Testing Risk Dominance and Payoff Dominance in Repeated Global Stag Hunt Games*

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Abstract

In any 2×2 global game, Carlsson and van Damme (1993b) showed that the game has a unique dominance solvable equilibrium that corresponds to the risk dominant equilibrium of the related common knowledge game with multiple strict equilibria. We test this prediction in repeated global stag hunt games. Under private information, a few cohorts coordinate on thresholds close to the global games prediction, but many cohorts coordinate on thresholds close to the efficient threshold. We argue that initial conditions and adaptive behavior play a key role in forming mutually consistent expectations in this game. We also investigate why the iterated dominance argument used to get uniqueness in the private information treatment is not salient.

JEL Classification: C72, C92, C73, D82

Keywords: Equilibrium Selection, Global Games, Risk Dominance, Payoff Dominance, Learning, Stag Hunt, Human Behavior, Experiments.

1 Introduction

Multiple strict equilibria arise in many economic situations: for example, team production, public good provision, currency attacks, bank runs, market entry, and technology adoption, see Cooper (1999). The refinements literature attempts to solve this indeterminacy by imposing additional rationality restrictions or by requiring additional robustness properties to refine the Nash equilibrium concept. However, because the equilibria are strict they survive all of the usual refinements, see van Damme (1991).

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In an innovative paper, Carlsson and van Damme (1993b) demonstrate that converting a complete information game with multiple strict equilibria into an incomplete information game, called a global game, results in many cases in a unique dominance solvable equilibrium prediction. The conversion is motivated by the observation that even in common information games, where the game form is common knowledge, players are uncertain about others utility from the game form. Usually, the theory of global games assumes a special case of this general problem in which the incomplete information game arises from players each observing a noisy signal of a common state variable.

Morris and Shin (2001) motivate the importance of global games analysis by observing that it is a "...heuristic device that allows the economist to identify the actual *outcomes* in such games, and thereby open up the possibility of systematic analysis of economic questions which may otherwise appear to be intractable." They argue that multiple equilibria is the consequence of two modeling assumptions: First, the economic fundamentals are assumed to be common knowledge; Second, players are assumed to be certain about others behavior in equilibrium, see also Morris and Shin (2000). They write, "...global games allow modelers to pin down which set of self-fulfilling beliefs will prevail in equilibrium."

While we agree with Morris and Shin that it is unlikely people have indeterminate beliefs, our purpose in this paper is to argue against the position that these beliefs can be determined purely by deduction alone. Instead, we urge a return to Nash's original interpretation of an equilibrium as the stochastic steady state of some "mass-action" game, see Nash (1950, p.21-23).[1] In our view, historical accident and dynamic process play a key role in forming mutually consistent expectations in games with multiple strict equilibria.

Carlsson and van Damme (1993b, p.1012) do not rely only on common knowledge of rationality to justify the global games' predictions. They argue that for a great variety of learning processes the sequence of choices will eventually converge to the set of strategies that survive iterated elimination of strictly dominated strategies, see Milgrom and Roberts (1989). This suggests that the global games approach may also be interpreted as the stochastic steady state of a realistic learning process, which we do here.

In this paper, we test the global games' prediction for the stag hunt game analyzed in Carlsson and van Damme (1993a). The stag hunt game models a situation in which symmetric players have two choices: a safe choice that guarantees a payoff of q and a risky choice that yields a higher payoff than q if enough other players choose it, but yields a lower payoff than q if too many players choose the safe choice. Specifically, consider the class of stag hunt game forms depicted in Table 1. The game has two strict equilibria either everyone chooses T, the risky choice, or everyone chooses B, the safe choice. The equilibria are Pareto ranked with all T being preferred by everyone to all B. While this favors T, strategic uncertainty, which is inherent in the strategy coordination problem, may led players to choose B instead. Intuitively, if the number of people who have to choose T or if q is close to 1, then it is more likely that people will choose B, the safe choice.

[1] Actually, Cournot (1838, p.81) may have been the first to characterize a mutual best response outcome as the steady state of a dynamic process. In translation, Cournot characterizes conditions for the equilibrium of a Cournot Duopoly to be "stable", where by "stable" he means "if either of the producers, ..., leaves it temporarily, he will be brought back to it by a series of reactions, ..."

Tab. 1: A Class of Stag Hunt Games when $0 < q < 1$

	T	B
T	1	0
B	q	q

2 Analytical Framework

To focus the analysis, consider complete information stag hunt game forms where n identical players, indexed by i, simultaneously choose between T and B. Let k denote the number of players, including i, that choose T. Each player i is matched with the other $n-1$ players and earns the average payoff from these matches, which is the matching protocol used in the experiment. (We call this a mean matching protocol.) Player i's payoff to T is $p(\frac{k}{n}) = \frac{k-1}{n-1} \cdot 1 + \left(1 - \frac{k-1}{n-1}\right) \cdot 0 = \frac{k-1}{n-1}$ for $k \geq 1$[2] and to B is q.

Consider the strategy assignment in which all n players choose T. Since $k = n$, the payoff to T is 1. Deviating from the strategy assignment yields q, which is less than 1 by assumption. Hence, playing T is a best response to the other $n-1$ players choosing T and by symmetry a strict Nash equilibrium.

Consider the strategy assignment in which all n players choose B. Since $k = 0$, the payoff to B is q. Deviating from the strategy assignment yields 0, which is less than q by assumption. Hence, playing B is a best response to the other $n-1$ players choosing B and by symmetry a strict Nash equilibrium.[3]

All of the players prefer all T, which yields them 1, over all B, which yields them less than 1. The presence of multiple Pareto ranked equilibria confronts the player with a strategy coordination problem. As mentioned earlier, equilibrium refinements don't resolve the multiplicity problem. An alternative approach to deducing a determinant prediction is equilibrium selection theory.

2.1 Equilibrium Selection

Harsanyi and Selten (1988) struggle with the choice of selection theory and ultimately give priority to Payoff Dominance, which compares the efficiency of equilibria and, if it exists, selects the equilibrium that all players prefer. In the class of stag hunt games under consideration this principle selects the all T equilibrium regardless of the value of q, which does not capture the intuitive notion discussed in the introduction that the likelihood of all T should depend on q.[4]

Harsanyi and Selten (1988) develop Risk Dominance as the selection theory when Payoff Dominance fails to make a unique prediction. For $n = 2$, Risk Dominance is equivalent to choosing the equilibrium with the larger basin of attraction under best response dynamics. It is straightforward to show that the all T equilibrium has the larger basin of attraction when $q < 1/2$ in which case both Payoff Dominance and Risk Dominance agree on the selection of all T. However, when $q > 1/2$

[2] Since k cannot be less than 1 when player i chooses T, define $p\left(\frac{k}{n}\right) \equiv 0$ for $k < 1$. Notice that $p(x)$ is non-decreasing with $p(0) = 0$ and $p(1) = 1$ as required by Carlsson and van Damme (1993a, p.239).

[3] There are no other strict Nash equilibria, see Carlsson and van Damme (1993a, Proposition 2.1).

[4] In the global games to be introduced below, Payoff Dominance will be sensitive to q, because when $q > 1$ a player using Payoff Dominance selects B as it now strictly dominates T

the all B equilibrium has the larger basin of attraction in which case Payoff Dominance and Risk Dominance conflict.

For $n > 2$, Harsanyi and Selten (1988, p.207-209) use the tracing procedure to select the Risk Dominant equilibrium. It is straight forward to check the conditions given in Proposition 3.1 of Carlsson and van Damme (1993a) to find the critical value of q, denoted q^*, that determines if Risk Dominance and Payoff Dominance conflict: $q^* = 1/2$ as in the case where $n = 2$. Risk Dominance selects all T when $q < 1/2$ and all B when $q > 1/2$.

2.2 Global Stag Hunt Games

Carlsson and van Damme (1993b) develop an equilibrium selection theory based on the idea that the payoff parameters of a game cannot be observed with certainty. The complete information stag hunt in Table 1 is replaced by a payoff perturbed game: a Global Stag Hunt game.

Following Carlsson and van Damme (1993a, Section 4) assume that everything about the Stag Hunt game is common knowledge except the payoff to the safe choice q. Each player receives a signal q_i that provides an unbiased estimate of q. The signals are noisy so q is not common knowledge amongst the players. Let Q denote a uniform random variable that is distributed on the interval that strictly contains $[0, 1]$, i.e., $q \sim \mathcal{U}[a, b]$ where $a < 0$ and $b > 1$. So it is possible that $q > 1$ in which case B strictly dominates T and it is possible that $q < 0$ in which case T strictly dominates B. Let $(E_1, E_2, \ldots, E_n)$ denote an n-tuple of zero mean independently and identically distributed random variables. The E_i are assumed to be independent of Q and to have support within $[-1, 1]$. For $\varepsilon > 0$, let $Q_i^\varepsilon = Q + \varepsilon E_i$. The incomplete information model is described by the following rules:

1. A realization $(q, q_1, q_2, \ldots, q_n)$ of $(Q, Q_1^\varepsilon, Q_2^\varepsilon, \ldots, Q_n^\varepsilon)$.
2. Player i observes q_i and chooses between T and B.
3. Each player i receives payoffs as determined the actual q, the Table 1, the mean matching protocol, and choices made in step 2.

Carlsson and van Damme (1993a, Proposition 4.1) states that in any strategy that survives iterated elimination of strictly dominated strategies in the Global Stag Hunt Game, player i chooses T if $q_i < p^*$ and B if $q_i > p^*$ where p^* is given by

$$p^* \equiv \sum_{k=1}^{n} \frac{p\left(\frac{k}{n}\right)}{n},$$

which is the expected value from choosing T when the number of players choosing T is uniformly distributed on $\{0, 1, \ldots, n-1\}$. In general, this will not give the same critical value as Risk Dominance when n is greater than two, but for the mean matching protocol $p^* = 1/2$. Remarkably this is true for any $\varepsilon > 0$ that are arbitrary small (smaller than $\frac{b-1}{2}$ and $\frac{-a}{2}$). Carlsson and van Damme's argument thus gives another reason to expect the Risk Dominant equilibrium if the players have arbitrarily small uncertainty about q. In the Global Stag Hunt Game, using a threshold of $1/2$ is the unique dominance solvable equilibrium.

Any thresholds $p \neq p^*$ cannot be constituted as a mutual best response or an equilibrium for every player in the group. To illustrate this, suppose all players except player j use the same threshold at p, that is, they choose T if $q_i < p$ and B if $q_i > p$. Let player j's best response threshold be c, which means at $q_j = c$, his expected payoffs for playing T and B are equal. Expected payoff from playing B is q_j for player j, while expected payoff from playing T depends on other players' strategies. When player j observes c, his expected payoff from playing T is $(p-\varepsilon)+\frac{1-c}{1-0}\cdot 2\varepsilon$. Letting expected payoffs from two choices to be equal, we get

$$c = \frac{p+\varepsilon}{1+2\varepsilon}. \tag{1}$$

For any $\varepsilon > 0$, the only value that can make $c = p$ is when $c = p = 1/2$. Additionally, when $p > 1/2$, $c < p$ and when $p < 1/2$, $c > p$ which suggests that the myopic best response dynamic for all players will gradually reach p^* in equilibrium.

To be concrete, let ε be equal to $\frac{1}{8}$, the value used in the experiment, in equation (1), then the equation for the best response threshold is

$$c = \frac{1}{10} + \frac{4}{5}p. \tag{2}$$

To see that Payoff Dominance is no longer an equilibrium in the global game, set $p = 1$, then $c = \frac{9}{10}$.

2.3 Bounded Rationality

Experimental evidence suggests that people only engage in a few rounds of iterative thinking about their opponents, see Crawford et al. (2010). This evidence makes us skeptical of predictions based on the iterative elimination of strictly dominated strategies at least without experience in the game. This has led to the use of non-equilibrium models of strategic thinking like Level-k models and cognitive hierarchy models.

Interestingly, the non-equilibrium models also predict play by all but half of the step-0 thinkers will correspond to Risk Dominance at least for initial play before the subjects have had a chance to experience the game. Camerer et al. (2004, section III.B) provide an alternative route to Risk Dominance in stag hunt games with their cognitive hierarchy model. Rather than requiring common knowledge of rationality and mutual consistency of beliefs and choices, they assume participants believe that they do more thinking than other participants. Participants are actually heterogeneous with step-0 thinkers playing uniformly, step-1 thinkers best responding to a belief that everyone else is a step-0 thinker, and so on. In two player symmetric coordination games, their cognitive hierarchy model has all step thinkers except for half the step-0 thinkers conforming with the Risk Dominance/Global Games selection criterion.

Tab. 2: Version of Global Stag Hunt Game Form Used In the Experiment

	T	B
T	500	100
B	$Q+E_i$	$Q+E_i$

3 Experimental Design

The stage game form used in the experiment is given in table 2[5]. The stage game was played 100 times to give adequate experience for the iterative elimination of strictly dominated strategies to convergence to equilibrium. The values of Q used in the experiment were integers in the interval 0 to 600, that is, $Q \in \{0, 1, 2, \ldots, 600\}$. The sequences of a hundred values of Q were generated by a computer using a uniform distribution. As stated in the instructions, "Many sequences of one hundred Qs were generated. One of these sequences will be used in today's session." The sequence was chosen to be representative of a uniform distribution even in small samples. The units denote twentieths of a cent.

Two treatments were conducted. In the baseline treatment of common information about Q, $E_i = 0$. In the private information treatment, Q was only observed with error. The private signal error was $E_i \in \{-50, -49, \ldots, 49, 50\}$. The sequences were generated in the same way as the Q sequences. The same sequence of $Q + E_i$ was used in all sessions of a treatment, but different sequences were used for the common information treatment and the private information treatment.

The instructions were read aloud to insure the game was common information among the participants. After the instructions the participants filled out a questionnaire to establish that the participants knew how to calculate their earnings. There were always mistakes on at least one questionnaire and the section on calculating earnings was always reread to the participants. Many more mistakes were made in the private information treatment than the common information treatment. Appendix A contains the instructions, questionnaire, and screen shots of the graphical user interface.

Three sessions of three cohorts or nine cohorts were conducted for each treatment. Each cohort consisted of eight participants. Thus, each treatment used 72 participants and the total number of participants was 144. The participants were Texas A&M University undergraduates recruited campus wide using ORSEE, see Greiner (2004).

The experiment was programmed and conducted with the software z-Tree, see Fischbacher (2007). The experiment was conducted in the Economic Research Laboratory at Texas A&M University, which has 36 networked participant stations, in February and March of 2013. A five dollar show up fee plus their earnings in the session were paid to the participants in private and in cash. The average earning is about \$29.19 for a session that lasted between 70 and 90 minutes.

After the decision making portion of the session was completed and while they waited for their earnings to be calculated, participants filled out a questionnaire that asked them to explain their behavior in the session.

[5] We transform the game to $G_2 = 400 * \{G_1 + 0.25\}$, where G_2 is the game used in the experiment and G_1 is the game derived in section 2, to avoid decimal points and negative earnings in any periods.

4 Experimental Results

A useful way to look at the data is with histograms of the frequency of T among a cohort by either the private signal, $Q + E_i$, or Q depending on whether the treatment is private information or common information.[6] Figures 1 to 18 report the histograms by 25 period intervals for the private information treatment and by 50 period intervals for the common information treatment. The private information treatment fills more bins, because usually there are eight observations per period, than the common information treatment, where all eight observations are for the same Q. Also, there appeared to be more learning going on with private information than common information.

Cohorts 1 to 9 were conducted under the private information conditions. Looking down the page, one can see how the histograms are changing with experience. Cohorts 1 and 2 in figures 1 to 4 show evidence of learning to play the unique equilibrium of the private information game, 300, that is, fewer participants are choosing T when the private signal is over 400 in each twenty-five period interval. These two cohorts are the only ones to do this.

Cohort 3 in figures 1 to 4 is more typical of the results in the private information treatment. In periods 76 to 100, the participants implemented an almost perfect step function at 450, that is, when the private signal was less than 450 everyone in every period choose T, the risky action associated with the Payoff Dominant equilibrium, and when the private signal was more than 450 almost everyone in every period choose B.

Cohort 4 in figures 5 to 8 shows some unraveling towards the unique equilibrium but for signals in (400,450] more than fifty percent of the play is T. Cohorts 5 and 6 in figures 5 to 8 and Cohorts 7 to 9 in figures 9 to 12 all converge on a transition from all T to all B at around a private signal of about 450, well above the unique global game equilibrium threshold of 300.

Cohorts 10 to 18 were conducted under the common information conditions. Cohort 10 in figures 13 and 14 is perhaps the most remarkable. Cohort 10 coordinated perfectly on Payoff Dominance as the selection principle, that is, when Q was in [0,500] all eight participants played T in every period from 51 to 100 and when Q was in (500,600] all eight participants played B in every period from 51 to 100. However, Cohort 10 is the only common information cohort to do this.

Cohort 15's histogram is almost a perfect step function but at Q equals 400. The remaining common information cohorts all appear to step down at a Q in [400, 500]. The threshold (step down) coordinated on is cohort specific.

[6] The histograms were produced using the R statistics program, see R Core Team (2012).

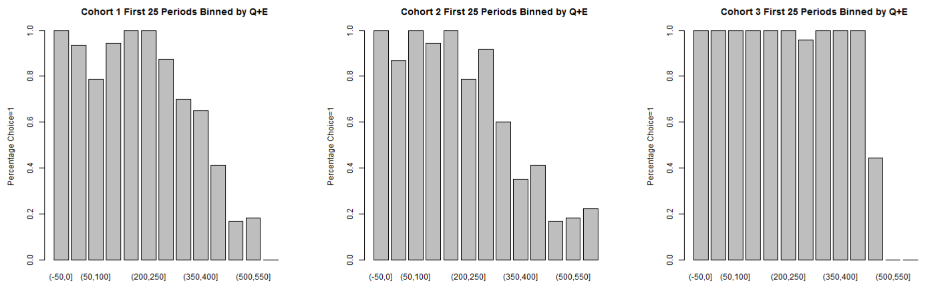

Fig. 1: Cohorts 1 to 3 periods 1 to 25

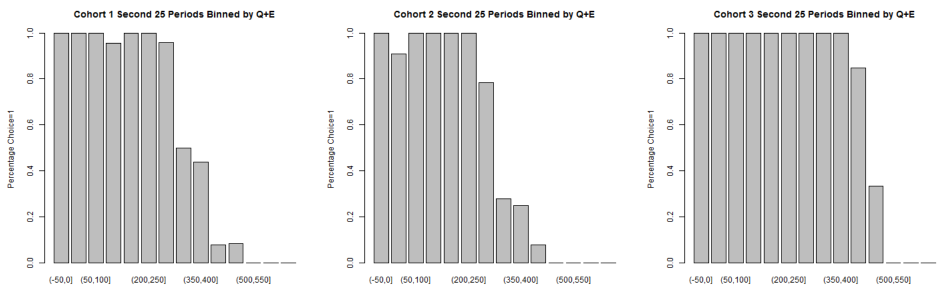

Fig. 2: Cohorts 1 to 3 periods 26 to 50

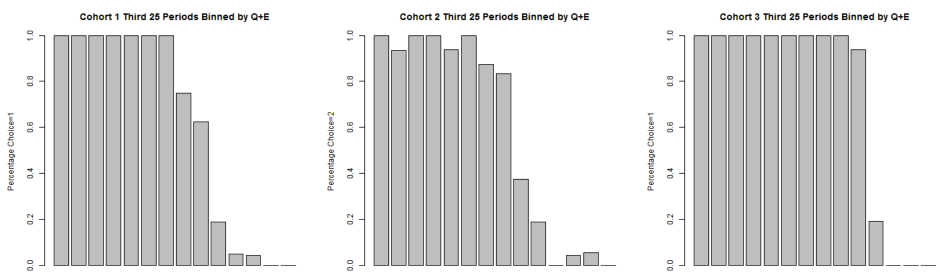

Fig. 3: Cohorts 1 to 3 periods 51 to 75

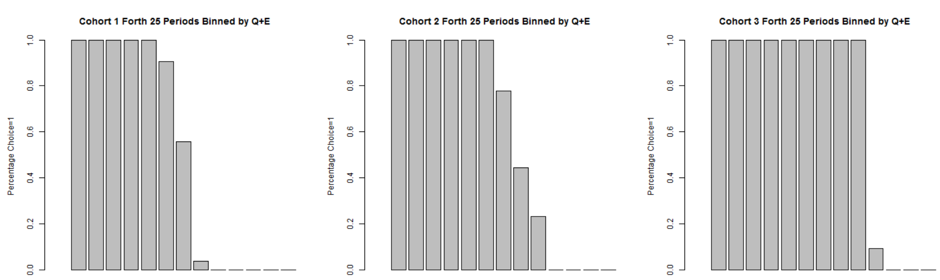

Fig. 4: Cohorts 1 to 3 periods 76 to 100

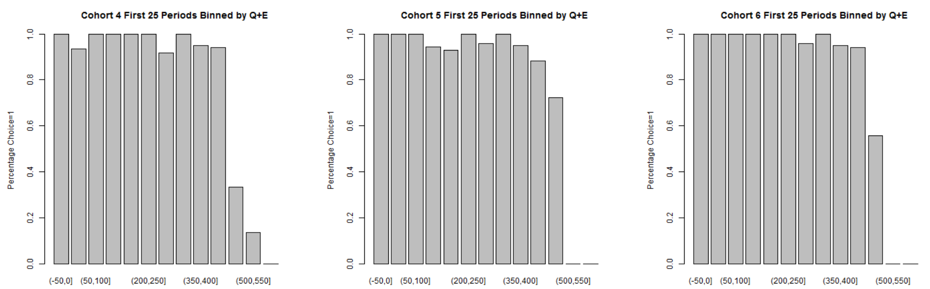

Fig. 5: Cohorts 4 to 6 periods 1 to 25

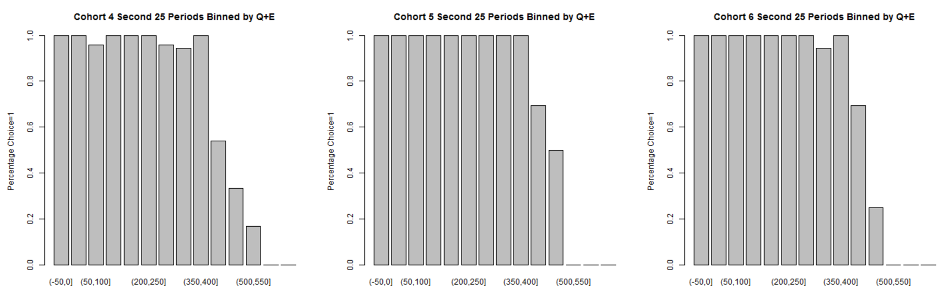

Fig. 6: Cohorts 4 to 6 periods 26 to 50

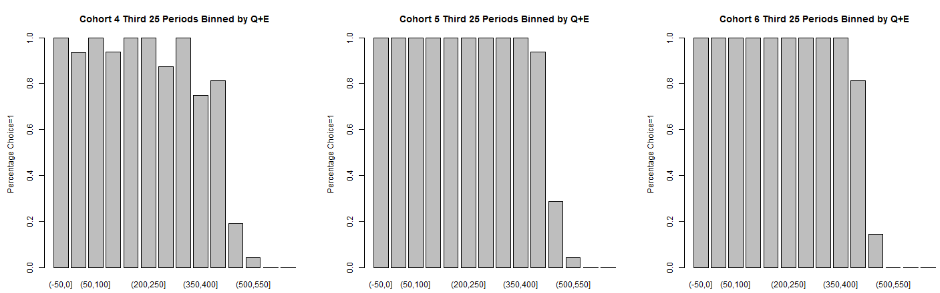

Fig. 7: Cohorts 4 to 6 periods 51 to 75

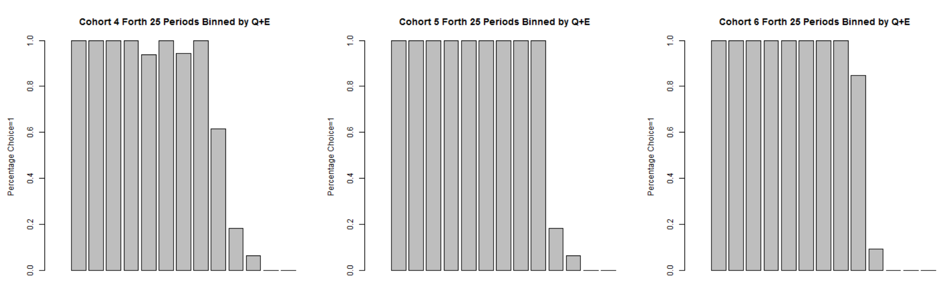

Fig. 8: Cohorts 4 to 6 periods 76 to 100

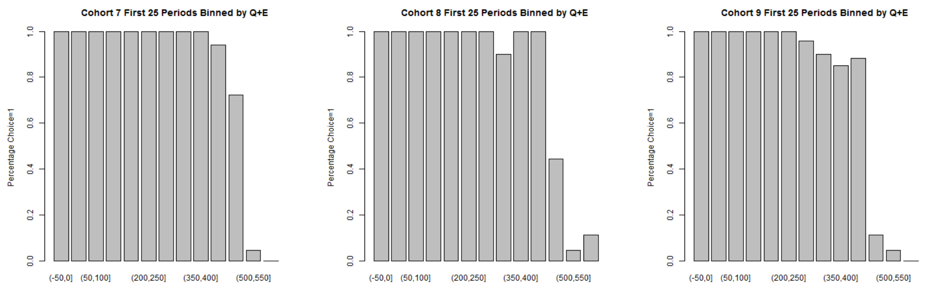

Fig. 9: Cohorts 7 to 9 periods 1 to 25

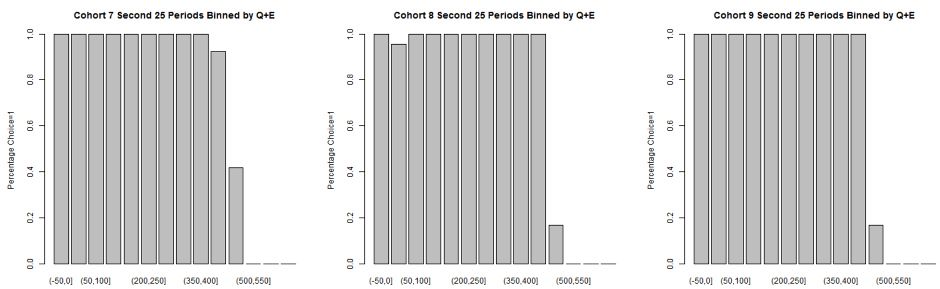

Fig. 10: Cohorts 7 to 9 periods 26 to 50

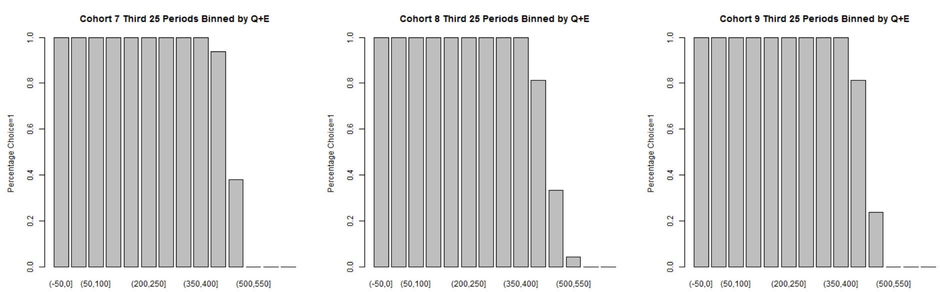

Fig. 11: Cohorts 7 to 9 periods 51 to 75

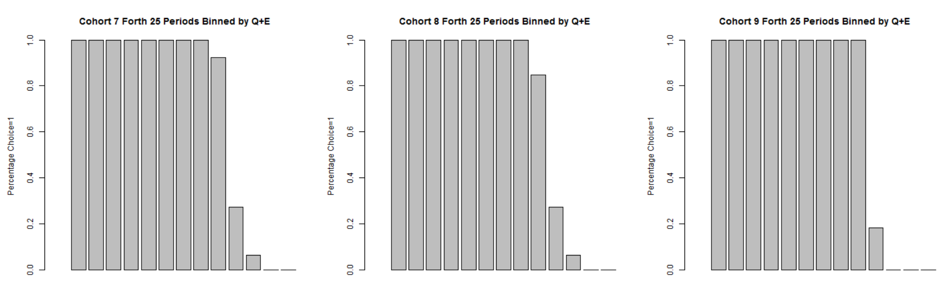

Fig. 12: Cohorts 7 to 9 periods 76 to 100

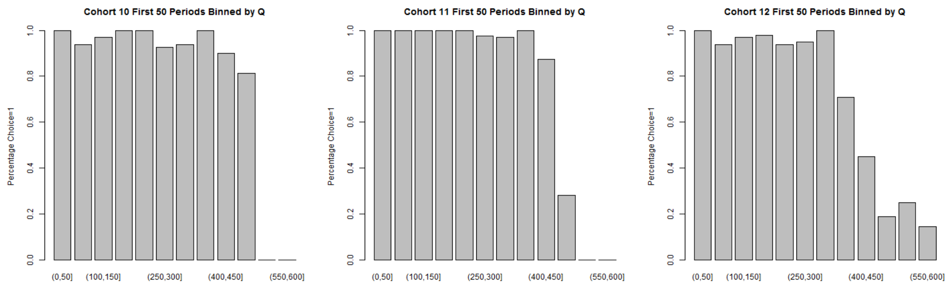

Fig. 13: Cohorts 10 to 12 periods 1 to 50

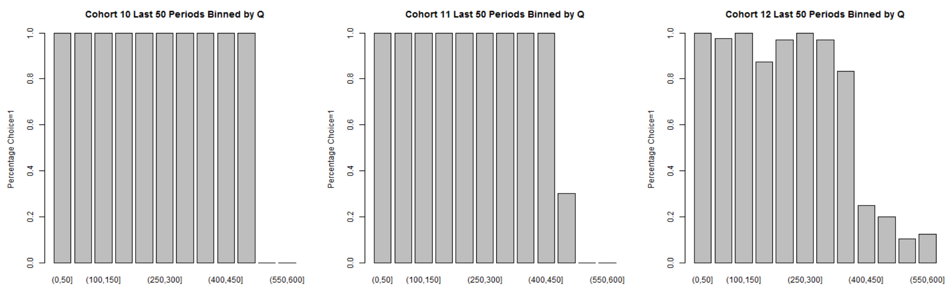

Fig. 14: Cohorts 10 to 12 periods 51 to 100

Fig. 15: Cohorts 13 to 15 periods 1 to 50

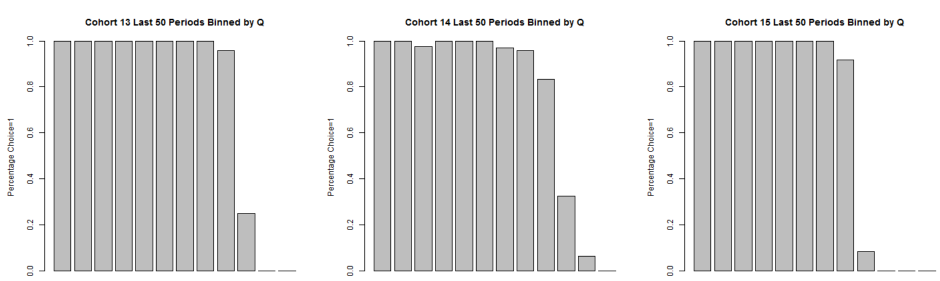

Fig. 16: Cohorts 13 to 15 periods 51 to 100

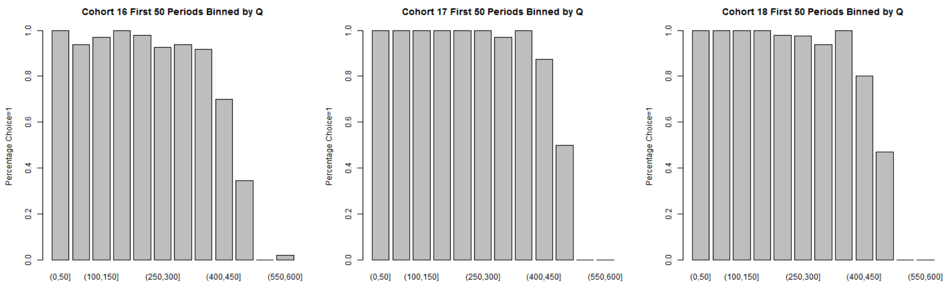

Fig. 17: Cohorts 16 to 18 periods 1 to 50

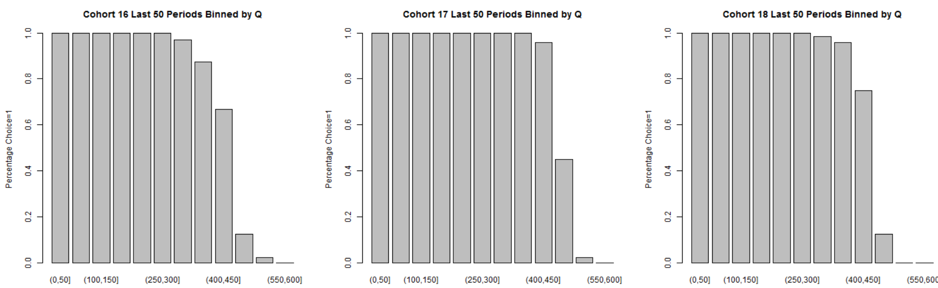

Fig. 18: Cohorts 16 to 18 periods 51 to 100

Cohort	Treatment	b_0	b_1	$Q+E=p^{-1}(0.5)$	Rank
cohort 1	Private	18.19322	-0.05566	326.9	1
cohort 2	Private	13.61744	-0.03688	369.3	2
cohort 3	Private	97.95560	-0.21550	454.8	11
cohort 4	Private	14.55148	-0.03331	436.8	7
cohort 5	Private	31.06881	-0.06750	460.3	15
cohort 6	Private	29.86815	-0.06791	439.8	8
cohort 7	Private	28.75324	-0.06249	460.1	14
cohort 8	Private	24.56898	-0.05394	455.5	12
cohort 9	Private	76.78000	-0.16730	458.9	13
cohort 10	Common	1195.455	-2.42100	494.0	18
cohort 11	Common	41.82621	-0.09081	460.6	16
cohort 12	Common	18.97667	-0.04660	407.2	4
cohort 13	Common	32.42025	-0.07150	453.4	10
cohort 14	Common	23.00271	-0.05080	452.8	9
cohort 15	Common	286.5956	-0.71550	400.6	3
cohort 16	Common	18.24756	-0.04320	422.4	5
cohort 17	Common	68.29392	-0.14474	471.8	17
cohort 18	Common	27.26117	-0.06254	435.9	6

Tab. 3: Estimated Logit Models and Critical Values by cohort for last 25 periods.

The histograms in Figures 1 to 18 appear to us to have the shape of a logistic function. In order to get a more precise measure of the heterogeneity of the various cohorts, we estimated the following logit model on the cohort data for periods 76 to 100:

$$p(Q+E)=\frac{e^{b_0+b_1(Q+E)}}{1+e^{b_0+b_1(Q+E)}},$$

where $p(Q+E)$ is the probability of T. Table 3 reports the estimated parameters and the critical value for the eighteen cohorts.[7]

While it is notable that the two values close to the Risk Dominant threshold of 300 occurred in the private information treatment and the one value essentially at the Payoff Dominant threshold of 500 occurred in the common information treatment, we can not reject the hypothesis that both treatments were drawn from the same distribution. The Mann-Whitney test statistic is 83 for the private information treatment and 88 for the common information treatment. For significance at the 10 percent level, the test statistic for the private information treatment would have to be less than 71.[8] Most estimated thresholds are around 450 regardless of treatment. A stochastic steady state appears to have emerged for most cohorts with a threshold in the interval [400,500]. These thresholds are cohort specific and would seem difficult to predict on an apriori basis.

Figures 19 and 20 illustrate the estimated logit models. The lines in the figures show the critical values at which fifty percent of the participants in a cohort are choosing T and fifty percent are

[7] The logit model was estimated using the glm() procedure in R, see R Core Team (2012). The reported estimate for cohort 12 excludes subject 17, who feel asleep twice, nodded off repeatedly, and appears to have played randomly. In the questionnaire, he wrote that he played randomly, which makes him a self-reported step-0 thinker and not a threshold user.

[8] See Conover (1980) table A7. The two-sample t statistic for a difference in treatment means is -0.8, which is also not statistically significant.

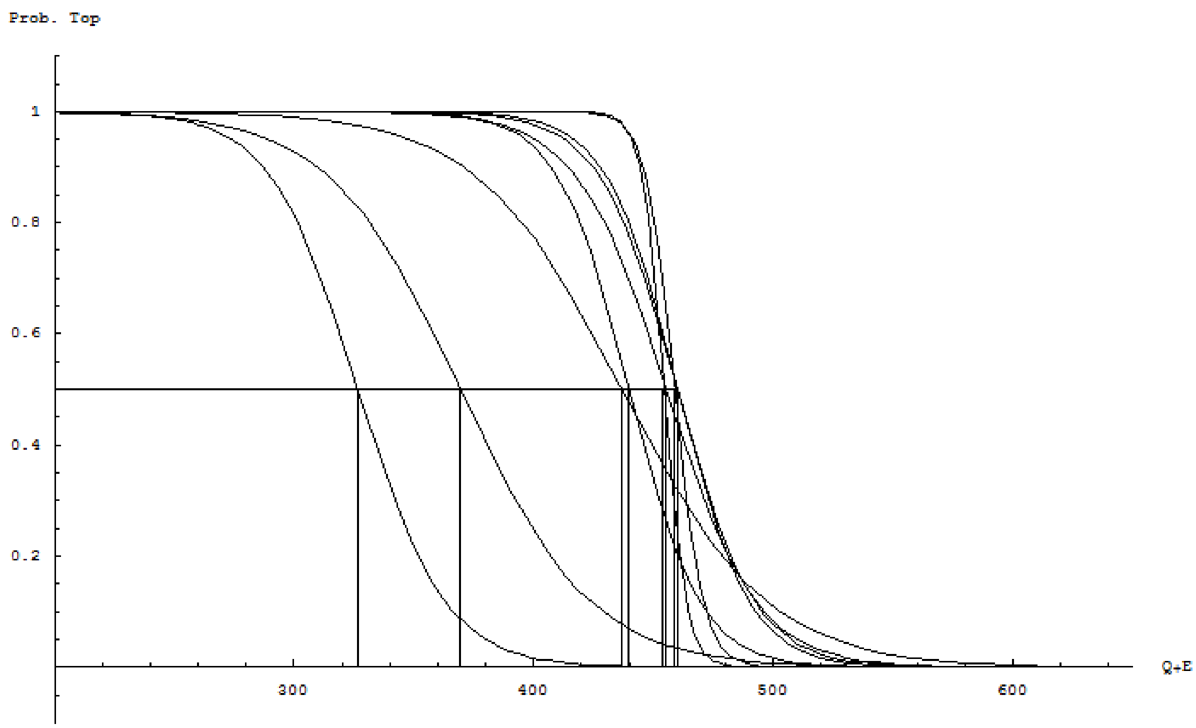

Fig. 19: Estimated Logit Models: Private Information Treatment

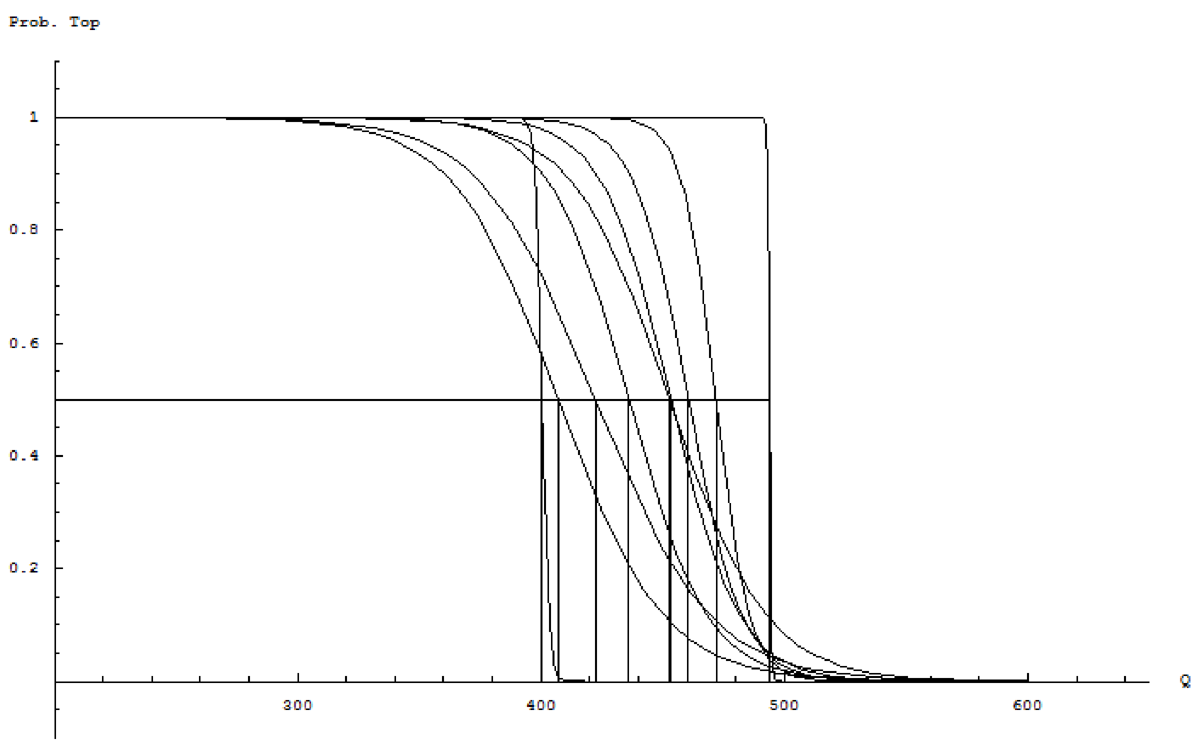

Fig. 20: Estimated Logit Models: Complete Information Treatment

choosing B. The private information cohorts have two outliers and seven tightly clustered around 450, while the common information cohorts have almost a uniform distribution in the [400,500] interval.

After the 100 choices were made, the subjects were asked to complete a debriefing questionnaire consisting of four questions. The first question was "What strategy did you use while playing this game? Please include details about what led you to choose A or B."[9] The answers were revealing. Seventy-two percent of the subjects in the private information treatment and ninety-two percent of the subjects in the common information treatment reported using a threshold. For example, a subject reported "I chose B when the odds were that Q was greater than 500. I used the estimate to decide this." Twenty-five different exact thresholds are mentioned in the 144 subject responses ranging from 300 to 500. One subject used a threshold of 300, the Risk Dominant threshold. The most common exact threshold was chose A if Q is less than 500 and B otherwise. It was chosen by nineteen percent of the subjects. Other popular choices were thresholds at 450, 400, and 440 to 445 in order of decreasing popularity.[10]

The last group comes, 440 to 445, from people who focused on what A earns when one participant chooses B. A typical answer was "I choose A or B depending on the spread that I was given for choice B. I calculated the costs of one of my 'teammates' deviating from A and choosing B. If one person deviated and I picked A I would receive 442, if 2 picked B I would get 385 and so on. If the bottom boundary of my spread for Q was greater than 442 I choose B. If it was not then I chose A."

Ten percent of the subjects reported what we call a fuzzy threshold. They would chose A for sure if Q was less than w and B for sure if Q was more than z, where $w < z$, and sometimes one or the other for Q in $[w, z]$. For example, a subject wrote "If B was over 500, I would choose B. If B was under 400 I automatically chose A. If B was between 400 and 500, I debated whether or not to choose B, more times than not deciding to do so."[11]

The second debriefing question was "Did you change your strategy over time?" Fifty-four percent of the subjects in the private information treatment and two-thirds of the subjects in the common information treatment reported changing their strategy over time.

The third debriefing question question was "If you changed your strategy, what made you change it." The typical response was the behavior of the other players in particular the need to coordinate on the same threshold. For example, a subject wrote "I was initially choosing the highest number of all those provided, so that was typically A unless B was a higher number. However, through the experiment other participants stopped choosing the highest number ($A = 500$) when B became more than 400." Our interpretation of this quote is that the participant started using what might be called a wishful thinking strategy (Maximax) because they write that the payoff to A was 500.

[9] This is a direct quote. Participant choices were labeled A and B in the experiment. The risky choice T used up to now was labeled A and the safe choice B was labeled B.

[10] If we treat a strict threshold player as someone who always chose A for Q below some value and always chose B for Q above the same value, then inspecting the individual data reveals that for the last 25 periods 76 percent of the subjects in the private information treatment and 81 percent of the subjects in the common information treatment were strict threshold players.

[11] Subjects using a fuzzy threshold seem to be engaged in fast and slow thinking popularized by Kahneman (2011). Schotter and Trevino (2013) exploit the difference in measured response time to accurately predict observed individual thresholds in a global game.

Over time they learned that the group was coordinating on a threshold of 400 and this led them to change their behavior. Reading the debriefing answers from the cohort that perfectly coordinated on the Payoff Dominant threshold of 500, cohort 10, we are now convinced that subjects initially started with a wishful thinking strategy rather than any equilibrium concept like Payoff Dominance. It is only after observing dis-coordination that they begin thinking about how to coordinate with the group.

The forth question asked participants "If you could play this game again, what would you do?" Fifty-one percent answered that they would do the same thing. Thirty-one percent answered that they would change their strategy especially using the strategy that they adopted at the end of the session earlier. Other frequently mentioned answers include wishing that they could communicate and that they chose A more often.

A comparison of the location of the logit estimate of the group threshold by 25 period bins reveals very little movement in the estimated threshold. For the nine private information cohorts, the average absolute value of the change from the estimated threshold in the first 25 periods and the last 25 periods is 22 units. For the nine common information cohorts, the average absolute value of the change from the estimated threshold in the first 25 periods and the last 25 periods is also 22 units. Interestingly, eight out of the nine private information cohorts decline between the first and last 25 periods, that is, in the direction predicted by the theory, while five of nine common information cohorts increase, which is slightly more than one would expect from chance.

It might seem puzzling that there is so little learning in the private information treatment when myopic best response dynamic theory suggests that subjects should be learning iterated dominance. If we always round down fractions to integers, it takes 20 best response iterations to go from the Payoff Dominant assignment of all use a threshold of 500 to the Risk Dominant assignment of all use a threshold of 300. Without rounding the process does not converge in a finite number of iterations. But notice that learning iterated dominance requires subjects to move to less efficient outcomes, which previous work suggests subjects are reluctation to do, see Van Huyck et al. (1997).

A calculation of the monetary incentive to deviate from an assignment may explain why subjects are not learning iterated dominance. In the private information treatment, the best response, c^*, to an assignment of all play a threshold p is given by the following equation: $c^* = 60 + \frac{4}{5}p$, which is derived in the same way as equation (2) in section 2.2. Consider an assignment to a threshold strategy combination of all use 450. The best response is a threshold of 420. However, the optimization premium, the monetary incentive to give a best response, is an average of *3.75 units or 0.2 cents*. This calculation is myopic because as behavior converges on 300 the group is moving to less efficient outcomes. If everyone conformed to a threshold of 450, they would each earn \$24.90 for the session. All participants using the Risk Dominant threshold of 300, which is what best response learning converges to, would earn an average of \$23.35 for the session, which is a \$1.55 dollar difference for the session and approximately a 1.6 cent difference per period. The lost efficiency is about eight times larger than the monetary incentive to best respond given an assignment to everyone to use 450 as their threshold. Previous work has shown that subjects are reluctant to converge towards less efficient outcomes. This reluctance combined with a low myopic incentive to best respond may explain the similar behavior observed under private and common information.

The low optimization premium relative to the inefficiency of the unique equilibrium is a property of the equilibrium solution. Scaling up the payoffs will make both larger by the same proportion. This can be seen in figure 21, which graphs the Expected Utility of the Payoff Dominant threshold, $Eu(q_i|500)$ in red, and the Risk Dominant threshold, $Eu(q_i|300)$ in blue, given a realization of q_i. The horizontal axis graphs q_i and the vertical axis graphs $Eu(q_i|p)$. Notice that the Expected Utility function is discontinuous at $Eu(500|500)$. At the Payoff Dominant threshold of all play 500 the expected utility from playing A is not 500, because on average half the participants observe a q_j above 500 and play B, which earns 100 per match, and half the participants observe a q_j below 500 and play A, which earns 500 per match, making the expected earnings 300. For observations $q_i \in \{0, 1, \ldots, 448, 449\}$ the player can be sure that in a Payoff Dominant assignment all of the other players receive a signal that induces them to play A and they all earn 500. Similar considerations give the Risk Dominant, $Eu(q_i|300)$, function.

The dashed line and black dot in the function give the best response, 460, to an assignment of all play 500. The area of the shaded triangle gives the expected earnings gained from deviating from the assignment to the best response. The difference between playing 460 and 500 is from observations $q_i \in \{460, 461, \ldots, 498, 499\}$ in which strategy 460 plays B while strategy 500 plays A. The average expected earnings lost from playing 500 is 6.67 (from the triangle area, 4,000, divided by 600). The area of the shaded polygon minuses the area of the shaded triangle gives the expected earnings lost from moving from the Payoff Dominance to the Risk Dominance (and global games solution). This loss is, on average, 33.33 or about five times larger than the gains from playing 460 instead of 500 when all other players play 500. Scaling the payoffs from 600 to 6,000 or 600,000 will not change the relative areas of the two shapes.

5 Discussion and Literature

Most of the experimental literature testing global games predictions focuses on variations of the speculative attack model of Morris and Shin (1998). The first test of global games predictions in the speculative attack model was Heinemann et al. (2004). In this game, an individual has two choices: 'attack' and 'not attack'. A player who attacks has an opportunity cost T. If a sufficient number of players choose to attack, they succeed and each of the attacking agents earns an amount Y. They assume that the number of players needed for a successful attack is a non-increasing function in Y. In this game, if $Y < T$, the dominant strategy is 'not attack'. There exists $\bar{Y}$ such that for $Y > \bar{Y}$, the dominant strategy is 'attack'. For Y such that $T < Y < \bar{Y}$, there are two pure Nash Equilibria, all 'attack' and all 'not attack'. The value of Y varied from period to period. Undominated threshold strategies were used by 92 percent of their subjects. In private information sessions, estimated mean thresholds were close to the unique equilibrium with low assurance conditions and below the unique equilibrium with high assurance conditions. In common information sessions, estimated mean thresholds were between the thresholds of the Payoff Dominant equilibrium and the global game solution. However, assuming subjects believe that other players choose to attack with a probability of $2/3$ for any state fit the data better. Estimated mean thresholds followed the comparative statics of the global game solution and were higher under private information than under common information. This implies that common information reduces the attack threshold

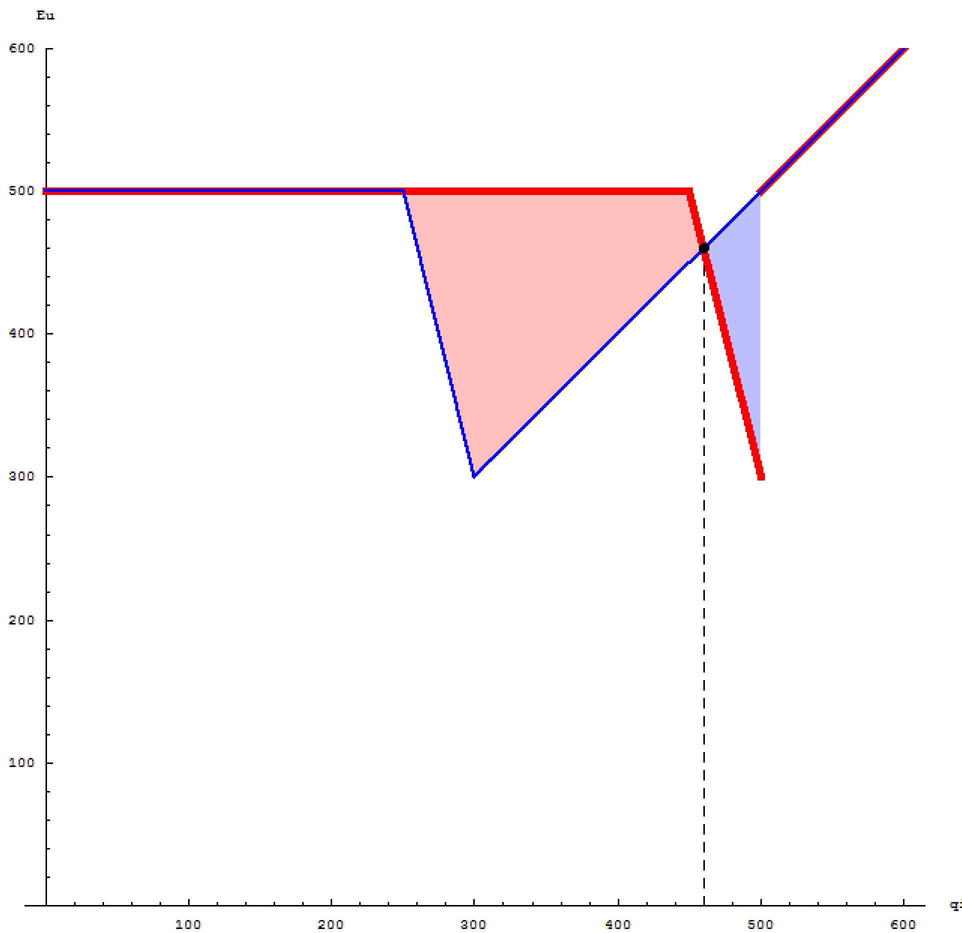

Fig. 21: The $Eu(q_i|500)$ function is indicated by the thick red discontinuous line and the $Eu(q_i|300)$ function by the thin blue continuous line.

and increases the prior probability of devaluation in the speculative attack game.

Kneeland (2012) classifies a restricted sample of subjects from Heinemann et al. (2004) into level-k types[12] and an equilibrium type. She estimates that around 70% of subjects are level-k types and 30% are equilibrium types. She suggests that "Under limited depth of reasoning, public information coordinates the beliefs of players with different depths of reasoning, increasing coordination."

Cornand (2006) has two more treatments in the speculative attack game as in Heinemann et al. (2004). In both treatments, subjects can observe two signals. In one treatment, subjects observe both private and common signals whereas subjects in another treatment observe two common signals. She finds that in the treatment with both private and common information, subjects use the public signal as a focal point. This implies that one clear public signal can control private information beliefs from private information.

Kawagoe and Ui (2010) consider a global game with ambiguous variance of noise terms (ε in this paper). They show in their experiment that low quality information (high ε) makes less players choose the safe action, whereas uncertainty of information quantity (ambiguous ε) makes more players choose the safe action. They suggest that providing a more precise variance of noise terms can decrease the probability of a credit crisis.

Duffy and Ochs (2012) model a speculative attack as a dynamic global game where subjects have multiple periods to decide whether to attack or not. They find little difference between static and dynamic games and suggest that treating a speculative attack game as a static game is reasonable. In contrast, Brindisi et al. (2011) observe a significant difference between static and dynamic global games in their two-person investment games. They show that endogenous timing for making a decision in global games sufficiently improves welfare. In their experiment, a player with optimistic beliefs about the profitability of investment invests earlier, which leads to an investment by others who would not invest otherwise. They argue, "the behavioral difference between static and dynamic global investments games is sufficiently different to justify a continued focus on behavior in dynamic games".

Shurchkov (2013) focuses on learning in a dynamic speculative attack global game. She finds that subjects act more aggressively than the theoretical predictions when faced with a high cost of attacking. In addition, the results show a high degree of learning where subjects adjust their beliefs about other subjects' behavior between the stages of the experiment.

In this literature, behavior follows the comparative static prediction of global games but the point estimates are not accurate. Subjects often coordinate on thresholds different from the global games prediction in favor of more efficient thresholds in which they can earn more if they can agree on the threshold. Allowing subjects to be able to observe other subjects' behavior, as in dynamic global games, can reduce strategic uncertianty which can move behavior towards more efficient thresholds. In addition, the differences in behavior under common and private information are not significant, which suggests low levels of learning to use iterated dominance in the private information condition.

Cabrales et al. (2007) analyzes a 2×2 game with a discrete signal that captures the logic of a global game. In their setting, after eliminating strictly dominated strategies; the game has a unique Nash equilibrium. In one treatment, the behaviors of the subjects converge to the theoretical

[12] She assumes 3 level-k types: $L1$,$L2$ and $L3$.

prediction after enough experience. In another treatment, there are some sessions that the behavior did not converge after 50 periods. The results of complete and incomplete information are similar, and they suggest that Risk Dominance plays a crucial role in explaining the behavior of the subjects.

Crawford et al. (2010) criticizes the global games approach on two grounds. First, there is no evidence that people initially perceive the uncertainty in a game as if they were playing a global game, that is, an incomplete information version of the game with special payoff perturbations. Instead, the incomplete information in a global games analysis is constructed to allow the iterated dominance argument. Second, the experimental evidence surveyed in their paper suggests that people stop far short of the many steps of iterated dominance that is needed to make a global games analysis yield a precise prediction.

There is a large literature on repeated stag hunt games, see Battalio et al. (2001) for references. Rankin et al. (2000) estimate thresholds from individual data from an experiment with similar stag hunt games, that is, in terms of this paper for $100 < Q < 500$. They also find a bias away from the risk dominance threshold towards more efficient thresholds. Stahl and Van Huyck (2002) using finite mixture models reject the threshold specification in favor of learning conditional behavior from individual data from an experiment with two ranges of experience: one with $100 < Q < 500$ and one with $300 < Q < 500$. Other differences include using random matching in Rankin et al. (2000) and mean matching in Stahl and Van Huyck (2002). The answers to the debriefing questionnaire used in the experiment reported here strongly support the view that subjects are using threshold strategies over learning conditional behavior.

6 Conclusion

The global games theory does not make accurate predictions in the global stag hunt game under private or common information. Only one cohort, cohort 1, was close to the predicted Risk Dominant threshold of 300. Cohort 1's estimated threshold was 327. Instead, behavior is systematically biased towards efficiency. Formally, a Mann-Whitney test fails to reject the hypothesis that both the common information and private information treatments were drawn from the same population.

There are strong cohort effects in the data. There is evidence of multiple equilibria in the common information treatment. For example, cohort 10 converged on Payoff Dominance, that is, all eight participants in the cohort behaved as if they were using Payoff Dominance for the last 50 periods. Cohort 15 converged on almost perfect implementation of a threshold of 400, half way between Payoff Dominance and Risk Dominance. The remaining cohorts converge to thresholds between 400 and 500. An inductive approach to equilibrium selection such as that proposed by Haruvy (1999) and Haruvy and Stahl (2004) might be able to make more accurate predictions in Global Stag Hunt games than the deductive selection principles examined in this paper.

Both estimated thresholds and self-reports reveal little tendency to converge toward either the Risk Dominant threshold or the Payoff Dominant threshold. The initial conditions appear to focus expectations and behavior converges on a threshold close to it. For the nine private information cohorts, the average absolute value change in the estimated thresholds between the first and last 25 periods is just 22 units. The common information cohorts had the same average change of 22 units. Interestingly, eight out of nine private information decline, while five of nine common information cohorts increase.

Under private information conditions, participants resist learning the iterative dominance solution perhaps because doing so requires them to adopt less efficient thresholds. The relationship between the myopic best response incentive and the lost efficiency is a property of the game rather than the size of monetary payoffs used in the experiment.

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Tab. 4: Treatment 1: Q and Q_i in each period

Period	$(Q, Q_1, Q_2, \ldots, Q_8)$	Period	$(Q, Q_1, Q_2, \ldots, Q_8))$
1	(275, 260, 269, 311, 265, 230, 296, 257, 266)	51	(329, 379, 303, 374, 314, 304, 328, 305, 317)
2	(113, 104, 91, 108, 122, 132, 154, 67, 155)	52	(236, 208, 236, 277, 255, 215, 235, 239, 240)
3	(496, 537, 462, 538, 494, 513, 504, 516, 501)	53	(544, 511, 524, 555, 555, 575, 519, 494, 502)
4	(403, 453, 403, 388, 386, 382, 358, 410, 420)	54	(92, 140, 54, 100, 123, 51, 65, 53, 60)
5	(66, 67, 29, 112, 70, 38, 92, 60, 110)	55	(463, 426, 465, 508, 504, 448, 456, 504, 462)
6	(548, 593, 585, 540, 571, 523, 517, 587, 543)	56	(259, 209, 291, 277, 242, 213, 271, 234, 250)
7	(323, 346, 337, 280, 274, 340, 281, 277, 362)	57	(397, 404, 418, 415, 362, 438, 404, 440, 347)
8	(121, 144, 161, 145, 153, 140, 135, 171, 151)	58	(497, 500, 451, 452, 472, 494, 503, 472, 453)
9	(577, 570, 539, 587, 534, 563, 577, 543, 586)	59	(455, 458, 480, 420, 438, 497, 448, 414, 488)
10	(363, 331, 379, 383, 365, 315, 357, 372, 368)	60	(119, 111, 75, 156, 117, 96, 82, 123, 107)
11	(15, -22, 60, 64, -7, 32, 60, 33, 28)	61	(576, 543, 619, 547, 601, 566, 597, 569, 549)
12	(315, 327, 334, 356, 288, 283, 299, 357, 294)	62	(477, 503, 503, 519, 479, 491, 481, 527, 478)
13	(432, 424, 396, 459, 470, 413, 413, 411, 412)	63	(46, 67, 85, 69, 88, 32, 87, 50, 22)
14	(482, 449, 456, 492, 472, 518, 479, 506, 480)	64	(169, 149, 152, 196, 124, 146, 166, 206, 219)
15	(125, 83, 141, 136, 108, 141, 84, 111, 124)	65	(204, 161, 176, 170, 173, 209, 231, 246, 162)
16	(37, 19, -6, 87, 17, 38, -10, 3, 76)	66	(225, 262, 241, 187, 242, 249, 175, 177, 232)
17	(486, 523, 528, 469, 521, 468, 482, 517, 505)	67	(513, 549, 552, 477, 546, 517, 557, 552, 483)
18	(165, 136, 173, 158, 127, 186, 169, 212, 152)	68	(5, 31, -1, 11, -42, 43, 2, 39, -34)
19	(19, 58, 25, -31, 4, 5, 42, 45, 33)	69	(420, 385, 414, 386, 385, 419, 416, 412, 397)
20	(335, 362, 331, 315, 361, 354, 359, 297, 354)	70	(47, 42, 75, 41, 34, 17, 30, 82, 57)
21	(243, 283, 203, 287, 229, 201, 281, 216, 195)	71	(307, 274, 292, 324, 356, 320, 310, 326, 324)
22	(475, 474, 458, 474, 428, 515, 503, 466, 429)	72	(551, 572, 519, 591, 559, 504, 534, 583, 594)
23	(247, 204, 217, 216, 270, 234, 261, 266, 218)	73	(576, 543, 589, 587, 526, 614, 538, 578, 580)
24	(220, 176, 247, 200, 255, 251, 242, 253, 201)	74	(158, 123, 172, 190, 195, 132, 172, 135, 117)
25	(429, 391, 420, 472, 407, 412, 423, 405, 423)	75	(87, 92, 90, 48, 129, 118, 119, 73, 48)
26	(110, 111, 107, 72, 102, 160, 60, 103, 67)	76	(412, 437, 455, 422, 412, 417, 380, 409, 375)
27	(329, 351, 355, 296, 350, 293, 368, 281, 289)	77	(433, 408, 383, 412, 464, 460, 468, 483, 404)
28	(290, 272, 335, 296, 332, 293, 299, 254, 328)	78	(180, 160, 168, 199, 155, 152, 148, 180, 130)
29	(502, 490, 466, 482, 485, 548, 540, 473, 523)	79	(591, 567, 626, 557, 594, 568, 603, 638, 609)
30	(15, -25, 37, 38, 57, 59, -30, 53, 43)	80	(370, 345, 344, 378, 408, 371, 354, 367, 375)
31	(106, 106, 131, 107, 131, 132, 70, 102, 86)	81	(600, 594, 642, 628, 609, 583, 622, 566, 571)
32	(402, 413, 402, 360, 423, 361, 402, 362, 381)	82	(192, 189, 189, 215, 185, 242, 240, 184, 222)
33	(55, 89, 85, 5, 95, 43, 7, 61, 30)	83	(337, 371, 324, 292, 356, 318, 371, 370, 364)
34	(596, 616, 602, 582, 613, 566, 582, 594, 563)	84	(116, 121, 101, 98, 163, 79, 139, 148, 68)
35	(4, -9, 4, -42, -5, 16, 14, 27, 28)	85	(361, 404, 358, 338, 342, 334, 398, 363, 401)
36	(484, 502, 470, 437, 450, 453, 485, 510, 473)	86	(342, 322, 351, 387, 308, 380, 388, 351, 390)
37	(56, 42, 9, 25, 57, 95, 84, 45, 43)	87	(550, 573, 510, 501, 510, 569, 576, 521, 511)
38	(282, 277, 328, 268, 290, 332, 240, 316, 318)	88	(51, 70, 76, 24, 55, 14, 24, 66, 73)
39	(230, 204, 261, 203, 252, 229, 217, 183, 274)	89	(582, 602, 595, 604, 586, 616, 540, 563, 585)
40	(426, 434, 439, 454, 422, 459, 440, 394, 467)	90	(309, 342, 288, 344, 276, 291, 324, 273, 296)
41	(39, 63, 16, 1, -9, 10, 7, 78, 11)	91	(508, 480, 533, 540, 495, 536, 506, 504, 523)
42	(253, 277, 227, 225, 263, 280, 242, 236, 206)	92	(157, 161, 192, 129, 199, 131, 185, 191, 171)
43	(74, 66, 108, 106, 117, 94, 87, 78, 63)	93	(367, 412, 375, 334, 358, 364, 412, 375, 378)
44	(325, 282, 348, 322, 307, 278, 375, 345, 350)	94	(201, 158, 201, 154, 233, 216, 228, 178, 199)
45	(117, 158, 74, 138, 141, 160, 112, 79, 123)	95	(143, 121, 112, 161, 121, 115, 132, 109, 141)
46	(399, 414, 360, 365, 390, 388, 362, 426, 449)	96	(224, 243, 196, 250, 260, 272, 176, 265, 258)
47	(308, 344, 280, 354, 310, 303, 349, 304, 352)	97	(502, 550, 464, 494, 529, 487, 472, 540, 549)
48	(255, 236, 290, 212, 228, 207, 245, 234, 272)	98	(211, 236, 209, 186, 189, 252, 259, 210, 229)
49	(571, 558, 612, 553, 575, 521, 603, 613, 587)	99	(287, 322, 321, 272, 243, 241, 265, 268, 333)
50	(174, 136, 139, 138, 213, 142, 186, 202, 144)	100	(319, 281, 294, 349, 275, 321, 272, 294, 290)

Tab. 5: Treatment 2: Q in each period

Period	Q	Period	Q
1	433	51	37
2	255	52	110
3	329	53	420
4	600	54	87
5	224	55	143
6	577	56	325
7	174	57	220
8	484	58	4
9	46	59	119
10	19	60	544
11	287	61	308
12	66	62	5
13	121	63	125
14	106	64	513
15	582	65	243
16	591	66	455
17	550	67	282
18	169	68	335
19	315	69	253
20	39	70	309
21	158	71	412
22	225	72	361
23	576	73	157
24	290	74	56
25	426	75	201
26	192	76	319
27	596	77	15
28	165	78	363
29	180	79	116
30	402	80	548
31	370	81	399
32	397	82	571
33	259	83	15
34	113	84	337
35	230	85	51
36	117	86	508
37	403	87	429
38	551	88	74
39	236	89	307
40	247	90	502
41	497	91	576
42	275	92	482
43	367	93	47
44	432	94	486
45	204	95	502
46	329	96	55
47	477	97	323
48	496	98	475
49	92	99	211
50	342	100	463

Supplementary Materials

Instructions used in the experiment

We provide here the instructions used in the 2 treatments, a treatment with private information and a treatment with common information. Participants were seeing these instructions from the screen while one of the authors (John Van Huyck) also read aloud during the experiment. After the instructions, another author (Ajalavat Viriyavipart) passed out the questionnaire to establish that the participants knew how to calculate their earnings.

1. A Private Information Treatment

Instructions

This session consists of one hundred separate decision making periods. You will participate in a group of eight people. At the beginning of period one, each of the participants in this room will be randomly assigned to a group of size eight and will remain in the same group for the entire one hundred decision making periods of the experiment. Hence, you will remain grouped with the same seven other participants for the next one hundred periods.

At the beginning of each period, you and all other participants will choose an action. An earnings table (on the next page) is provided which tells you the earnings you receive given the action you and all other participants chose. The actions you may choose are row A or row B. During a period everyone will have a private estimate of the same earnings table.

Your earnings are located in each cell. Units are twentieths of a cent. Your choice will be matched with the choices of the other participants in your group. You will receive the average of these earnings. The following table lists your choices A and B in the rows, and other participants in your group's choices in the columns.

Table

You have 2 choices, A and B, for all 100 periods. If you chose A and 5 other participants chose A and 2 chose B, then you would earn (500*5 + 100*2)/7 = 385.71 points or 19.29 cents. If you chose A and 2 other participants chose A and 5 chose B, then you would earn (500*2 + 100*5)/7 = 214.29 points or 10.71 cents. You will always receive Q points or Q/20 cents if you chose B.

What is Q?

When you choose B, your earning is Q. Q is an integer between 0 and 600 randomly determined by the computer. That means any number between 0 and 600 is equally likely to be picked by the computer.

One hundred values of Q have been generated by a computer. Many sequences of one hundred Qs were generated. One of these sequences will be used in today's session. All participants in the session will have the same value of Q in each period.

Before you make a decision you will not be told what Q is but instead you will receive an estimate of Q, which we will denote by E. Let's be more precise. After the computer randomly determines Q, it also picks a random integer between Q - 50 and Q + 50. This is your estimate E. Any number between Q - 50 and Q + 50 is equally likely to be picked by the computer. Although E does not tell you what Q is exactly, it gives an estimate of it. For example if you receive an estimate E = 406, then you know that Q is not less than 406 - 50 = 356 and it is not more than 406 + 50 = 456.

Note that although Q will be the same for you and the other participants, your estimates can be different. That is, for the same Q, the computer also randomly picks other estimates exactly in the same manner for all other participants. All of these estimates are chosen independently. Therefore, it is very likely that they will be different numbers; however, all estimates will be between Q - 50 and Q +50.

Making a choice

Making a choice consists of clicking on the button representing the row of your choice, which changes the numbers (in the table) to green and activates a confirmation button below the earnings table. You may either confirm your choice or change it by clicking on the button representing the other row. Your choice is not final until you have clicked on the confirm button.

After you have made a choice, a "please wait" message will be displayed and then the outcome will be reported.

Summary

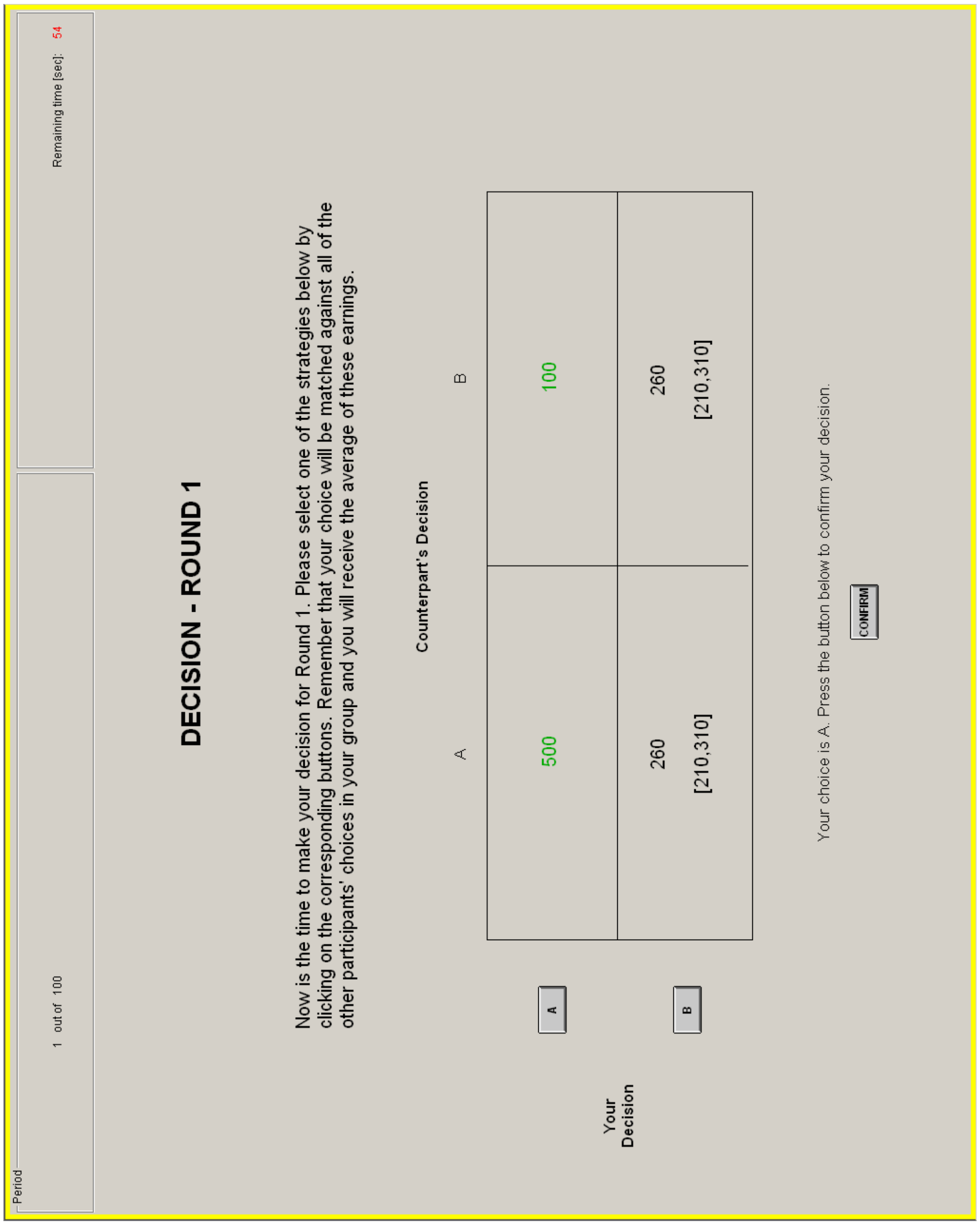
*** The experiment consists of one hundred separate decision making periods.

*** You have been randomly assigned to a group of size eight and will remain in the same group for the entire one hundred decision making periods of the experiment.

*** You make a choice by clicking on a button, which changes the numbers to green. You must also confirm your choice by clicking on the 'confirm' button.

*** Each period, if you choose A, your choice will be matched with all of the other choices and your earnings will be the average outcome. If you choose B, you will earn Q as explained before.

*** Your balance at the end of the session will be paid to you in private and in cash.



Screenshot 1 (Private Information Treatment)

Questionnaire

	A	B
A	500	100
B	280 [230,330]	280 [230,330]

Suppose the actual Q is 300, please calculate your earnings below. Please do not put your name or UIN in this questionnaire.

Your choice	Number of A's	Number of B's	Your earnings
A	7	0	500
A	0	7	
B	7	0	300
B	0	7	
A	5	2	
A	2	5	
B	5	2	
B	2	5	

2. A Common Information Treatment

Instructions

This session consists of one hundred separate decision making periods. You will participate in a group of eight people. At the beginning of period one, each of the participants in this room will be randomly assigned to a group of size eight and will remain in the same group for the entire one hundred decision making periods of the experiment. Hence, you will remain grouped with the same seven other participants for the next one hundred periods.

At the beginning of each period, you and all other participants will choose an action. An earnings table (on the next page) is provided which tells you the earnings you receive given the action you and all other participants chose. The actions you may choose are row A or row B. During a period everyone will have the same earnings table.

Your earnings are located in each cell. Units are twentieths of a cent. Your choice will be matched with the choices of the other participants in your group. You will receive the average of these earnings. The following table lists your choices A and B in the rows, and other participants in your group's choices in the columns.

Table

You have 2 choices, A and B, for all 100 periods. If you chose A and 5 other participants chose A and 2 chose B, then you would earn (500*5 + 100*2)/7 = 385.71 points or 19.29 cents. If you chose A and 2 other participants chose A and 5 chose B, then you would earn (500*2 + 100*5)/7 = 214.29 points or 10.71 cents. You will always receive Q points or Q/20 cents if you chose B.

What is Q?

When you choose B, your earning is Q. Q is an integer between 0 and 600 randomly determined by the computer. That means any number between 0 and 600 is equally likely to be picked by the computer.

One hundred values of Q have been generated by a computer. Many sequences of one hundred Qs were generated. One of these sequences will be used in today's session. All participants in the session will have the same value of Q in each period.

Making a choice

Making a choice consists of clicking on the button representing the row of your choice, which changes the numbers (in the table) to green and activates a confirmation button below the earnings table. You may either confirm your choice or change it by clicking on the button representing the other row. Your choice is not final until you have clicked on the confirm button.

After you have made a choice, a "please wait" message will be displayed and then the outcome will be reported.

Summary

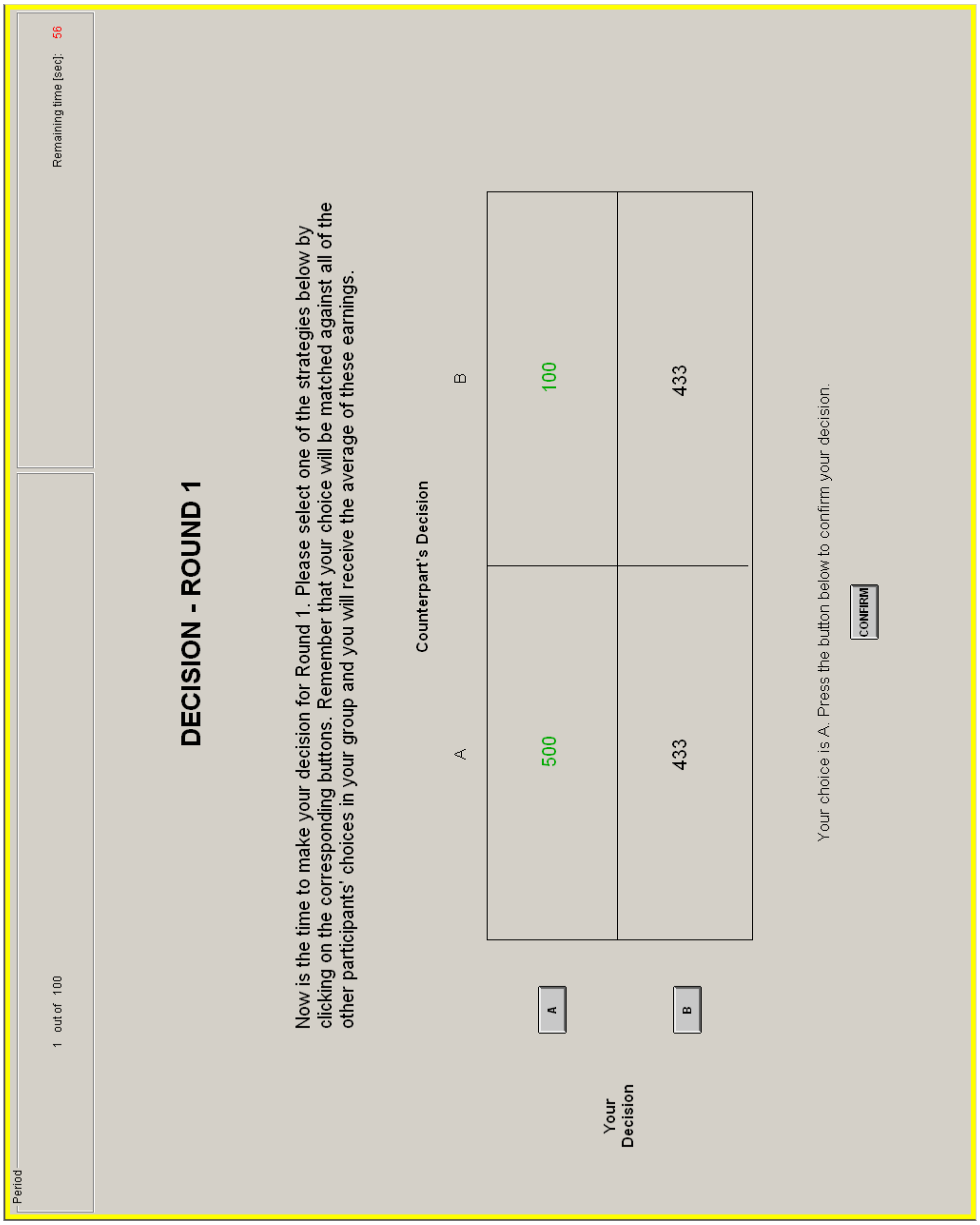
*** The experiment consists of one hundred separate decision making periods.

*** You have been randomly assigned to a group of size eight and will remain in the same group for the entire one hundred decision making periods of the experiment.

*** You make a choice by clicking on a button, which changes the numbers to green. You must also confirm your choice by clicking on the 'confirm' button.

*** Each period, if you choose A, your choice will be matched with all of the other choices and your earnings will be the average outcome. If you choose B, you will earn Q as explained before.

*** Your balance at the end of the session will be paid to you in private and in cash.



Screenshot 2 (Common Information Treatment)

Questionnaire

	A	B
A	500	100
B	280	280

Please calculate your earnings below. Please do not put your name or UIN in this questionnaire.

Your choice	Number of A’s	Number of B’s	Your earnings
A	7	0	500
A	0	7	
B	7	0	280
B	0	7	
A	5	2	
A	2	5	
B	5	2	
B	2	5	