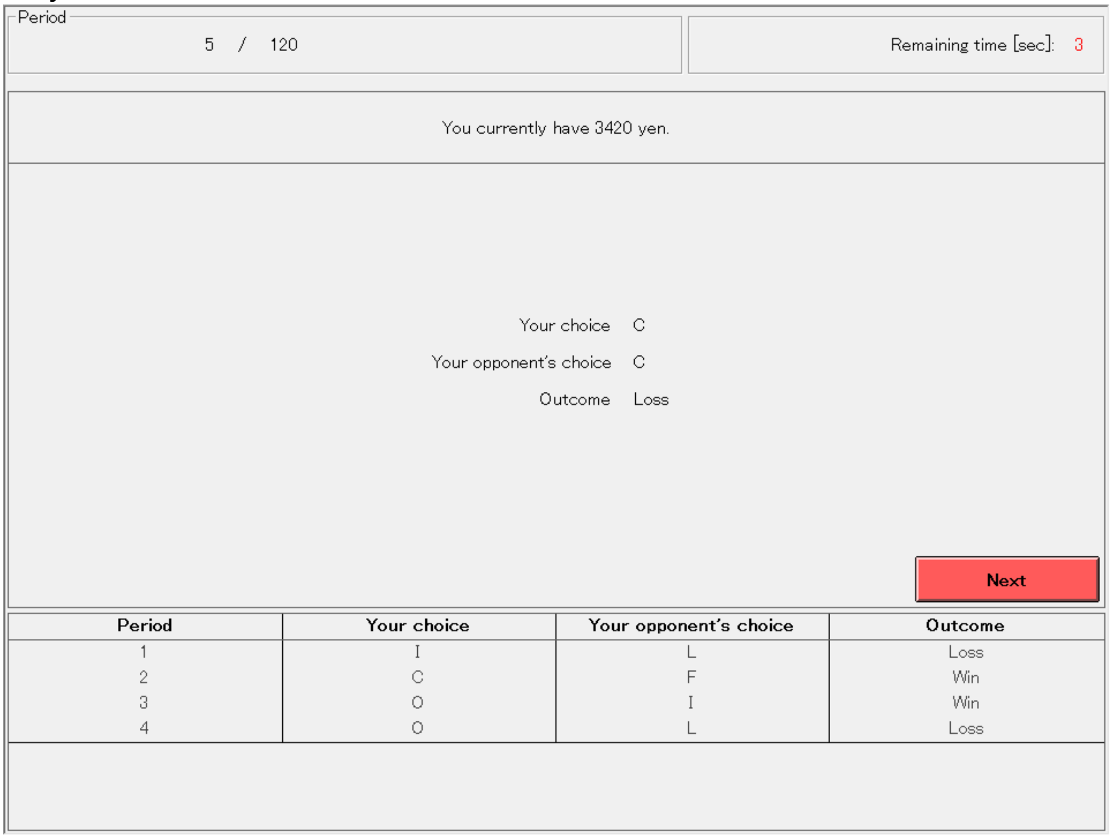
The screen above will be displayed on Player Y's selection screen. The screen display is the same as player X's display. In the middle left is the Player Y standing. Wins and losses represent the wins and losses of Player Y. You can choose and click either one of "C", "L", "F", "I", or "O". Once all of you finish choosing an action, the outcome will be displayed.

Player X Outcome Screen



The screen above is Player X's outcome screen. Similarly to the selection screen, it shows the current round on the top left, and the history on the bottom. It shows your current money total on the upper middle of the display and your choice, your opponent's choice, and the outcome below. Once you have checked the outcome screen, click Next.

Player Y Outcome Screen



The screen above is Player Y's outcome screen. The screen display is the same as Player X's display. Once you have checked the outcome screen, click Next.

If you have any questions, raise your hand quietly. A staff member will answer your questions privately.

Below is the description of the experimental procedures.

Experimental Procedures

1. We will begin by assigning seats. Follow the staff directions and take a card. Please take a seat according to the number indicated on the card.

2. Once you take a seat, there will be 5 minutes for you to think over the experiment.

3. 5 minutes later, the experiment will begin with the announcement, ”The experiment starts now. Please look at the display.”

If you have any questions, raise your hand quietly. A staff member will answer your questions privately.