ESSAYS IN COOPERATION AND COMPETITION

by

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A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Department of Economics

West Lafayette, Indiana

May 2022

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ACKNOWLEDGMENTS

I would like to take this opportunity to express my deepest gratitude towards my Ph.D. committee members Prof. Brian Roberson, Prof. Joe Mazur, Prof. Yaroslav Rosokha and Prof. Timothy Cason, for their guidance, patience, and support. Their guidance has transformed how I approach a problem and present ideas to others, significantly improving my research skills. Their passion and high standards for research have inspired me to push myself throughout my Ph.D. journey.

I am thankful to Purdue University Research Center in Economics for the continued support. I would like to thank Dr. Masha Shunko from Washington University for her guidance during my Ph.D. I would like to thank former and fellow graduate students, Dr. Stanton Hudja, Dr. Hajime Shimao, Dr. Chen Wei, Dr. Daniel Woods, Junya Zhou, Xinxin Lyu and Jieqiong Jin, for helping me navigate many difficult issues in this journey. I would also like to show gratitude to my friends and fellow students Indulekha, Debasmita, Mason, Danyang, Town, Dan, William, Tony, Aaron, and, Xiaotian for all the stimulating discussions and support throughout these years.

I am thankful to my partner, Soumendu, for helping me overcome the hurdles of my Ph.D. journey and helping me see the light during the darkest of times. I am grateful to my parents, Mr. Basudev Modak and Mrs. Minakshi Modak, for nurturing my curiosity from a young age and their continuous support for my education. Their countless sacrifices, hard work, and support have enabled me to become the person I am today.

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ABBREVIATIONS

Chapter 1

MMC	Multi-Market Contact
IRPD	Infinitely Repeated Prisoners' Dilemma
PD	Prisoners' Dilemma
NE	Nash Equilibrium
AA	American Airlines
UA	United Airlines
ORD	O'Hare International Airport
DFW	Dallas Fort Worth Airport
IAH	George Bush Intercontinental Airport, Houstan
S-Grim	Strong Grim Trigger
DBF(2011)	Dal Bó and Fréchette, 2011
E	Easy
H	Hard
C	Cooperation
D	Defection
AC	Always Cooperate
AD	Always Defect
Grim	Grim Trigger
TFT	Tit-for-Tat
DTFT	Defect Tit-for-Tat
S-TFT	Strong Tit-for-Tat
S-DTFT	Strong Defect Tit-for-Tat
SFEM	Strategy Frequency Estimation Method

Chapter 2

FOSD	First-Order Stochastically Dominates
FOS	First-Order Stochastically
FGM	Farlie-Gumbel-Morgenstern

OS2016	Olszewski and Siegel, 2016

ABSTRACT

This dissertation is a collection of three papers, each one being a chapter. The running subject of interest in all the papers is the strategic behavior of individuals in different environments. In the first chapter, I experimentally investigate collusive behavior under simultaneous interaction in multiple strategic settings, a phenomenon which I call *multiple contacts*. I investigate how multiple contacts impact collusive behavior when the players are symmetric or asymmetric. The second chapter is a joint work with Dr. Brian Roberson. In this chapter, we examine the role of cognitive diversity in teams on performance in a large innovation contest setting. We use a theoretical model to derive conditions under which increasing diversity can improve the performance in the large contest. Finally, in the third chapter, a joint work with Dr. Yaroslav Rosokha and Dr. Masha Shunko, we experimentally study players' behavior when they interact in an infinitely repeated environment, where the state of the world in each period is stochastic and dependent on a transition rule. Our main questions are how the transition rule impacts behavior and whether asymmetry in players impacts this.

In the first chapter, I study the phenomenon of multiple contacts using a laboratory experiment with multiple symmetric or asymmetric prisoners' dilemma games. When agents interact in multiple settings, even if defection or deviation from collusion in one setting can not be credibly punished in the same setting, it may be punishable in other settings. This can increase the incentive to collude. I observe a statistically significant increase in probability of punishment in one game after defection in another game under multiple contacts, but only when the games are asymmetric in payoffs. While punishment of defection increases in some situations, I do not find any significant increase in collusion due to multiple contacts in either symmetric or asymmetric environment. In addition to this result, to find further support for the theory which suggests that agents should use different strategies under multiple contacts, I estimate the underlying strategies that subjects use in my experiment. To this end, I modify popular strategies (e.g., Grim Trigger, Tit-for-Tat, etc.) to condition on the history observed in multiple strategic settings. I find that only for games with asymmetric

payoffs subjects use these modified strategies in the presence of multiple contacts.

The second chapter is a theoretical work. In our model of large team innovation contest, teams develop an innovation using the skills or perspectives (tools) belonging to individual team members and the costly effort they provide. Prizes are awarded based on the values of the teams' innovations. Within a team, the team members posses different skills or perspectives (tools) which may be applied to innovation problems. For a given innovation problem and a given level of team effort, different combinations of tools within a team may generate different values for the team innovation. In this context, we examine the issues of individual team performance as a function of a team's own composition and the overall performance of the contest as a function of the compositions of the teams. We find that the question of whether increasing diversity leads to an increase in expected performance, for both an individual team and the overall contest, depends on the efficiency with which teams are able to effectively apply diverse sets of tools to innovation problems. Thus, our paper provides a channel – other than a direct cost of diversity – through which diversity can be beneficial or detrimental depending on how efficient teams are at utilizing diverse sets of team member tools.

The final chapter is another experimental study. We study an enviroment where individuals interact with each other in a prisoners' dilemma game repeatedly over time. However, the payoffs of the prisoners' dilemma game is decided stochastically using a transition rule. We vary the transition rule from alternation to random and study the change in subject behavior when the interaction is either symmetric or asymmetric. Our results show that in asymmetric environment, alternation can improve cooperation rates. With random transition rule, symmetric environment is more conducive to cooperation. We find that asymmetric environment with random transition rules performs the worst in terms of cooperation rates.

1. DO MULTIPLE CONTACTS MATTER?

1.1 Introduction

Individuals, firms, and countries, often interact in multiple infinitely repeated strategic settings simultaneously. For example, airlines compete on multiple routes day in day out. Nations interact on multiple fronts, including trade deals, military treaties, and climate actions. These interactions are also infinitely repeated in nature. I call this phenomenon of agents simultaneously and repeatedly interacting in multiple strategic settings *multiple contacts*. In this paper, I use laboratory experiments to study the impact of multiple contacts on strategic behavior.

Although the phenomenon of multiple contacts is commonplace, this is extensively studied only in the industrial organization and management literatures, where it is called *multi-market contact* (MMC, henceforth).[1] MMC studied in these literatures is because MMC can potentially lead to tacit collusion which negatively affects consumer welfare. When firms repeatedly interact with each other in a market, they can engage in tacit collusion in the presence of credible threat of punishment against unilateral defection or deviation from collusion. However, whether the threat of punishment is credible depends on profitability of the market, patience of the firms involved, among other market and firm characteristics. Therefore, some markets might be profitable to attempt collusion in where others not. Additionally these firms can meet not in one but in multiple markets, that is, there can be multiple contacts among firms or MMC. Then the fundamental question is whether the presence of MMC facilitates tacit collusion by enhancing the threat of punishment.

[1]↑ There is considerable research in the industrial organization and the management literature on the impact of MMC on prices among other strategic variables. The applications include airlines (Bilotkach, 2011; Ciliberto and Williams, 2014; Evans and Kessides, 1994; Prince and Simon, 2009), computer industry (Kang, Bayus, and Balasubramanian, 2010), insurance (Lin and McCarthy, 2018), cellular telephone industry (Busse, 2000; P. M. Parker and Röller, 1997), cement (Jans and Rosenbaum, 1997), and banking (Heggestad and Rhoades, 1978; Pilloff, 1999), among others. However, the predominant focus has been on observable actions (e.g., prices, quality levels, market entry).The notable exception is Kang, Bayus, and Balasubramanian, 2010 which studies retaliatory tactics used by firms in the personal computer industry. Companies use the introduction of new products for retaliation rather than using prices. To the best of my knowledge, this is the only paper that looks at firms' strategies in the presence of MMC.

The idea that MMC can facilitate tacit collusion was first proposed by Edwards, 1955. Bernheim and Whinston, 1990 using infinitely repeated Bertrand competition games showed that under some conditions MMC can influence strategic behavior by increasing the threat of punishment, i.e., the punishment to deviation from collusion becomes costlier. The intuition is that failure to collude in one market can be punished in other markets. Thus the threat of retribution in other markets can force firms to collude in a market where they otherwise would not. From an anti-trust perspective, multiple contacts can therefore prove to be detrimental to competition. This intuition or logic is not exclusive to market games and can be applied to many situations where agents are engaged in multiple repeated strategic interaction with the same opponent. The specific requirements of these interactions are that these interactions must be infinitely repeated, there should be a conflict between long run incentive to collude/cooperate accompanied by short run incentive to defect, and finally, agents must be able to punish defection.

In this paper, I study the implications of multiple contacts on how agents behave in infinitely repeated prisoner's dilemma (IRPD, henceforth). In the prisoner's dilemma (PD, henceforth) game, cooperation is the strategic equivalent of collusion in a market game.[2] There are multiple advantages to using PD games. First, agents have to choose from only two (cooperation and defection) actions, which helps me make the experiment as simple as possible without compromising the basic features of the testing environment. Collusive outcomes are equivalent to mutual cooperation, and Nash equilibrium (NE, henceforth) outcomes of other games (for example, market games) correspond to mutual defection in the PD game.[3] Second, it captures the conflict between long term collusion and short term failure to collude in terms of the actions cooperation and defection. Finally, the PD games have been studied widely in the experimental literature, which allows me to utilize the existing

[2]↑ In Salz and Vespa, 2020, the experiment uses an oligopoly game, but the subjects choose between two quantity options 0 and 1, and the profits are such that they make the oligopoly game is a PD game.

[3]↑ Given the definition of subgame perfect NE for if a firm wants to deviate from collusive path, it is best for the firm to choose the stage game NE action for the IRPD games. However, it is free to choose anything other actions than the collusive action. Correspondingly, for the rest of the paper, I will use the terms cooperation and collusion interchangeably, and I will use the term defection for the failure to collude/cooperate.

research and methodology to understand the behavior of subjects in my environment.

In the previous literature (including industrial organization, management, and experimental economics) studying multiple contacts, the main focus has been on the incidence of cooperation and whether multiple contacts lead to higher rates of cooperation. Contrary to this line of research, I focus on *how* cooperation is enforced in the presence of multiple contacts. Specifically, in addition to incidence of cooperation, my goal is to provide empirical evidence on incidence of punishment and strategies used by agents. Why is this important? As I have stated earlier, the potential impact of multiple contacts is due to the fact that agents can punish defection in one game, across multiple games. I call this *cross punishment*. So, to find the effect of multiple contacts, I examine if subjects in my experiment use strategies that have this property of cross punishment. Such strategies which condition actions in each game on the history of all games.

One of the important features of MMC is that it can it can only enhance the threat of punishment if at least some of the strategic settings or games are different from each other. Bernheim and Whinston, 1990 state this as the *Irrelevance Result*. When all the strategic settings are identical, pooling the incentives across games implies that the incentives are multiplied by a constant leading to no change in the incentive for long term cooperation. As a result, if a setting can not sustain cooperation on its own, multiple contacts across multiple identical settings can not make cooperation sustainable. There are multiple ways to make the settings different. For this paper, I have chosen two such ways. One way is to make the settings symmetric between players but different across games. Specifically, I use two symmetric IRPD games, among which agents can sustain cooperation in one game (Easy game), but not in the other (Hard game). This type of multiple contacts with different games has been previously studied in the experimental literature. I call this the *different games* treatment. Another way is to use an asymmetric setting where one agent is advantaged while the other is not. The advantaged agent has incentive to cooperate if the other agent cooperate as well, but the disadvantaged agent has no incentive to cooperate. Therefore, cooperation can not be sustained in such a setting. The agents then interact in two asymmetric settings with the advantaged player switching between the two settings. In the experiment, I use one asymmetric IRPD game, but the subjects play it twice, once as the advantaged agent, once as the disadvantaged agent. I call this the *different roles* treatment.[4]

My laboratory experiment utilizes a 2×2 factorial design. The first dimension of comparison is the number of contacts – subjects either interact with one opponent in each (single contact) of the two IRPD games or one opponent in two (multiple contacts) IRPD games. The second dimension of comparison is the source of difference between the two strategic settings (different games vs. different roles). In the different games treatment, with multiple contacts cooperation can be maintained in both games through the credible threat of punishment in the Easy Game in response to defection in the Hard Game, even though punishment is not credible in the Hard Game in isolation. A similar logic applies in the different roles treatments, when the incentives are pooled across the two roles. I have chosen parameters such that the incentive to cooperate and the punishment payoffs are identical across the different game and different role treatments. Subjects play thirty supergames in each session of each treatment.

From the experimental data I find that under multiple contacts subjects subjects an increased tendency to cross punish their opponents but in the *different roles* treatment. However, this is not accompanied by an increase in the average cooperation levels compared to single contact. This is possible because different strategies can lead to the same level of cooperation depending on the history. In the *different games* treatment I do not see any increase in the tendency to cross punish. However, I find that subjects increase cooperation in the Hard Game, although this increase in marginally statistically significant or not significant at all depending on the supergames I consider. For the Easy game, the cooperation

[4]↑ This environment is not unlikely. Consider the airlines industry, where airlines engage in MMC. In many routes only some airlines have a hub (or two hubs) while other have no hubs (or one hub). This provides an advantage to airlines with higher number of hubs and among the different routes they operate in, their roles can be reversed. For example, both American Airlines (AA) and United Airlines (UA) fly the two routes Chicago O'Hare Airport (ORD) - Dallas Fort Worth (DFW) and Chicago O'Hare Airport (ORD) - George Bush Intercontinental Airport, Houstan (IAH). ORD is a hub for both AA and UA. But DFW is a hub for AA and IAH is a hub for UA. Therefore, in the ORD-DFW route, AA is the advantaged agent, while in the ORD-IAH route UA is the advantaged agent.

level goes down in the later supergames of the experiment under multiple contacts compared to single contact.

The theory of multiple contacts is driven by the use of strategies that incorporate the multiple contacts setting. The increase in the tendency to cross punish under multiple contacts that I observe can be supported by many such strategies. Therefore, a change in strategies between single contact and multiple contacts can be expected. To check this, I estimate the implied strategies used by the subjects. In particular, I first modify popular strategies including Grim Trigger, Tit-for-Tat, and Defect Tit-for-Tat for my multiple contacts environment such that actions in each game is conditioned on the history of actions in both games. I call these *Strong strategies* (e.g., Strong Grim Trigger, S-Grim henceforth). My theory assumes that subjects use the S-Grim strategy in both different games and different roles treatments. However, my strategy estimation finds that subjects use these Strong strategies in the presence of multiple contacts only in the different roles treatment.

The rest of the paper is organized as follows: First, in section 2, I review related literature. Next, in section 3, I develop the theoretical background. In section 4, I present the experimental design for the simplified environment with two IRPD games and my theoretical hypotheses for the chosen parameters. In section 5, I carry out the analysis of the data. In particular, I analyze the choice to cooperate in each game. In section 6, I conduct an estimation of underlying repeated-game strategies that subjects use. Finally, in section 7, I conclude.

1.2 Literature Review

Multiple contacts have been a subject of inquiry for a significant amount of empirical research in industrial organization literature. Most of the empirical papers are focused on the effects of MMC, on the intensity of competition in terms of prices, service quality or other strategic variables in different industries. However, there is only a handful of papers that investigate this concept using experimental methodologies. Some of the very early experimental papers attempted to find evidence for the "mutual forbearance" hypothesis first propounded by Edwards, 1955 but the interactions between firms are in only one period.[5] In simple terms, the hypothesis states that MMC among firms can facilitate collusion in the markets where these contacts take place. R. Feinberg and Sherman, 1985 is one of the earliest papers to find some support for the hypothesis using a market experiment. In their subsequent work, R. M. Feinberg and Sherman, 1988, the authors develop a model to elucidate the "mutual forbearance" hypothesis using a parameter that captures conjectural forbearance in the profit maximization equations of the firms. In the same paper, the authors test the theory using market experiments where subjects play Bertrand competition in three markets. The authors find their experimental results to support their hypothesis as they find that the average price is higher when firms interact with the same rival in all three markets compared to different rivals in different markets. A more recent paper, Güth et al., 2016 further studies mutual forbearance in the context of strategic substitutes and complements with finitely repeated market games of different lengths. Their main result is that there is more cooperation in the case of strategic complements than strategic substitutes. However, they do not find support for of "mutual forbearance". In the papers mentioned above, there is no strategic difference between single contact and multiple contacts. Therefore the effects they find are behavioral.[6] These papers are inherently different from current paper, as these use one-shot or finitely repeated games.

Phillips and Mason, 1992 reformulated the "mutual forbearance" hypothesis using the insights from Bernheim and Whinston, 1990 to develop the theory they test in an indefinitely repeated Cournot competition setting with MMC. They compare quantity setting decisions in single markets (firms interact only in one market) with that in multiple markets (firms interact with the same rival in two markets) with different demand and cost conditions in each

[5]↑ According to Jayachandran, Gimeno, and Varadarajan, 1999 mutual forbearance is "a form of tacit collusion in which firms avoid competitive attacks against those rivals they meet in multiple markets". The anti-competitive behavior is proposed to appear because "multimarket competition increases the familiarity between firms and their ability to deter each other."

[6]↑ Cason and Davis, 1995 also studies MMC in asymmetric Bertrand competition environment. However, the main question that the authors study is the effect of communication among the subjects on collusion concerning price decisions.

market.[7] The result from their experiment shows that under MMC cooperation becomes easier in the market where it is more difficult to cooperate in single market conditions. Hence, this result provides partial support to the theory from Bernheim and Whinston, 1990 in the Cournot environment. The authors also studied the effect of MMC when markets are subject to different regulations (one market is affected while the other is not) in Phillips and Mason, 1996. They find that a sufficiently restrictive regulation can lead to more competition, but a lenient restriction can lead to more collusion in the unaffected market. My paper is different from these papers primarily because I primarily use PD games and I expand my analysis to include asymmetries of payoffs.

Recently a couple of papers have studied this phenomenon using PD games. In Yang, Kawamura, and Ogawa, 2016, the authors experimentally study multiple contacts using two symmetric IRPD games, in only one of which cooperation can be sustained in equilibrium under the discounted factor employed. In two of the three treatments in the experiment, the subjects play only one of the PD games (single contact treatments). In the third treatment, the subjects play two PD games simultaneously (multiple contacts treatment). In the experiment, they observe that the subjects tend to cooperate more under multiple contacts in the game that cannot sustain cooperation on its own. On the other hand, the cooperation rate falls for the other game with multiple contacts. A recent paper, Laferriere et al., 2021 this too. They study simultaneous multiple contacts as well as sequential contact. The authors do not find any impact of multiple contacts on the strategic behavior when the contacts are simultaneous. In their sequential multiple contact treatments, the subjects choose actions in the two games one after the other and can see the action chosen in the first game. In this treatment, the authors find an increase in cooperation in the game that cannot sustain cooperation in isolation.

[7]↑ The authors simulate infinite horizon repeated interactions using finite repetitions with an unknown end period. The caveat I should point out is that the simulated discount factor in this experimental design changes from almost one in the earlier periods to significantly less than one in the later periods of interactions.

My paper differs from these papers in several ways. First, I study how strategic behavior is impacted by multiple contacts using both symmetric and asymmetric IRPD games. In each case, I study the impact of multiple contacts on the tendency to cooperate. My paper is the first experimental work to study multiple contacts with asymmetric strategic setting. Second, although my symmetric treatment is similar to the experiment in Yang, Kawamura, and Ogawa, 2016, my experimental design is different, and allows me to isolate the effect of multiple contacts from the effect of increased complexity from playing multiple games simultaneously. Specifically, in my single contact treatments, subjects play two games with two different players instead of playing one game with one other player. I make this design decision to make sure that subjects face the same complexity level due to the number of games played in all my treatments. Laferriere et al., 2021 also uses this design. Finally, in addition to looking at just the actions, I also investigate the strategies used by subjects in different environments, particularly under multiple contacts to explore if strategies used by subjects are affected by multiple contacts.

IRPD games have been studied extensively in the experimental literature. Most papers concentrate on studying under what conditions subjects cooperate. For a comprehensive probe into this strand of literature, see Dal Bó and Fréchette, 2018. Some of the conditions that are considered are payoffs and discount factors (Bó, 2005; Dal Bó and Fréchette, 2011), continuous-time (Bigoni et al., 2015; Friedman and Oprea, 2012), monitoring (Aoyagi, Bhaskar, and Fréchette, 2019; Camera and Casari, 2009; Rand, Fudenberg, and Dreber, 2015), decisions by teams (Cason and Mui, 2019), identity (Kamei, 2017), number of players (Camera, Casari, and Bigoni, 2012) and communication (Cason and Mui, 2019; Cooper and Kühn, 2014) among others. To this end, I study if playing multiple games simultaneously can enhance the tendency to cooperate. I also utilize the methodologies introduced in this literature to estimate strategies. I use the Strategy Frequency Estimation Method introduced in Dal Bó and Fréchette, 2011, and the strategies that are explored in Fudenberg, Rand, and Dreber, 2012. Estimation of strategies has received a lot of attention. Some papers estimate strategies from the observed actions chosen by subjects (Breitmoser, 2015; Dal Bó and Fréchette, 2011; Fudenberg, Rand, and Dreber, 2012), while other ask subjects to choose strategies from a list or construct strategies (Cason and Mui, 2019; Dal Bó and Fréchette, 2019; Romero and Rosokha, 2018). In this paper, I adopt the former approach. Moreover, for my multiple contacts environment, I introduce two new strategies, which I call Strong Tit-for-Tat (S-TFT, henceforth) and Strong Defect Tit-for-Tat (S-DTFT, henceforth), by modifying the Tit-for-Tat and Defect Tit-for-Tat strategies to fit my multiple contacts environment.[8]

Asymmetric IRPD games are scarcely investigated experimentally. Some early papers Schellenberg, 1964; Sheposh and Gallo Jr, 1973 study asymmetric prisoner's dilemma games. Among the early papers, J Keith Murnighan, 1991; John K Murnighan, King, and Schoumaker, 1990 also study asymmetric IRPD games and the authors study the pattern of actions chosen by subjects. These papers find that subjects alternate actions between cooperation and defection in these games. In recent years, very few papers study asymmetric PD, mainly in one-shot or finitely repeated environments (Ahn et al., 2007; Aksoy and Weesie, 2013; Haesevoets et al., 2019). Bone et al., 2015 use a symmetric IRPD game in their experiment. However, they study if punishment (punishment is an added action besides cooperation and defection that reduces payoff of the player who is punished) is detrimental to cooperation and who is more likely to punish. The asymmetry comes in terms of the difference between players in their power to punish. My paper adds to this literature by studying the tendency to cooperate when players play multiple asymmetric games. I study if players in different roles (high payoff or low payoff) cooperate differently. I find that subjects cooperate more when they have a higher incentive to cooperate than their rival in asymmetric PD games. My paper contributes by studying cooperative behavior in asymmetric IRPD games and estimating strategies in this environment. Additionally, to the best of my knowledge, my paper is the first paper to econometrically estimate the frequency of strategies used in the asymmetric IRPD games.

[8]↑ S-Grim strategy was introduced in Bernheim and Whinston, 1990.

1.3 Theoretical Background

In this section, I lay out the theoretical model underlying my experiment. I want to study the circumstances under which multiple contacts can lead to a change in the strategic behavior of players. Interacting the multiple identical environments simultaneously does not change the incentives to have an effect on strategies. Bernheim and Whinston, 1990 refer to this as the irrelevance result. As I have mentioned before, I require some source of heterogeneity or differences in the strategic settings for multiple contacts to make an impact. I examine two sources of differences (i) difference in games (ii) different in players. In the first case I use two different symmetric infinitely repeated PD games. While in the second scenario, I use an asymmetric infinitely repeated PD game which is played twice in the two different roles.

I use two sets of payoffs from which I can construct two symmetric PD games and one asymmetric game. This also allows us to make the symmetric and asymmetric environments equivalent. Let us consider two sets of payoffs, and call them the Easy (E) and Hard (H) payoffs respectively. The symmetric game in which both players face the Easy payoffs, I call the Easy game. Both players are in the Easy role. In the other game, which I call the Hard game, both players get the Hard payoffs. Both players are in the Hard role in this game.[9] In the asymmetric game, one player has Easy payoffs (Easy role) and the other player receives the Hard payoffs (Hard role). The symmetric stage games and the asymmetric game are shown in Figure 1.1 and Figure 1.2 respectively.

In the following discussion, I are going to use only Grim Trigger strategy when talking about individual games and an equivalent strategy for the multiple contacts case. In infinitely repeated games, the set of strategies in infinite. I cannot analyze the entire of set of strategies. I choose to study this family of strategies for a few reasons. First, these are the simplest strategies that I can analyze analytically. Second, these assign the harshest possible punishment to unilateral deviation, which is why I get the minimum discount factor require

[9]↑ In the symmetric games, the terms "role" and "game" can be used interchangeably.

to sustain cooperation. Finally, in this literature studying infinitely repeated PD games (see Dal Bó and Fréchette, 2018 for review), the general practice is to use Grim Trigger strategy obtain the lowest threshold discount factor. I acknowledge the fact that I can use other strategies and obtain higher threshold discount factors.

Player 1 (Easy Role)	Player 2 (Easy Role): C	D
C	c^E, c^E	a^E, b^E
D	b^E, a^E	d^E, d^E

(a) Easy Game

Player 1 (Hard Role)	Player 2 (Hard Role): C	D
C	c^H, c^H	a^H, b^H
D	b^H, a^H	d^H, d^H

(b) Hard Game

Figure 1.1. Symmetric Stage Games

Player 1 (Easy Role)	Player 2 (Hard Role): C	D
C	c^E, c^H	a^E, b^H
D	b^E, a^H	d^E, d^H

Figure 1.2. Asymmetric Stage Game

1.3.1 Different Games, Symmetric Players

In this setting, players are engaged in two different symmetric games. When there are no multiple contacts, players play the two games with two separate opponents in isolation. Therefore I can analyze the two games separately with strategies for each game. That is, the strategies for each game considers history of actions and states what actions will be chosen conditioned on this history for that game alone. Under multiple contacts, the players play the two games simultaneously with the same opponent. The two games can not be analyzed separately. A strategy in this case combines the history of actions from both games and the states the actions for both games conditioned on the history.

I first consider the case with no multiple contacts. When the two symmetric games are played in isolation, Stahl, 1991 provides the set of sub-game perfect equilibria of an infinite repetition of these games as a function of the discount factor. There exists a discount factor $\delta^{*\mathrm{i}}$ (threshold discount factor) where $\mathrm{i} = E, H$,[10] such that for all discount factor $\delta < \delta^{*\mathrm{i}}$, defection in the only equilibrium action. However for any discount factor $\delta \geq \delta^{*\mathrm{i}}$ there is a multiplicity of equilibria which can support both defection and cooperation. For calculating $\delta^{*\mathrm{i}}$ I consider the payoff from long term cooperation, versus the payoffs from unilateral deviation when the other player is using the Grim Trigger strategy. $\delta^{*\mathrm{i}}$ gives us the lowest discount rate required to sustain cooperation in these games. This is because Grim trigger strategy is most strict punishment strategy. If players use others strategies like Tit-for-tat, they need higher discount factors to sustain cooperation. I choose the payoffs for my experiment in such a way that $\delta^{*E} < \delta^{*H}$.

When the players play two games simultaneously with the same opponent, the incentive to cooperate in the two games can be pooled together. Similar to the individual games, I can find a minimum threshold discount factor required to sustain cooperation in both games. For purpose I use the equivalent of Grim Trigger strategy in this this multiple contacts environment. In the S-Grim strategy players start by cooperating in all games, and defects in all games in there is defection in any game in the history of the play. Bernheim and Whinston, 1990 also used the S-Grim strategy for their analysis. Using this S-Grim strategy I can find a threshold discount factor such that for all discount factors above it, cooperation can be sustained in both games. S-Grim strategy uses the harshest punishment possible for unilateral defection. Therefore the threshold discount factor is the minimum required

[10]↑ $\delta^{*\mathrm{i}} = \dfrac{b^{\mathrm{i}} - c^{\mathrm{i}}}{b^{\mathrm{i}} - d^{\mathrm{i}}}$ for $\mathrm{i} = E, H$

discount factor to sustain cooperation in both games.

Cooperation in both games for all periods (given the other player uses S-Grim strategy) gives the players the following discounted payoff.

$$U_{CC,SG} = \frac{c^E + c^H}{1 - \delta} \tag{1.1}$$

On the other hand, if a player deviates to defection, then she gets the following discounted payoff.

$$U_{dev,SG} = (b^E + b^H) + \frac{\delta(d^E + d^H)}{1 - \delta} \tag{1.2}$$

Notice that with multiple contacts when a player wants to defect in one game, it is better to defect in both games than in only one game given that the other player uses the S-Grim strategy. Given that the other player is using S-Grim, defecting in one game and cooperating the other is a sub-optimal outcome since $b^E + b^H > c^E + b^H$ and $b^E + b^H > b^E + c^H$. Equating equations (1.1) and (1.2) I get a threshold discount factor which I denote by $\hat{\delta}^{Sym}$.[11] Irrespective of the payoff parameter values in the symmetric PD games, $\hat{\delta}^{Sym}$ lies between the threshold factors from the two symmetric PD games. In my case, I have chosen payoff parameters such that $\delta^{*E} < \delta^{*H}$. Therefore, $\delta^{*E} < \hat{\delta}^{Sym} < \delta^{*H}$.

1.3.2 Same Game, Asymmetric Players

In the asymmetric game, Easy role player will have a threshold discount of δ^{*E} and the Hard role player will have a threshold discount factor of δ^{*H}. For cooperation to be sustained in the equilibrium, the discount factor must be such that both players will have incentive to cooperate. Hence, the discount factor required to sustain cooperation in the asymmetric game is the maximum of the two threshold discount factors given by

$$\delta^* = \max\{\delta^{*E}, \delta^{*H}\} = \frac{b^H - c^H}{b^H - a^H}$$

[11] ↑ $\hat{\delta}^{Sym} = \dfrac{(b^H + b^E) - (c^H + c^E)}{(b^H + b^E) - (a^H + a^E)}$.

I now consider the situation when the players play the asymmetric game twice (once as in Easy role and once in Hard role) simultaneously with the same opponent and for infinite repetitions. In one game the player is in the Easy role and in the other she is in the Hard role. I again assume that players use the S-Grim strategy and find a threshold discount factor such that cooperation can be sustained in both games. Cooperation in the both games for all periods (given the other player uses S-Grim strategy) gives the players the following discounted payoff.

$$U_{CC,SG} = \frac{c^E + c^H}{1-\delta} \tag{1.3}$$

On the other hand, if a player deviates to defection, then she gets the following discounted payoff. Again, for a player it is better to deviate in both games than only one.

$$U_{dev,SG} = (b^E + b^H) + \frac{\delta(d^E + d^H)}{1-\delta} \tag{1.4}$$

Equating equations (1.3) and (1.4) I get a threshold discount factor which I denote by $\hat{\delta}^{Asym}$.[12] Notice that the payoffs from continued cooperation and deviation is same for symmetric and asymmetric payoff.[13] Therefore, I have $\hat{\delta}^{Asym} = \hat{\delta}^{Sym}$ and $\hat{\delta}^{Asym} < \delta^*$.[14]

1.4 Experimental Environment, Design, and Procedure

1.4.1 Design and Parameters

In this paper I aim to better understand the effect of multiple contacts on the tendency to cooperate in infinitely repeated prisoner's dilemma games. As I have stated above, for multiple contacts to have an effect I need the strategic environments to be different from each other. I showcased two such circumstances, that is, two sources of heterogeneity and I study them using a laboratory experiment. I want to compare these two types of heterogeneity to see if they lead to similar effects of multiple contacts on subject behavior. Therefore, I have a 2×2 between-subject design, as shown in Table 1.1, with two main treatment variables for

[12]↑ $\hat{\delta}^{Asym} = \dfrac{(b^H + b^E) - (c^H + c^E)}{(b^H + b^E) - (a^H + a^E)}$.

[13]↑ Compare eq. (1.1) to eq. (1.3) and eq. (1.2) to eq. (1.4).

[14]↑ From before I know $\delta^* = \delta^{*H}$, therefore $\hat{\delta}^{Asym} < \delta^*$.

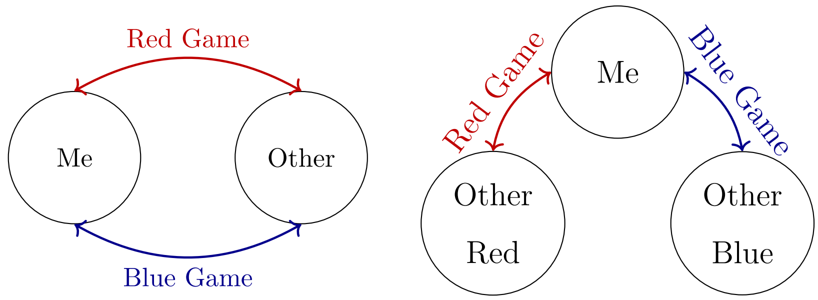
my experiment, contact (single contact versus multiple contacts), and type of heterogeneity (different games versus different roles).

Table 1.1. Treatments

	Different Games	Different Roles
Single Contact	SGame	SRole
Multiple Contacts	MGame	MRole

Figure 1.3 shows how I implement multiple contacts and single contact in the experiment. As par the concept of multiple contacts, subjects must interact in multiple strategic environments with each other. In my experiment, I only use two, two-player strategic environments and each of these environments is an IRPD game with a common discount factor. In the experiment, I implement this by showing the subjects the stage games of both IRPD games simultaneously and making them choose an action for each game. I call these stage games the "Red Game" and the "Blue Game". In the multiple contacts treatments, each subject interacts with one other subject, whom I refer to as "Other". This is shown in Figure 1.3a In the single contact treatments, each subject should have contact with another subject through one game only, i.e., each subject should play only one game with another subject. However, to make the multiple and single contact treatments comparable and to maintain the same level of complexity, even in the single contact treatments each subject plays two games ("Red Game" and "Blue Game") but with two different subjects.[15] In the Single Contact treatments, each subject plays the "Red" Game with "Other Red" and "Blue" Game with "Other Blue" simultaneously as in shown in Figure 1.3b.

[15]↑ In the literature of multiple contacts, in some papers (Güth et al., 2016; Phillips and Mason, 1996, 1992; Yang, Kawamura, and Ogawa, 2016), for their equivalent single Contact treatment, the subjects play only one of the games at a time. However, other papers (R. Feinberg and Sherman, 1985; R. M. Feinberg and Sherman, 1988; Laferriere et al., 2021) use this method for their single contact treatments where subjects play multiple games with different opponents.



(a) Multiple Contacts (b) Single Contact

Figure 1.3. Implementation of Multiple Contacts and Single Contact

For my experiment, I implement the infinitely repeated interaction as indefinitely repeated interaction using random termination protocol of Roth and J Keith Murnighan, 1978. In the experiment, I call each of these infinitely repeated interactions or supergame a "round" and one repetition of the stage games a "period". For all my treatments I use the discount factor $\delta = 0.75$. Therefore for my random termination protocol, the probability of continuation was 0.75. This protocol was described to the subjects as the computer randomly choosing a number between 1 and 8. If the number is lower than or equal to 6, then the supergame will have an additional period; otherwise, the supergame will end. At the end of each supergame, I rematch subjects randomly. All the sessions of each treatment had 30 supergames. Each treatment had four sessions, each session with a different set of supergame lengths pre-drawn from a Geometric Distribution with probability of success of 0.75. But the supergame lengths were common across treatments.[16]

[16]↑The supergame lengths are shown in Table A.3.

Own Choice \ Other's Choice	C	D
C	48	12
D	50	25

(a) Easy Payoffs

Own Choice \ Other's Choice	C	D
C	30	8
D	50	25

(b) Hard Payoffs

Figure 1.4. Stage Game Payoffs

In our Different Games treatments, we use two symmetric PD games and for the Different Roles treatments, we use one asymmetric PD game. To form these game we use two sets of payoffs shown in Table 1.4. For these payoffs, the threshold discount factors for the Easy game and the Hard game in the SGame treatment are $\delta^{*E} = 0.08$, $\delta^{*H} = 0.8$ respectively. The same for the asymmetric game in the SRole treatment is $\hat{\delta}^{Asym} = 0.8$. For the multiple contact treatments, I design the treatments such that I get the same threshold discount for both treatments $\hat{\delta}^{Sym} = \hat{\delta}^{Asym} = 0.44$.[17]

During the experiment, in the Different Games treatments the “Red Game” and the “Blue Game” that subjects see are the Easy Game and the Hard Game respectively. The games are shown in the left panel of Figure 1.5. In the Different Roles treatments, I refer to the asymmetric game as the “Red Game” when subjects play it in the Easy role and as the “Blue Game” when they play it in the Hard role as in the right panel of Figure 1.5. Each subject plays the games as Player 1.

[17]↑ Following Spagnolo and Blonski, 2001 I also find the different threshold discount factors such that cooperation is risk dominant in single contact and multiple-contacts treatments. For the SGame treatment, the risk dominance threshold discount factor is 0.395 for the Easy game and 0.881 for the Hard game. Therefore cooperation is a risk dominant action in the Easy game but not in the Hard game give my discount factor of 0.75. For the SRole treatment, this threshold discount factor is 0.816. Therefore cooperation in not a risk dominant action in the asymmetric game. Dal Bó and Fréchette, 2018 finds that the difference between the employed threshold discount factor and the risk dominance threshold (Δ) is a good predictor of observing cooperation in symmetric IRPD games. In my case, for SGame treatment $\Delta^{*E} = 0.355$ therefore I should expect to see a considerable level of cooperation in the Easy game.

		Player 2 A	Player 2 B
Player 1	A	48, 48	12, 50
Player 1	B	50, 12	25, 25

(a) Red Game

		Player 2 X	Player 2 Y
Player 1	X	30, 30	8, 50
Player 1	Y	50, 8	25, 25

(b) Blue Game

(c) Different Games

		Player 2 A	Player 2 B
Player 1	A	48, 30	12, 50
Player 1	B	50, 8	25, 25

(d) Red Game

		Player 2 X	Player 2 Y
Player 1	X	30, 48	8, 50
Player 1	Y	50, 12	25, 25

(e) Blue Game

(f) Different Roles

Figure 1.5. Stage Games in the Experiment
Notes: In the experiment, the actions are named "A", "B" for the "Red Game" and "X", "Y" for the "Blue Game" in place of "C", "D" respectively.

The discount factor of 0.75 and the Easy payoffs are taken from Dal Bó and Fréchette, 2011. These payoffs have also been used in other papers like Romero and Rosokha, 2018. My Easy game corresponds to their $r = 48, \delta = 0.75$ treatment. I take this route to provide my experimental results some external validation. In my single contact treatments, I assume that the subjects play the Easy game and the Hard game independently. If the cooperation rate in my experiment matches that in the literature, then my assumption about the subject behavior will be validated. The Hard payoffs were chosen to satisfy the condition that $\delta^{*H} > 0.75$ and that $\hat{\delta}^{Sym} = \hat{\delta}^{Asym}$ to be considerably lower than 0.75. Finally, I also wanted to restrict the differences between the payoffs, and to that end I changed only the payoffs from cooperation. Figure 1.6 shows the flow of the experiment.

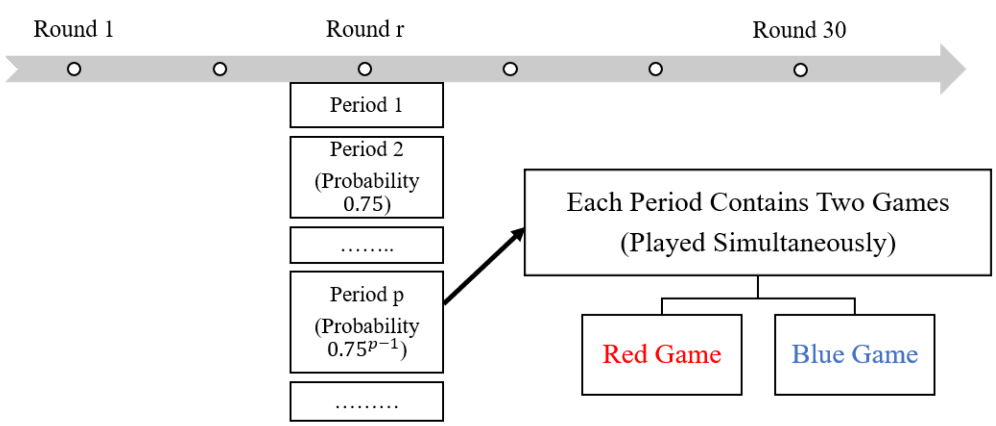


Figure 1.6. Flow of the Experiment

1.4.2 Hypotheses Development

From the theory and comparing different treatments, I formulate the following hypotheses that I test experimentally. The theory assumes that under multiple contacts subjects can use strategies that cross punish defection in each game. Hard payoffs can not be used to punish defection in the Easy or Hard game/role. So cross punishment implies defection in Hard game/role is punished in the Easy game/role. This is implemented in different ways under symmetric and asymmetric settings. In the symmetric setting, when a player defects in the Hard game, both are in the Hard role. Then when the player is punished by her opponent in the Easy game, both are in the Easy role. But for the asymmetric setting, when a player defects in the Hard role, her opponent is in the Easy role. Then if the opponent chooses to punish this when the player in Easy role, the opponent is in Hard role. Given the stage game payoffs I use, in the SGame treatment, the threshold discount factor that can sustain cooperation in equilibrium is 0.08 for the Easy game and 0.80 for Hard game. For the SRole treatment, the minimum discount factor required to sustain cooperation in equilibrium in the asymmetric game is 0.80. With multiple contacts, the threshold discount factor to sustain cooperation in equilibrium (in both MGame and MRole treatments) becomes 0.44 which is lower than 0.75. I now provide two general hypotheses based on my theoretical predictions.[18] Our first hypothesis deals with the effect of multiple-contact. I will use the term "role" and "game" interchangeably for the symmetric treatments.

Hypothesis 1.1. *Differences in cooperation rates due to multiple contacts:*

1. ***(MGame vs. SGame)***

   (a) *Subjects have a higher probability to punish defection by opponent in Hard game by defecting in the Easy game in MGame treatment compared to the SGame treatement.*

   (b) *Cooperation rate in the Hard game is higher in MGame treatment than in SGame treatment.*

2. ***(MRole vs. SRole)***

[18]↑ For a comprehensive look at my theoretical predictions please check Table A.1.

(a) *Subjects have a higher probability to punish defection by ooponent in Hard role by defecting in the Hard role in MRole treatment compared to the SRole treatement.*

(b) *Cooperation rates in both the Easy and Hard roles are higher in treatment MRole than in treatment SRole.*

The theoretical predictions suggest that cooperation cannot be sustained in the asymmetric PD with single contact. However, cooperation can be sustained in both the Easy and Hard roles when there are multiple contacts. Therefore, I expect to find higher degree of cooperation by subjects in both roles under multiple contacts compared to single contact. When considering symmetric payoffs, I know that under single contact, cooperation is a possible equilibrium outcome in the Easy game but not in the Hard game. Whereas, multiple contacts can enforce cooperation in both games in equilibrium. Therefore, I expect that subjects are more likely to cooperate in the Hard game with multiple contacts. Our second hypothesis considers the effect of asymmetry in payoffs.

Hypothesis 1.2. *Differences in cooperation rates due to asymmetry of payoffs:*

1. ***(MGame vs MRole)*** *Players can sustain cooperation in both the Easy and Hard roles in both treatments.*

2. ***(SGame vs SRole)*** *Players can sustain cooperation in the Easy role but not in the Hard role in SGame treatment. Players cannot sustain cooperation in either roles in SRole treatment.*

With multiple contacts, my theory suggests that cooperation can be sustained by subjects in both roles in equilibrium. Therefore, I can not postulate any difference in behavior from my theory. In case of single contact, cooperation can be sustained in equilibrium by the subjects in Easy role in SGame treatment. Therefore, I expect to find lower cooperation levels under asymmetry of payoffs for the Easy role. Again, from the theoretical perspective I cannot predict any difference in cooperation rates for the Hard role arising from payoff asymmetry.

1.4.3 Procedure

I conducted the experimental sessions at the Vernon Smith Experimental Economics Laboratory in August 2020. Subjects were recruited from a pool of under-graduate students at Purdue University using ORSEE (Greiner, 2015). For each treatment I conducted four sessions, which amounted to 16 sessions in total.[19] A total of 192 students participated in 16 sessions with 12 subjects in each session. I implement a between subject design. Each subject participated in only one of the sessions of this study.

The computerized experimental sessions used oTree (D. L. Chen, Schonger, and Wickens, 2016) to record subject decisions. Subjects were given instruction at the beginning of the session. Each session started with instructions, followed by an incentivized quiz, and then the experiment. At the end of the experiment there was a demographic survey and finally subjects were paid individually.[20] Each session took about one hour to complete. The instructions were shown on the screen (Appendix A.3.1 contains the instructions the subjects were given). At the end of the instructions there was an incentivized quiz with 8 questions. The subjects could earn \$0.25 for each correctly answered question. After submitting the answers of the quiz, the subjects were shown the correct option, the option they chose and the amount of money they would receive for the quiz (Appendix A.3.2 contains the quiz questions that the subjects were asked). After the quiz the subjects began the experiment part of the session which starts with a reminder of the instructions.

The subjects were guaranteed a payment of \$5 for appearing for the session. The subjects earned an average of \$18.36, with a minimum of \$16.50 and a maximum of \$21.50 (including the \$5 show up fee).[21] The average number of periods per round was 4.05 with a minimum of 1 period and a maximum of 13 periods. The subjects earned in points during the experiment. At the end of the experiment, the points were converted into dollar amounts using an

[19]↑ I could not have larger session size than 12 because of Covid-19 protocols, implemented by Purdue University. I also conducted a pilot session with 6 subjects to adjust the conversion rate and the time for the experiment.
[20]↑ The flow of a session is shown in Figure A.1 in the Appendix A.2.
[21]↑ This is at par with the hourly wage rate in West Lafayette, Indiana.

exchange rate such that the average earning in every session would be similar.[22] For more details on the experimental sessions refer to Table A.2 and Table A.3.

1.5 Results

In this section, I discuss the results from my laboratory experiment. For most observations and results, I use the last 10 supers and nonparametric tests. For comparison between treatments I use nonparametric permutation test (testing if data from two treatments come from the same distribution), and for comparison across supergames I use nonparametric randomization test (testing if data from two different sets of supergames come from the same distribution), unless stated otherwise. For robustness checks, I redo the tests with last 5 or 15 supergames and using Probit regression. Before getting into testing the hypotheses, I discuss some of the preliminary takeaways from the data. After that I test the hypotheses by only looking at the actions chosen by subject. Finally, I discuss the strategy estimation part of my paper.

1.5.1 Preliminary Takeaways

In this subsection I discuss some general takeaways from the data. Figure 1.7 shows the average cooperation rates for all periods in each supergame for each of my treatments.[23] My first observation is that, in the SGame treatment, subjects learn to cooperate in the Easy game and defect Hard game. This behavior is in line with the theory, which hypothesizes that in the SGame treatment, given my stage game payoffs and discount factor, cooperation can be sustained in the Easy game's equilibrium but not in that of the Hard game. In the data, the average cooperation level for all periods in the Easy game starts at 60.7% in the first 10 supergames and increases to around 87.3% by the last 10 supergames of the experiment. Conversely, in the Hard game the cooperation level for all periods on average is 7.7% in the first 10 supergames but reduces to only 3.5% in the last 10 supergames. The differences between the first 10 and last 10 supergames are statistically significant at $\alpha < 0.001$ for the

[22]↑ he subjects were told the exchange rate in the instruction, before the experiment.

[23]↑ Figure A.3 in the appendix shows the average cooperation level for the first period in each supergame for each of my treatments.

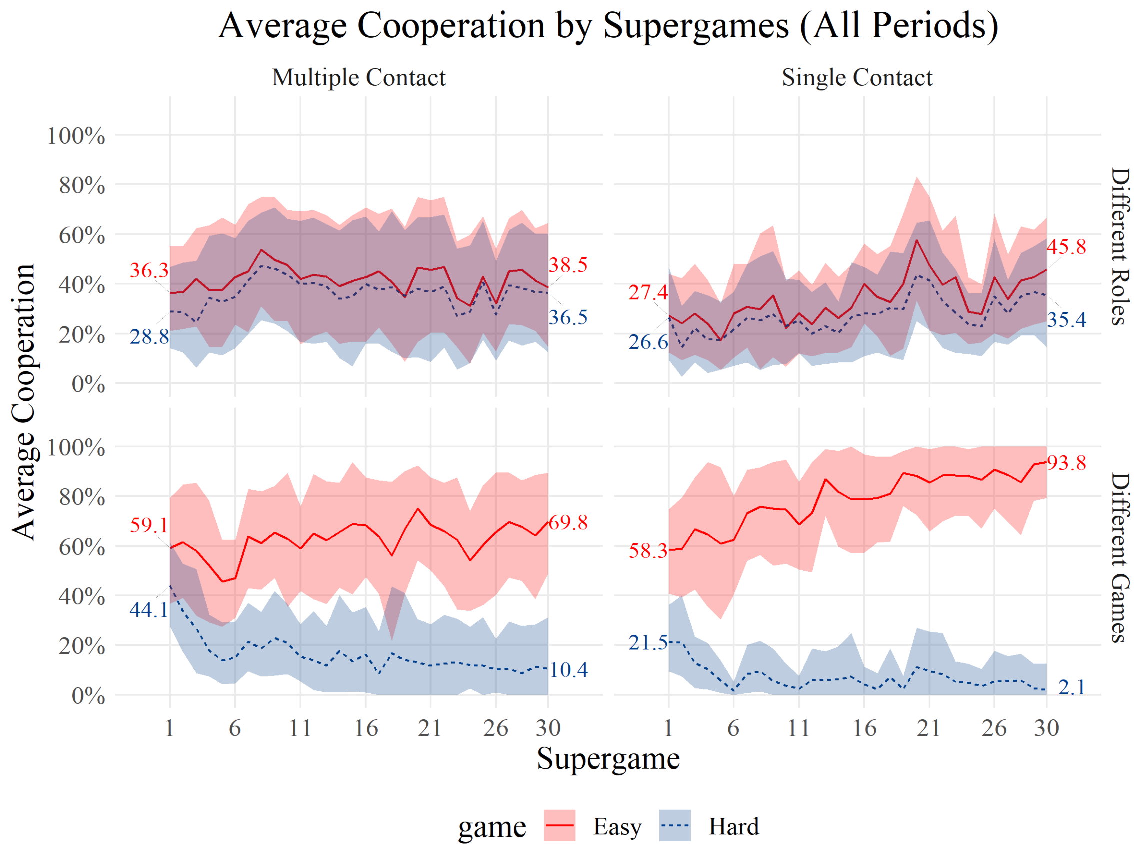


Figure 1.7. Average Cooperation rates in Treatments for each Round (All Periods)
Notes: The shaded areas are the Two-Stage Clustered Bootstrap 95% Confidence Intervals (clustered at session level, randomized at subject level).

Easy game and for the Hard game with p-value 0.01.[24]

Second, Figure 1.8 shows that there is no economically meaningful difference between the overall cooperation levels in the Easy game of the SGame treatment of my experiment and that $r = 48, \delta = 0.75$ treatment of Dal Bó and Fréchette, 2011. This observation is also supported when looking at first period cooperation rates.[25] In my experiment, the average cooperation rates over all supergames in this game are around 75% for all periods and 84%

[24]↑ Figure A.13 (Figure A.12) shows the average cooperation for all (first) periods in the first and last 5 and 10 supergames. Table A.14 show the z-stat estimates from the nonparametric test for the first and last 5 supergames, 10 supergames and 15 supergames. I also conduct a Probit Regression (clustered at session level), the estimates of which are in Table A.15. I find similar patterns in the cooperation rates from the robustness checks.

[25]↑ Figure A.4 shows the first cooperation rates per round for my SGame treatment and Dal Bó and Fréchette, 2011 $r = 48, \delta = 0.75$ treatment.

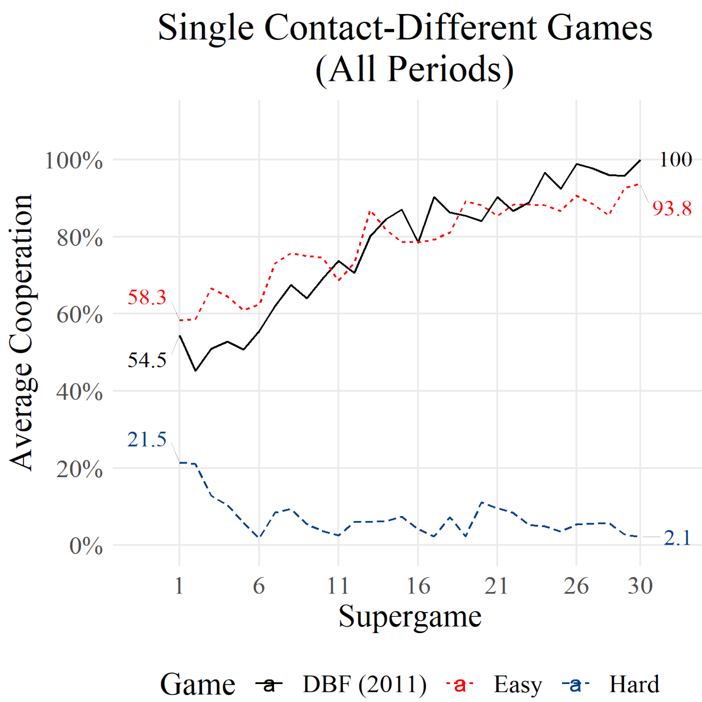


Figure 1.8. Average Cooperation rates in Single Contact and Symmetric Treatment and $r = 48, \delta = 0.75$ Treatment in Dal Bó and Fréchette, 2011 for each Round (All Periods)

for the first period, which are very similar to the corresponding numbers from Dal Bó and Fréchette, 2011 (average cooperation rate of 76.42% for all periods, and 85% for the first period). I also use a Probit regression (clustered at session level) to test if there is any statistically significant difference between the cooperation levels from the two experiments in the supergames 26-30 and 21-30 (see Table A.4 for the z-stat estimates and p-values). I do not find any statistically significant difference.

This external validation is important since it helps rule out any significant behavioral spillover in the Easy game from the Hard game in terms of reducing the tendency to cooperate. In the literature many papers investigate if actions in games are affected by playing multiple games together, simultaneously or sequentially. In most of these papers, there is no strategic implication of playing multiple games. Many papers study PD games in this context. However, they study the effects on the actions taken in the PD game when subjects play other games.[26] In my SGame and SRole treatments, subjects play two PD games simultaneously with two different opponents. Therefore there is no strategic difference between my setting and play one PD game in isolation. From the comparison, stated in the last paragraph, I do not find any economically or statistically significant difference in cooperation levels between my Easy game (played simultaneously with the Hard game) in the SGame treatment and their $r = 48, \delta = 0.75$ treatment (played in isolation). Since the payoffs for the Hard game have not been used in the literature, I can not rule out behavioral spillover on this game. However, my payoff matrix is very similar to the $r = 32, \delta = 0.75$ treatment in Dal Bó and Fréchette, 2011. In both these games cooperation can not be sustained in equilibrium. The cooperation levels that I find in my Hard game in SGame treatment are economically equivalent to the $r = 32, \delta = 0.75$ treatment. Moreover, my data follows a similar pattern as the data from other papers with $\delta - \delta^* < 0$ and $\delta - \delta^{RD} < 0$ (see Dal Bó and Fréchette, 2018 for a comprehensive overview). Unfortunately, I can not rule out behavioral spillover in the SRole treatment. Other spillover effects like learning across multiple games

[26]↑ The other games considered are Stag-Hunt game (Duffy and Fehr, 2018), Trust game (Albert et al., 2007), Alternation games (Bednar et al., 2012; T. X. Liu et al., 2019) or Self-interest game (Bednar et al., 2012) among other games, with the PD game.

(see Mengel, 2012) might also be present in my single contact treatments.

My third observation concerns the SRole treatment. According to the theory, cooperation cannot be sustained in equilibrium for the asymmetric PD game given my payoffs and discount factor. However, as Figure 1.7 (all periods) and Figure A.3 (first period), both roles have statistically significant cooperation (95% confidence intervals for each round do not contain 0) levels in the SRole treatment in first period and all periods.[27] Finally, I note that even with asymmetric payoffs (in both single contact and multiple contacts cases), the cooperation rates are higher in Easy role compared the Hard role. I test this using a Wilcoxon Matched-Pairs Signed-Rank Test. The estimates are presented in Table A.5. I find that the cooperation levels for the Easy role are greater than (statistically significant) that in the Hard role for every treatment.

Observation 1. *Subjects learn to cooperate in the Easy game and learn to left in the Hard game in the SGame treatment.*

Observation 2. *Cooperation rates in the Easy game in the SGame treatment are similar to those in the literature.*

Observation 3. *Subjects cooperate in both Easy and Hard role in SRole treatment.*

Observation 4. *Subjects cooperate more when they are playing in Easy game/role than in Hard game/role.*

[27]↑ In Table 1.2 I also see that average cooperation in the last ten supergames for first period or all periods are statistically different than 0 (using bootstrapped *t*-statistics).

1.5.2 Action Choices

Table 1.2. Average Cooperation Rates (in Percentage)

	First Period		All Periods	
	Easy	Hard	Easy	Hard
SGame	92.5***	6.9*	87.2***	3.9*
	(5.5)	(3.9)	(7.2)	(2.0)
MGame	71.7***	12.3+	60.5***	10.7*
	(10.2)	(8.6)	(9.6)	(6.1)
SRole	47.3***	34.6***	34.0***	28.9***
	(10.7)	(8.9)	(6.4)	(5.6)
MRole	45.0**	37.3**	36.9***	33.4**
	(13.8)	(13.6)	(10.4)	(10.3)

Notes: Table shows average cooperation rate over multiple supergames. The statistics considers the supergames 21-30 of the sessions. Two-stage Cluster (clustered at session level, randomized at subject level) Bootstrap Standard Errors are in parentheses. Significance levels are due to p-values from one-sided t-test. Significance - $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001

In this subsection, I examine the data for evidence supporting or contradicting my hypotheses by looking at the action choices made by the subjects. In the experiment I see a considerable level of learning. Therefore, I use the later part of the experiment for further analysis. Table 1.2 shows the average cooperation rates for the last 10 supergames considering the first period only and all periods.[28] The first period average cooperation rate gives me an idea regarding the intention of the subject, whereas the all period average cooperation rate can inform on the type of strategies the subjects might be using. I find that the

[28]↑ I also use the last 5 supergames and last 15 supergames of the sessions. The estimates are in Table A.7. My findings do not change considerably only when considering these supergames.

cooperation levels always drop as I move from first period rates to all periods rates. This can indicate that subjects use punishing strategies, subjects start defecting at later periods of a supergame, or both.

For the rest of the paper, unless stated otherwise, a subject's action portfolio in a stage game is represented by (x, y) where x and y both can take values from $\{C, D\}$. x is the action taken in Easy game and y is the action in Hard game. Therefore action profile for a stage game is represented by $((x_1, y_1), (x_2, y_2))$. Also when I mention SGame or SRole treatment, every subject faces two opponents. But for expediency, when comparing with MGame or MRole treatment, I use the term opponent to mean both of them.

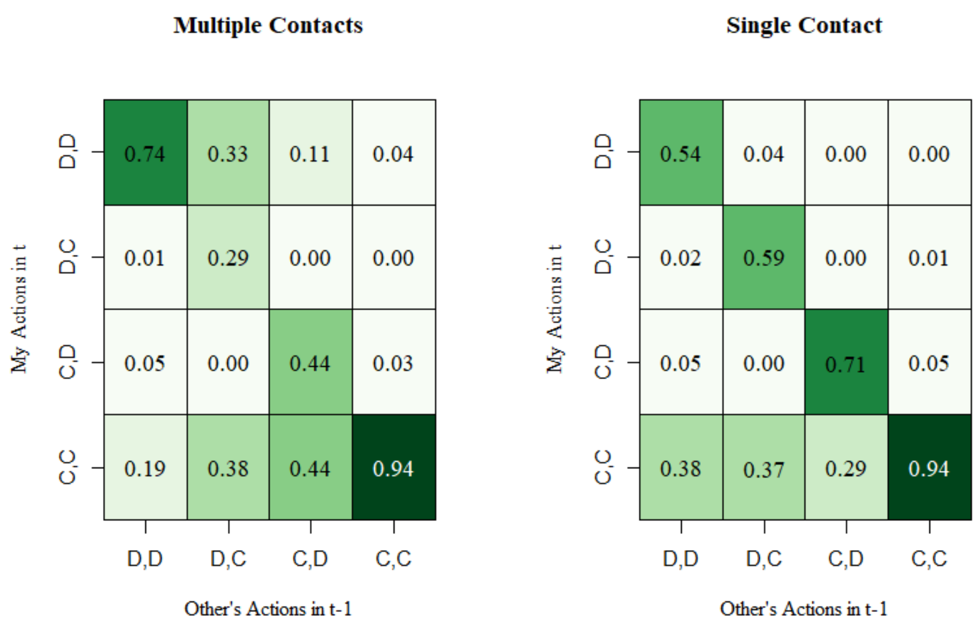


Figure 1.9. Conditional Probabilities for Different Roles Treatments
Notes: Each 4×4 matrix is a matrix of conditional probabilities, such that each cell shows the probability choosing actions (represented in the rows) at t when opponent chose actions (represented in the columns) at $(t-1)$. The action profile x,y implies x is chosen in Easy game, and y is chosen in Hard game with x,y $\in \{C, D\}$. The data used is from the supergames 21-30.

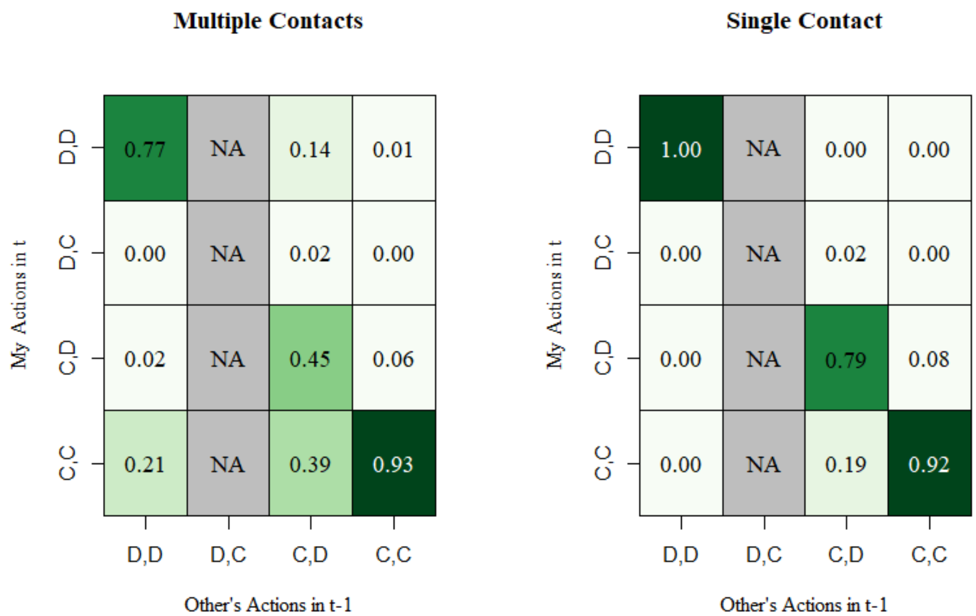


Figure 1.10. Conditional Probabilities for Different Games Treatments
Notes: Each 4×4 matrix is a matrix of conditional probabilities, such that each cell shows the probability choosing actions (represented in the rows) at t when opponent chose actions (represented in the columns) at $(t-1)$. The data used from the supergames 21-30. NA implies there is no observation where a subject chose the actions C,C at $(t-1)$.

Table 1.3. Difference in the probability of punishment at t given defection by opponent(s) in $(t-1)$ when a subject chooses (C,C) in $(t-1)$

	Prob((D,D)|(C,D))	Prob((D,D)|(D,C))	Prob((C,D)|(C,D))	Prob((C,D)|(D,C))	Prob((D,C)|(C,D))	Prob((D,C)|(D,C))
MGame - SGame	13.63% (14.00)	0 (0)	-33.11% (27.54)	-0.8% (6.24)	0 (0)	0 (0)
MRole - SRole	11.11%** (14.91)	29.49%** (23.01)	-26.98% (29.73)	0 (0)	0 (0)	-30.4%** (29.09)

Notes: Each column represents the difference in conditional probabilities between multiple contacts and single contact given a subject chose (C,C) in t. Prob$((x_1, y_1) \mid (x_2, y_2))$ implies the conditional probability that subject chooses x_1 in Easy game/role, and y_1 in Hard game/role, given opponent in Easy game/role chooses x_2 and opponent in Hard game/role chooses y_2 and subject chose (C,C) in $t-1$ with $x_1, x_2, y_1, y_2 \in \{C, D\}$. The data used is from the supergames 21-30.
Significance: * at 0.1, ** at 0.5, *** at 0.01

My first hypothesis deals with the effects of multiple contacts on the tendency to cross punish and the average cooperation rate. To check the change in the punishment behavior, I use two approaches. First, I look at the conditional probability of cross punishment. Second, I look at the strategies that subjects use under the different treatments. The second approach is relegated to the next subsection. What I want to find here is if under multiple contacts, defection by a subject in the Hard game/role is met by punishment when she is in the Easy game/role. In theory, punishment is used if an agent receives the sucker's payoff, that is, she cooperates while the opponent defects, in any earlier periods. Therefore, I consider the conditional probability of punishment when the subject cooperates in both games, (C, C) in the previous period, $t-1$. I do not consider the cases when the subject chooses (C, D), (D, C) or (D, D) at period $t-1$. The logic behind is that if the subject does not receive the sucker's payoff in case of (C, D) or (D, D) and if the subject chose (D, C) or (D, D), there is no way to say if its due to cross punishment or because the subject prefers to defect in the Easy game/role. Also, I do not consider the case when opponent in both games chooses to defect at $(t-1)$ because that does not allow us to check if there is cross punishment.[29]

Table 1.3 shows the difference in probabilities of cross punishment between multiple contacts and single contact treatments. In the SRole and SGame treatment, when the opponents actions are C and D (represented by (C, D)) for the Easy and Hard role respectively, subjects are more likely repeat this action profile or they continue to choose (C, C). Compared to this, in the multiple contacts treatments, subjects choose (D, D) along with (C, D) and (C, C). But they are now less likely to choose (C, D) but more likely to choose (C, C). I find that cross punishment is statistically significant at $\alpha = 0.05$ only when comparing the different roles treatments.

[29]↑ For simplicity, I only consider 1 period histories. In practice, punishment can be used after multiple periods. But this complicates the history. For n period history, the number of possible of histories are $(2 \times 2)^n$.

Table 1.4. Comparison Between Treatments

	First Period		All Periods	
	Easy	Hard	Easy	Hard
MGame - SGame	-3.05**	1.05	-4.37***	2.16*
	(0.001)	(0.148)	(0.0)	(0.021)
MRole - SRole	-0.25	0.32	0.44	0.72
	(0.408)	(0.379)	(0.323)	(0.235)
SRole - SGame	-6.24***	4.44***	-9.03***	5.55***
	(0.0)	(0.0)	(0.0)	(0.0)
MRole - MGame	-3.01**	3.21**	-3.46***	4.23***
	(0.002)	(0.002)	(0.0)	(0.0)

Notes: Table shows the t-stats estimated using Nonparametric Permutation Test to compare the average cooperation between test. The statistics considers the supergames 21-30 of the sessions. The p-values are listed in parentheses.
Significance: $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001

The other part of first hypothesis is regarding the effect of multiple contacts on cooperation levels. Table 1.4 shows the estimates from comparison of average cooperation rates between treatments.[30] For this comparison I first consider the SGame and MGame treatments. I find that with multiple contacts the level of cooperation goes up in the Hard game, where as it is lower in the Easy game. The increase in cooperation rate in the Hard game is in line with my theoretical prediction in Hypothesis 1.1. But the statistical significance of the change in cooperation rates in the Hard game is not robust. The increase in the average all period cooperation rate (p-value < 0.05) in the Hard game is statistically significant when using nonparametric permutation test. But these effects are not statistically significant when using Probit regression (see Table A.9). The decrease in the cooperation rate in the

[30]↑ I also use a Probit regression (clustered at session level) to compare the treatments. The estimates are in Table A.9.

Easy game is in line with the previous literature (Güth et al., 2016; Yang, Kawamura, and Ogawa, 2016). This is not inconsistent with the theory because the theory predicts multiple equilibria. Continued mutual cooperation in both games is supported in equilibrium but it is not uniquely supported. I find that the reduction in cooperation rate in the Easy role is statistically significant (p-value < 0.01 (first period), p-value < 0.001 (all periods)).[31] When considering the different roles treatmets, I find similar effect of multiple contacts on the first period cooperation rates for the Easy and Hard roles as in the case of different games treatments. I see that cooperation rate drops for the Easy role and increases in the Hard role. However, both these effects are not statistically significant.[32] I now summarize these findings in Result 1.5.1.

Result 1.5.1. *Effect of multiple contacts:*

1. *(MGame vs SGame)*
   (a) *There is no statistically significant increase in cross punishment to defectors due to multiple contacts when subjects themselves cooperate in both games.*
   (b) *There is no statistically significant increase in cooperation in the Hard game, but there is a statistically significant decrease in cooperation in the Easy game due to multiple contacts.*
2. *(MRole vs SRole)*
   (a) *There is a statistically significant increase in cross punishment to defectors due to multiple contacts when subjects themselves cooperate in both games.*
   (b) *There is no statistically significant change in cooperation in the Easy or Hard game due to multiple contacts.*

Now I investigate the impact of asymmetry of strategic settings (in my case, payoffs) on the levels of cooperation. I observe in Table 1.2 that the cooperation level in the Easy role

[31]↑ This effect is present and statistically significant when I use data from the last 5 or 15 supergames (see Table A.8). I also run Probit Regression to test this (see Table A.9). The fall in cooperation in the Easy game is still statistically significant.
[32]↑ I come to the same conclusion when using other ranges of supergames (see Table A.8) or using Probit regression (see Table A.9).

has dropped due to asymmetry of payoffs both under single contact and multiple contacts treatments while it has increased for the Hard role under both single contact and multiple contacts treatments. I find that the differences in cooperation rates are statistically significant for both the Easy role (see Table 1.4). The difference in cooperation rates in the Hard role due to asymmetry of payoffs under the single contact treatment contradicts my theoretical prediction in Hypothesis 1.2. This stems from the fact that high levels of cooperation are observed in the Hard role of SRole treatment which itself contradicts my theoretical model. The drop in cooperation in the Easy games is in line with my theoretical predictions in Hypothesis 1.2. I summarize my findings in Result 1.5.2.[33]

Result 1.5.2. *Effect of asymmetry among players:*

1. *(MGame vs MRole) Subjects cooperate less in Easy role and more in Hard role under Multiple Contacts Different Roles treatment compared to Multiple Contacts Different Games treatment. Both these effects are statistically significant.*

2. *(SGame vs SRole) Subjects cooperate less in Easy role and more in Hard role under Single Contact Different Roles treatment compared to Single Contact Different Games treatment. Both these effects are statistically significant.*

I also look at the average payoffs that subjects earned in each supergame in the four treatments. For most of the paper, I concentrate on the cooperative outcome (C, C) for the single contact treatments and the outcome $((C, C), (C, C)$ for the multiple contacts treatments, but the folk theorem encompasses many other possibilities. I first consider single contact treatments. In Figure A.5, I show the average payoffs that the subjects receive over supergames in the SGame treatment for the Easy game (left panel) and the Hard game (right panel). For the Easy game, given the discount factor, the folk theorem covers all the feasible payoffs (convex set with boundary marked in black dashed line) which are individually rational (payoff greater than 25). For the Hard game, the folk theorem payoffs do not include the cooperative outcome. The payoffs in the experiment are in accordance with my theory for both Easy and Hard games. Similarly for the asymmetric game, in the single contact

[33]↑ I further use the last 5 supergames of my the experiment which provides similar conclusion. Again, my findings do not change when I use Probit Regression for my analysis. See Table A.8.

case, cooperative outcome is not supported for my discount factor. However, the payoffs tell a different story (see Figure A.6). I find some presence of payoffs from the cooperative outcome. More surprisingly, I also find incidence of payoffs that are not individually rational. Furthermore, subjects do not try to obtain equal payoffs for both players. The same patterns persist when I consider supergames 26-30 for the SGame and SRole treatments (see Figures A.7 and A.8).

I now consider the multiple contacts treatments. The folk theorem payoffs for the combined games in MGame and MRole treatments contain all the feasible payoffs (including the cooperative outcome) which are also individually rational (payoff greater than 50). There is a stark difference between the MGame and MRole treatments in terms of payoffs from the experiment (see Figure A.10 in the Appendix). In the MGame treatment, the most frequent payoff is one that corresponds to mutual cooperation in the Easy game and mutual defection in the Hard game $(73, 73)$. This payoff $(73, 73)$ is very close to the efficient frontier containing $(78, 78)$ corresponding to mutual cooperation in both games but it is easier to coordinate on than the latter. On the other hand, for the MRole treatment, the most frequent payoff is $(50, 50)$ corresponding to mutual defection in both roles but I also see incidence of mutual cooperation in the both roles. However, in both the treatments I find considerable presence of payoffs that are not individually rational. I also find this for the SRole treatment. This might be because the asymmetric games and the multiple contacts environment are more complex than the SGame environment to play in such that subjects can not play in a way to receive individually rational payoffs. Again, I find a similar pattern for supergames 26-30 (see Figure A.11).

1.5.3 Strategy Estimation

In the previous subsection, I listed some results regarding the effect of multiple contact and asymmetry of agents on punishment behavior and average cooperation levels. My theory models subject choices, assuming that the subjects use the Grim Trigger strategy in each role in the single contact treatments and the S-Grim strategy for the multiple contacts treatments. Using this assumption, I hypothesized that a subject would punish defection by another subject in the Hard game/role by defecting when the subject is in the Easy game/-role and therefore could sustain cooperation in both settings under multiple contacts. As we see in Result 1.5.1 there is some support to this hypothesis. But when comparing the cooperation rates between single contact with multiple contacts treatments, I do not find the expected differences. In the different games treatments, I see a statistically significant drop in the Easy game's cooperation rate with a statistically insignificant rise in the Hard game's cooperation rate. My hypothesis states that with my chosen discount rate, subjects should be able to sustain cooperation in both games in the MGame treatments given that both subjects use the S-Grim strategy. However, given the experimental data, the subjects do not appear to use the S-Grim Trigger strategy. I also do not find any significant difference in cooperation rates between single and multiple contacts treatments in the different roles treatments. However, a negligible difference in average cooperation rate does not necessarily imply that the subjects use the same strategies under both treatments. Therefore, to further investigate this discrepancy I estimate the strategies that the subjects use. Before estimating strategies in the multiple contacts treatments, I look at the strategy subjects use the single contact treatment.

In my SGame treatment, cooperation could be supported in the Easy game but not in the Hard game and the average cooperation rates that I observe for this treatment are concordant with this conjecture. However, many other strategies can support cooperation. Although subjects in this treatment, cooperate almost perfectly on average in the later supergames, I find that their behavior is dispersed across sessions. Therefore, it is interesting to see what strategies the subjects use, other than the Grim Trigger strategy. On the other hand in the SRole treatment, subjects should not theoretically cooperate in either role, but I do not find support for this in my experimental data. I witness significant levels of cooperation by subjects in both roles. This implies that subjects must be using some cooperative strategies, which warrants more inquiry. The average corporation levels indicate that at least some subjects use strategies other than the Grim Trigger strategy.

I use a finite mixture estimation approach to formally estimate the strategies resulting in my experiment's observed action choices. Finite mixture models have been used in various studies, including Dal Bó and Fréchette, 2011; Fudenberg, Rand, and Dreber, 2012; Romero and Rosokha, 2018; Rosokha and Wei, 2020 to estimate the frequency with which subjects use a strategy, usually called Strategy Frequency Estimation Method (SFEM) in this literature. I particularly implement the algorithm used in Romero and Rosokha, 2018. I start by fixing the set of K strategies. For each subject, n, and each strategy k, I compare the actual actions observed in the experiment and the strategy k's prescribed actions given the opponent subject's actions. I denote by x the number of periods for which the prescribed and the actual actions matched and by y the number of periods for which the actions do not match.[34] So I get two matrices X and Y of dimensions $K \times N$ of all combinations of subjects and strategies, then I define a Hadamard product P.

$$P = \beta^{X} \circ (1 - \beta)^{Y} \tag{1.5}$$

where β is the probability with which subjects play according to a strategy, and $(1 - \beta)$ is the probability with which subjects deviate from a strategy. Thus, each entry of the matrix P $(P(k, n))$ is the likelihood that subject n's observed actions come from the strategy k. Then I take the matrix dot product of P and Φ, where Φ is a $K-$vector whose k^{th} entry is the probability with which a strategy k is used by all subjects. The product gives the likelihood that my data matches my estimation model. I then estimate the entries of the vector Φ and the scalar β.

For all my main estimation exercises, I again use the last 10 supergames of the sessions. The assumptions that I have to make here are that subjects' behavior in the last 10 supergames has stabilized, and subjects use the same strategies in all the supergames under

[34]↑ For example: Suppose for a PD game, I want to estimate strategy using data from a super game (round in my case). In the super game, let the history of actions of subject n be (C, C, C, C, C) and that of the opponent subject be (C, D, C, C, D). The super game has 5 periods. When I consider the strategy $k =$ Grim Trigger, subject n's prescribed actions given the history of play by the opponent is (C, C, D, D, D). The prescribed action and the actual actions match for 2 periods and do not match for 3 periods. Therefore, for the strategy $k =$ Grim Trigger and individual n $X_{(k,n)} = 2$ and $Y_{(k,n)} = 3$.

consideration.[35] To check the validity of this assumption, I vary supergames that I consider to check if the estimates vary substantially.

Single Contact Strategies

I first estimate the strategies subjects use in the Easy and Hard roles in single contact treatments. To reiterate, in SGame and SRole treatments, subjects subject two PD games, one in Easy role and one in Hard role with two different opponents. I can therefore assume that the actions in one game is not contingent on the history of play in the other game. Following this logic, I estimate the strategies used in Easy and Hard games separately. In the meta-analysis paper, Dal Bó and Fréchette, 2018, the authors find that Always Cooperate (AC), Always Defect (AD), Grim Trigger (Grim), Tit-for-Tat (TFT), and Defect Tit-for-Tat (DTFT) account for most behavior in the indefinitely repeated PD literature. I primarily use this set of strategies for my strategy estimation exercises.[36] I use the same set of strategies for both SGame and SRole treatments. I do this for two reasons. First, this allows us to compare behavior across the two treatments. Second, there is no previous literature to inform the strategies subjects use in asymmetric PD games.

Table 1.5 presents the frequency estimates of strategies subjects use in the Easy and Hard roles for treatments SGame and SRole. In the Easy role in the SGame treatment, the most common strategies are Grim and the TFT (76.8%), while the most common strategy is AD (65.2%) in the Hard role. This observation is in line with my theory. The estimated frequencies of strategy use do not achieve statistical significance for any strategies in SGame Easy role. This can be due to two reasons. First, the subjects are cooperative. Always Cooperate, Grim Trigger and Tit-for-Tat generates the same histories unless defection is observed. The second reason might be that data from my experiment are dispersed across sessions, because of which, I get very high standard errors for all my estimates. I expected that the most common strategy would be the Grim Trigger strategy. However, I find that

[35]↑ Cason and Mui, 2019 shows that at the later supergames of experimental session there is only 10-15% change in the strategies used by the subjects.
[36]↑ I also estimate the mixture model with 20 strategies from Fudenberg, Rand, and Dreber, 2012. I provide these estimates in table A.11.

Table 1.5. Estimated Frequencies of Strategies in Single Contact Treatments

	SGame		SRole	
	Easy	Hard	Easy	Hard
AC	16.7		5.8	2.7
	(12.1)		(4.6)	(3.7)
Grim	39.3	6.6	10.2	6.8
	(28.9)	(4.3)	(11.2)	(8.5)
TFT	37.5	0	33.5*	21.2*
	(29.0)	(3.5)	(8.4)	(6.9)
AD	6.3	65.2*	37.9*	43.0*
	(3.8)	(12.7)	(7.2)	(6.9)
DTFT		28.3	12.7	26.7*
		(12.6)	(7.1)	(7.6)
Cooperative	93.7*	6.6	49.4*	30.7*
	(4.0)	(4.3)	(9.6)	(8.3)
Defective	6.3	93.4*	50.6*	69.3*
	(4.0)	(4.3)	(9.6)	(8.3)
β	98.2	97.8	92.5	90.9
	(0.7)	(1.0)	(1.3)	(1.6)
$\mathcal{L}$	-183.4	-212.9	-538.7	-609.7
	(58.4)	(68.2)	(85.1)	(99.1)

Notes: Table shows estimated frequencies (in percentage). Estimation includes actions from Supergames 21-30. Two-Stage Cluster Bootstrapped Standard Errors from 3000 bootstraps (clustered at session level, randomized at period level) in parentheses. The strategies included here are: AC - Always Cooperate, Grim - Grim Trigger, TFT - Tit-for-Tat, AD - Always Defect, DTFT - Defect Tit-for-Tat. Blank implies frequency is 0 with 0 SE.

* - Frequency estimates are significantly different from 0 at $\alpha = 0.05$ (95% Bootstrapped CIs of estimates do not include 0)

subjects use other strategies like TFT and AC. All these strategies are categorized as cooperative (Cason and Mui, 2019; Fudenberg, Rand, and Dreber, 2012) and, account for 93.7% of the used strategies in the Easy role compared to 6.6% in the Hard role. On the other hand, for the Hard role, the defecting strategies AD and DTFT account for around 93.4% of the used strategies compared to 6.3% in the Easy role.

In the SRole treatment, the most frequent strategies used are shared between the Easy and the Hard role. Although the most common strategy is AD in the Easy role (37.9%) and the Hard role (43%), subjects use cooperative strategies more in the Easy role than the Hard role (49.4% vs. 30.7%). Subjects have the incentive to cooperate in the Easy role while her opponent does not (since, the opponent is in her Hard role). Therefore, I see an intention to cooperate in subjects in the Easy role. Although subjects in the Hard role use defecting strategies frequently, there is some use of cooperative strategies. This might be because subjects know that their opponents would want to cooperate, and hence they attempt to cooperate. Also, note that the mixture model's performance in SGame treatment is worse than SRole treatment in terms of β and $\mathcal{L}$. I summarize my findings in the following result.[37]

Result 1.5.3. *Strategies in single contact treatments:*

1. *(SGame) Subjects use cooperative strategies (Always Cooperate, Tit-for-Tat, Grim) in Easy role and defecting strategies (Always Defect, Defect Tit-for-Tat) in Hard role.*
2. *(SRole) Subjects use common strategies in both Easy and Hard roles. Although defecting strategies are most prevalent, in both roles, subjects also choose cooperative strategies. Cooperative strategies are chosen more commonly in the Easy role compared to the Hard role.*

Multiple Contacts Strategies

I next estimate the strategies used by subjects in the two games they play simultaneously. For this exercise, in some of the strategies that I use subjects choose actions in the two games

[37]↑ I also perform this exercise with last 5 supergames. The results are presented in Table A.10. My results do not change qualitatively by restricting the supergames to last 5 supergames.

that might condition one game's actions on history of play in either one or both games. My theoretical model assumes that subjects in multiple contact treatments use strategies like S-Grim strategy. Figure 1.11 shows the strategy in an automaton form. In the S-Grim strategy, a subject starts by cooperating in both games and continues to cooperate until the opponent defects in either game or both. Then the subject continues to defect in both games in all future periods. My hypothesis used this S-Grim strategy; however, as I see in Result 1.5.1, my data does not support this hypothesis. Therefore I want to estimate the strategies that the subjects choose. For this purpose, I introduce two more strategies – Strong TFT and Strong DTFT. Figure 1.11 shows the automaton representation of these strategies.

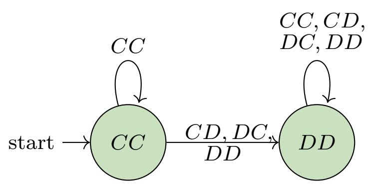


Figure 1.10. Strong Grim

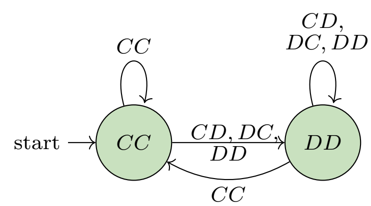


Figure 1.10. Strong TFT

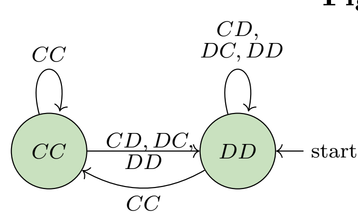


Figure 1.10. Strong DTFT

Figure 1.11. Automaton Representation of Multiple Contacts Strategies

In the Strong TFT (S–TFT) strategy, a subject starts by cooperating in both games and continues to cooperate in both games if the opponent cooperates in both games. If the opponent defects in either one or both games, the subject defects in both games for one period. If the opponent cooperates in both games, the subject goes back to cooperating in both games. Strong DTFT (S–DTFT) strategy operates like S-TFT, except it starts with defection in both games. I expect that subjects do not use the strong strategies in the single contact treatments, but subjects do use them under the multiple contact treatments. The other strategies I use are the combinations of the individual strategies that I use in the first estimation exercise –- AC, Grim, TFT, AD, DTFT. For example, AC-TFT implies, a subject plays according to AC in the Easy role and TFT in the Hard role; TFT - DTFT implies, a subject plays according to Tit-for-Tat in the Easy role and Defection Tit-for-Tat in the Hard role.

Table 1.6. Estimated Frequency of Strong Strategies and other Most Common Strategies for Two Games Simultaneously (in Percentage)

	SGame		SRole		MGame		MRole	
AC-AC	0 (0.1)		4.0 (3.3)		0 (2.0)		0 (2.3)	
AD-AD	2 (2.0)		34.4* (8.3)		18.8 (7.3)		38.9* (8.7)	
S-Grim			0 (0.4)		2.1 (2.4)		1.2 (7.7)	
S-TFT			0 (1.3)		0 (1.9)		25.1 (10.7)	
S-DTFT	1.9 (1.8)		0 (3.1)		0 (5.4)		11.4 (6.5)	
Other Most Frequent Strategies	Grim-AD	28.3 (22.1)	TFT-TFT	26.1 (7.8)	Grim-AD	14.9 (9.5)	TFT-TFT	9.5 (7.1)
	TFT-AD	22.9 (20.2)	DTFT-DTFT	13.9 (6.8)	TFT-AD	14.0 (10.3)	TFT-DTFT	4.4 (4.5)
	TFT-DTFT	10.0 (11)	TFT-DTFT	6.9 (4.4)	Grim-DTFT	12.5 (12.1)	DTFT-DTFT	3.5 (4.5)
Aggregating over Strategies								
Strong	1.9 (1.8)		0 (3.5)		2.1 (5.7)		37.7* (13)	
Same Strategy in Both Games/Roles	5.1 (3.2)		80* (10.5)		37.5* (11.8)		51.9* (11)	
Cooperative in Easy Game/Role	93.8* (3.9)		49.3* (10.3)		69.7* (9.1)		17.9 (9)	
Cooperative in Hard Game/Role	6.7 (4.3)		34.2* (8.1)		9.3 (5.7)		11.6 (8.2)	
Defecting in Easy Game/Role	4.3 (3)		50.8* (10.8)		28.2 (9.4)		44.5* (10.5)	
Defecting in Hard Game/Role	91.3* (4.4)		65.8* (8.6)		88.6* (7.8)		50.8* (11.9)	

Notes: Table shows estimated frequencies with Two-Stage Cluster Bootstrapped Standard Errors from 3000 bootstraps (clustered at session level, randomized at supergame level). Estimation includes actions from supergames 21-30. The entire list of estimated parameters are in Table A.12. Blank implies frequency is 0 with 0 SE.
* - Frequency estimates are significantly different from 0 at $\alpha = 0.05$ (95% Bootstrapped CIs do not include 0)

For the single contact treatments, I make the assumption that subjects play two games in isolation. However, that assumption might not hold. Therefore, I estimate strategies for the SGame and SRole treatments along with the MGame and MRole treatments by considering the two games together without the restriction that subjects play the two games in isolation. Table 1.6 shows the estimated frequency of the Strong strategies, and some groups of strategies for the four treatments.[38] I report the estimated proportion for AC-AC and AD-AD separately since these are combinations of individual game strategies as well as strong type strategies. I do not include these when I calculate the cumulative frequency of the strong type strategies.

From the estimation, I find that for the SGame and SRole treatments, the proportion of strong strategy usages are minimal. However, I also do not find frequent use (2.1%, not statistically different from 0 at $\alpha = 0.05$) of the strong strategies in MGame treatment. The subjects may be using some more complicated strong type strategies. Although I do not find strong strategies in the MGame treatment, I find that the strategies being used differ from those in the SGame treatment. I find that subjects use more defecting strategies like AD and DTFT in the Easy game (28.2%, not statistically different from 0 at $\alpha = 0.05$) under MGame while under SGame the most prevalent strategies are cooperative strategies (93.8%, statistically different from 0 at $\alpha = 0.05$).

I find that under MRole treatment, the proportion of subjects using strong strategies (37.7%) is significantly different from zero at $\alpha = 0.05$, with S-TFT being the second most frequently used strategy (25.1%). The use of strong strategies in the MRole treatment is substantially higher than that in SRole treatment 0%. This indicates that even though I do not find any differences in cooperation rates due to multiple contacts, it affects the strategies being used. I summarize my observations in the following result.

From the strategy estimation exercise on single games, I find that in the SRole treatment, many strategies are used in both the Easy and Hard roles. However, that exercise does not tell us if the same subjects used the same strategies in both roles. In this exercise, I use subjects' actions in both roles and map the strategy prescribed actions. Therefore, in this exercise, a strategy like AD-AD or TFT-TFT implies that a subject uses AD and TFT

[38]↑ The complete list of estimates is in Table A.12.

in both roles. I find that in SRole a large frequency (80% statistically different from 0 at $\alpha = 0.05$) of use of same strategies in both roles, significantly higher than that in the SGame treatment (5.1%). This result is noteworthy. In the asymmetric case, subjects play two roles; in one, they are advantaged while in the other, they are not. However, they still use the same strategies in both roles. Among the strategies that are used, I can theoretically support the use of AD-AD (34.4%), I also see use of TFT-TFT (26.1%) and DTFT-DTFT (13.9%). TFT is a cooperative strategy, and the subjects use it in both Easy (more advantaged than the opponent) and Hard (more disadvantaged than the opponent) roles which contradicts my hypothesis. I also find a considerable incidence of these strategies in the multiple contacts treatments, of which AD-AD is the most commonly used strategy.

Result 1.5.4. *Strategies in all treatments:*[39]

1. *Subjects do not use strong strategies in SGame and SRole treatments.*
2. *Subjects use same strategies in both Easy and Hard roles in SRole, MGame, and MRole treatments with Alway Defect - Always Defect being the most commonly used strategy among this class of strategies.*
3. *Subjects do not use strong strategies in MGame treatment. But the strategies used are different from those in SGame treatment and more defecting in nature.*
4. *Subjects use strong strategies in MRole treatment, although S-Grim is not used frequently. Strong Tit-for-Tat and Strong Defect Tit-for-Tat strategies are more commonplace.*

1.6 Discussion

In this paper, I theoretically and experimentally investigate the effect of multiple contacts on cooperative behavior in symmetric and asymmetric PD games. In particular, I study the impact of multiple contacts on both the observable outcomes (i.e., the average level of cooperation) and unobservable outcomes (i.e., strategies). In addition, I explore the differences

[39]↑ I use only the last 10 supergames for my strategy estimation. But I also perform this exercise with the last 5 supergames. The results are presented in Table A.13. My results do not change qualitatively by restricting the supergames to the last 5 supergames.

in the impact of multiple contacts under two different conditions.

I utilize the theory from Bernheim and Whinston, 1990 to develop hypotheses on the effect of multiple contacts. I then take my theoretical environment to the laboratory. I conduct a controlled laboratory experiment with a 2×2 between subject design. The first factor varies the number of contacts; Single Contact vs. Multiple Contacts. In the single contact treatments, subjects simultaneously play two IRPD games with two different opponents. In the multiple contacts treatments, subjects simultaneously play two IRPD games with the same opponent. The second dimension varies the payoffs (symmetry vs. asymmetry of payoffs). In the symmetric treatments with single contact, in one of the two IRPD games I use – Easy game – cooperation is theoretically possible, whereas in the other one– the Hard game – defection is the only equilibrium outcome. The asymmetric payoff treatments are different from the symmetric treatments in that cooperation is not possible in the asymmetric PD game with single contact. Importantly, with multiple contacts, it is possible to sustain cooperation in both roles/games both symmetric and asymmetric payoffs. The way multiple contacts works is that defection in the Hard game can be punished in the Easy game.

In my experimental data, I find that multiple contacts do influence the cooperative behavior of subjects in the IRPD games. However, these effects vary based on whether payoffs are symmetric or asymmetric. In the case of symmetric payoffs, I find that with multiple contacts the cooperation levels in the Hard game increases (although insignificantly) from its single contact levels, but with a significant drop in the cooperation level in the Easy game. On the other hand, when the payoffs are asymmetric, I do not see any significant change in cooperation levels in either the Easy or the Hard role. My results are somewhat in line with previous papers on multiple contacts. Some of these papers find an increase in cooperation rate due to multiple contacts in the equivalent Hard Game while others did not (Phillips and Mason, 1992 found an increase in cooperation levels, while Güth et al., 2016; Yang, Kawamura, and Ogawa, 2016 did not). But, Güth et al., 2016; Phillips and Mason, 1992; Yang, Kawamura, and Ogawa, 2016 also found a decrease in cooperation rate in the equivalent Easy game. What I find additionally is that under asymmetry of payoffs, subjects punish defection in the Hard game in the Easy game under multiple contacts even the cooperation rates are not different from that under single contact. This suggests that the subjects must be using different strategies under multiple contacts in this case. None of the existing papers investigate the strategies their subjects used and if multiple contacts influence the strategy choices.

The theory behind my hypotheses relies on the use of the S-Grim strategy, which conditions future actions on the history of all previous strategic interactions. Although my data do not show significant differences in cooperation rates, the question still remains whether strategies are different under multiple contacts. To this end, I econometrically investigate the strategies the subjects use in each of my four treatments using Strategy Frequency Estimation Method (Dal Bó and Fréchette, 2011).

First, I estimate strategies for the Single Contact treatments assuming that subjects player the two games in isolation. I find that the most commonly used strategies in the symmetric games are in line with my theoretical predictions and past literature (see Dal Bó and Fréchette, 2018 for a review). However, I also find that subjects use cooperative strategies quite heavily in the asymmetric treatments, which contradicts my predictions. I discover that the common strategies used in the games with symmetric payoffs are not best suited for the games in the asymmetric treatment. I then estimate strategies for all four treatments by combining both the Easy and the Hard role actions. For this exercise, I introduce two new strategies, along with the Strong Grim strategy. The Strong strategies' main characteristic is that when choosing each game's actions in each period, the history of actions in both games are considered. There are a few exciting outcomes of this exercise. I find that in none of the single contact treatments do subjects use Strong strategies. However, I do not find subjects using Strong strategies even in the multiple contacts symmetric treatment. On the other hand, in the multiple contacts asymmetric treatment, I find that subjects use Strong strategies extensively. I believe this is because subjects can still get high payoffs in the multiple contacts symmetric treatment by just cooperating in the Easy game. However, the subjects needed to coordinate in both roles to obtain high payoffs in the multiple contacts asymmetric treatment. Hence the subjects needed to use Strong strategies.

My results have several implications, both in the industrial organization or management literature and the experimental literature. First, in the industrial organization literature, researchers pay more attention to the outcome than the process. Even though studying prices and quality in the presence of multi-market contact is essential, equal, if not more, attention should be paid to *how* firms reached these outcomes. I should investigate how firms plan to retaliate against other firms in the face of defection, where defection can imply a drop in prices or betterment of quality. As I have shown in this paper, there are no indications of increased collusion or cooperation in multiple contacts environment in the case of asymmetric payoffs. However, there is a stark difference in the type of strategies that might be at play. Uncovering strategies used by firms might be relevant for antitrust issue in unobserved scenarios. But estimating strategies of firms can be complicated. It is less complicated to look at conditional responses. My results also suggest that it would be more informative, to assess the presence of MMC in an industry, to look at the responses after a hike or drop of prices or of other variables. Second, I find that most studied strategies in the experimental literature are not best suited for games with asymmetric payoffs. In the literature, extensive attention is paid towards PD game with symmetric payoffs. Given that all real-life scenarios entail asymmetry, it is worthwhile to understand how subjects react to it. My findings suggest that conclusions from the research in symmetric games may not offer the best explanations for asymmetric games; more attention should be paid to this particular case. Finally, I also find that subjects in asymmetric games tend to cooperate even in situations where I cannot predict cooperation theoretically. It should be interesting to determine how individuals choose their actions when every stakeholder in the situation is not the same.

2. TEAM INNOVATION CONTESTS WITH COGNITIVE DIVERSITY

2.1 Introduction

Ranging from early examples such as the 1714 longitude prize up through modern innovation-competition platforms such as Kaggle.com, drivendata.org, challenge.gov, NineSigma and Innocentive, innovation contests have played and continue to play an important role in the economy. Furthermore, note that all of the modern innovation-competition platforms listed here feature competition that is open to teams of problem solvers. When thinking about a team of problem solvers facing an innovation problem, a fundamental issue that comes to mind is the role of cognitive diversity — which may be thought of as differences in skills or perspectives. In particular, as Scott Page discusses in his 2019 book "The Diversity Bonus: How Great Teams Pay Off in the Knowledge Economy," there is a consensus that cognitive diversity leads to better team performance.

As an example, consider "Blackett's Circus," a World War II era British operations research team that was tasked with a number of challenging innovation problems including the use of radar in the aiming of anti-aircraft guns. When Patrick Maynard Stuart Blackett, who would go on to become a Nobel Laureate in Physics, was tasked with forming his team,[1] he selected: three physiologists, one (female) mathematician, two physicists, one astronomer, one army officer, and one surveyor. As reflected in the group's unofficial name (Blackett's Circus), it is clear that when Blackett was faced with a variety of challenging innovation problems he valued having a group of individuals with diverse skills and perspectives. For a more recent example, consider the Event Horizon Telescope which involved more than 200 scientists including physicists, astrophysicists, astronomers, and computer scientists among others. The goal of this large scale collaboration is to "bring black holes into focus" and by linking telescopes from around the world, the Event Horizon Telescope array has already produced our first images of a black hole. When these images were released to the public, Dr. Katherine Bouman [a computer scientist, tasked with creating the image from the infor-

[1]↑ For more on Peter Blackett and the history of operations research see Budiansky, 2013.

mation collected from telescopes around the world and a spokesperson for the collaboration] mentioned in an interview (Stein, 2019) that she hardly knew what a black hole was when she started on the project. In her words, she "brought the computer science mindset, but the project brought in people from so many different areas."

Using data from 1956 – 2000 on academic research in fields such as science, engineering, the social sciences as well as in patenting, Wuchty, Jones, and Uzzi, 2007 find that papers produced by a team of (two or more) researchers generate higher citation counts and are more likely to fall into the category of "exceptionally high-impact research." In the literature that followed, Uzzi et al., 2013 found that teams are more likely to introduce novel innovations to the literature and that novel innovations are twice as likely to generate high citation counts, and Freeman, Ganguli, and Murciano-Goroff, 2015, using a survey of academic authors, found that the primary motivation for collaboration is the value generated by the combination of the specialized knowledge and skills of individual members of the research team. Moreover, the theoretical literature on the case of a (single) team working to solve an innovation problem — that features technical uncertainty about whether or not the problem may be solved — finds that the level of diversity in the skills or perspectives of the team members may be more important than the team members' ability levels (Hong and Page, 2004, Page (2008), and Marcolino, Jiang, and Tambe, 2013). To summarize, cognitive diversity is a fundamental consideration for teams of innovation problem solvers and may even dominate considerations regarding individual ability.

Given the growing role played by team-based innovation-competition platforms, a natural question that arises is how does team composition and cognitive diversity affect team performance in a competitive setting. For example, one takeaway from the literature on contests[2] is that it is generally the case that total effort and expected winner performance increase as the playing field becomes more level. Note however that if team-level cognitive diversity increases for some but not all teams, then the playing field may become less level.

[2]↑ Classic examples from the contest theory literature include Baye, Kovenock, and De Vries, 1993 and Che and I. L. Gale, 1998. For a more recent example see Brookins and Jindapon, 2021.

In such a case, does an increase in cognitive diversity adversely affect the expected performance of the contest? Also related is the issue of whether an individual team has incentive to increase its own level of cognitive diversity. In particular, do there exists situations in which having less diversity would provide a competitive edge for a team? The contribution of this paper is that it sheds light on the important issue of the role of cognitive diversity within the context of large team innovation contests.

To examine these issues, we construct a framework for examining the role of team composition in a large contest between teams of diverse individuals facing an innovation problem. Our large team contest utilizes the large contest framework developed by Olszewski and Siegel, 2016 and Bodoh-Creed and Hickman, 2018 in which an arbitrarily large number of heterogeneous individuals compete for a set of prizes. Given our focus on team composition and team performance, our framework extends the analysis on large contests to allow for competition between heterogeneous teams. Our approach also utilizes the "productivity based" innovation competition framework – along the lines of DiPalantino and Vojnovic, 2009 and Chawla, Hartline, and Sivan, 2019 among others[3] – in which the value of an individual's innovation depends on both the techniques or approaches (tools) that the individual applies to the innovation problem and the amount of work that the individual uses to develop the innovation.

Our team-based innovation activity setup is also related to Bendor and Page, 2019 which involves an innovation problem and a single team consisting of members with problem-solving tools that can be applied to the innovation problem.[4] In moving to an environment with competition between teams, our focus on "productivity based" innovation differs from Bendor and Page, 2019 who examine innovation activity in a context with technical uncertainty about whether or not the problem may be solved. In our framework, each team's tool ef-

[3]↑ In particular, in DiPalantino and Vojnovic, 2009, each contestant has a private problem-solving effectiveness level, which is drawn from a continuous distribution function and may be thought of as the amount of effort exerted per unit cost of effort.

[4]↑ As in Bendor and Page, 2019 we assume that each team member is time-constrained in the sense that they only have access to a single tool.

fectiveness level depends on the composition of the tool effectiveness levels of the individual team members and is private information for the team. Then, given the team's tool effectiveness level the individual team members choose effort levels and the value of a team's project is a function of the team's tool effectiveness and the effort contributions of the individual team members.[5]

In this large innovation contest framework, we find that the questions of whether broadly increasing diversity leads to an increase in expected performance for the overall contest or unilaterally increasing diversity is advantageous for a team, depends on two key components: the measurement of diversity and the efficiency with which teams are able to utilize diverse sets of team member tools. In the discussion that follows, we will elaborate on these two key components. To briefly summarize, we allow teams to differ with respect to the efficiency with which they are able to utilize diverse tool sets, and find that if, on average, teams are sufficiently efficient in utilizing diverse tool sets, then increasing tool diversity is beneficial for the performance of the contest. However, if teams are, on average, sufficiently inefficient at utilizing diverse tool sets, then increasing tool diversity can actually be detrimental to the performance of the contest. Similarly, an individual team has incentive (disincentive) to increase its own diversity if the team is sufficiently efficient (inefficient) at utilizing diverse sets of tools. However, an individual team always has incentive to increase the efficiency with which it utilizes diverse tool sets. Thus, our paper provides a channel – other than a direct cost of diversity – through which diversity can be beneficial or detrimental depending on how efficient teams are at utilizing diverse sets of team member tools.

Beginning with the measurement of diversity, our focus is on the relationship between the tool effectiveness levels of the individual team members. We assume, as in Bendor and Page, 2019, that the effectiveness of an individual team member's tool on the given innovation problem is a random variable, and thus, for an M-member team we are interested in

[5]↑ Our approach to aggregating the effort contributions of individual team members into the value of a joint project builds on the analysis of two teams competing in a private values all-pay auction as in Eliaz and Wu, 2018.

the realization of a random M-tuple that provides the realization of the tool effectiveness levels for each of the M team members. Loosely speaking, more cognitively diverse teams have a larger range of possible perspectives or problem-solving styles and this results in a larger range of tool effectiveness levels. That is, because similar tools are more likely to generate similar tool effectiveness levels on a given problem, the different perspectives of the team members are reflected in the dependence structure of the effectiveness levels of the team members' tools. Formally, we define cognitive diversity using the concordance partial ordering of multivariate joint distributions, which provides a pairwise ranking for joint distribution functions with regards to how similar the M-tuples of tool effectiveness levels of the M individual team members are. Our analysis of changes in the level of cognitive diversity focuses on transformations of the teams' joint distributions of tool effectiveness levels that vary with respect to the concordance of the teams' joint distributions while holding constant the individual team member's univariate marginal distributions of tool effectiveness[6] – along with their related measures of central tendency and dispersion.

Regarding the way in which teams aggregate the tool effectiveness levels of the individual team members into the team's tool effectiveness level, we focus primarily on the case that this aggregation, which may be heterogeneous across teams, lies on a one-dimensional efficiency spectrum. At the lower bound of this spectrum, a team's tool effectiveness level is the minimum of the team members' tool effectiveness levels (i.e., what Hirshleifer, 1983 terms the "weakest-link"). At the upper bound of this spectrum, the team's tool effectiveness level is the maximum of the team members' tool effectiveness levels (i.e., what Hirshleifer, 1983 terms the "best-shot"). Outside of this one-dimensional efficiency spectrum, the results are more nuanced. However, for a given combination of (i) a functional form of each team's mapping from individual to team tool effectiveness and (ii) a functional form for each team's joint distribution of tool effectiveness levels, it is possible to numerically show how a particular cognitive diversity increasing transformation affects the performance of each team and

[6]↑ That is, we focus on transformations of the teams' m-copulas and hold constant the teams' sets of univariate marginal distributions.

the overall performance of the contest, and we examine several such examples.

To summarize, our results on transformations of cognitive diversity levels across teams, may be stated as follows. There exists a threshold level of average team efficiency above which any transformation of cognitive diversity levels that weakly increases cognitive diversity for all teams results in an increase in the equilibrium expected performance of each team, or equivalently the total value of all innovation activity. Conversely, there exists a threshold level of average team efficiency below which any transformation of cognitive diversity levels that weakly increases cognitive diversity for all teams results in a decrease in the equilibrium expected value of all innovation activity. That is cognitive diversity is only beneficial for the overall contest when the teams are, on average, sufficiently efficient with the utilization of diverse tool sets. Regarding individual teams, we find that a team has incentive to unilaterally increase its own cognitive diversity only if the team is sufficiently efficient at utilizing a diverse set of tools. If the team is sufficiently inefficient at utilizing diverse tools, then the team has incentive to unilaterally decrease its own level of cognitive diversity. However, all teams have incentive to increase the efficiency with which they utilize diverse tools.

A practical implication of our results is that training programs aimed at increasing the efficiency with which teams utilize diverse tool sets are crucial for realizing the benefits of cognitive diversity for both the team and the contest designer.

2.2 Literature Review

We begin by examining the relationship between our model of a large team innovation contest and the vast and growing literature on innovation contests. Adamczyk, Bullinger, and Möslein, 2012 provides a review of 201 articles on this subject from April 1959 to July 2011. Overall there are two lines of investigation in this literature. The first line concerns the optimal contest design and optimal prize distribution, which is the most studied question and includes papers such as Ales, Cho, and Körpeoğlu, 2017; Archak and Sundararajan, 2009; Cavallo and Jain, 2012, 2013; Che and I. Gale, 2003; Ding and Wolfstetter, 2011;

Erkal and Xiao, 2021; Fu, J. Lu, and Y. Lu, 2012; Luo et al., 2015; Schöttner, 2008. Within the optimality of contest design line, important considerations include: (i) whether entry to the contest should be restricted (Ales, Cho, and Körpeoğlu, 2021; Ghosh and McAfee, 2012; Taylor, 1995), (ii) the number of contests (Hu and Wang, 2021; Körpeoğlu, Korpeoglu, and Hafalir, 2017), (iii) the duration (Korpeoglu, Körpeoğlu, and Tunç, 2021) and (iv) the role of feedback in dynamic contests (Mihm and Schlapp, 2019). The second stream of papers on innovation contests deal with different contest environments, equilibrium characterization and comparative statics (Halac, Kartik, and Q. Liu, 2017; Moscarini and Squintani, 2010; Schmidt, 2008; Segev, 2020; Terwiesch and Y. Xu, 2008). Almost all of the papers in both streams focus exclusively on the case that the contestants are individuals. Our paper contributes to this second stream by studying competition between teams instead of individual participants. Candoğan, Korpeoglu, and Tang, 2020 also study innovation contests with finite number of identical teams. They model uncertainty in outcome and interaction among team members using normal distributions. Their notion of diversity is in terms of the variance of uncertainty due to the interpersonal interaction. Our focus differs in that we deal with heterogeneous teams and general distributions of skills/tools in an environment where diversity is a function of the dependence structure of the team members' tool effectiveness levels.

Diversity can take various forms such as surface level (age, sex and race/ethnicity) or deep level (attitudes, beliefs, values, knowledge or skill) (Harrison, Price, and Bell, 1998). Our paper concentrates on cognitive diversity which fits into the deep level category. Cognitive diversity may be thought of as differences in perspectives or viewpoints which in our paper is manifested in the stochastic effectiveness or quality levels of the individual team members' tools. In the management literature many researchers have studied the question of how cognitive diversity impacts performance both in the non-competitive (Aggarwal and Woolley, 2019; Kilduff, Angelmar, and Mehra, 2000; Olson, Parayitam, and Bao, 2007; Pitcher and Smith, 2001; Shin et al., 2012) and competitive (Hoogendoorn, S. C. Parker, and Van Praag, 2017) settings. There is mixed evidence regarding whether cognitive diversity positively impacts outputs by the teams. However, there are only a few but influential theoretical works in this area. Hong and Page, 2004, 2001 are the two earlier papers to investigate the question of problem solving when individuals are heterogeneous or cognitively diverse. Individual problem solvers vary in their *perspective* (the way individuals represent the problem to themselves) and *heuristics* (the algorithm to generate a solution). The authors start with individuals who are not capable to solve the problem on their own but if they work together the problem can be solved. Hong and Page, 2004 further shows that a team of randomly selected individuals from a diverse population can outperform a team of best-performing individuals. LiCalzi and Surucu, 2012 considers a similar environment. They further find that a team can outperform individuals. In this model, authors use correlation as a measure of homophily and they find that higher homophily (correlation) requires larger teams to find a solution.

Authors in this literature study different types of tasks. Marcolino, Jiang, and Tambe, 2013; Marcolino, H. Xu, et al., 2014 study a context where team members vote on actions from a large action space. In this setting, Marcolino, Jiang, and Tambe, 2013 finds a similar result as in Hong and Page, 2004. That is, a diverse team of weaker agents can outperform a team of better agents. Marcolino, H. Xu, et al., 2014 extends this result by characterizing the conditions under which it holds. Forecasting is another such application where diversity is valuable. Lamberson and Page, 2012 study teams in forecasting tasks where heterogeneity is represented through covariance among predictive accuracies or types. The more similar individuals are in their types, the higher the covariance. In this paper, the authors characterize the optimal team composition. They find that if the teams are small, teams should be made of agents with best predictive accuracy, but with large teams, teams with low covariance among types should outperform. This second result is in congruence with findings in Marcolino, H. Xu, et al., 2014. Our paper contributes to this literature by introducing a competitive setting using the context of innovation contests. Our approach to modeling diversity – using the statistical concept of concordance to compare joint distributions to capture diversity – is closest to those used in Lamberson and Page, 2012 (uses covariance of predictive accurance) and LiCalzi and Surucu, 2012 (correlation). Our results are also in line with these papers, as we find that under some circumstances diversity can improve performance in an innovation contest.

This brings us to the contest literature. In this literature, team contests are primarily modeled with a finite number of teams and a finite number of team members. This literature is large and expanding. The issues that researchers address include equilibrium characterization with or without private information (Brookins and Ryvkin, 2016; Chade and Eeckhout, 2020; Eliaz and Wu, 2018; Fu, J. Lu, and Pan, 2015); the equilibrium effects of asymmetries in team production both across and within teams (Chowdhury and Topolyan, 2016a,b; Kolmar and Rommeswinkel, 2013); and prize or information sharing across team members (Barbieri, Kovenock, et al., 2019; Barbieri and Malueg, 2016; Feng et al., 2021; Nitzan and Ueda, 2011) among others. We contribute to this literature by demonstrating the existence of equilibrium when the number of teams are large and characterize the equilibrium in the limit case. We further examine the differences between situations equivalent to "best-shot" and "weakest-link" in our environment.

Many papers studying team contests address the question of asymmetry across team members. In these papers, the heterogeneity among the team members arises in terms of cost of effort or resource (ability, power) available tot them (H. Chen and N. Lim, 2017; Choi, Chowdhury, and Kim, 2016; Chowdhury, Lee, and Sheremeta, 2013; Fallucchi et al., 2021; Parreiras and Rubinchik, 2015 among others). We model diversity or differences among team members differently. In our environment, the team members are ex-ante identical in terms of cost of effort and claim to the group reward. However, they differ in their viewpoints or perspectives which is captured by the distribution of the quality of their own ability/skills/tools. If the members are cognitively diverse, due to their varied perspectives, the effectiveness of their tools on a particular innovation problem can be widely different. In our case, diversity affects the outcomes of the team contest through the team's tool effectiveness level and its subsequent affect on the effort levels that the team members contribute. Furthermore, in the literature on contests with asymmetric teams, the analysis has focused exclusively on the case of two teams. In this paper, we modify the large contest framework developed by Olszewski and Siegel, 2016 and Bodoh-Creed and Hickman, 2018, for the case of a large number of heterogeneous individuals, to allow for competition between a large number of heterogeneous teams.

2.3 Contest Model

We are interested in a contest with an arbitrarily large, but finite number N of teams and prizes. An arbitrary team is denoted by $n \in \{1, 2, \ldots, N\}$. Each team consists of M team members, where an arbitrary team member is denoted by $m \in \{1, 2, \ldots, M\}$. In the contest, the teams compete over a set of N prizes denoted by $\mathcal{Y}_N = \{y_{(p)}\}_{p=1}^{N}$, where each prize p takes a value $y_{(p)} \in [0, 1]$ and the values of the prizes are ordered as follows $y_{(1)} \geq y_{(2)} \geq \ldots \geq y_{(N)} \geq 0$. The empirical prize distribution is denoted as Φ_N. The team that submits the highest value innovation wins the first prize $y_{(1)}$. The team that submits the second-highest value innovation wins the second prize $y_{(2)}$, and so on for the remaining prizes. In the case of one or more ties, if k teams tie for the p^{th} position, then each of the k teams get the prize for the $k + p - 1$ position.[7] For each prize p, the team that wins the p^{th} prize shares the value of the p^{th} prize, $y_{(p)}$, equally among its M team members. Note that it may be the case that there exists a $\underline{p} < N$ such that $y_{(\underline{p})} > 0$ but $y_{(p)} = 0$ for all $p > \underline{p}$, i.e. the number of nonzero prizes may be strictly less than N.

We model the innovation activity of each team as a two-stage process. The following two subsections provide the details on the two stages of innovation activity. To briefly summarize, in the first stage each team selects an approach, technique, or method for generating an innovation. We assume that the individual team members may differ with regards to their problem solving type and/or the skills (or tools) that they possess. Furthermore, from an ex ante perspective the effectiveness of a particular tool on the given problem is stochastic. In the first, or tool, stage, members realize the effectiveness of their tools for the problem at hand. Then, the team's tool effectiveness level depends on how efficient the team is in

[7]↑ Note that this tie-breaking rule ensures that the sum of the prizes that are awarded when ties occur is always less than or equal to the sum of the values of the prizes that are awarded when ties do not occur. For example, if two teams tie for the p^{th} position, then both teams are awarded the prize for the $p + 1$ position and $2y_{(p+1)} \leq y_{(p)} + y_{(p+1)}$. Our results continue to hold for a range of tie-breaking rules that hold the sum of the prizes with ties at or below the sum of the prizes without ties.

aggregating/utilizing its members' tools. A team knows its own (team) tool effectiveness level but only knows the distribution of tool effectiveness levels for the other teams. In the second, or effort, stage, each team member chooses a costly effort level. The value of the team's innovation is a function of the team tool effectiveness level and the level of effort expended by each team member. We begin by describing the first (tool) stage of the game and then turn to the second (effort) stage.

2.3.1 First (Tool Effectiveness Level) Stage

In the first stage, the teams are given the problem and each member of each team individually realizes the effectiveness of their tool for the given problem. Next, each team's *team tool effectiveness level*, which for compositional purposes is shortened to just *team tool*, is determined by how the team is able to utilize the combination of its team members' tools. Let n denote an arbitrary team and m denote an arbitrary team member. For team member m of team n, the effectiveness of their tool is a random variable, denoted by $\widetilde{x}_n^m \in [0,1]$, drawn from the univariate distribution function G_n^m, which is assumed to be continuously differentiable and strictly increasing on $[0,1]$ with $G_n^m(0) = 0$. Given a realization of each team member m's stochastic tool effectiveness level x_n^m, a team has an M-tuple of tool effectiveness levels $\mathbf{x}_n = (x_n^1, ..., x_n^M) \in [0,1]^M$. Team n's M-tuple of effectiveness levels $\mathbf{x}_n$ is observable to the members of team n but is private information for team n.

Because similar tools are likely to generate similar tool effectiveness levels on a given problem, the different perspectives of the team members are reflected in the dependence structure of the effectiveness levels of the team members' tools. Let $G_n(\cdot)$ denote the joint distribution of team n's M-tuple of effectiveness levels $\mathbf{x}_n$. Note that the set of univariate distribution functions $\{G_n^m\}_{m=1}^M$ described above, one univariate distribution for each team member m of team n, corresponds to the set of M univariate marginal distributions of the joint distribution $G_n(\cdot)$.

Let $t_n(\cdot)$ denote team n's mapping from its M-tuple of effectiveness levels into the team n tool. We assume that each team n's tool aggregation function $t_n(\cdot)$ is bounded above by the best tool within team n and bounded below by the worst tool within team n, i.e. $t_n : [0,1]^M \to [0,1]$ such that for each $\mathbf{x}_n \in [0,1]^M$ $t_n(\mathbf{x}_n) \in [\min_m\{\mathbf{x}_n\}, \max_m\{\mathbf{x}_n\}]$. We also assume that t_n is weakly increasing in each of its M arguments.

Each team n's tool aggregation function, $t_n(\cdot)$ and each team n's joint distribution of M-tuples of team member tool effectiveness levels, $G_n(\cdot)$, are common knowledge, and each team $n' \neq n$ forms beliefs about the distribution of the value of team n's tool which is denoted by $H_n(\cdot)$, where $H_n(z) = \Pr(t_n(\mathbf{x}_n) \leq z)$ and the M-tuple $\mathbf{x}_n$ is distributed according to $G_n(\cdot)$. When necessary, we let h_n denote the corresponding probability distribution function of H_n. We now turn to the issue of cognitive diversity and examine how the distribution of the value an arbitrary team n's tool, $H_n(\cdot)$, is affected by the level of cognitive diversity of team n.

Cognitive Diversity

In our framework, a team's level of cognitive diversity is a characteristic of the dependence structure of the joint distribution from which the random M-tuple that provides the realization of the tool effectiveness levels for each of the M team members is drawn. Loosely speaking, more cognitively diverse teams have a larger range of possible perspectives or problem-solving styles and this results in a larger range of tool effectiveness levels. To formalize our notion of cognitive diversity, we now relate cognitive diversity to the concordance partial ordering of multivariate joint distributions, which provides a pairwise ranking for joint distribution functions with regards to how similar the M-tuples of tool effectiveness levels of the M individual team members are.

Recall that for team n the M-tuple of the team member tool effectiveness levels $\mathbf{x}_n$ is drawn from the joint distribution $G_n(\cdot)$ with support contained in $[0,1]^M$ and with the set of univariate marginal distributions $\{G_n^m\}_{m=1}^M$. Our analysis of changes in the level of cognitive diversity focuses on transformations of the teams' joint distributions of tool effectiveness levels that hold constant the individual team member's univariate marginal distributions of tool effectiveness (i.e. holding constant the set $\{G_n^m\}_{m=1}^M$). That is, we hold constant the characteristics of the individual team members' distributions of tool effectiveness levels. In the analysis that follows, it will be convenient to work with the copula for G_n, the function C_n that maps team n's set of univariate marginal distributions of team members' tool effectiveness levels, $\{G_n^m\}_{m=1}^M$, into team n's joint distribution of tool effectiveness levels, G_n.

Let $\mathbb{I}$ denote the unit interval $[0, 1]$, and let $\mathbf{u} \in \mathbb{I}^M$ denote an arbitrary M-tuple corresponding to the M-tuple $\left(G_n^1(x_n^1), \ldots, G_n^M(x_n^M)\right)$ for an arbitrary $\mathbf{x} \in \mathbb{I}^M$. An M-copula, or copula for short, may be defined as a function, denoted by C, that maps $\mathbb{I}^M$ into $\mathbb{I}$ such that: (i) $C(\mathbf{u}) = 0$ for every $\mathbf{u} \in \mathbb{I}^M$ such that $u^m = 0$ for one or more m and $C(\mathbf{u}) = u^m$ for every $\mathbf{u} \in \mathbb{I}^M$ such that $u^{m'} = 1$ for all $m' \neq m$, and (ii) for every $\mathbf{u}, \hat{\mathbf{u}} \in \mathbb{I}^M$ such that $u^m \leq \hat{u}^m$ for all $m = 1, \ldots, M$, the C-volume of the M-box $[u^1, \hat{u}^1] \times [u^2, \hat{u}^2] \times \ldots \times [u^M, \hat{u}^M]$ is weakly positive.[8] It follows from Sklar's theorem in M-dimensions that there exists a copula C_n for joint distribution G_n such that for all $\mathbf{x}_n = (x_n^1, \ldots, x_n^M) \in \mathbb{I}^M$:

$$C_n\left(G_n^1(x_n^1), \ldots, G_n^M(x_n^M)\right) \equiv G_n(\mathbf{x}_n).$$

In Definition 2.3.2 below we formally define cognitive diversity using the concordance partial ordering of multivariate joint distributions.[9] The concordance concept is well known in the statistics literature, and Definition 3.1 given below follows Nelsen, 2007.

Definition 2.3.1. *Let $C_1(\mathbf{u})$ and $C_2(\mathbf{u})$ where $\mathbf{u} \in \mathbb{I}^M$ be $M-$copulas, and let $\bar{C}_1$ and $\bar{C}_2$ denote the corresponding $M-$dimensional joint survival functions corresponding to C_1 and*

[8]↑Given that an M-copula C forms an M-variate joint distribution with univariate marginal distributions that are uniform on the unit interval, the C-volume of the M-box $[\mathbf{u}, \hat{\mathbf{u}}] = [u^1, \hat{u}^1] \times [u^2, \hat{u}^2] \times \ldots \times [u^M, \hat{u}^M]$ is simply the measure of the support of C that lies in the M-box $[\mathbf{u}, \hat{\mathbf{u}}]$.
[9]↑ For more details see Nelsen, 2007.

C_2*, respectively.* [10] C_1 *is* ***more concordant*** *than* C_2 *if for all* $\mathbf{u} \in \mathbb{I}^M$*, both* $C_1(\mathbf{u}) \geq C_2(\mathbf{u})$ *and* $\bar{C}_1(\mathbf{u}) \geq \bar{C}_2(\mathbf{u})$ *hold.*

We now use concordance to characterize the different perspectives aspect of cognitive diversity which is the focus of our analysis.

Definition 2.3.2. *For an arbitrary team* n *and two joint distributions of team tool qualities,* G_n *and* G'_n *with the same set of univariate marginal distributions* $\{G_n^m\}_{m=1}^M$ *and copulas* C_n *and* C'_n*, respectively, team* n *is said to be* ***more cognitively diverse*** *with the joint distribution* G_n *than with the joint distribution* G'_n *if* $C\left(G^1\left(x^1\right), \ldots, G^M\left(x^M\right)\right) \leq C'\left(G^1\left(x^1\right), \ldots, G^M(x^M)\right)$ *and* $\bar{C}\left(G^1\left(x^1\right), \ldots, G^M(x^M)\right) \leq \bar{C}'\left(G^1\left(x^1\right), \ldots, G^M(x^M)\right)$ *for all* $\mathbf{x} = \left(x^1, \ldots, x^M\right) \in \mathbb{I}^M$.

Now that we have defined cognitive diversity in terms of the concordance partial order, we turn to describing how the distribution of effectiveness of the team tool is determined. Recall that each team n utilizes a tool aggregation function $t_n(\cdot)$ that maps the M-tuple of team member tool effectiveness levels into the team n tool. For the purpose of analytical tractability, we will focus on the case that the tool aggregation function $t_n(\cdot)$ is a convex combination of the highest and lowest effectiveness levels of its members' tools, where $\alpha_n \in [0, 1]$ denotes the weight placed on the most effective tool.

Given the M-variate joint distribution function of team n's tool effectiveness levels G_n, the distribution of the highest effectiveness level of the team members' tools is given by,

$$\text{Prob}\left(\max\left\{\tilde{x}_1, \ldots, \tilde{x}_M\right\} \leq x\right) = G_n(x, x, \ldots, x) = G_n(\mathbf{x}). \tag{2.1}$$

Similarly, the distribution of the lowest effectiveness level of the team members' tools is given by,

$$\text{Prob}\left(\min\left\{\tilde{x}_1, \ldots, \tilde{x}_M\right\} \leq x\right) = 1 - \overline{G}_n(x, x, \ldots, x) = 1 - \overline{G}_n(\mathbf{x}). \tag{2.2}$$

[10]↑In terms of the joint distribution G_n, the joint survival function is defined as $\bar{G}_n(\mathbf{x}) = P[\mathbf{X} \gg \mathbf{x}]$, where: (i) for any two M-tuples $\mathbf{x}, \mathbf{x}' \in \mathbb{I}^M$, $\mathbf{x} \gg \mathbf{x}'$ denotes that $x_m > x'_m$ for all $m = 1, \ldots, M$ and (ii) $\mathbf{X}$ is a random M-tuple distributed according to G_n. Similar to how we define copula C_n for G_n, the joint survival function may be calculated as $\bar{C}_n(G_n^1(x_n^1), \ldots, G_n^M(x_n^M)) \equiv \bar{G}_n(\mathbf{x})$.

Let $\alpha_n \in [0,1]$, which we refer to as team n's efficiency level, denote the weight that team n places on the best idea within the team n members, with the remaining weight $1-\alpha_n$ being placed on the worst idea within team n. In this mixture model, the distribution of the value of team n's tool is constructed from the expressions in 2.1 and 2.2 as:

$$H_n(x) = \alpha_n G_n(\mathbf{x}) + (1-\alpha_n)\left(1-\overline{G}_n(\mathbf{x})\right). \tag{2.3}$$

Note that when $\alpha_n = 1$ the distribution of the team tool corresponds to the distribution of highest effectiveness level of the team members' tools. This is the case of maximum efficiency. On the other hand, if $\alpha_n = 0$ the distribution of the team tool is that of the lowest effectiveness level of the team members' tools. This is the case of minimum efficiency. As α_n increases from 0 to 1, the level of efficiency increases.

Before moving to the relationship between the team tool distribution and its efficiency, we recall the definition of first order stochastic dominance which will be used extensively in the remainder of the paper.

Definition 2.3.3. *A distribution function H* ***First-Order Stochastically dominates*** *another distribution function H' (henceforth denoted as $H \succ^{FOSD} H'$) if for all $x \in [0,\omega]$,*

$$H(x) \leq H'(x). \tag{FOSD}$$

Now, we state a proposition on the relationship between the distribution of the effectiveness level of the team tool $H_n(\cdot)$ and the efficiency level α_n.

Proposition 2.3.1. *For any team n with joint distribution G_n, when the efficiency level of team n increases from α_n to α'_n and the corresponding distribution of the effectiveness level of the team n tool given in equation (2.3) changes from $H_n(\cdot)$ to $H'_n(\cdot)$, the new distribution of the team n tool H'_n first order stochastically dominates the original distribution of the team n tool H_n, i.e. $H'_n \succ^{FOSD} H_n$.*

Next, we turn to establishing a relationship between efficiency of a team, its level of cognitive diversity and the distribution of the effectiveness of its team tool.

Proposition 2.3.2. *For any team n with an arbitrary set of M univariate distribution functions $\left(G_n^1, \ldots, G_n^M\right)$, there exists a threshold level of efficiency, $\alpha_1 \in [0,1)$ ($\alpha_2 \in (0,1]$), such that for each pair of copulas C_n and C_n' with the joint distribution $C_n\left(G_n^1, \ldots, G_n^M\right)$ being more cognitively diverse than the joint distribution $C_n'\left(G_n^1, \ldots, G_n^M\right)$, the distribution of the team n tool $H_n(\cdot)$ corresponding to the copula C_n first order stochastically dominates (dominated by) the distribution of the team n tool $H'(\cdot)$ corresponding to the copula C_n' if the team n efficiency level satisfies $\alpha_n \in (\alpha_1, 1]$ ($\alpha \in [0, \alpha_2)$).*

The proofs of theses two propositions are provided in the appendix.

2.3.2 Second (Effort Choice) Stage

It takes effort for a team to develop a team project. In the second (effort) stage, all of the team members in all of the teams simultaneously choose costly effort levels, where $\mathrm{e}_n^m \in \mathbb{R}_+$ denotes the effort chosen by team member m in team n. The value of team n's project, denoted by $V_n : [0,1] \times \mathbb{R}_+^M \to \mathbb{R}_+$, is a function of team n's (private) team tool effectiveness level $x_n \in [0,1]$ and team n's M-tuple of effort levels $\mathbf{e}_n = (\mathrm{e}_n^1, ..., \mathrm{e}_n^M) \in \mathbb{R}_+^M$. We assume that all teams share the same team project value function $V(\cdot)$ which is strictly increasing and concave in the individual effective effort levels.

2.3.3 Prize Allocation and Payoffs

In the case that team n wins prize y, which is shared equally among the M team members, the utility for an arbitrary team member m of team n who chose effort level e_n^m to develop the team project is given by

$$\frac{y}{M} - \mathrm{e}_n^m.$$

We let $Y\left(\cdot, V_{-n}\right) : V \to \mathcal{Y}_N$ denote the prize assignment function given by

$$Y\left(V_n, V_{-n}\right) = \sum_{n=1}^{N} y_{(n)} \mathbb{1}\left[V_n = V_{(n)}\right]. \tag{2.4}$$

In equation (2.4), $\mathbb{1}$ is an indicator function which is equal to 1 when the argument $V_n = V_{(n)}$ is true, otherwise it is equal to 0. The ex post utility of team member m becomes

$$U_n^m \left(\left(\mathrm{e}_n^m, \mathbf{e}_n^{-m} \right), \mathbf{e}_{-n}; x_n \right) = \frac{Y \left(V_n \left(x_n, \left(\mathrm{e}_n^m, \mathbf{e}_n^{-m} \right) \right), V_{-n}(x_{-n}, \mathbf{e}_{-n}) \right)}{M} - \mathrm{e}_n^m$$
$$\forall m \in \{1, \ldots, M\}, n \in \{1, \ldots, N\}.$$

We reformulate the expected utility of a team member using the technique from Chawla, Hartline, and Sivan, 2019 to represent it in terms of expected utility of a bidder in an N object all pay auction. Let $b_n^m = x_n \mathrm{e}_n^m$ be referred to as the effective effort of team player m of team n.

$$U_n^m \left(\left(b_n^m, \mathbf{b}_n^{-m} \right), \mathbf{b}_{-n}; x_n \right) = x_n \frac{Y \left(V_n \left(b_n^m, \mathbf{b}_n^{-m} \right), V_{-n}(\mathbf{b}_{-n}) \right)}{M} - b_n^m \tag{2.5}$$
$$\forall m \in \{1, \ldots, M\}, n \in \{1, \ldots, N\}.$$

2.3.4 Two-Stage Game

To summarize, we examine the two-stage extensive-form team innovation game, denoted by $\Gamma_N(N, M, \{G_n\}_{n=1}^N, \Phi_N, \mathcal{Y}_N, V)$, where $N \geq 2$ teams, each with M cognitively diverse individuals. Innovation activity involves two-stages; the first (tool selection) and second (effort choice) stages. In the first stage, the team members' of each team n realize their tool effectiveness levels from the joint distribution G_n. The team projects are ordered by the rank of the team project qualities, where project qualities are determined by the team project value function V, with the corresponding prizes from $\mathcal{Y}_N$ allocated to the teams from the prize distribution Φ_N. The prize is then equally split among the M team members.

2.3.5 Equilibrium

Our two-stage team innovation game is a Bayesian Game and we examine Bayesian-Nash equilibria. For our game $\Gamma_N \left(N, M, \mathcal{Y}_N, \{G_n\}_{n=1}^N, \Phi_N, V \right)$, a Bayesian-Nash equilibrium is an $N \times M$ matrix of effective effort strategies $\beta_n^m : [0, 1] \to \left[0, \frac{1}{M} \right]$, one effective effort strategy for each team member $m \in \{1, \ldots, M\}$ of each team $n \in \{1, \ldots, N\}$, such that each team member m of each team n is best responding to the effective effort strategies of the other $N \cdot M - 1$ other players.

For existence of the equilibrium we make use of the following two assumptions:

Assumption 1. *For each team member m in each team n and $\epsilon > 0$ and $(\mathbf{x}, \mathbf{b})$, there exists a sufficiently large N and a neighborhood $\chi_{(\mathbf{b}_n^{-m}, \mathbf{b}_{-n})}$ of $(\mathbf{b}_n^{-m}, \mathbf{b}_{-n})$ such that*

$$\epsilon > U_n^m\left(\left(b_n^m, \mathbf{b}_n^{-m}\right), \mathbf{b}_{-n}; x_n\right) - U_n^m\left(\left(b_n^m, \tilde{\mathbf{b}}_n^{-m}\right), \tilde{\mathbf{b}}_{-n}; x_n\right), \quad \textit{for all } \tilde{\mathbf{b}}_n^{-m}, \tilde{\mathbf{b}}_{-n} \in \chi_{(\mathbf{b}_n^{-m}, \mathbf{b}_{-n})}.$$

Assumption 2. *$\Pi_{n=1}^N H_n$ is absolutely continuous over $[0,1]^N$*

Theorem 2.3.1. *For sufficiently large N, there exists a Bayesian-Nash Equilibrium for the finite two-stage contest represented by the extensive form game, $\Gamma_N\left(N, M, \mathcal{Y}_N, \{G_n\}_{n=1}^N, \Phi_N, V\right)$.*

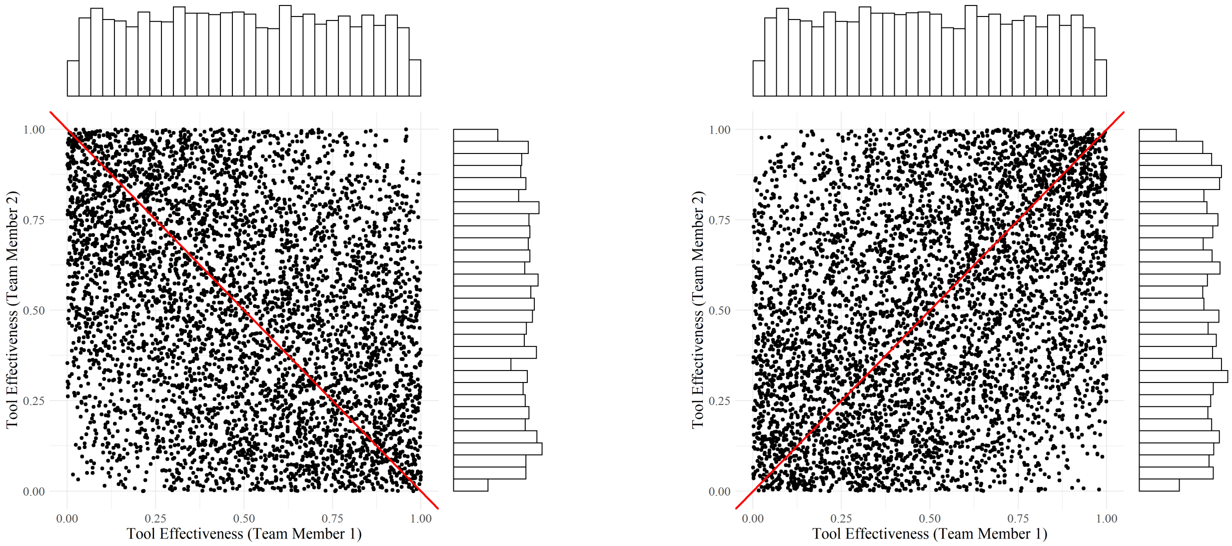
Given assumptions 1 and 2, existence of equilibrium for the N-team contest in Theorem 2.3.1 follows from corollary 1 of Carbonell-Nicolau and McLean, 2018. Assumption 1 refers to the payoff security assumption required for existence of a Bayesian-Nash equilibrium in Carbonell-Nicolau and McLean, 2018. However, in our setting, payoff security is guaranteed for a contest with a sufficiently large number of teams.

2.3.6 An Example

Now, we will go over the basic features of our model using a simplified example. In this example we will make use of a series of simplifying assumption in order to illustrate the basic mechanics of our setup. First, we restrict our focus to two-member teams, which allows us to visualize an arbitrary team n's joint distribution G_n. We further assume that the univariate marginal distributions of the team members are given by the Uniform distribution over $[0,1]$ and that the copula used to construct the joint distribution of team members' tool effectiveness levels G_n is from a specific parametric family of copulas. In particular, we use the Farlie-Gumbel-Morgenstern (FGM) family of copulas given by,

$$C_\theta\left(G^1, G^2\right) = G^1 G^2 + \theta G^1 G^2\left(1 - G^1\right)\left(1 - G^2\right),$$

where G^m is the marginal distribution of team member $m = 1, 2$, and the parameter θ controls the dependence structure with $\theta \in [-1, 1]$. When $\theta = 0$, the copula becomes $C_\theta(G^1, G^2) = G^1 G^2$, the independent copula, which implies the tool effectiveness levels of the two members are independent. As θ goes to -1, the random variables become negatively dependent, where as when θ goes to 1, the random variables become positively dependent. In Figure 2.1 we show the scatter-plots of tool effectiveness levels of the two team members when $\theta = -1, 1$. As we see in panel (a), with $\theta = -1$, there is weak negative dependence and in panel (b), with $\theta = 1$, there is weak positive dependence. For this specific copula we can only achieve weak dependence (positive or negative). From the two scatterplots, we can see that in case of weak negative dependence in panel (a), there is a higher concentration of points in the second and fourth quadrant, along the negative 45° line (in red), whereas, for the scatterplot with weak positive dependence in panel (b), the points are more concentrated on the first and third quadrants along the positive 45° line (in red). One obvious shortfall of this copula is that it can only model weak dependence. However, we use this family of copula for two reasons. First, this makes the example analytically tractable. Second, even if this family can only model weak dependence structure, we can illustrate our results showcasing the importance of even weak levels of diversity.



(a) $\theta = -1$ (b) $\theta = 1$

Figure 2.1. Jointly Distributed Tool Effectiveness Levels of Team Members (Using FGM Copula and varying θ)

Recalling that that the pair of univariate marginal distributions are Uniform on $[0, 1]$, the joint distribution for a team with dependence parameter θ_n is given by

$$G_n\left(x_n^1, x_n^2\right) = x_n^1 x_n^2 + \theta_n x_n^1 x_n^2 \left(1 - x_n^1\right)\left(1 - x_n^2\right).$$

As previously discussed, a team's tool effectiveness level is a random draw of either the best or the worst of its members' tool effectiveness levels. The probability that the effectiveness level is the maximum of the members' levels is α, which we call the efficiency level of the team. The distribution of the best effectiveness level is

$$\text{Prob}\left(\max\{X_n^1, X_n^2\} \leq x\right) = G_n(x, x) = x^2 + \theta x^2 (1-x)^2$$

and that of the worst effectiveness level is

$$\begin{aligned}\text{Prob}\left(\min\left\{X_n^1, X_n^2\right\} \leq x\right) &= \text{Prob}\left(X_n^1 \leq x\right) + \text{Prob}\left(X_n^2 \leq x\right) - \text{Prob}\left(X_n^1 \leq x,\right) \\ &= x + x - x^2\left(1 + \theta_n\left(1-x\right)^2\right) \\ &= 2x - x^2\left(1 + \theta_n\left(1-x\right)^2\right).\end{aligned}$$

Therefore, for a team n with efficiency level α_n the distribution of the team n tool is

$$H_n(x) = \alpha_n\left(x^2 + \theta x^2(1-x)^2\right) + (1-\alpha_n)\left(2x - x^2\left(1 + \theta_n\left(1-x\right)^2\right)\right).$$

In figure 2.2, we show how the distribution of team tool effectiveness levels changes in response to changes in a team's level of cognitive diversity and its efficiency level (represented by α). A team's level of cognitive diversity is represented using the joint distribution function and the dependence level of the individual tool effectiveness levels. For the FGM copula in this example, the parameter θ controls the dependence level. We therefore vary the levels of θ and α. As we move from the left panels to the right, the efficiency level (α) increases. As we move from top panels to bottom, the cognitive diversity decreases, that is, the individual tool effectiveness levels become more concordant as θ increases.

First, the distribution of the best tool effectiveness level within a team always FOS dominates that of the worst. Furthermore, the distribution of the team tool effectiveness level always lies somewhere between these two extremes as it is the mixture of the maximum and the minimum. It FOS dominates the distribution of the minimum effectiveness level and is FOS dominated by that of the maximum effectiveness level. For this copula, the efficiency level threshold (denoted by $\alpha_1 \in [0,1)$) defining whether changing the dependence structure leads to the changed team tool effectiveness level distribution to FOS dominate the former is 0.5. If the efficiency level is higher than 0.5, that is, if it is more than equally likely that the team tool effectiveness level is the best of the members' tool effectiveness levels then increasing diversity (that is, we moving from bottom panels to the top panels, the individual effectiveness levels become less concordant) makes the new distribution FOS dominate the

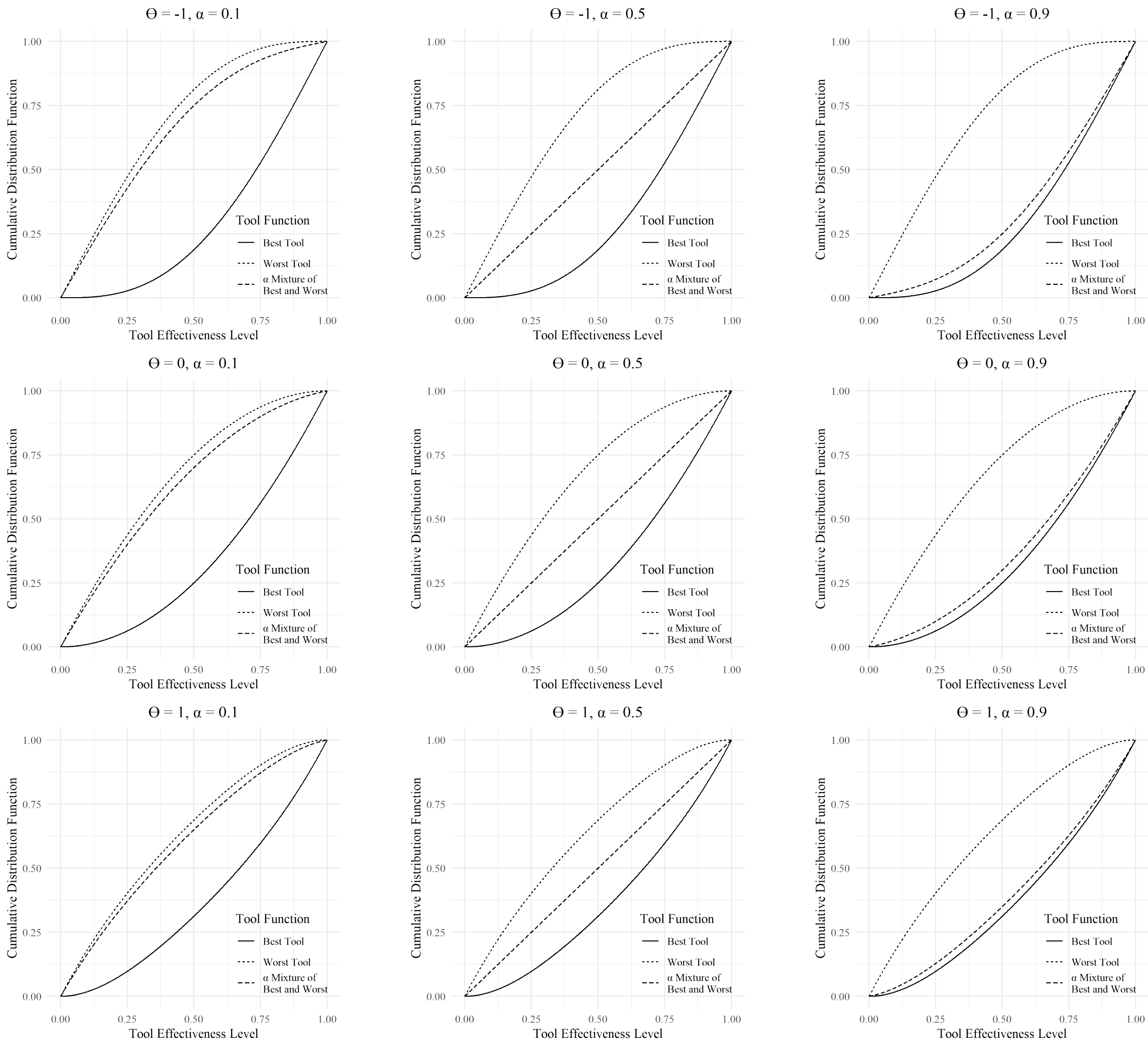


Figure 2.2. Change in Distribution (using FGM copula) of Team Tool Effectiveness Level with Change in Joint Distribution of Individual Tool Effectiveness Level (θ) and team Efficiency Level (α)

initial one. In this example, for $\alpha = 0.9$ (right panels), as θ changes from 1 to 0 to -1, the team distribution achieves higher ranking in terms of First Order Stochastic Dominance. But with $\alpha = 0.1$ (left panels), as θ changes from 1 to 0 to -1, the team distribution achieves lower ranking in terms of First Order Stochastic Dominance.

Even with the simplified example, we can not analytically solve for the equilibrium for the generalized asymmetric team contest with a finite number of teams. We continue with this example in a later section where we approximate the equilibrium using our large contest environment.

2.4 Limit Contest

In this section, we analyze our team contest when the number of teams becomes arbitrarily large, while holding constant the number of members of each team.[11] This limiting case approximation seems reasonable given that in the innovation-competition platforms that we have in mind there are no limits on the number of participating teams and the the number of teams is often quite large, but the teams involved in these activities consist of a limited number of team members. When the number of teams is large, we can modify the approach developed in Olszewski and Siegel, 2016 and approximate the equilibrium effective effort of each team member using a direct revelation mechanism. From the previous section recall that $H_n(\cdot)$ denotes the distribution of the team tool effectiveness level of team n. Then, $\hat{H}(\cdot; N) = \frac{\sum_{n'=1}^{N} H_{n'}(\cdot)}{N}$ can be interpreted as the expected percentile ranking of tool effectiveness level in the contest with N teams. As N increases, we assume that this ranking $\hat{H}(\cdot; N)$ converges pointwise to a distribution $\hat{H}(\cdot)$ which we refer to as the rank distribution. Similarly, we assume that the empirical distribution of prizes Φ_N converges pointwise to a limiting distribution $\hat{\Phi}$.

Claim 2.4.1. *The limit distribution $\hat{H}(\cdot)$ is given by*

$$\hat{H}(x) = \hat{\alpha}\hat{G}(x) + (1 - \hat{\alpha}) \left(1 - \hat{\overline{G}}(x)\right), \quad \forall x \in [0, 1] \tag{2.6}$$

[11] For simplicity we assume each team comprises of the same number of members. However, our results do not depend on this assumption.

where $\hat{G}(\cdot) = \lim_{N\to\infty} \frac{\sum_{n'=1}^{N} G_{n'}(\cdot)}{N}$, $\hat{\overline{G}}(\cdot) = \lim_{N\to\infty} \frac{\sum_{n'=1}^{N} \overline{G}_{n'}(\cdot)}{N}$ *and* $\hat{\alpha}(\cdot) = \lim_{N\to\infty} \frac{\sum_{n'=1}^{N} \alpha_{n'}(\cdot)}{N}$.

For a large contest, the equilibrium level of effective effort by a team member m of team n with team tool effectiveness level x_n can be approximated by a tariff mechanism that implements an assortative allocation which maps a prize $y_n = \hat{\Phi}^{-1}\left(\hat{H}(x_n)\right)$ to the team n.[12] A tariff mechanism for a team tool x is a prize-effective effort pair (y, b) which maximizes the utility of a team member U_n^m. To derive this tariff mechanism we make use of the following three assumptions.

Assumption 3. *Assumptions on the limiting prize distribution -*

1. $\hat{\Phi}$ *has full support.*

2. $\hat{\Phi}$ *is strictly increasing in the support of prizes.*

Assumption 4. $U(x, y, b) \geq U(x, 0, 0)$ *for each type* x *and its prescribed prize-effective effort pair* (y, b) *with an equality for at least one type* x.

Assumption 5. *In-team symmetry -*

1. *The value function* V *is symmetric in the effective effort choices of the team members.*

2. *We only consider in-team symmetric equilibria.*

Given assumptions 3, 4 and 5, the following theorem adopts corollary 2 of Olszewski and Siegel, 2016 (OS2016, henceforth) to show that such a tariff mechanism for each team member exists in our environment.

Theorem 2.4.1. *For any* $\epsilon > 0$, *there is an* N *such that for* $N' \geq N$, *in any equilibrium of the* N *teams contest, each of a fraction of at least* $1-\epsilon$ *of the teams obtains with probability at least* $1-\epsilon$ *a prize that differs by at most* ϵ *from* $\hat{\Phi}^{-1}\left(\hat{H}(x_n)\right)$, *and each member of team* n *chooses effective effort with probability at least* $1-\epsilon$ *within* ϵ *of* $\beta(x_n)$ *given by*

$$\beta(x_n) = \frac{1}{M^2} \int_0^{x_n} \frac{z\hat{h}(z)}{\hat{\Phi}'\left(\hat{\Phi}^{-1}\left(\hat{H}(z)\right)\right)} dz \tag{2.7}$$

[12] $\hat{\Phi}^{-1}(z) = \inf\left\{y : \hat{H}(y) \geq z\right\}$ for $z \geq 0$

From Theorem 2.4.1, we see that the equilibrium effective effort function depends only on the distribution of team quality ranking and the prize distribution.

2.5 Effect of Diversity and Efficiency

In this section, we explore how changing cognitive diversity in teams changes the performance in the team contest. As we have seen in the previous section any change in performance can come through the rank distribution of the team tool qualities or the prize distribution. Till now we have assumed a general function for the selection of team quality and depending on that we have a general rank distribution. For this general function we examine how how first order stochastic dominance of the rank distribution of team tools affects expected performance in the contest. We find that if one rank distribution of team tool qualities first order stochastically dominates another, then the expected performance of any team member in the contest under the first distribution is higher than that under the latter distribution.

Theorem 2.5.1. *Suppose $\beta_1(x)$ and $\beta_2(x)$ are the equilibrium individual bidding functions for limiting team tool distributions $\hat{H}_1(x)$ and $\hat{H}_2(x)$ defined on $[0, 1]$, respectively. If $\hat{H}_1(x) \succ^{FOSD} \hat{H}_2(x)$, then $E[\beta_1] > E[\beta_2]$ where $E[\beta_{\mathrm{i}}]$ is the expected bid for $\hat{H}_{\mathrm{i}}$ where* $\mathrm{i} = 1, 2$.

Given theorem 2.5.1, we can now state our results regarding the impact of a change in cognitive diversity. Recall that any change in cognitive diversity leads to a change in the distribution of the tool effectiveness level of the team. Therefore when cognitive diversity of every team changes, it can lead to a change in the rank distribution of the limit contest. And as we see in the theorem 2.5.1, any change in the rank distribution leads to a change in the equilibrium effective effort levels. We state our result below.

Result 2.5.1. *As the cognitive diversity of each team weakly increases, the expected effective effort of any member m of an arbitrary team n and team n's expected performance increases (decreases) in the limit team contest if the limiting average efficiency level of the teams is higher (lower) than a threshold efficiency level.*

This result is regarding the performance of the overall contest with respect to the limit contest and from the perspective of the contest organizers. For the contest organizer what matters is the value of the team innovative projects. What we find is that an increase in the limiting average diversity among team members can, but does not necessarily, increase the value of each team's project. Something to note here is that every team's level of diversity does not need to strictly increase. For this result to hold we need the limiting average distribution to represent more diverse teams. We now present a result with respect to a team's incentive to increase its own diversity.

Recall that for a team n with an efficiency level α_n and joint distribution function $G_n(\cdot)$, the distribution of team tool effectiveness level is given by,

$$H_n(x) = \alpha_n G_n(\mathbf{x}) + (1-\alpha_n)\left(1 - \overline{G}_n(\mathbf{x})\right).$$

But the effective effort level is given by equation 2.7 which depends on the limiting rank distribution of tool effectiveness levels $\hat{H}(x)$. Moreover, in equilibrium, team members find it optimal to report the true level of team tool effectiveness. Therefore the prize, y, that team n receives is given by

$$\hat{\Phi}(y) = \hat{H}(x_n),$$

where x_n is the team n tool effectiveness level. The equilibrium utility for a member of team n with team tool x_n becomes

$$U^*(x_n) = \frac{\hat{\Phi}^{-1}\left(\hat{H}(x_n)\right)}{M} - \frac{\beta(x_n)}{x_n}.$$

From the envelope theorem, we see that

$$\frac{dU^*}{dx_n} = \frac{1}{M}\frac{\hat{h}(x_n)}{\hat{\Phi}'\left(\hat{\Phi}^{-1}\left(\hat{H}(x_n)\right)\right)} + \frac{\beta(x_n)}{x_n^2} > 0,$$

and thus the equilibrium utility for a member of team n is an increasing function of the team tool effectiveness level x_n. From Proposition 2.3.2 we see that there exists a threshold level of efficiency $\alpha_1(\alpha_2)$, such that for efficiency levels above (below) it, as the joint distribution of individual tool effectiveness level $(G_n(\cdot))$ becomes less concordant, that is, the team becomes more diverse, the distribution of team tool effectiveness level $H_n(x)$ becomes higher (lower) ranked in terms of first order stochastic dominance. By the property of first order stochastic dominance, if $H_n'(x) \succ^{\text{FOSD}} H_n(x)$, then the expected equilibrium utility is higher under $H_n'(x)$ than $H_n(x)$ since it is an increasing function of x_n. Therefore, for efficiency levels above α_1 (below α_2) as the joint distribution of individual tool efficiency levels becomes more diverse, the expected equilibrium utility $U^*(x)$ goes up (down). We summarize this in the following result.

Result 2.5.2. *As cognitive diversity of a team increases, the team members' equilibrium expected utilities increases (decreases) in the limit team contest if the limiting average efficiency level of the team is higher (lower) than threshold level efficiency level given by Proposition 2.3.2.*

Therefore, we can conclude that a team finds it to be in its own best interest to increase its own level of team diversity when the team's efficiency level exceeds the threshold value.

2.5.1 Continued example

Here we continue with the example from section 2.3.6. To complete the environment we first have to find the limiting rank distribution for the limit contest. For a team n with efficiency level α_n, the team tool effectiveness level is given by

$$H_n(x) = \alpha_n \left(x^2 + \theta x^2(1-x)^2\right) + (1-\alpha_n)\left(2x - x^2\left(1+\theta_n\left(1-x\right)^2\right)\right).$$

Then the rank distribution for the large contest is given by,

$$\begin{aligned}\hat{H}(x) = \lim_{N\to\infty} \frac{\sum_{n=1}^{N} H_n(x)}{N} = &\lim_{N\to\infty} \frac{\sum_{n=1}^{N} \alpha_n\left(x^2 + \theta x^2(1-x)^2\right) + (1-\alpha_n)\left(2x - x^2\left(1+\theta_n\left(1-x\right)^2\right)\right)}{N}, \\ &= \hat{\alpha} x^2\left(1 + (1-x)^2\hat{\theta}\right) + (1-\hat{\alpha})\left(2x - x^2\left(1+(1-x)^2\hat{\theta}\right)\right).\end{aligned}$$

The last equality is driven by the following assumptions,

1. $\lim\limits_{N\to\infty} \frac{\sum\limits_{n=1}^{N} \alpha_n}{N} = \hat{\alpha} \in [0,1]$

2. $\lim\limits_{N\to\infty} \frac{\sum\limits_{n=1}^{N} \theta_n}{N} = \hat{\theta} \in [-1,1]$

3. $\left\{\sum\limits_{n=1}^{N} \alpha_n\right\}_{N=1}^{\infty}$ and $\left\{\sum\limits_{n=1}^{N} (1-\alpha_n)\right\}_{N=1}^{\infty}$ are strictly increasing.

4. $\lim\limits_{N\to\infty} \sum\limits_{n=1}^{N} \alpha_n = \infty$ and $\lim\limits_{N\to\infty} \sum\limits_{n=1}^{N} (1-\alpha_n) = \infty$

and by using the Stolz-Cesàro theorem. The corresponding probability density function is

$$\hat{h}(x) = 2\left(1-\hat{\alpha}\right) + 2\left(2\hat{\alpha}-1\right)x\left(1+\hat{\theta}(1-x)(1-2x)\right).$$

We also need a prize distribution. Again, for simplicity, we assume that the prize distribution is a Uniform distribution over the $[0,1]$ interval. With this limit rank distribution $\hat{H}(x)$ and prize distribution $\hat{\Phi}(x)$, we have that the equilibrium effort of a member of a team with tool effectiveness level x is given by

$$\begin{aligned}
\beta(x) =& \frac{1}{2^2}\int_0^x z\hat{h}(z)dz,\\
=& \frac{x^2}{4}\left(\left(1-\hat{\alpha}\right) + \frac{2}{3}\left(2\hat{\alpha}-1\right)\left(\hat{\theta}+1\right)x - \frac{3}{2}\left(2\hat{\alpha}-1\right)\hat{\theta}x^2 + \frac{4}{5}\left(2\hat{\alpha}-1\right)\hat{\theta}x^3\right).
\end{aligned}$$

For this example we can analytically derive some comparative statics on the equilibrium effective effort but our result is in terms of expected effective effort from the perspective of the contest organizer which is given by

$$\begin{aligned}
\mathbb{E}[\beta] =& \int_0^1 \beta(x)\hat{h}(x)dx\\
=& \int_0^1 \frac{x^2}{4}\left(\left(1-\hat{\alpha}\right) + \frac{2}{3}\left(2\hat{\alpha}-1\right)\left(\hat{\theta}+1\right)x - \frac{3}{2}\left(2\hat{\alpha}-1\right)\hat{\theta}x^2 + \frac{4}{5}\left(2\hat{\alpha}-1\right)\hat{\theta}x^3\right)\cdot\\
& \left(2\left(1-\hat{\alpha}\right) + 2\left(2\hat{\alpha}-1\right)x\left(1+\hat{\theta}(1-x)(1-2x)\right)\right)dx\\
=& \frac{4\hat{\alpha}^2\left(\hat{\theta}^2-9\hat{\theta}+21\right) - 2\hat{\alpha}\left(2\hat{\theta}^2+3\hat{\theta}-63\right) + \hat{\theta}^2+12\hat{\theta}+126}{5040}
\end{aligned}$$

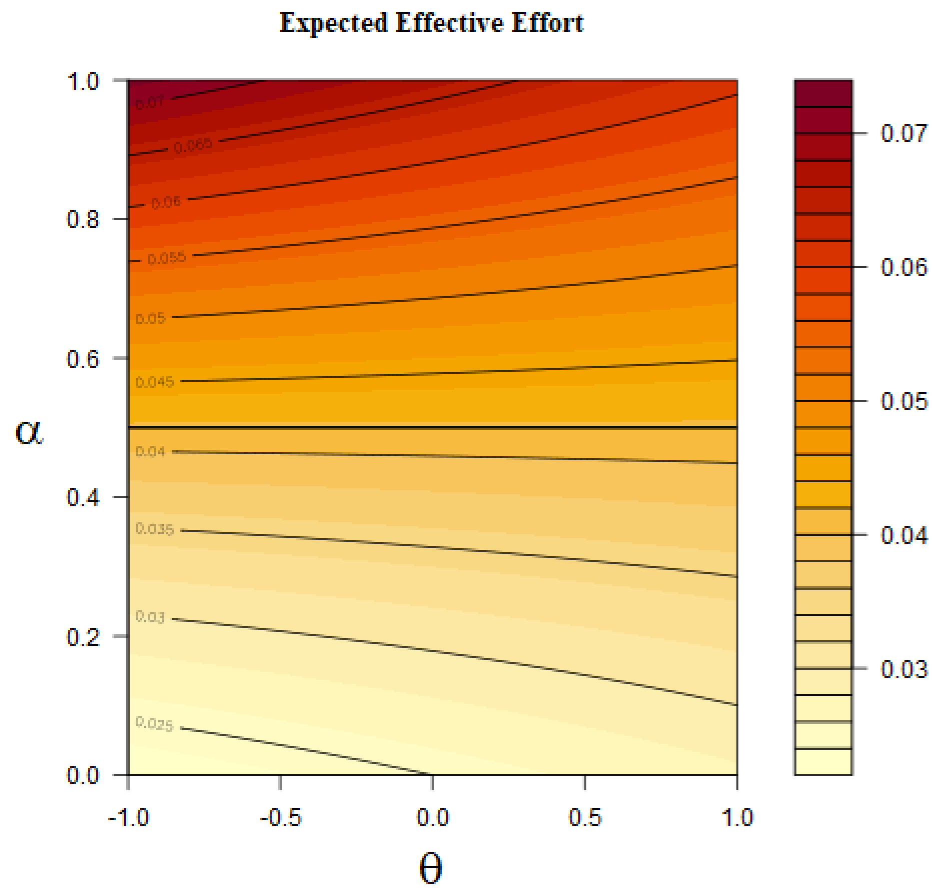


Figure 2.3. Change in Expected Equilibrium Effective Effort due to Change in Diversity ($\hat{\theta}$) and Efficiency ($\hat{\alpha}$)

Figure 2.3 shows the equilibrium effort levels as diversity (in terms of change in $\hat{\theta}$ in the FGM copula) and efficiency level ($\hat{\alpha}$) within teams change. Figure 2.3 is a heatmap with colors moving from yellow to red as the expected equilibrium effort levels increase. We also show a level curves using black curves. We can see that these level curves change direction depending on the efficiency level $\hat{\alpha}$. When the limiting efficiency $\hat{\alpha}$ is above 0.5, as diversity in the limiting distribution goes up, that is, $\hat{\theta}$ in the limiting rank distribution going down from 1 to -1, we see that the expected equilibrium effective effort goes up. Since the value of a team project is an increasing function of the effective effort of the team members, the expected value also goes up. On the other hand, if the limiting efficiency level is below 0.5, we get the opposite result. That is, the expected equilibrium effective effort and the expected equilibrium value of the team's project goes up as the level of diversity goes down, that is, $\hat{\theta}$ in the limiting rank distribution going up from -1 to 1. We also see that irrespective of the level of diversity, the higher the level of efficiency, the higher the level of expected equilibrium bid and the value of team project.

2.6 Discussion

To summarize, we find that when the number of teams in a contest becomes arbitrarily large, the equilibrium performance of any team member can be approximated by a tariff mechanism that maps an effective effort and a prize to a tool effectiveness level. We also examine how cognitive diversity affects the performance of the team contest. Our results imply that cognitive diversity can be beneficial or detrimental to performance in team contests depending on the teams' efficiency level. In essence, cognitive diversity can be fruitful in improving the performance in a team contest if the teams can utilize the benefits cognitive diversity brings. In our model, with higher cognitive diversity, a team is more likely to receive high-quality tools. However, it is also likely to receive very low-quality tools. But if the team has the tools to use only the worst quality tool among all the tools from its team members, then diversity is detrimental to team performance. On the other hand, if the team has the tools to develop the best tool from its team members, then an increase in cognitive diversity is advantageous to a team and the contest organizers.

3. TRANSITION RULE TYPE OF INTERACTION IN STOCHASTIC DYNAMIC GAME

3.1 Introduction

Many economic situations involving strategic interactions between individuals, firms or other agents are repeating in nature. Moreover, the characteristics of these interactions (for example, payoffs) can change over time depending on some underlying processes. More formally, the characteristics of the stage game in a period depends on the state of the world in that period which is decided by a stochastic process. In these situations, if the agents are aware of the exact stochastic nature of the repeated strategic interaction, which we call the transition rule, they can internalize it and respond accordingly. Therefore, the behavior of these agents would depend on the transition rule. In this paper, using a laboratory experiment, we explore how economic agents involved in repeated interactions change behavior with different transition rules that decide the nature of these interactions. We concentrate only on interactions which can be modeled as social dilemma games.

Examples of these types of economic situations are numerous. Take for example, a market environment. Firms interact with each other repeatedly in the same market. But the market characteristics (demand, costs among others) can change over time and these changes can depend on some underlying transition rule. The firms can become aware of this transition rule by doing market research or just learn over time. Being aware of this rule can help them shape their responses in the market. This environment has been studied by Rotemberg and Saloner, 1986.[1] Other examples can include teamwork on a repeated basis where the tasks can be of different types. Multi-server queuing system catering to tasks of varying types arriving stochastically lends itself well to this environment and can model many economic activities. A team of emergency medical technicians responding to different types of medical emergencies would be an example of multi-server queuing system.

[1]↑ Green and Porter, 1984 study a version of this stochastic game where the agents can not monitor the state of the world.

In our paper, by holding the payoffs in each state constant, we change the transition rule. We examine two transition rules – *alternating* and *random*. To minimize the complexity of the stochastic game, we restrict the number of states to two. We use Prisoners' Dilemma (PD, henceforth) games in both states. One state has high payoffs (High state) and the other has low payoffs (Low state) from mutual cooperation. Again, we do this for simplicity. By changing only one of the payoff parameters, the sources behind change in behavior are minimized. Under both rules, the state of the world in the next period is not known deterministically. We make this choice to ensure that the two rules have similar complexity for the subjects in the experiment. Under the alternating transition rule, the probability that the state of the world in the next period is different from that in the current state is more than that with the random transition rule. We then compare how subjects behave under these two transition rules. Also to provide some benchmark, we use a combination of payoffs and discount factor that has been used in the literature without any stochasticity.

What can cause a difference in behavior between the two transition rules? When the states are alternating, the continuation value of mutual cooperation in the High state is lower than under the random transition rule because the future is discounted. On the other hand, by the same logic, the continuation value of mutual cooperation in the Low state is higher under the alternating rule than the random rule. Therefore, under alternation the continuation values of the two states are closer to each other than under random arrival of states. However, since the difference between the two states is only in the payoffs from mutual cooperation, there is no difference in payoffs from deviation from mutual cooperation. As a result, the difference in agents' behavior between the two transition rules can only be driven by the continuation value of mutual cooperation in each state.

For both our transition rules, we vary the type of interaction between the players – *symmetric* or *asymmetric*. Under symmetry, in each period, both players are in the same state of the world, and face the same set of payoffs. Therefore, they face a symmetric infinitely repeated PD (IRPD, henceforth) game with payoffs that vary stochastically over time according to a transition rule. In contrast, under asymmetry, in each period, one player is in the

High state where as the other is in the Low state. As result, in each period of a supergame, the players play the same asymmetric IRPD game, but who is in the High/Low state is determined by the transition rule. Note that, the infinite game under both types of interactions is still symmetric. If the subjects follow only history-contingent strategies (not depending on the state), then strategies under the two types of interactions should provide similar payoffs. But state-contingent or state- and history-contingent strategies can lead to very different incentives under the two types of interactions. Another point to note here is that, in the laboratory, ex-post, due to the indefinite nature of the supergame, the supergames as a whole may not be symmetric when in every period the interaction is asymmetric. In some supergames, one subject might only be in the Low state without ever switching to the Low state, whereas their opponent will always be in the High state by the definition of asymmetric interaction. This phenomenon is more likely under the random transition rule than the alternating transition rule. This can also influence the behavior of subjects in the experiment as they learn over the supergames.[2]

We conduct a 2×2 design between subject experiment to examine how behavior varies due to the transition rules in a stochastic dynamic game and how this is affected by the type of strategic interaction (symmetric vs. asymmetric). We have four main hypotheses. In all our treatments, mutual cooperation can be supported in both High and Low states in equilibrium. However, we know from the literature of IRPD, support in the equilibrium does not imply that cooperation will be observed in the experiment. We utilize the concept of SizeBAD which is shown as a determinant of cooperation in this literature (see Dal Bó and Fréchette, 2018). SizeBAD implies the size of basin of attraction of Always Defect (AD, henceforth) strategy. The idea is that, the higher the SizeBAD, the riskier it is to be cooperative – to choose Grim type strategy – due to the strategic uncertainty inherent in these games. We calculate the SizeBAD for all our treatments and derive our hypotheses. First, in the asymmetric environment, we expect subjects to cooperate more when the states alternate compared to when they arrive randomly. In the second hypothesis, we compare the alternating and random transition rules in the symmetric environment. We hypothesize

[2]↑ In each session, subjects played 30 supergames.

that in the High state, cooperation rate will be higher under random transition rule and the opposite to hold true in the Low state. Third, we expect subjects to cooperate more when the interaction is symmetric and they are in High state. Finally, we expect to see higher cooperation rates in the High state compared to the Low state when the interaction is symmetric.

Our results indicate that subjects respond to the transition rule but only under the asymmetric interaction. We observe cooperation rates to be higher under alternation compared random arrival of states where the interaction is asymmetric. In the case of symmetric interaction, there is no significant difference in the cooperation rates (by State or combined) between the two transition rules. In our experiment, asymmetric treatment with random arrival of states leads to the lowest level of cooperation rates irrespective of the states. Switching to alternation of state or symmetric interactions improves cooperation. In both states, as we move from asymmetric to symmetric interactions, cooperation increases but only with random transition rule. Finally, we only observe higher cooperation rates in the High state in the treatment with symmetric interactions and alternating transition rule. Even if cooperation is supported in each state in all our treatments, we observe significant amount of defection everywhere. Especially asymmetry of environment can lead to a breakdown of cooperation. Our experiment shows two avenues that can help in improving cooperation rates in these types of stochastic environment. First, alternation of states increases cooperation when the players are asymmetric in each period. On the hand, the players can be made symmetric to make them more cooperative.

The rest of the paper is organized as follows: First, in section 2, we review the related literature. In section 3, we develop the theoretical background. In section 4, we present the experimental design for the experiment and hypotheses for the chosen parameters. In section 5, we examine the results of our data analysis. Finally, in section 6, we conclude.

3.2 Literature Review

In this paper, we use a stochastic dynamic game to examine the behavior of individuals when they face different social dilemmas depending on the state of the world. We use the PD game for our stage games. Recently, there are some papers that study stochastic repeated PD games. Kloosterman, 2020; Rosokha and Wei, 2020; Salz and Vespa, 2020; Vespa and Wilson, 2019 are some among these. Vespa and Wilson, 2019 study the difference in behavior when the states of the world are decided exogenously or endogenously. Here, the authors concentrate on the whether the behavior in these games are history-contingent or state-contingent. In Salz and Vespa, 2020, the authors use data from the laboratory to estimate a structural model. Their purpose is to show if considering only Markov strategies leads to prediction errors. Kloosterman, 2020 uses a variation of the stochastic IRPD where only in the first two periods the game is stochastic. Finally, in Rosokha and Wei, 2020, the stochastic game is in a queuing setting. They vary discount rates and examine the effect of visibility of the state of the world. We add to this literature by examining the change in probabilities of arrival of the state of the world and the type of game, i.e., symmetric versus asymmetric.

Since we use PD games as the basis of our stochastic game, our paper is among the papers that study IRPD game. This is a vast and growing literature. One of the primary research questions in this literature is to find out what factors lead to increased cooperation in this game. Dal Bó and Fréchette, 2018 is a meta analysis that uses data from 15 papers in this literature to find out the primary drivers of cooperation in symmetric IRPD games. Other than a few early papers, asymmetric PD games are less studied in this literature (J Keith Murnighan, 1991; John K Murnighan, King, and Schoumaker, 1990). These papers concentrate on the pattern of actions chosen by subjects. Our contribution is two-fold in this literature. We aim to figure out how the probabilistic nature of which stage game subjects face every period determines their cooperative nature and whether symmetry and asymmetry of the game influence the cooperative behavior. We find that alternating asymmetric environments can increase cooperative behavior. We also find that symmetry of payoffs lead to higher cooperation rates.

Another related strand of literature studies multiple games being played together. The main crux of the issue here is whether there are behavioral spillovers or strategic differences when these games are played simultaneously or sequentially. Laferriere et al., 2021; Modak, 2021; Yang, Kawamura, and Ogawa, 2016 examine a situation where subjects play multiple PD games simultaneously in an infinitely repeated setting. These papers explore if playing two games together can lead to more cooperation in situations in which one game cannot support cooperation on its own. All these papers use symmetric stage games, only Modak, 2021 studies asymmetric games as well. Laferriere et al., 2021 includes a treatment where subjects play two stage games but sequentially. However, their setting is different from ours. In this treatment, the subjects plays two games in each period of a supergame but one after the other (deterministic). In our experiments, subjects play only one game in a period but the type of the game is decided by the state of the world. Due to the indefinitely repeated nature of the laboratory experiments, subject may not get an opportunity to play both games in a supergame.

3.3 Theoretical Background

In this paper, we look at the behavior of individuals who face different social dilemmas over time. The social dilemmas vary in a probabilistic way which is known to the individuals. Our aim is to find out how individuals internalize this probabilistic rule and modify their behavior accordingly. Our second point of interest is the difference in this behavior when individuals interact in a symmetric versus an asymmetric environment.

3.3.1 Equilibrium of Stochastic Game

Here we discuss the stochastic game that is being played by the subjects. Let $\Gamma\,(U_1, U_2, A_1, A_2, \Theta, P, \delta)$ be the stochastic dynamic game, where $U_{\rm i}$ is the stage game utility of player i, $A_{\rm i}$ is the stage game actions of player i, Θ is the set of states, $P : \Theta \times \Theta : [0, 1]$ is the transition probability matrix and δ is the discount factor. Note that the transition probability is fully characterized by states at t and $t+1$. In our stochastic game, players are engaged in an infinitely repeated game, where the state of world θ varies every period. How the state changes in every period is given by the transition matrix P. In each period, the players play a stage game, whose payoffs are decided by the state. In this paper, we only look at PD games, and consider two states, High and Low. We consider both symmetric and asymmetric stage games. In the symmetric case, the games look as in Figure 3.1. Whereas, in the asymmetric case, in each period, one player is in High state, while the other is in Low state. Figure 3.2 shows the payoff matrix of the asymmetric game when player 1 is in High state and player 2 in Low state.

In this subsection we discuss two types of strategies and the conditions when some of the strategies under these types are Subgame Perfect Nash Equilibria (SPNE, henceforth). The two types are history-contingent and state- and history-contingent strategies. For the rest of this subsection, we only consider strategies with respect to PD games. For PD games, $A_{\mathrm{i}} = \{C, D\}$, and for this exposition $\Theta = \{High, Low\}$. We will use a_{i} for the actions taken by player i and θ_t for the state at period t. Finally, the transition probability matrix is given by

$$P = \begin{bmatrix} \rho & 1-\rho \\ 1-\rho & \rho \end{bmatrix}$$

We call ρ the degree of persistence, as it is the probability with which the state of the world will remain the same in the next period. As ρ increases from 0 to 1, the probability that the same state persists in the next period increases.

Player 1 (High State)	Player 2 (High State): C	Player 2 (High State): D
C	c^H, c^H	a^H, b^H
D	b^H, a^H	d^H, d^H

(a) High State

Player 1 (Low State)	Player 2 (Low State): C	Player 2 (Low State): D
C	c^L, c^L	a^L, b^L
D	b^L, a^L	d^L, d^L

(b) Low State

Figure 3.1. Symmetric Stage Games

Player 1 (High State)	Player 2 (Low State): C	Player 2 (Low State): D
C	c^H, c^L	a^H, b^L
D	b^H, a^L	d^H, d^L

Figure 3.2. Asymmetric Stage Game

History-contingent strategies only consider the history of actions irrespective of the current and history of states. For example, consider a strategy where the player starts by cooperating irrespective of the state; continues to cooperate, but defects if there is defection in the history. We call this the Strong Grim Trigger (S-Grim, henceforth). Next, there are state-, and history-contingent strategies. For example, a strategy where a player plays Grim strategy when the state is High, but AD when the state is Low. In this strategy, a player starts by cooperating and continues to cooperates when they are in High state, but defects if there is defection in High state in the history of the play. We call this strategy Grim-High for the rest of the paper. A counter part of this strategy is where subjects play Grim in the Low state and AD in the High state. We call this Grim-Low Strategy.

To check whether these strategies are SPNE, we check for the incentive for one shot deviation in each state $\theta = \{High, Low\}$. We first consider the S-Grim strategy. We use this strategy because this provides the strictest punishment for punishment. Therefore, the conditions under which this strategy is an equilibrium is the least restrictive condition for achieving conditional cooperation. To evaluate whether the S-Grim is an equilibrium strategy we compare the incentive from continued mutual cooperation (denoted by, V^{MC}_{S-Grim} in eq. (3.1)[3]) following the S-Grim strategy and that from the one-shot deviation in each state plus the continuation value given that the opponent is playing the S-Grim strategy (denoted by, V^{Dev}_{S-Grim} in eq. (3.2)).

$$
\begin{aligned}
V^{MC}_{S-Grim} &= \begin{bmatrix} c^H \\ c^L \end{bmatrix} + \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix} V^{MC}_{S-Grim} \\
\Rightarrow V^{MC}_{S-Grim} &= \left(I - \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix} \right)^{-1} \begin{bmatrix} c^H \\ c^L \end{bmatrix}
\end{aligned} \tag{3.1}
$$

$$
V^{Dev}_{S-Grim} = \begin{bmatrix} b^H \\ b^L \end{bmatrix} + \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix} V^{MD} \tag{3.2}
$$

$$
\begin{aligned}
V^{MD} &= \begin{bmatrix} d^H \\ d^L \end{bmatrix} + \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix} V^{MD} \\
\Rightarrow V^{MD} &= \left(I - \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix} \right)^{-1} \begin{bmatrix} d^H \\ d^L \end{bmatrix}
\end{aligned} \tag{3.3}
$$

[3]↑ I is the identity matrix of dimension 2.

Own Choice \ Other's Choice	C	D
C	48	12
D	50	25

(a) High State

Own Choice \ Other's Choice	C	D
C	32	12
D	50	25

(b) Low State

Figure 3.3. Stage Game Payoffs

S-Grim is an SPNE if $V^{MC}_{S-Grim} - V^{Dev}_{S-Grim} \geq 0$. This inequality gives us a relationship between the discount factor δ and the persistence level ρ. Also, note that for this strategy, it does not matter if the stage is symmetric or asymmetric. In the experiment, the payoffs we use for the High and Low states are given in Figure 3.3. We use these payoffs to numerically show the relationship between the discount factor and persistence level in Figure 3.4. Note that the darker region (colored green) is the region where S-Grim is a SPNE. For this set of payoffs, we see that as persistence level increases the minimum level of discount factor required for S-Grim to be an SPNE also increases. This is primarily driven by the fact that, as the persistence level increases the continuation value of mutual cooperation decreases when a player is in the Low state. This is because with high persistence level, they will have a higher probability of remaining in the Low state in the next period with the low payoff from mutual cooperation. This is due to discounting of future. Therefore, as discount factor increases, the continuation value does not depend as much on the persistence level and the one-shot deviation is no longer profitable.

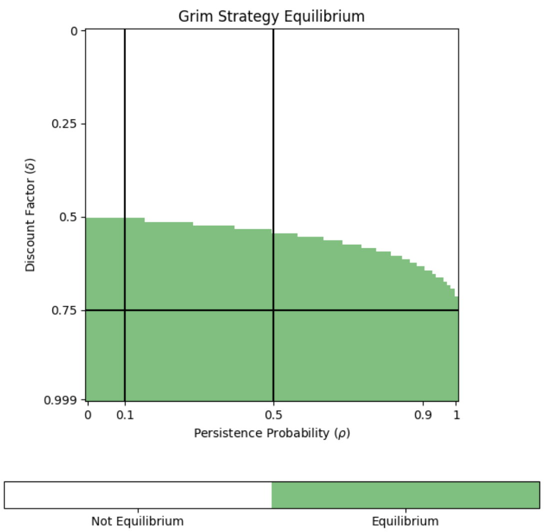


Figure 3.4. Strong Grim Strategy as Subgame Perfect Nash Equilibrium

We next consider Grim-High and Grim-Low strategies. The conditions for S-Grim to a SPNE does not depend on whether the stage games are symmetric or asymmetric. However, that is not true for Grim-High and Grim-Low strategies. The valuation for continued mutual cooperation following these strategies are shown in the following equations. For symmetric games, the valuations are shown in eq. (3.4, 3.5). While, for the asymmetric games, these are shown in eq. (3.6, 3.7).

$$V^{MC}_{Grim-H-Sym} = \left(I - \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix}\right)^{-1} \begin{bmatrix} c^H \\ d^L \end{bmatrix} \tag{3.4}$$

$$V^{MC}_{Grim-L-Sym} = \left(I - \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix}\right)^{-1} \begin{bmatrix} d^H \\ c^L \end{bmatrix} \tag{3.5}$$

$$V^{C}_{Grim-H-Asym} = \left(I - \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix}\right)^{-1} \begin{bmatrix} a^H \\ b^L \end{bmatrix} \tag{3.6}$$

$$V^{C}_{Grim-L-Asym} = \left(I - \delta \begin{bmatrix} \rho & (1-\rho) \\ (1-\rho) & \rho \end{bmatrix} \right)^{-1} \begin{bmatrix} b^H \\ a^L \end{bmatrix} \tag{3.7}$$

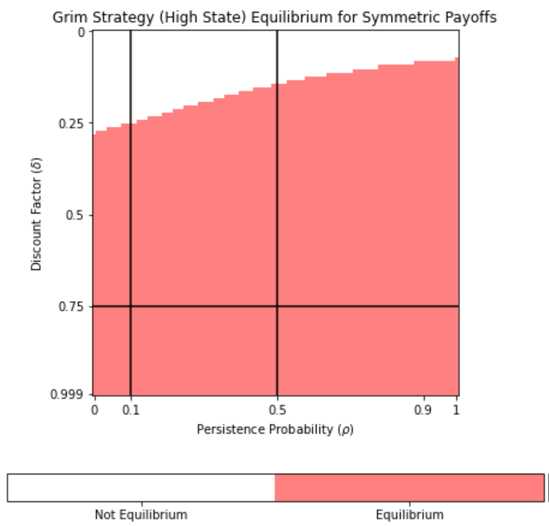
Note that there is no incentive for a player to deviate from defection. So to check for SPNE we need to check if there is a profitable one-shot deviation in the state where they are cooperating. For example, for Grim-High in the symmetric case, we need to check if

$$V^{MC}_{Grim-H-Sym}(\theta = High) \geq b^H + \delta \begin{bmatrix} \rho & (1-\rho) \end{bmatrix} V^{MD}$$

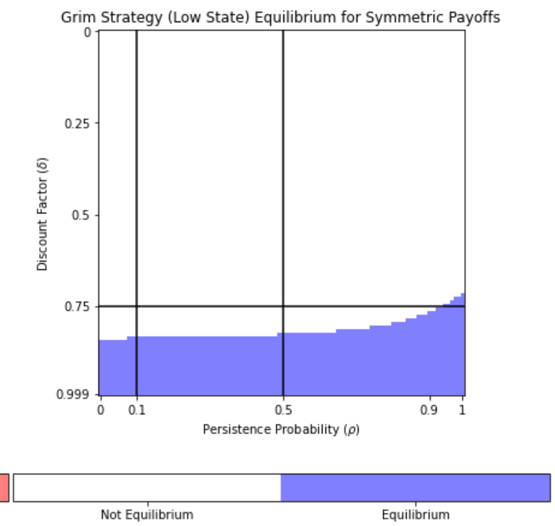
Again these inequalities give us relationships between the discount factor and the persistence level as to when these strategies are SPNE. We use the payoff matrices from the experiment to numerically derive these relationships in Figure 3.5. Note that for our payoffs, the incentives from conditional cooperation under these strategies are flipped between states in the asymmetric case (see eq. (3.6, 3.7) and Figure. 3.3). Therefore, the relationship between discount factor and the persistence level boils down to one as shown in 3.5c. It is interesting to see that the relation between the minimum discount factor and persistence level is decreasing for symmetric games but increasing for asymmetric game. This is because in the symmetric game, each of the strategy lead to high continuation value in the state they are cooperating in if the persistence value is high. With low persistence, the state changes to the one where they are mutually defecting leading to low payoffs. On the other hand, with the asymmetric game, players receive sucker's payoff in the state they are cooperating in and the temptation payoff in the other. As a result, with low persistence they get higher continuation value in the state they are cooperating in. Only with high discount factor, the impact of persistence is alleviated.

3.3.2 SizeBAD - Determinant of cooperation

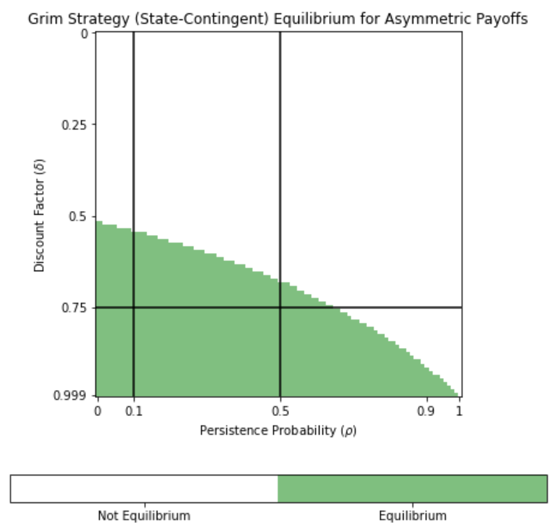
Infinitely repeated games admit a large number of strategies which are also equilibrium strategies. In the previous subsection, we show that at least two strategies are equilibria



(a) Grim-High – Symmetric Games



(b) Grim-Low – Symmetric Games



(c) Grim-High & Grim-Low – Asymmetric Games

Figure 3.5. State-Contingent Strategies as Subgame Perfect Nash Equilibrium

given our payoffs, transition rules and discount factors. Moreover, S-Grim strategy is an equilibrium in each treatment, therefore continued mutual cooperation can be sustained in all treatments. The analysis of equilibrium does not give us any insight as to which strategies subjects will choose under each treatment. However, we know from the previous literature (see Dal Bó and Fréchette, 2018) in the area of infinitely repeated games, there are multiple determinants of cooperation besides mutual cooperation being supported in equilibrium. One such factor is SizeBAD. In this subsection, we will discuss the insights we can gather by exploring the concept of SizeBAD for our setting.

In the case of deterministic IRPD game, SizeBAD is the size of basin of attraction of Always Defect against Grim Trigger strategy. For our environment, we adopt SizeBAD as the size of basin of attraction of Always Defect against Strong Grim Trigger Strategy. We define SizeBAD as the maximum probability with which the other player must be playing S-Grim to make AD optimal to the player. The SizeBAD is given by the value of p that satisfies the equation

$$\begin{aligned} &pV(\text{S-Grim}, \text{S-Grim}) + (1-p)V(\text{S-Grim}, \text{AD}) \\ =&pV(\text{AD}, \text{S-Grim}) + (1-p)V(\text{AD}, \text{AD}) \end{aligned} \tag{3.8}$$

where $V(\text{i}, \text{j})$ is the value of playing strategy i where other is playing strategy j. For example, when SizeBAD = 40%, a player needs to believe that other is playing S-Grim with 40% probability or lower to find using AD optimal. As SizeBAD increases, cooperation becomes weaker due to strategic uncertainty.

Our environment is that of stochastic IRPD. We adopted the calculation in the following way. We assume that players make their decision regarding which strategy to use (S-Grim or AD) in the first period of a supergame after they observe the state of the world in that period. Therefore, we consider the two states separately. However, for the asymmetric treatments, when one player in the High state, the other player is in the Low state. Hence, the effective SizeBAD is taken to be the highest of between those of the two states. For example, if in an asymmetric treatment, for the High state the SizeBAD is 0.6 and for Low state it is 0.4, then the effective SizeBAD is 0.6. A similar mechanism is used when we find the minimum discount factor required for a strategy to be SPNE in an asymmetric IR game. We use this concept to derive our hypotheses in the next section.

3.4 Experimental Design

As stated above, the purpose of this paper is to find out of how individuals modify behavior in response to different probabilities of state arrival (alternating vs. random) and different types of interaction (symmetric versus asymmetric). We study these variations using a 2×2 between subject design as shown in Figure 3.6. In our experiment, the subjects play a stochastic IRPD game. The stochastic game has two states which have different payoffs from mutual cooperation. Therefore, we have two stage games shown in Figure 3.3. For all our treatments, we used the discount factor $\delta = 0.75$. We induce infinite repetition using the protocol developed in Roth and J Keith Murnighan, 1978. To the subjects we explained it as follows – in each match[4], at the end of each period, the computer is going to roll a 12-sided die; if the number is greater than 9, the match will proceed to the next period, else, the match will end. To check if the subjects understood the procedure, we made them practice drawing random numbers for 10 rounds (see Appendix C.2.1).

Type of Interaction

Persistence		Asymmetric	Symmetric
	Alternating	Asym-Alt	Sym-Alt
	Random	Asym-Ran	Sym-Ran

Figure 3.6. Treatments

In each of the treatments, in every period subjects can see the stage games for both states. But, in each period they are told which state they are in, i.e., which stage game is relevant in that particular period. The stage games for the experiment are in Figure 3.7

[4]↑ In the experiment, we call a supergame, a match.

and the screen that the subjects view is in Appendix C.2.1. In the symmetric treatments, each subject and their opponent are in the same state together – high state (Red Game) or low state (Blue Game). Whereas, in the asymmetric treatments, when one subject is in the High state (Red Game), their opponent is in the Low state (Blue Game) and vice versa. We test two levels of persistence – alternating vs. random. In case of the alternating rule, the transition probability matrix is given by eq. (3.9) and for the random rule, the same is given by eq. (3.10). For alternating, we do not make alternation absolute as it would make the infinitely repeated game deterministic. This would make the two treatments different for the subjects as it would take away the uncertainty regarding which state the subjects would face in the next period. In the experiment, subjects were told how the state would change in the following way – "if you are playing XXX game in the current period, in the next period you will play XXX game with probability ρ and YYY game with probability $1 - \rho$"[5]

Player 1 \ Player 2	A	B
A	48, 48	12, 50
B	50, 12	25, 25

(a) Red Game

Player 1 \ Player 2	X	Y
X	32, 32	12, 50
Y	50, 12	25, 25

(b) Blue Game

(c) Symmetric Games

Player 1 \ Player 2	A	B
A	48, 32	12, 50
B	50, 12	25, 25

(d) Red Game

Player 1 \ Player 2	X	Y
X	32, 48	12, 50
Y	50, 12	25, 25

(e) Blue Game

(f) Asymmetric Games

Figure 3.7. Stage Games in the Experiment
Notes: In the experiment, the actions are named "A", "B" for the "Red Game" and "X", "Y" for the "Blue Game" in place of "C", "D" respectively.

$$P_{alt} = \begin{bmatrix} 0.1 & 0.9 \\ 0.9 & 0.1 \end{bmatrix} \qquad (3.9) \qquad\qquad P_{ran} = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} \qquad (3.10)$$

We conducted the experimental sessions at the Vernon Smith Experimental Economics Laboratory in December 2021 and February 2022. Subjects were recruited from a pool of

[5]↑ The instructions are in Appendix C.2.1. In the instructions, XXX and YYY were replaced Red or Blue and ρ was replaced by the value of the probability that the same state would persist in the next period which were either 50% (random) or 10% (alternating)

under-graduate students at Purdue University using ORSEE (Greiner, 2015). For each treatment, we conducted three sessions, which amounted to 12 sessions in total with a total of 186 subjects. The supergame-lengths for the sessions are listed in Table C.4. The average number of periods per round was 4.31 with a minimum of 1 period and a maximum of 19 periods. We use a between subject design where each subject participated in only one of the sessions of this study.

The computerized experimental sessions used oTree (D. L. Chen, Schonger, and Wickens, 2016) to record subject decisions. Subjects were given instruction at the beginning of the session. Each session started with a demographic questionnaire, instructions, followed by a quiz, and then the experiment. The instructions were shown on the screen (Appendix C.2.1 contains the instructions the subjects were given). At the end of the instructions there was a quiz with 5 questions. Subjects had to get each questin correct before they could move to the next question. The questions can be found in Appendix C.2.1.

The subjects were guaranteed a payment of \$5 for appearing for the session. Each session lasted for not more than 1 hour. The subjects earned an average of \$22.87, with a minimum of \$19.75 and a maximum of \$26.25 (including the \$5 show up fee). The subjects earned in points during the experiment. At the end of the experiment, the points were converted into dollar amounts using an exchange rate such that the average earning in every session would be similar.[6]

3.4.1 Hypotheses

The effective SizeBAD for each of our four treatments are listed in Table 3.1.

[6]↑ The subjects were told the exchange rate in the instruction, before the experiment.

Table 3.1. Effective SizeBAD

	High State		Low State	
	Asymmetric	Symmetric	Asymmetric	Symmetric
Alternating	0.362	0.298	0.362	0.362
Random	0.455	0.284	0.455	0.455

We derive the following hypotheses given the SizeBAD of each of treatments. Our first hypothesis compares the effect of persistence of the state of the world in the asymmetric environment.

Hypothesis 3.1. *Cooperation rates are higher under Asym-Alt treatment compared to Asym-Ran treatment.*

From Table 3.1 we can see that both in the High and Low states, under Random the SizeBAD is higher than that under Alternating. Therefore, we expect subjects to find it easier to cooperate in Asym-Alt treatment compared to Asym-Ran treatment. The next hypothesis again compares the effect of persistence but in the symmetric environment. We consider the two states separately. In the High state, the SizeBAD is larger in Sym-Alt treatment compared to Sym-Ran treatment. But this is switched in the Low state. This follows from the fact that in the High (Low) state, under alternation, the continuation value of mutual cooperation is lower (higher) than that under random arrival of states.

Hypothesis 3.2. *(a) In the High State, cooperation rates are higher in the Sym-Ran compared to Sym-Alt.*

(b) In the Low State, cooperation rates are higher in the Sym-Alt compared to Sym-Ran.

In the next hypothesis, we compare the effect of asymmetry of environments. In Table 3.1, we see that there is no difference between symmetry and asymmetry in the Low State. But in the High state, irrespective of the transition rule, SizeBAD is lower under symmetry. Therefore subjects should find it easier to cooperate under symmetry in the High state compared to asymmetry.

Hypothesis 3.3. *In the High State, cooperation rates are higher in the symmetric treatments compared to asymmetric treatments.*

Finally, we have a hypothesis regarding difference in cooperation in the High and Low states. Given the way we define effective SizeBAD for asymmetric treatments, there is no difference between High and Low states. But for symmetric treatments, SizeBAD is higher under Low states than High state. We thus have the following hypothesis.

Hypothesis 3.4. *cooperation rates are higher in the High state compared to the Low state in the symmetric treatments.*

3.5 Results

We now present the results of our experimental study. Figure 3.8 shows the average all periods cooperation rate in each state (High or Low) in each supergame of the experiment for each treatment. We also present the 95% confidence interval (using two-stage clustered bootstrap), shown by the shaded region. The plots for the first period average cooperation rates with their confidence intervals are in Figure C.1. In Table 3.2 we present the average cooperation rates for all periods and first periods, by state, in the last 15 supergames with the clustered standard errors and the 95% confidence intervals.

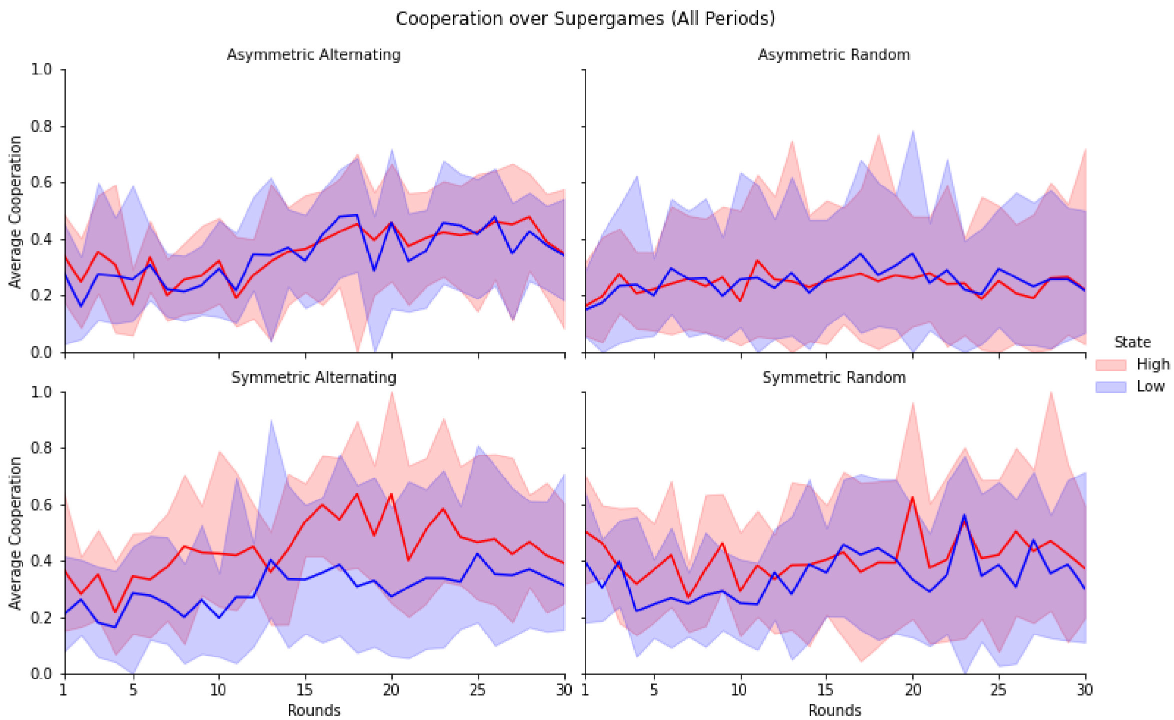


Figure 3.8. Average Cooperation rates in Treatments for each Round (All Periods)
Notes: The shaded areas are the Two-Stage Clustered Bootstrap 95% Confidence Intervals (clustered at session level, randomized at subject level).

Table 3.2. Average Cooperation Rate in the Last 15 Supergames

	All Periods			First Period		
	High	Low	All	High	Low	All
Asym-Alt	0.419	0.393	0.408	0.472	0.427	0.45
	(0.065)	(0.063)	(0.066)	(0.083)	(0.052)	(0.068)
	[0.219, 0.501]	[0.2,0.469]	[0.216, 0.475]	[0.22, 0.558]	[0.269, 0.485]	[0.25,0.517]
Asym-Ran	0.249	0.263	0.264	0.306	0.301	0.304
	(0.11)	(0.108)	(0.111)	(0.136)	(0.124)	(0.125)
	[0.072, 0.496]	[0.083, 0.502]	[0.075, 0.511]	[0.064, 0.592]	[0.083, 0.565]	[0.078, 0.571]
Sym-Alt	0.482	0.34	0.421	0.589	0.335	0.465
	(0.081)	(0.122)	(0.094)	(0.03)	(0.14)	(0.088)
	[0.346, 0.663]	[0.145, 0.639]	[0.264, 0.647]	[0.535, 0.637]	[0.107, 0.67]	[0.317, 0.656]
Sym-Ran	0.44	0.391	0.423	0.527	0.436	0.471
	(0.129)	(0.124)	(0.121)	(0.116)	(0.12)	(0.117)
	[0.252, 0.724]	[0.21, 0.664]	[0.205, 0.691]	[0.291, 0.774]	[0.227, 0.697]	[0.25, 0.73]

Notes: This table presents the average cooperation rates for the last 15 supergames. The clustered bootstrapped SE are in parenthesis and the 95% confidence intervals are in square brackets.

There are several key takeaways from this table and the graphs. The first key takeaway is that cooperation levels are significantly higher than zero (the confidence intervals do not include 0). This is in line with our theory, since cooperative outcomes are equilibrium outcomes given our payoff parameters, transition rules, and discount factor. We can observe that there is a slight increase in cooperation rate over supergames. These increases are statistically significant in the alternating treatments for both states. For the random treatments, we only observe a statistically significant increase in cooperation rate in the Sym-Ran treatment for Low state, however this effect is no longer present when we consider only the first periods. Tables C.1 and C.2 contain the regression results for this analysis. We also find that cooperation levels are the lowest in the Asym-Ran treatment. For the rest of the three treatments cooperation rates are similar. We now focus on our hypotheses and present the corresponding results.

Table 3.3 presents the comparison results for our four treatments using all periods cooperation rates (see Table C.3 for the same with first period action choices). For this part of the analysis we are going to use the last 15 supergames of the experiment and Nonparametric permutation test. For the Nonparametric Permutation test, we first calculate the cooperation rate of every subject in each supergame, then averaged it over the supergames. Therefore, our unit of observation is a subject. In this table, we provide the results for each state separately and combined.

Table 3.3. Average Cooperation and Treatment Effects (All Periods)

	High State			Low State			All States		
	Asymmetric		Symmetric	Asymmetric		Symmetric	Asymmetric		Symmetric
Alternating	0.419	H3: $\sim$	0.482	0.393	$\sim$	0.34	0.408	$\sim$	0.421
	(0.065)	(0.41)	(0.081)	(0.063)	(0.436)	(0.122)	(0.066)	(0.98)	(0.094)
	H1: $\vee^{**}$		H2 (a): $\wr$	H1: $\vee^{*}$		H2 (b): $\wr$	$\vee^{**}$		$\wr$
	(0.018)		(0.573)	(0.069)		(0.494)	(0.032)		(0.95)
Random	0.249	H3: $<^{***}$	0.44	0.263	$<^{*}$	0.391	0.264	$<^{**}$	0.423
	(0.11)	(0.009)	(0.129)	(0.108)	(0.079)	(0.124)	(0.111)	(0.029)	(0.121)

Notes: This table shows the average cooperation in the last 15 supergames of the experiment for all periods. Clustered bootstrap S.E. for the cooperation levels are reported in parenthesis below. We also provide treatment effects in terms of greater than, less than or equality. For this we provide the p-values of the two-sided test of comparison of average cooperation levels of two treatments using Non-parametric permutation test in the parenthesis below.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We first consider Hypothesis 3.1 considering the different levels of persistence in the asymmetric environment. We hypothesized that cooperation should be higher when the states were alternating rather than randomly realized. Our data confirms this hypothesis whether we consider the two states separately or combine them. Moreover, this result also holds when we only consider the first period actions (see Table C.3). We summarize this in the following result.

Result 3.5.1. *Cooperation rates are higher in the Asym-Alt treatment compared to Asym-Ran treatment.*

Our second hypothesis compares the two levels of persistence in the symmetric environment. We hypothesized to observe higher cooperation in the High state (Low state) under Sym-Ran (Sym-Alt) treatment. However, our data show that there is no significant difference between the cooperation rates under the two treatments in either state. Thus, we have the following result.

Result 3.5.2. *(a) In the High state, cooperation rates are same across Sym-Alt and Sym-Ran treatments.*

(b) In the Low state, cooperation rates are same across Sym-Alt and Sym-Ran treatments.

Our finding that cooperation rates are higher under Asym-Alt treatment compared to Asym-Ran treatment can be compared with alternation in repeated Battle of the Sexes game. In experiments with repeated Battle of the Sexes games, subjects often use alternation between the two equilibria to reach an efficient outcome (Cason, Lau, and Mui, 2013; Duffy, Lai, and W. Lim, 2017; Lau and Mui, 2008). This is also referred to as "turn-taking". Turn-taking can be used to achieve efficient outcomes in other games as well, like common-pool-resources assignment game (Janssen and Ostrom, 2006). In our case, subjects could coordinate on mutual cooperation as a Pareto optimal outcome. However, in the asymmetric environment, one person always receives higher payoff than their opponent from mutual cooperation. In the case of alternating states, it becomes easy to coordinate on the Pareto outcome as the player receiving the higher payoff from mutual cooperation alternates as the state alternates, leading to a more equitable outcome. Here the alternation of states becomes a coordinating device. In the case of random arrival of states (i.e., the random treatment), turn-taking between subjects is less frequent than in the alternating treatment, essentially invalidating the coordination device. In the symmetric environment, alternation does not serve the additional purpose of a coordination device.

Next, we consider the comparison between symmetry and asymmetry of environment. In hypothesis 3.3 we stated that we expect cooperation rates to be higher only in the High state under symmetry compared to asymmetry, irrespective of the persistence level. From the data, we find that cooperation is higher in Sym-Ran treatment compared to Asym-Ran treatment. This hold true for High state and combining both States considering all periods or just the first period. We summarize this in the following result. Although we do not hypothesize to see any difference in cooperation rates in the Low state, we find this higher cooperation rates in Sym-Ran treatment compared to Sym-Alt treatment when we use data from all periods.

Result 3.5.3. *In the High state, cooperation rates are higher with in the Sym-Ran treatment compared to the Asym-Ran treatment.*

Although we expected to see higher cooperation rates due to symmetry under both rules, we only observe the difference in the case of random transition rule. Cooperation is riskier under asymmetry due to strategic uncertainty, therefore hard to maintain. But difficulty in maintaining cooperation can be aggravated in the laboratory due to the indefinite nature of the game. In the asymmetric treatments, the payoffs are always unequal for mutual cooperation. On top of that, in the indefinite game that subjects play in the laboratory, it is possible that subjects in the random treatment never switch between states even if there are more than one period in a supergame. Therefore, a subject can remain in the Low state for all periods, whereas their opponent is always in the High state maintaining and accumulating unequal payoffs in case of mutual cooperation in all periods. In this event, the subject in the Low state can choose to unilaterally deviate to defection to close the payoff gap, effectively breaking down cooperation. Symmetry of environments in such a situation can act as the coordination device with mutual cooperation leading to equal payoffs. Thus we see a statistically significant increase in cooperation rates with Sym-Ran treatment compared to Asym-Ran treatment. In case of alternating transition rule, the alternation of states helps the subjects to reach high and equal payoffs through mutual cooperation in the asymmetric treatment. Therefore symmetry of environments do not add much incentive to increase the cooperation rate. Hence we do not find any statistically higher cooperation rates in the Sym-Alt treatment compared to the Asym-Alt treatment.

Table 3.4. Difference in Cooperation Rates between High State and Low State (Last 15 Supergames)

	All Periods		First Period	
	Asymmetric	Symmetric	Asymmetric	Symmetric
Alternating	0.026	0.142*	0.045	0.254***
	(0.711)	(0.056)	(0.627)	(0.006)
Random	-0.015	0.049	0.005	0.091
	(0.82)	(0.51)	(0.949)	(0.348)

Notes: This table shows the difference in average cooperation between High State and Low State in the last 15 supergames of the experiment. p-values of the two-sided test of comparison of average cooperation levels of two states using Non-parametric permutation test in the parenthesis below.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Hypothesis 3.4 we state that cooperation in the High state is expected to be higher in the Low state in the symmetric treatments. We compare subjects' behavior across the two states. Table 3.4 reports the change in cooperation rate from Low state to High state for the last 15 supergames. We find that only in the Sym-Alt, High state has a statistically significant higher cooperation level compared to Low state. This is summarized in Result 3.

Result 3.5.4. *In Sym-Alt treatment, cooperation rates are higher in the High state compared to Low state.*

3.6 Discussion

In this paper, we study a stochastic dynamic game with Prisoner dilemma stage games. Our setting is an infinitely repeated game with the payoffs of the stage game in each period decided by the state of the world in that period. The stochastic part of the game is reflected in how the states change across time periods. The state in a period is only dependent on that in the last period. We call this persistence. The higher the persistence, the higher the likelihood that the same state persists in the next period. We only have two states of the world – High and Low. The difference between these two states in only in the payoff from mutual cooperation. We utilize a laboratory experiment to study how individuals internalize different levels of persistence and how this behavior differs when environments change from symmetric to asymmetric.

We have four main hypotheses using the concept of sizeBAD which is shown to be a determinant of cooperative behavior in the literature. First, for the asymmetric environment, we expect that cooperation to be higher in the alternating treatments compared to the random treatments. But for the symmetric environment, our hypothesis is state dependent. In the High state, we expect higher cooperation rates in with random transition rule compared to alternating transition rule and the opposite for Low state. In case of the comparison between symmetry and asymmetry of interaction, we hypothesize that the effect is only in the High state. So our third hypothesis is that we expect in High state cooperation rates to be higher in symmetric environments. Coordination to mutual cooperation in the asymmetric treatments can be difficult because one player is always disadvantaged. Therefore it is easy to break cooperation as it is driven by the incentives of the disadvantaged player. Finally, we expect cooperation rates to be higher in the High state than in the Low state only in the symmetric treatments.

Our results partially confirm most of our hypotheses. We find that only in the asymmetric environment, alternating states leads to higher cooperation rates compared to random arrival of states. The alternation of states acts as a coordination devices to coordinate on mutual cooperation. On the other hand we find that symmetry of payoffs can also improve cooperation only but only the states arrive randomly. Alternation of states can increase cooperation sufficiently in the asymmetric environment, such that symmetry does not add any extra incentive to cooperate. Finally, we find subjects to cooperate significantly more in the High state but only in the Symmetric Alternating treatment.

In our paper, with asymmetric environments, changing states is like changing the status of a player. In our asymmetric environment, one player has higher incentives than the other always. As the state changes, the player who receives the higher incentive is flipped. We find that Asymmetric Random treatment is least conducive to cooperation. This can be due to the indefinite nature of the laboratory experience. Due to random change in states in either of the random treatments, subjects can get stuck in the Low state for multiple periods without even going to the High state before a supergame ends. This can discourage cooperative behavior because there is inequity in payoffs in the asymmetric environment. On the other hand, with alternating states, the subjects can easily switch between High and Low states. So over periods, the inequity of payoffs can disappear with alternation in the asymmetric environment leading to higher incentive to cooperate. Therefore we find alternation as a tool to increase in cooperation. The other tool that can incentivize cooperative behavior is symmetry of payoffs. However, both these tools together does not seem to lead to much higher cooperation rates.

The results from the current experiment are dependent of the set of parameters we used, therefore, generalization should be done with caution. For example, we use a moderate level of discount factor. Increasing the discount factor can influence our result that alternation of task improves performance. If teams are fixed and long term, then randomization of tasks might work as good as alternation. On the other hand, with teams that work together for only short periods of time, symmetric teams might perform better than asymmetric teams whether tasks are alternated or randomized. Another limitation of this work, is that our asymmetry is in itself symmetric. That is, the players are inherently symmetric. The asymmetry is realized through the state of the world. Because of this alternation of states can effectively make the indefinite game symmetric in the laboratory (the infinite game is symmetric). However, this might not work if one player is disadvantaged in all states as the dynamic game becomes asymmetric. In this case, alternation or turn-taking might not be an conducive to mutual cooperation. These limitations lend themselves to the future work, where we vary the payoff parameter and/or discount factor in the same setting, or allow for heterogeneous players leading to asymmetric dynamic game. Finally, here our stage games are prisoners' dilemma games and this can be extended to include other games, for example, team production.

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A. DO MULTIPLE CONTACTS MATTER?

A.1 Theoretical Predictions

Table A.1. Summary of Theoretical Predictions

Treatments		Expected	Threshold δ		
Payoff	Contact	Strategy	Easy	Hard	Combined
Symmetry	Single	(GT, All D)	0.08	0.8	
Symmetry	Multiple	Strong GT			0.44
Asymmetry	Single	(All D, All D)	0.8	0.8	
Asymmetry	Multiple	Strong GT			0.44

Notes: Expected Strategies - Strategies supported in Subgame Perfect Nash Equilibrium.

A.2 Experiment

Table A.2. Summary of Sessions by Treatment

Treatments	Administration			Demographics		
	Sessions	Subjects	Avg. Earnings	% Male	Avg. Age	ECON Classes
SGame	4	48	\$19.24	44.7%	21.5	2
MGame	4	48	\$19.07	60.4%	20.6	2
SRole	4	48	\$17.31	37%	20.5	1
MRole	4	48	\$17.83	55.3%	19.5	1

Notes:
There were 12 subjects per session.
ECON Classes column shows the median number of economics classes (self-reported) taken by the subjects.

Table A.3. Supergame Lengths and Conversion Rates

Round → Sessions ↓	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	Points per $
Pilot	11	2	1	3	4	3	1	2	3	8	2	6	9	2	4	8	4	4	1	4	9	7	3	1	2						500
Session1	3	3	1	2	10	9	5	1	1	1	4	9	4	8	3	4	5	2	1	1	1	8	1	6	8	1	7	7	2	1	760
Session2	5	1	1	2	2	3	4	6	6	2	9	1	2	2	1	1	1	9	10	1	8	2	8	13	2	6	1	6	3	1	760
Session3	4	12	3	2	1	6	1	2	2	4	9	2	10	6	2	4	10	2	4	3	2	1	2	3	3	8	5	2	2	1	760
Session4	1	1	6	2	8	5	5	2	2	5	2	11	2	3	10	2	4	13	9	1	1	1	5	2	6	4	2	1	6	2	780

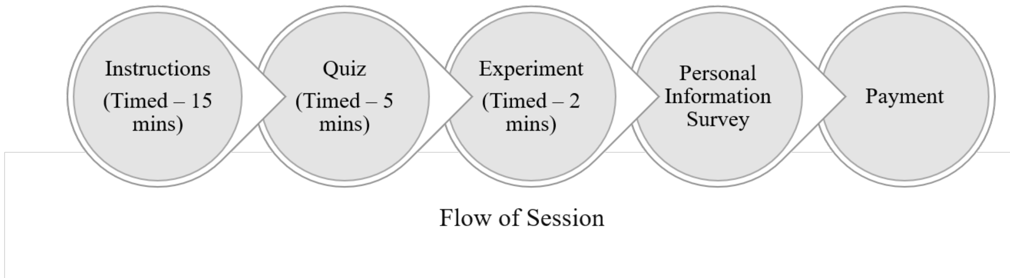


Figure A.1. Flow of the Session

A.2.1 Results

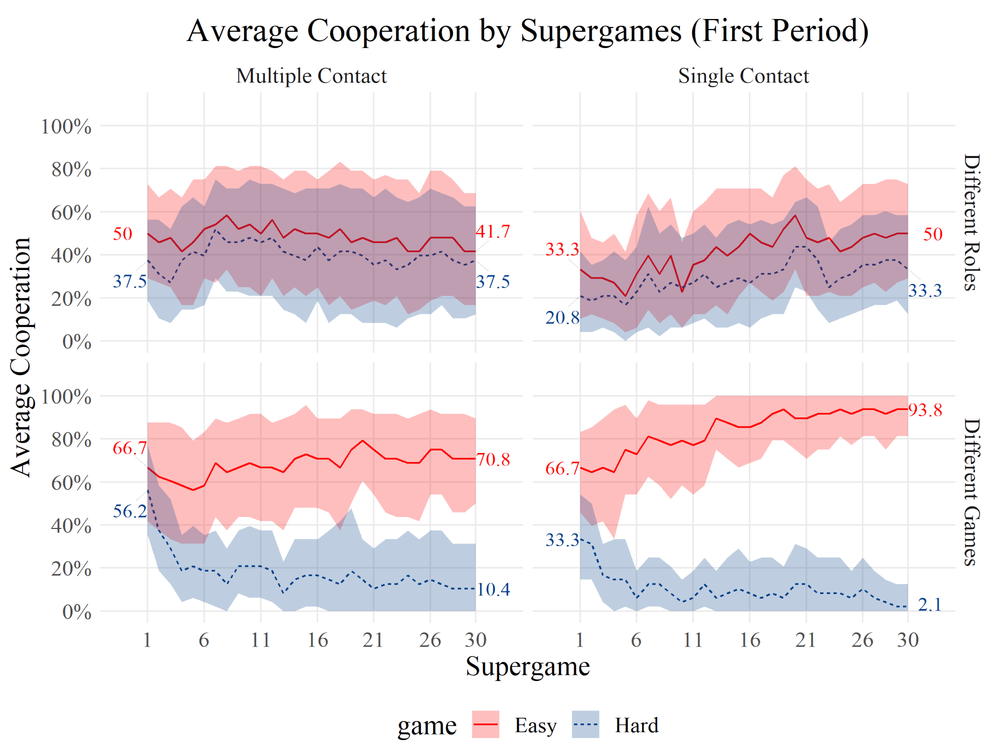


Figure A.3. Cooperation rates by Roles and Treatments for all Supergames (First Period)

Notes: The shaded areas are the Two-Stage Clustered Bootstrap 95% Confidence Intervals (clustered at session level, randomized at subject level).

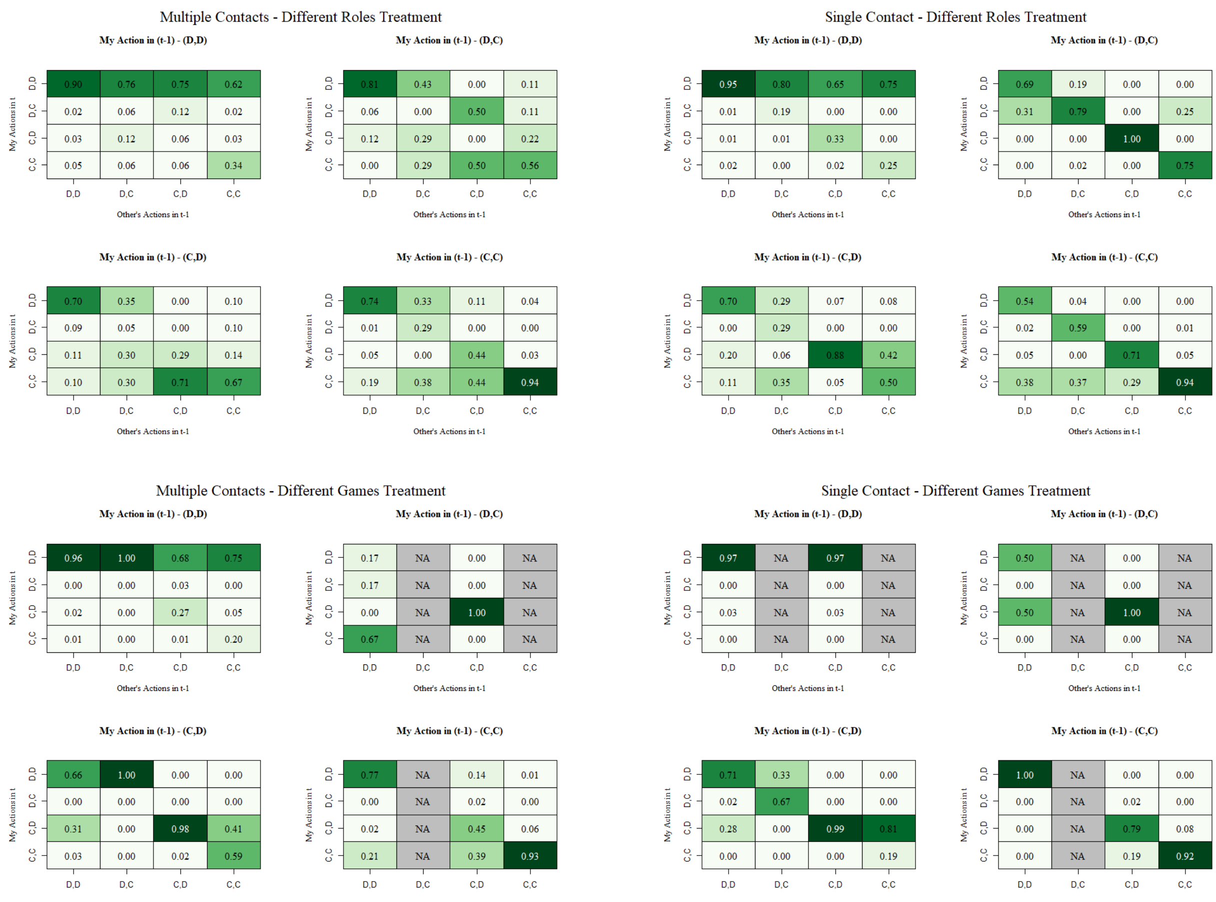


Figure A.2. Conditional Probability of Subject's Action at t given Actions at $t-1$
Notes: Each 4×4 matrix is a matrix of conditional probabilities, such that each cell shows the probability choosing actions (represented in the rows) at t when opponent chose actions (respresented in the columns) and subject chose actions (represented in the subtitle of the matrix) at $(t-1)$. The action profile x,y implies x is chosen in Easy game, and y is chosen in Hard game with x,y $\in \{C, D\}$. The data used is from the supergames 21-30. NA implies there is no observation such that a subject chose the action (represented in the subtitle of the matrix) at $(t-1)$.

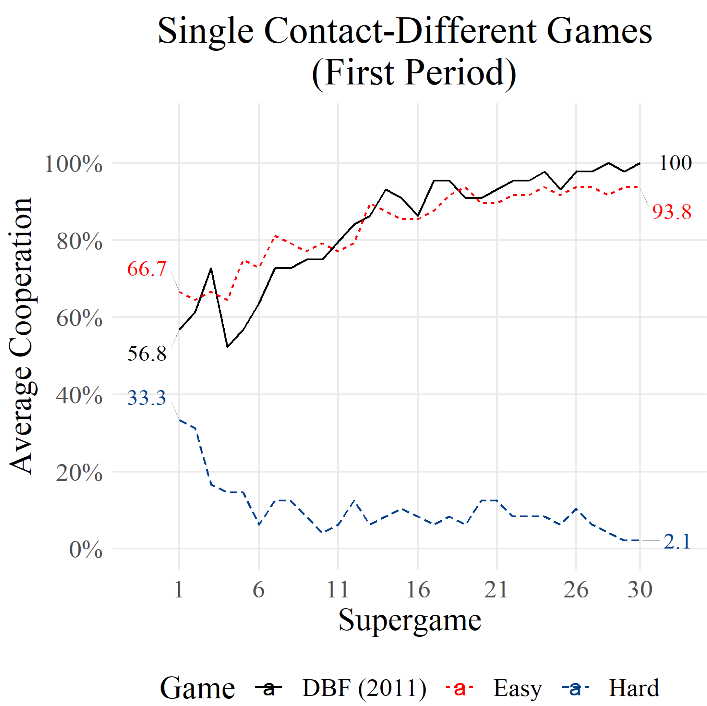


Figure A.4. Average Cooperation rates in Single Contact and Symmetric Treatment and $r = 48, \delta = 0.75$ Treatment in Dal Bó and Fréchette, 2011 for each Supergame (First Period)

Notes: DBF(2011) implies Dal Bó and Fréchette, 2011. The shaded areas are the Two-Stage Clustered Bootstrap 95% Confidence Intervals (clustered at session level, randomized at subject level).

Table A.4. Comparison between DBF (2011) $r = 48, \delta = 0.75$ treatment and Easy Game in SGame treatment

Supergames 1-30		Supergames 16-30		Supergames 21-30		Supergames 26-30	
First	All	First	All	First	All	First	All
0.02	0.08	-0.93	-0.35	-1.20	-0.59	-1.37	-1.28
(0.985)	(0.939)	(0.353)	(0.723)	(0.23)	(0.554)	(0.169)	(0.2)

Notes: Table shows the z-stats estimated using Probit Regression clustered at session level to compare the average cooperation between $r = 48, \delta = 0.75$ treatment of Dal Bó and Fréchette, 2011 and Easy Game of SGame treatment. The statistics considers the supergames 26-30, 21-30, 16-30, and 1-30 of the sessions. For each of these we consider only the First Period (First) and All Periods (All). The p-values are listed in parentheses.
Significance: $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001

Table A.5. Difference between Hard Role/Game and Easy Role/Game (Wilcoxon Matched-Pair Signed Rank Test)

	Supergames 1-30		Supergames 16-30		Supergames 21-30		Supergames 26-30	
	First	All	First	All	First	All	First	All
SGame	-32.33***	-62.707***	-24.617***	-47.731***	-20.273***	-38.821***	-14.56***	-25.981***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
MGame	-26.817***	-49.372***	-20.494***	-36.858***	-16.882***	-30.76***	-12.083***	-21.143***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
SRole	-10.458***	-7.397***	-9.259***	-5.641***	-7.14***	-4.456***	-5.191***	-3.064**
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.002)
MRole	-8.854***	-9.918***	-5.657***	-6.482***	-4.454***	-4.965***	-3.053**	-4.503***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.002)	(0.0)

Notes: Table shows the z-stats estimated using Wilcoxon Matched-Pair Signed Rank Test to compare the average cooperation between Hard Game/Role and Easy Game/Role (Hard - Easy). The statistics considers the supergames 26-30, 21-30, 16-30, and 1-30 of the sessions. For each of these we consider only the First Period (First) and All Periods (All). The p-values are listed in parentheses.
Significance: $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001

Table A.6. Difference between Hard Role/Game and Easy Role/Game (Probit Regression)

	Supergames 1-30		Supergames 16-30		Supergames 21-30		Supergames 26-30	
	First	All	First	All	First	All	First	All
SGame	-12.17***	-11.03***	-9.62***	9.50***	-11.02***	-10.99***	-26.71***	-14.51***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
MGame	-3.61***	-3.21**	-3.43**	-3.31**	-3.5***	-3.54***	-3.33**	-3.09**
	(0.0)	(0.001)	(0.001)	(0.001)	(0.0)	(0.0)	(0.001)	(0.002)
SRole	-5.21***	-9.18***	-4.53***	-5.5***	-4.29***	-4.21***	-3.28**	-4.73***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.001)	(0.0)
MRole	-3.10**	-2.87**	-2.15+*	-3.19**	-3.20**	-3.02**	-3.51***	-2.46+*
	(0.002)	(0.004)	(0.012)	(0.001)	(0.001)	(0.003)	(0.0)	(0.014)

Notes: Table shows the z-stats estimated using Probit Regression clustered at session level to compare the average cooperation between Hard Game and Easy Game. The statistics considers the supergames 26-30, 21-30, 16-30, and 1-30 of the sessions. For each of these we consider only the First Period (First) and All Periods (All). The p-values are listed in parentheses.
Significance: $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001

Table A.7. Average Cooperation Rates (in Percentage)

	Rounds 26-30				Rounds 16-30			
	First Period		All Periods		First Period		All Periods	
	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard
SGame	93.3***	5.0+	88.1***	4.3+	91.5***	7.4*	83.8***	4.3*
	(0.0)	(0.083)	(0.0)	(0.074)	(0.0)	(0.047)	(0.0)	(0.029)
MGame	72.5***	11.7	64.4***	9.4+	71.9***	13.3+	59.5***	11.4*
	(0.0)	(0.102)	(0.0)	(0.053)	(0.0)	(0.057)	(0.0)	(0.043)
SRole	49.2***	35.8***	37.7***	32.6***	48.2***	34.2***	33.6***	28.5***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
MRole	45.5**	38.3**	39.2***	34.4**	46.2**	38.5**	37.8***	34.8**
	(0.001)	(0.003)	(0.0)	(0.001)	(0.001)	(0.004)	(0.0)	(0.001)

Notes: Table shows average cooperation rate over multiple supergames. The statistics considers the supergames 26-30 and 16-30 of the sessions, the first and all periods. Two-stage Cluster (clustered at session level, randomized at subject level) Bootstrap Standard Errors are in parentheses. Significance levels are due to p-values from one-sided t-test.
Significance - $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001

Table A.8. Comparison Across Treatments (Nonparametric Permutation Test)

	Supergames 26-30				Supergame 16-30				Supergames 1-30			
	First Period		All Periods		First Period		All Periods		First Period		All Periods	
	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard
MGame - SGame	-3.02**	1.3	-3.5***	1.55+	-2.96**	1.22	-4.16***	2.4**	-2.48**	1.87*	-3.17***	3.21***
	(0.003)	(0.103)	(0.0)	(0.059)	(0.003)	(0.113)	(0.0)	(0.009)	(0.009)	(0.035)	(0.0)	(0.0)
MRole - SRole	-0.39	0.27	0.2	0.26	-0.22	0.51	0.66	0.95	0.98	1.45+	1.75*	1.9*
	(0.343)	(0.399)	(0.42)	(0.402)	(0.419)	(0.303)	(0.251)	(0.165)	(0.158)	(0.07)	(0.045)	(0.03)
SRole - SGame	-5.84***	4.5***	-7.64***	5.34***	-6.13***	4.44***	-8.99***	5.68***	-7.12***	3.95***	-9.91***	5.64***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
MRole - MGame	-3.01**	3.31**	-3.36**	4.34***	-2.97**	3.31***	-3.29***	4.39***	-2.57**	3.27***	-3.35***	4.03***
	(0.002)	(0.001)	(0.002)	(0.0)	(0.002)	(0.0)	(0.0)	(0.0)	(0.007)	(0.0)	(0.0)	(0.0)

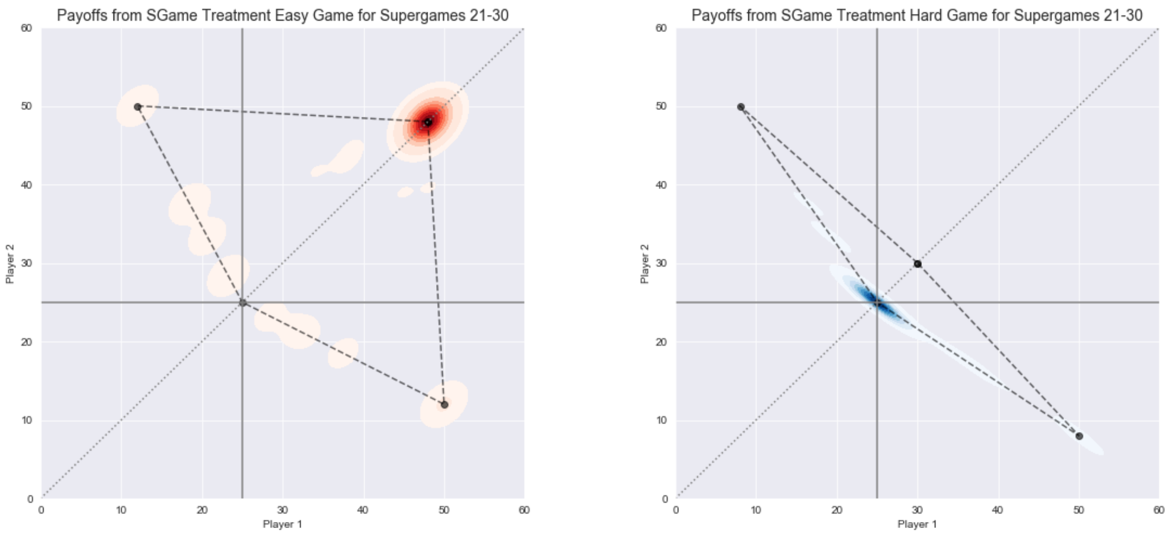
Notes: Table shows the t-stats estimated using Nonparametric Permutation Test to compare the average cooperation between test. The statistics considers the supergames 16-30, 26-30 and 1-30 of the sessions. The p-values are listed in parentheses. $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001

Table A.9. Comparison Across Treatments (Probit Regression)

	Supergames 26-30				Supergames 21-30				Supergame 16-30				Supergames 1-30			
	First Period		All Periods		First Period		All Periods		First Period		All Periods		First Period		All Periods	
	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard
MGame - SGame	-2.5*	1.05	-1.8+	-1.18	-2.41*	0.82	-2.06*	1.72+	-2.50*	0.84	-2.41*	1.44	-1.85+	1.73+	-1.69+	2.06*
	(0.012)	(0.293)	(0.071)	(0.238)	(0.016)	(0.411)	(0.04)	(0.085)	(0.013)	(0.4)	(0.016)	(0.15)	(0.064)	(0.084)	(0.092)	(0.04)
MRole - SRole	-0.26	0.18	0.22	0.24	-0.16	0.2	0.03	0.19	-0.13	0.31	0.41	0.57	-0.58	0.9	1.0	1.08
	(0.793)	(0.854)	(0.827)	(0.811)	(0.875)	(0.844)	(0.975)	(0.849)	(0.896)	(0.758)	(0.685)	(0.569)	(0.561)	(0.369)	(0.317)	(0.282)
SRole - SGame	-4.11***	4.78***	-4.07***	5.06***	-4.2***	4.16***	-4.55***	7.22***	-4.43***	3.68***	-5.66***	5.47***	-4.47***	3.67***	-5.62***	5.97***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
MRole - MGame	-2.04*	1.82+	-2.41*	2.56*	1.91+	1.77+	-2.45*	2.1*	-1.82+	1.74+	-1.74+	2.02*	-1.57	2.08*	-1.63	1.93+
	(0.042)	(0.069)	(0.016)	(0.011)	(0.057)	(0.077)	(0.014)	(0.036)	(0.068)	(0.082)	(0.081)	(0.044)	(0.115)	(0.038)	(0.103)	(0.053)

Notes: Table shows the z-stats estimated using Probit Regression clustered at session level to compare the average cooperation between test. The statistics considers the supergames 26-30, 21-30, 16-30, and 1-30 of the sessions. The p-values are listed in parentheses. * at 0.1, ** at 0.05, *** at 0.01, $^{+}$ at 0.001

A.2.2 Payoffs



(a) Easy Game

(b) Hard Game

Figure A.5. Subject Payoffs on the Feasible Set for Supergames 21-30 (Single Contact Different Games)

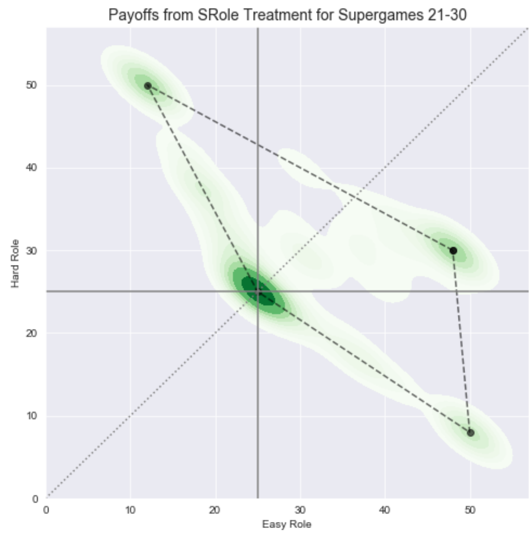
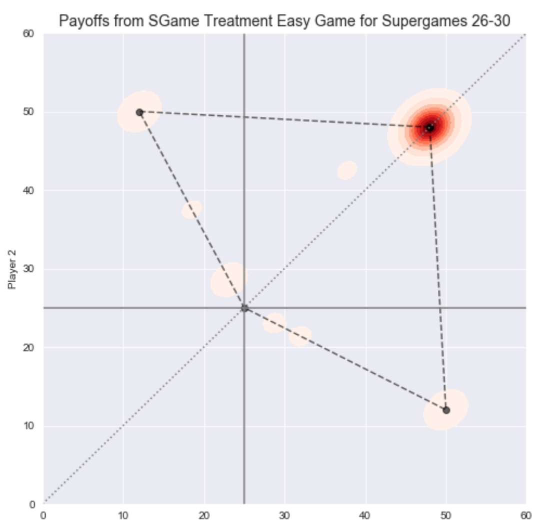
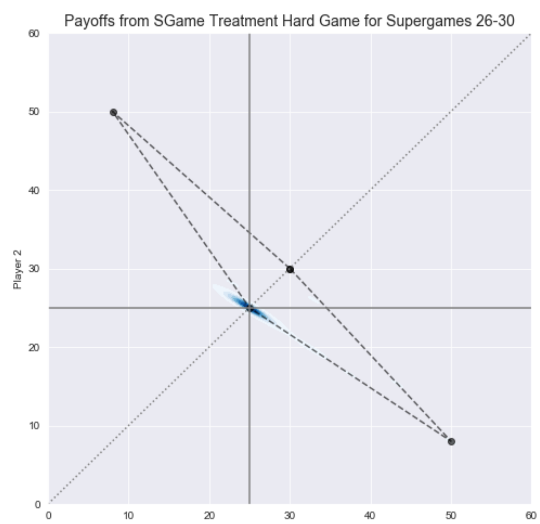


Figure A.6. Subject Payoffs on the Feasible Set for Supergames 21-30 (Single Contact Different Roles)



(a) Easy Game



(b) Hard Game

Figure A.7. Subject Payoffs on the Feasible Set for Supergames 26-30 (Single Contact Different Games)

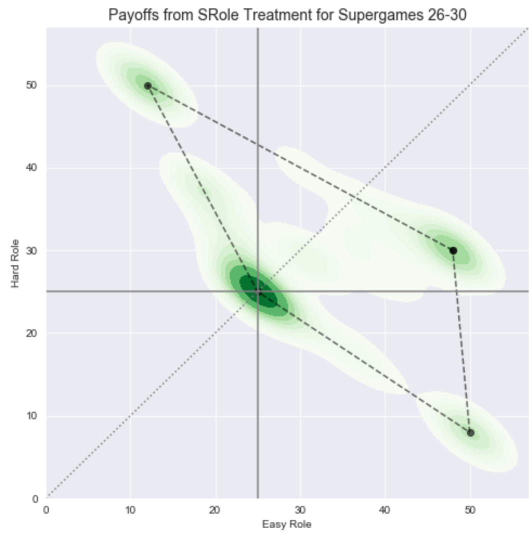


Figure A.8. Subject Payoffs on the Feasible Set for Supergames 26-30 (Single Contact Different Roles)

(a) Symmetric Games

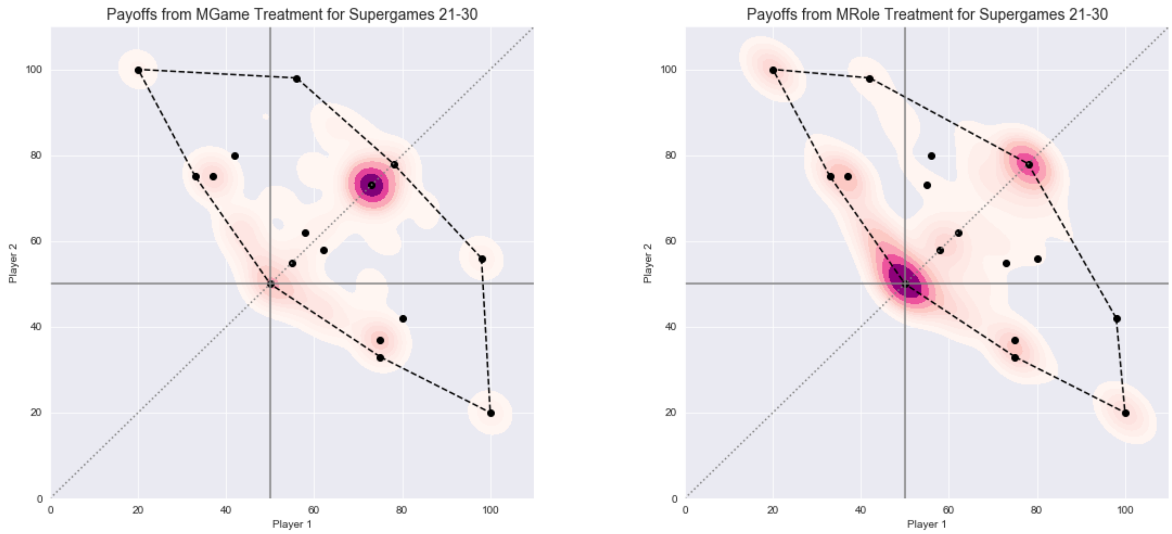
Player 1 \ Player 2	(C,C)	(C,D)	(D,C)	(D,D)
(C,C)	$78, 78$	$56, 98$	$42, 80$	$20, 100$
(C,D)	$98, 56$	$73, 73$	$62, 58$	$37, 75$
(D,C)	$80, 42$	$58, 62$	$55, 55$	$33, 75$
(D,D)	$100, 20$	$75, 37$	$75, 33$	$50, 50$

(b) Asymmetric Games

Player 1 \ Player 2	(C,C)	(C,D)	(D,C)	(D,D)
(C,C)	$78, 78$	$56, 80$	$42, 98$	$20, 100$
(C,D)	$98, 42$	$73, 55$	$62, 62$	$37, 75$
(D,C)	$80, 56$	$58, 58$	$55, 73$	$33, 75$
(D,D)	$100, 20$	$75, 33$	$75, 37$	$50, 50$

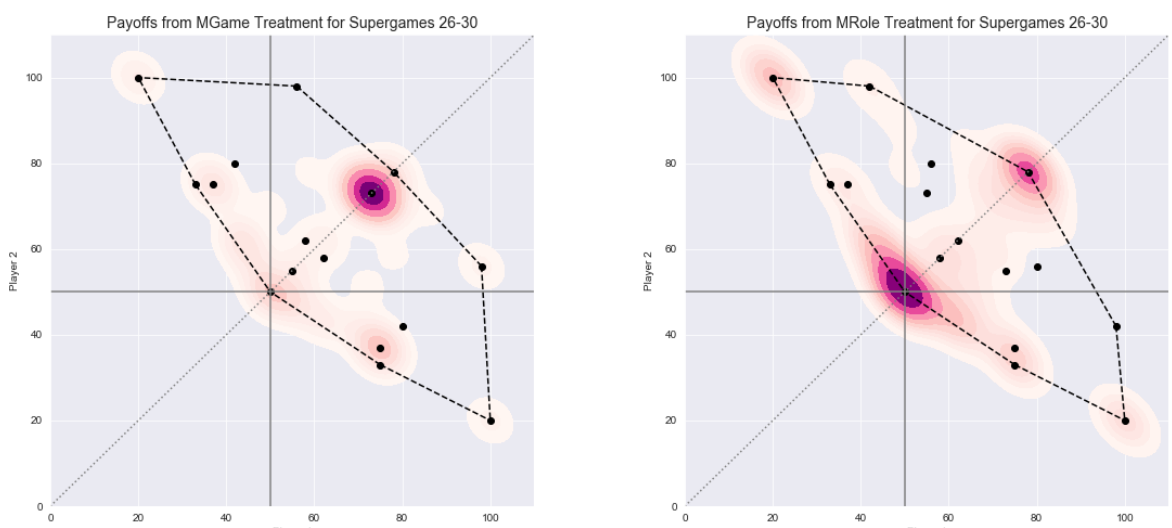
Figure A.9. Effective Payoff Matrices (Multiple Contacts)

Notes: The payoffs are calculated by combining the actions in the two games. The action xy (xy ∈ {(C,C), (C,D), (D,C), (D,D)}) in the combined games represent action $x \in$ {C,D}) in the Easy Game (Easy Role) and action $y \in$ {C,D}) in the Hard Game (Hard Role) for the M-Sym (M-Asym) treatment



(a) Symmetric Games (b) Asymmetric Games

Figure A.10. Subject Payoffs on the Feasible Set for Supergames 21-30 (Multiple Contacts)



(a) Symmetric Games (b) Asymmetric Games

Figure A.11. Subject Payoffs on the Feasible Set for Supergames 26-30 (Multiple Contacts)

A.2.3 Strategy Estimation

Table A.10. Estimated Percentage of Strategies with Confidence Intervals in Single Contact Treatments

	SGame (Easy)				SGame (Hard)				SRole (Easy)				SRole (Hard)			
	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI
AC	20.04	18.15	0	50	2.05	2.03	0	5	11.91	4.84	0	21.03	6.8	4.04	0	14.99
Grim	73.71	23.57	0	95.24	0	1.36	0	3.85	0	5.65	0	9.14	7.43	13.3	0	39.59
TFT	0	19.57	0	52.79	1.42	2.37	0	8	36.27	11.45	8.35	55.36	19.24	10.6	0	37.85
AD	6.25	4.16	0	14.4	61.95	25.3	0	100	38.41	8.72	19.32	53.36	41.97	7.15	28.2	55.41
DTFT	0	0	0	0	34.58	24.42	0	91.16	13.41	10.27	0	35.39	24.55	7.55	10.82	38.1
Cooperative	93.75	4.16	85	100	3.47	3.01	0	10.01	48.18	10.13	25.07	66.66	33.48	8.79	19.33	49.6
Defecting	6.25	4.16	0	14.4	96.53	3.01	88.23	100	51.82	10.13	28.8	72.22	66.52	8.79	47.37	78.82
β	98.89	0.97	96.25	100	97.99	0.94	95.65	99.28	95.1	1.45	92.55	97.97	93.86	1.71	91.1	97.33
$\mathcal{L}$	-65.4	39.9	-147.8	0	-93.8	30.6	-153.0	-38.8	-212.7	38.2	-255.7	-107.6	-243.8	42.1	-286.6	-120.5

Notes: Estimation included actions from Rounds 26-30 with 99% Confidence intervals and Cluster Bootstrapped Standard Errors from 100 bootstraps. The strategies included here are: AC - Always Cooperate, AD - Always Defect, TFT - Tit for Tat, DTFT - Defection Tit for Tat, Grim - Grim Trigger.

Table A.11. Estimated Percentage of 20 Strategies in Single Contact Treatments

	SGame (Easy)				SGame (Hard)				SRole (Easy)				SRole (Hard)			
	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI
AC	0	5.07	0	17.02	0	0.03	0	0	0	0.35	0	0	0	0.8	0	3.67
AD	6.25	3.86	0	14.29	65.12	12.66	43.8	95.83	37.98	7.17	23.82	51.46	43.12	7.09	30	57.89
TFT	29.91	25.3	0	82.36	0	2.5	0	8.81	15.17	8.41	0	30.34	13.85	6.38	0	27.12
DTFT	0	0.08	0	0	28.25	12.31	0	50	12.02	6.42	0	24.96	23.36	7.04	5.51	33.39
TF2T	8.86	6.74	0	24.75	0	1.21	0	4.35	10.64	7.61	0	23.77	9.05	4.95	0	16.22
TF3T	5.85	5.1	0	17.36	0	0.63	0	2.33	1.07	2.02	0	6.46	1.34	1.97	0	6.55
2TFT	0	9.27	0	26.65	3.31	2.52	0	8.37	0	7.3	0	23.71	7.16	7.13	0	22.58
2TF2T	6.38	6.65	0	24.68	0	0.29	0	0.01	4.83	5.36	0	17.85	0	1.83	0	5.94
T2	0	3.95	0	13.48	0	0.08	0	0	0	0	0	0	0	0.21	0	0
Grim	21.07	20.74	0	67.43	3.32	2.42	0	8.33	12.72	10.34	0	30.62	0	2.81	0	10.1
Grim2	10.6	7	0	25.95	0	0.26	0	0	5.19	8.02	0	26.26	0	1.81	0	6.08
Grim3	0.8	5.17	0	16.91	0	0.66	0	2.47	0	1.82	0	5.69	0	1.42	0	4.6
WSLS	0	1.01	0	0	0	0.04	0	0	0	0.14	0	0	0	0	0	0
2WSLS	10.29	8.42	0	25.82	0	0.07	0	0	0	0	0	0	0	0	0	0
CtoD	0	0.3	0	0	0	1.39	0	4.17	0.38	2.57	0	7.96	0	1.4	0	4.74
DTF2T	0	0.1	0	0	0	0.75	0	3.38	0	2.26	0	7.34	0	2.36	0	7.55
DTF3T	0	0.11	0	0	0	0.27	0	0	0	1.11	0	3.93	2.1	1.84	0	5.78
DGrim2	0	0.09	0	0	0	0.19	0	0	0	0.37	0	0	0.02	2.11	0	6.12
DGrim3	0	0.15	0	0	0	0.18	0	0	0	0.81	0	2.98	0	1.24	0	4.08
DCAlt	0	0	0	0	0	0	0	0	0	0	0	0	0	0.04	0	0
β	98.49	0.79	96.76	99.76	97.79	0.93	95.82	99.46	94.2	0.97	92.71	96.48	92.05	1.52	89.52	95.49
$\mathcal{L}$	-170.5	59.1	-268.5	-39.9	-212.9	65.6	-325.5	-68.4	-469.3	70.9	-552.7	-277.4	-567.6	101.2	-705.4	-312.8

Notes: Estimation included actions from supergames 21-30 with 95% Confidence intervals and Cluster Bootstrapped Standard Errors from 3000 bootstraps. Strategies are taken from Fudenberg, Rand, and Dreber, 2012 and their description.

- SGame Treatment - Including all 20 strategies does not increase the performance of the mixture model. In the Easy game, the percentage of behavior explained by Always D still remains 6.25%. The rest is accounted by cooperative strategies. TFT and Grim are still the most frequently used strategies. In the Hard Game, the percentage of behavior explained by Always D and DTFT remains the same as the estimation with 5 strategies.
- SRole Treatment - Including all 20 strategies improves the performance, however it is still worse than that of the S-Sym treatment. These strategies do not explain behavior in these asymmetric PD games as accurately as the symmetric PD games. Proportion of behavior estimated to be explained by Always D and DTFT remains the same. In both games subjects still use some common strategies but the Easy game uses more strict strategies like Grim and Grim 2 strategies.

Table A.12. Strategy Estimates for Multiple Games/Roles (All 28 Strategies, Last 10 Supergames)

	SGame				SRole				MGame				MRole			
	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI
S-Grim	0	0	0	0	0	0.39	0	3.03	2.14	2.38	0	9.46	1.21	7.74	0	37.57
S-TFT	0	0	0	0	0	1.32	0	6.44	0	1.91	0	9.5	25.06	10.71	0	50
S-DTFT	1.94	1.82	0	9.79	0	3.09	0	12.75	0	5.4	0	23.84	11.38	6.46	0	29.71
AC-AC	0	0.12	0	1.04	4.01	3.27	0	13	0	2.02	0	8.91	0	2.31	0	9.82
AC-Grim	0	1.11	0	7.71	0	0.22	0	1.91	0	0.16	0	0	0	0.11	0	0.81
AC-TFT	0	2.56	0	11.11	0	0.57	0	4.45	0	0.49	0	4.12	0	0.19	0	1.57
AC-AD	8.51	12.99	0	58.32	0	0.57	0	4.17	0	1.7	0	10.04	0	0.56	0	4.17
AC-DTFT	9.24	8.52	0	33.3	0	1.77	0	6.41	8.99	4.65	0	21.24	0	0.41	0	3.53
Grim-AC	0	0.12	0	1.07	0	0.21	0	1.44	0	0.3	0	2.07	0	0.28	0	2.14
Grim-Grim	3.09	2.45	0	10.26	1.59	6.17	0	25.42	0	0.41	0	2.8	0	0.1	0	0
Grim-TFT	0	1.39	0	7.68	0	3.88	0	17.19	0	1.73	0	9.3	0	0.22	0	0
Grim-AD	28.3	22.08	0	78.19	5.76	4.68	0	17.65	14.91	9.52	0	45.7	0	1.15	0	6.91
Grim-DTFT	8.08	9.42	0	38.22	0	1.99	0	9.96	12.53	12.07	0	53.33	2.02	2.43	0	10
TFT-AC	0	0.14	0	1.11	0	0.89	0	5.25	0	0.35	0	2.01	0	0.35	0	3.12
TFT-Grim	3.66	2.43	0	10.75	2.55	5.52	0	28.02	0	0.31	0	2.48	0	1.2	0	8.86
TFT-TFT	0	1.39	0	7.86	26.09	7.8	0	37.67	9.31	5.36	0	22.66	9.47	7.05	0	32.14
TFT-AD	22.92	20.19	0	75.04	2.39	3.15	0	14.29	13.99	10.27	0	40.53	2.02	2.3	0	8.33
TFT-DTFT	9.95	11	0	45.83	6.86	4.37	0	16.84	9.97	13.02	0	57.09	4.37	4.51	0	17.65
AD-AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AD-Grim	0	0	0	0	0	0.34	0	2.92	0	0	0	0	0	0.12	0	0
AD-TFT	0	0	0	0	0	0.09	0	0	0	0	0	0	0	0.08	0	0
AD-AD	2	2.01	0	11.11	34.43	8.32	14.02	57.14	18.79	7.27	0	31.51	38.94	8.65	16.67	58.97
AD-DTFT	2.31	1.85	0	10.39	0	1.38	0	9.23	0	1.6	0	9.09	0	0	0	0
DTFT-AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0.27	0	1.75
DTFT-Grim	0	0	0	0	0	0.72	0	4.64	0	0	0	0	2.09	1.54	0	7.11
DTFT-TFT	0	0	0	0	0	0.6	0	3.99	0	0	0	0	0	1.42	0	5.37
DTFT-AD	0	0.16	0	1.21	2.47	2.81	0	10.71	0	1.99	0	10.81	0	1.87	0	7.32
DTFT-DTFT	0	0.17	0	1.4	13.85	6.83	0	30.34	9.37	5.92	0	26.24	3.45	4.47	0	18.91
Strong	1.94	1.82	0	9.79	0	3.49	0	14.57	2.14	5.71	0	25.26	37.65	12.99	5.56	70.84
Equal	5.09	3.23	0	15.44	79.97	10.53	38.15	94.89	37.47	11.81	3.05	59.99	51.86	11.02	22.43	80.97
Cooperative in Easy	93.75	3.88	83.33	100	49.25	10.31	23.57	75	69.7	9.09	42.14	91.67	17.88	8.97	0	44
Cooperative in Hard	6.74	4.25	0	19.05	34.24	8.1	14.82	55.56	9.31	5.69	0	25	11.55	8.18	0	39.25
Defecting in Easy	4.31	2.98	0	12.81	50.75	10.82	20.97	75.75	28.16	9.44	0	49.9	44.48	10.54	20.05	72.14
Defecting in Hard	91.32	4.42	78.99	100	65.76	8.57	40.82	83.98	88.55	7.84	63.63	100	50.8	11.86	22.43	80.95
β	96.15	1.28	92.54	98.88	86.69	2.1	81.9	92.56	91.88	2.88	84.44	98.63	89.18	3.07	80.09	95.54
$\mathcal{L}$	-337.1	79.2	-531.6	-126.9	-786.3	116.5	-1023.2	-415.5	-586.8	153.017	-938.662	-160.136	-688.4	128.0442	-987.998	-347.897

Notes: Estimation included actions from Supergames 21-30 with 95% Confidence intervals and Cluster Bootstrapped Standard Errors from 3000 bootstraps.

Table A.13. Strategy Estimates for Multiple Games/Roles (All 40 Strategies, Last 5 Supergames)

	SGame				SRole				MGame				MRole			
	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI	Est	Std Err	Low CI	High CI
S-Grim	0	0	0	0	0	0.3	0	0	2.61	2.97	0	7.9	5.43	14.62	0	44.38
S-TFT	0	0	0	0	0	2.23	0	6.33	0	2.39	0	8	22.42	13.87	0	45.83
S-DTFT	0	2.35	0	7.1	0	2.81	0	8.96	4.03	4.2	0	12.22	11.48	7.59	0	29.74
AC-AC	0.48	0.66	0	2.09	7.93	4.17	0	14.29	0	1.28	0	4.06	2.27	3.15	0	10.73
AC-Grim	0	0.55	0	1.44	0	1.15	0	4.16	0	0.08	0	0	0	0.21	0	0
AC-TFT	0	0.77	0	2.49	0	2.82	0	9.51	0	1.63	0	5.06	0	0.15	0	0
AC-AD	0	14.14	0	35.25	0	0	0	0	0	6.47	0	18.01	2.03	2.26	0	5.72
AC-DTFT	28.35	13.81	0	37.16	1.22	2.14	0	5.06	19.34	11.14	0	42.81	0	0.42	0	0
Grim-AC	0.31	0.85	0	2.03	0	0.76	0	2.62	0	0.34	0	0.08	0	0	0	0
Grim-Grim	0	0.47	0	1.33	0	3.64	0	5.76	0	0.01	0	0	0	0	0	0
Grim-TFT	1.15	0.95	0	3.24	0	1.93	0	6.23	0	2.17	0	6.16	0	0.75	0	0
Grim-AD	57.29	20.17	0	66.94	0	2.22	0	7.25	10.39	9.98	0	29.29	1.67	2.19	0	7.1
Grim-DTFT	4.91	14.55	0	44.63	0	1.84	0	4.68	0	7.46	0	21.12	0	1.79	0	5
TFT-AC	1.25	0.82	0	2.83	0	2.07	0	5.39	0	0.46	0	0.15	0	0.21	0	0
TFT-Grim	0	0.44	0	1.22	10.3	10.03	0	29.89	0	0.41	0	0	0	1.4	0	0
TFT-TFT	0	0.94	0	2.97	16.7	9.94	0	30.82	7.82	5.17	0	14.03	5.34	7.18	0	22.18
TFT-AD	0	13.73	0	37.87	3.94	2.74	0	8.06	10.83	15.38	0	47.75	0	1.97	0	6.81
TFT-DTFT	0	9.47	0	27.84	7.83	5.13	0	18.38	20.82	13.61	0	42.78	4.71	3.79	0	10.53
AD-AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AD-Grim	0	0	0	0	0	0.73	0	2.12	0	0	0	0	0	0	0	0
AD-TFT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AD-AD	6.25	2.13	0	6.56	35.88	8.09	17.21	48.11	15.74	7.74	0	29.4	42.57	9.67	20.28	57.98
AD-DTFT	0	1.69	0	4.96	0	1.51	0	5.22	0	1.93	0	5.65	0	0	0	0
DTFT-AC	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01	0	0
DTFT-Grim	0	0	0	0	0	1.3	0	3.79	0	0	0	0	2.08	1.43	0	3.96
DTFT-TFT	0	0	0	0	0	0.38	0	0	0	0	0	0	0	1.63	0	4.65
DTFT-AD	0	0	0	0	1.44	2.91	0	8.29	0	2.3	0	7.57	0	0	0	0
DTFT-DTFT	0	0	0	0	14.76	5.84	0	24	8.41	4.62	0	15.12	0	0	0	0
Strong	0	2.35	0	7.1	0	3.38	0	9.2	6.64	6.47	0	20	39.33	16.11	6.95	63.62
Equal	6.73	2.12	0	8.02	75.27	11.89	35.65	86.67	31.97	11.24	1.99	43.26	50.18	14.32	20.28	75.03
Cooperative in R	93.75	4.2	83.22	100	47.92	10.16	26.02	67.98	69.21	9.79	46.92	85.19	16.02	9.5	4	36.71
Cooperative in B	3.2	2.91	0	9.38	34.93	8.65	14.8	50.05	7.82	5.23	0	16	9.69	8.76	0	28.01
Defecting in R	6.25	2.87	0	9.21	52.08	10.63	25	70	24.15	8.41	4.95	37.94	44.65	10.34	20.28	62.04
Defecting in B	96.8	3.09	86.21	99.25	65.07	9.21	41.67	78.94	85.54	9.17	68.35	100	50.98	9.98	32.62	64.87
β	97.08	1.03	94.71	98.72	90.4	2.19	86.64	95.12	93.94	2.19	89.64	98.11	90.51	3.04	83.02	96.24
$\mathcal{L}$	-136.2	29.0	-189.3	-65.9	-330.4	45.0	-370.6	-193.9	-253.5	54.3	-305.1	-94.1	-318.8	59.5	-397.5	-169.8

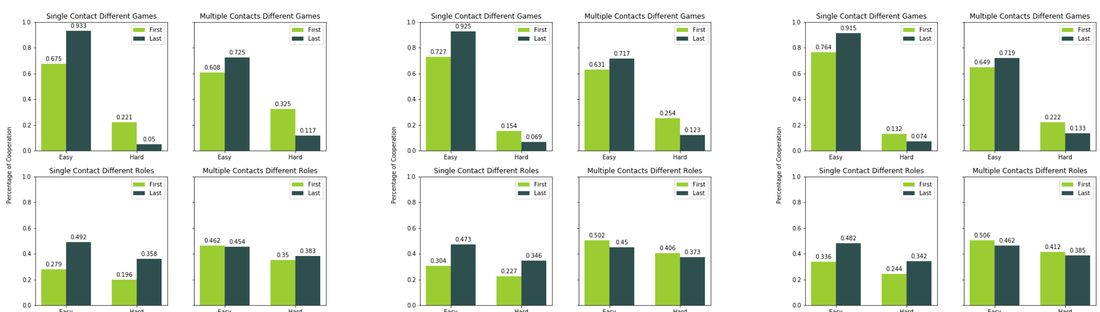
Notes: Estimation included actions from Supergames 26-30 with 95% Confidence intervals and Cluster Bootstrapped Standard Errors from 100 bootstraps.

A.2.4 Learning

Table A.14. Comparison Across First and Last Supergames (Nonparametric Randomization Test)

	First and Last 5 Supergames				First and Last 10 Supergames				First and Last 15 Supergames			
	First Period		All Periods		First Period		All Periods		First Period		All Periods	
	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard
SGame	2.1***	-1.6***	2.96***	-0.96**	1.7***	0.96**	2.44***	-0.64*	1.36**	-0.71*	1.69***	0.39+
	(0.0)	(0.0)	(0.0)	(0.003)	(0.0)	(0.009)	(0.0)	(0.01)	(0.003)	(0.037)	(0.0)	(0.09)
MGame	0.91+	-1.72***	1.22*	-1.29***	0.69	-1.24**	0.63	-0.99**	0.58	-0.87*	0.26	0.65+
	(0.075)	(0.0)	(0.022)	(0.0)	(0.129)	(0.006)	(0.133)	(0.009)	(0.172)	(0.038)	(0.318)	(0.062)
SRole	1.98**	1.56**	2.14***	1.98	1.57**	1.16*	1.18*	1.12*	1.32*	0.92+	1.06*	1.0*
	(0.001)	(0.009)	(0.0)	(0.0)	(0.007)	(0.029)	(0.016)	(0.023)	(0.019)	(0.073)	(0.022)	(0.03)
MRole	-0.07	0.27	0.75+	0.78+	0.42	0.26	-0.12	-0.02	0.34	0.22	0.05	0.02
	(0.453)	0.338	(0.098)	(0.093)	(0.258)	(0.344)	(0.426)	(0.492)	(0.309)	(0.366)	(0.458)	(0.485)

Notes: Table shows the z-stats estimated using Nonparametric Randomization Test to compare the average cooperation between Last few supergames and First few supergames (Last - First) in the Easy Game/Role (Easy) and Hard Game/Role (Hard). The statistics considers the supergames 1-5 and 26-30, supergames 1-10 and 21-30, supergames 1-15 and 16-30 of the sessions. For each of these cases we consider the First Period (First) and All Periods (All). The p-values are listed in parentheses.
Significance: $^{+}$ at 0.1, * at 0.05, ** at 0.01, *** at 0.001



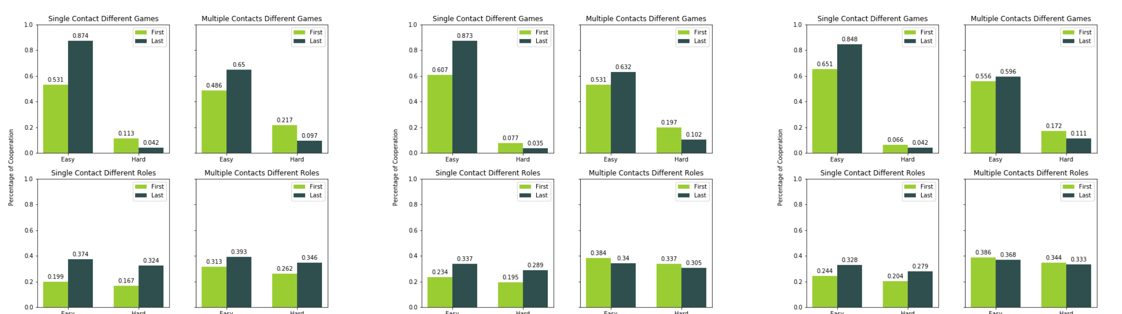
(a) First and Last 5 Supergames (b) First and Last 10 Supergames (c) First and Last 15 Supergames

Figure A.12. Difference between Average Cooperation in First and Last Supergames (First Period)

Table A.15. Comparison Across First and Last Supergames (Probit Regression)

	First and Last 5 Supergames				First and Last 10 Supergames				First and Last 15 Supergames			
	First Period		All Periods		First Period		All Periods		First Period		All Periods	
	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard
SGame	2.59*	-5.38***	2.80**	-3.44**	2.05*	-2.03*	2.69**	-1.98*	2.33*	-1.48	3.06**	-1.17
	(0.010)	(0.0)	(0.005)	(0.001)	(0.041)	(0.043)	(0.007)	(0.047)	(0.020)	(0.139)	(0.002)	(0.243)
MGame	3.03**	-1.68+	5.39***	-1.97*	1.47	-1.42	2.52*	-2.27*	1,15	-1.15	1.02	-2.25*
	(0.002)	(0.092)	(0.0)	(0.049)	(0.142)	(0.157)	(0.012)	(0.023)	(0.248)	(0.252)	(0.310)	(0.025)
SRole	3.65***	1.69+	6.07***	6.38***	5.84***	2.54*	5.88***	3.22**	14.09***	3.25**	3.45**	6.19***
	(0.0)	(0.091)	(0.0)	(0.0)	(0.0)	(0.011)	(0.0)	(0.001)	(0.0)	(0.001)	(0.001)	(0.0)
MRole	-0.12	0.63	2.03*	2.58*	-0.94	-0.54	-1.29	-0.93	-0.98	-0.58	-0.63	-0.42
	(0.907)	(0.528)	(0.042)	(0.01)	(0.349)	(0.587)	(0.199)	(0.351)	(0.327)	(0.563)	(0.531)	(0.678)

Notes: Table shows the z-stats estimated using Probit Regression clustered at session level to compare the average cooperation between Last few supergames and First few supergames (Last - First) in the Easy Game/Role (Easy) and Hard Game/Role (Hard). The statistics considers the supergames 1-5 and 26-30, supergames 1-10 and 21-30, supergames 1-15 and 16-30 of the sessions. For each of these cases we consider the First Period (First) and All Periods (All). The p-values are listed in parentheses.
Significance: $^{+}$ at 0.1, ** at 0.05, *** at 0.01, *** at 0.001

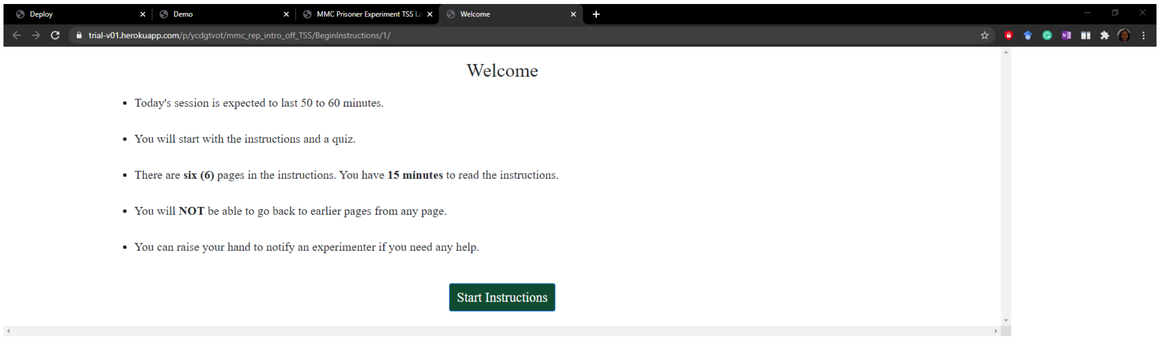


(a) First and Last 5 Supergames (b) First and Last 10 Supergames (c) First and Last 15 Supergames

Figure A.13. Difference between Average Cooperation in First and Last Supergames (All Periods)

A.3 Experiment Details

A.3.1 Instructions



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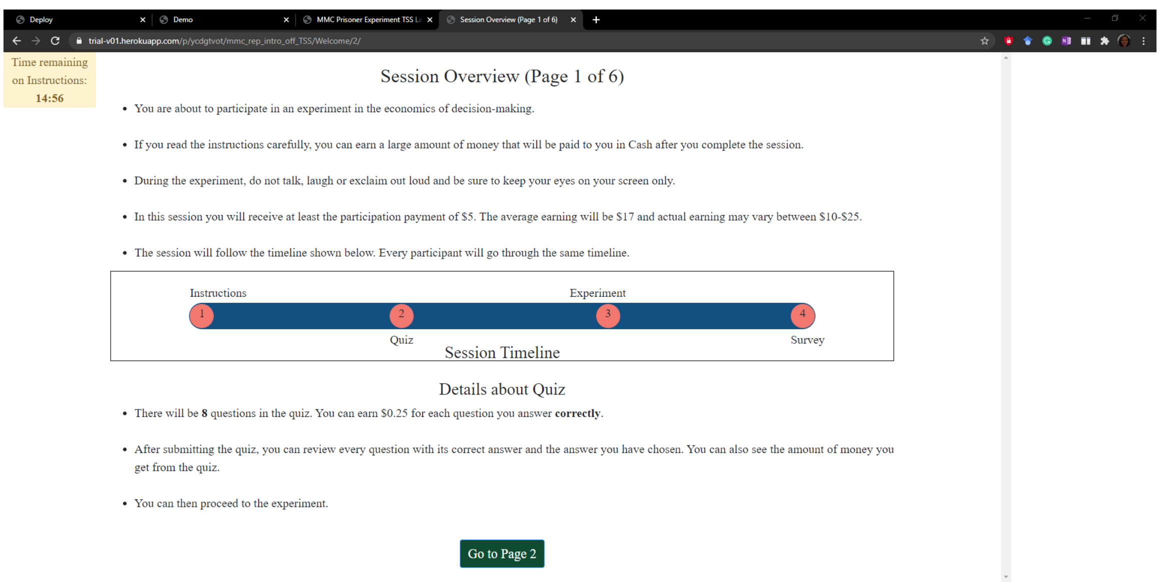
Welcome

- Today's session is expected to last 50 to 60 minutes.
- You will start with the instructions and a quiz.
- There are **six (6)** pages in the instructions. You have **15 minutes** to read the instructions.
- You will **NOT** be able to go back to earlier pages from any page.
- You can raise your hand to notify an experimenter if you need any help.

Start Instructions



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Time remaining on Instructions: **14:56**

Session Overview (Page 1 of 6)

- You are about to participate in an experiment in the economics of decision-making.
- If you read the instructions carefully, you can earn a large amount of money that will be paid to you in Cash after you complete the session.
- During the experiment, do not talk, laugh or exclaim out loud and be sure to keep your eyes on your screen only.
- In this session you will receive at least the participation payment of \$5. The average earning will be \$17 and actual earning may vary between \$10-\$25.
- The session will follow the timeline shown below. Every participant will go through the same timeline.

Details about Quiz

- There will be **8** questions in the quiz. You can earn \$0.25 for each question you answer **correctly**.
- After submitting the quiz, you can review every question with its correct answer and the answer you have chosen. You can also see the amount of money you get from the quiz.
- You can then proceed to the experiment.

Go to Page 2

Time remaining on Instructions: **14:32**

How Rounds Work (Page 2 of 6)

- There will be **30 Rounds** in the experiment.
- Each round will last for a random number of **Periods**. The number of periods in each round will be determined randomly using the following procedure:
  - At the end of each period the computer will generate a random number between 1 and 8 ({1, 2,..., 8}) with each number being equally likely.
  - If the computer generates a number less than 7, then the **Round continues** for at least one more period (**75% Probability**).
  - If the computer generates a number equal to 7 or greater, then the **Round ends** (**25% Probability**).
- At the **start of each round**, you will be paired with **two other randomly chosen participants**. We will refer to the participants you will be paired with as **Other Red** and **Other Blue**.
- In each period of a round you will participate in **two games simultaneously** (Red Game and Blue Game). You will participate in Red Game with **Other Red** and Blue Game with **Other Blue** respectively.

Go to Page 3

Time remaining on Instructions: **14:08**

Games, Actions and Points (Page 3 of 6)

- For each **Game**, you can choose between two **Actions**: Action A and Action B in Red Game ; Action W and Action Y in Blue Game .
- In the experiment, you will work with **Points**. At the end of the experiment, points will be converted to Dollars. Today's exchange rate is **680 Points = $1**.
- For each **Game**, your points will be decided by your action and the action of the other participant (Other Red for Red Game and Other Blue for Blue Game).
- You, Other Red, and Other Blue need to choose and confirm your actions in each period in a timely manner. If you do not confirm your actions in a timely manner, you will be given a warning. After the warning you will have another 30 seconds. If you do not choose and confirm your actions in the 30 seconds after the warning, an action will be chosen randomly for each game for that period.
- The tables below show the points corresponding to your actions and the other participants' actions in each game and they will remain unchanged across all the matches in the experiment.

Points Tables

Red Game				
My Action	A	B	A	B
Other Red's Action	A	A	B	B
My Points	48	50	12	25
Other Red's Points	48	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other Blue's Action	W	W	Y	Y
My Points	30	50	8	25
Other Blue's Points	30	8	50	25

Cosider the Points Tables above:

- If you choose Action W and Other Blue chooses Action W in Blue Game , then you will receive 30 points and, Other Blue will receive 30 points.
- If you choose Action A and Other Red chooses Action B in Red Game , then you will receive 12 points and, Other Red will receive 50 points.
- If you choose Action Y and Other Blue chooses Action W in Blue Game , then you will receive 50 points and, Other Blue will receive 8 points.
- If you choose Action B and Other Red chooses Action B in Red Game , then you will receive 25 points and, Other Red will receive 25 points.

Go to Page 4

Deploy | Demo | MMC Prisoner Experiment TSS L... | How History is Recorded and Di...

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Time remaining on Instructions: **13:44**

How History is Recorded and Displayed (Page 4 of 6)

The history of all variables in a Round will be recorded in two history tables, like in the figure below. In the following table, you can see an example history of a Round in which the computer picked actions at random.

History Tables

Period	1	2	3	4	5	6
My Action	A	A	A	B	B	?
Other Red's Action	A	B	B	B	B	?
My Points	48	12	12	25	25	?
Other Red's Points	48	50	50	25	25	?
Number	2	3	2	2	1	

Period	1	2	3	4	5	6
My Action	Y	W	Y	Y	Y	?
Other Blue's Action	W	Y	Y	Y	W	?
My Points	50	8	25	25	50	?
Other Blue's Points	8	50	25	25	8	?
Number	2	3	2	2	1	

The recorded variables include:

- Period -- Period number (6 is the current Period number in this example)
- My Action -- Your action in every period of the current round for that game. In this example, in period 2, your action is A in Red Game .
- Other Red's Action -- Action of Other Red in every period of the current round. In this example, in period 3, Other Red's action is B.
- Other Blue's Action -- Action of Other Blue in every period of the current round. In this example, in period 4, Other Blue's action is Y.
- My Points -- Your points in each period of the current round for that game.
- Other Red's Points -- Points received by Other Red in each period of the current round in Red Game .
- Other Blue's Points -- Points received by Other Blue in each period of the current round in Blue Game .
- Number -- Random number generated by the computer at the end of the period to decide if the round continues for another period. A random number is drawn from {1,2,..., 8} with each number being equally likely.

There are ?s for "My Action", "Other Red's Action", "Other Blue's Action", "My Points", "Other Red's Points", and "Other Blue's Points" in Period 6 because that period is in progress in this example.

Go to Page 5

Deploy | Demo | MMC Prisoner Experiment TSS L... | Taking Actions (Page 5 of 6)

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Time remaining on Instructions: **13:24**

Taking Actions (Page 5 of 6)

- On the page where you take actions, there will be buttons for the actions for each game as you can see in the figure below.
- When you choose an action, it will appear in a statement below the buttons.
- When you have chosen an action in each game, a button "Confirm Actions" will appear. You can change your actions as many times as you want before pressing "Confirm Actions" button.
- Pressing the "Confirm Actions" button will confirm your actions for that period.

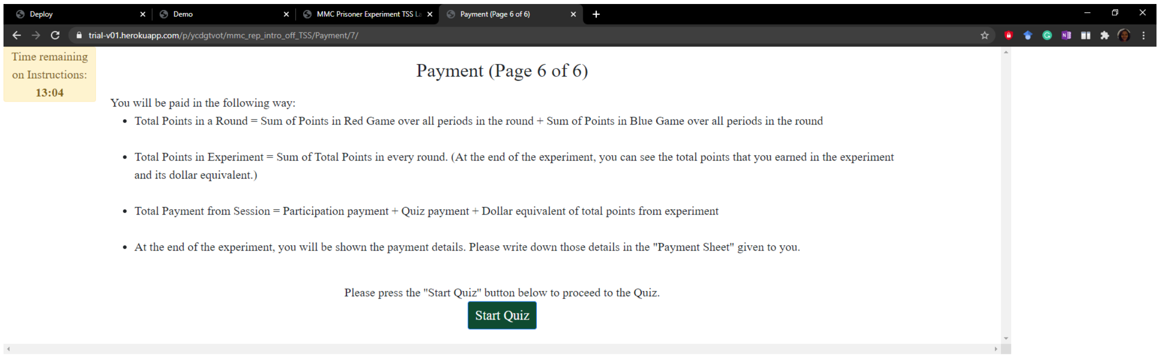
Action Buttons

Please Choose Your Action in Red Game	Please Choose Your Action in Blue Game
A	W
B	Y
You have chosen Action B in Red Game.	You have chosen Action W in Blue Game.

Confirm Actions

You can see the Points tables and the History tables when you take actions in each period of each round.

Go to Page 6



Time remaining on Instructions: **13:04**

Payment (Page 6 of 6)

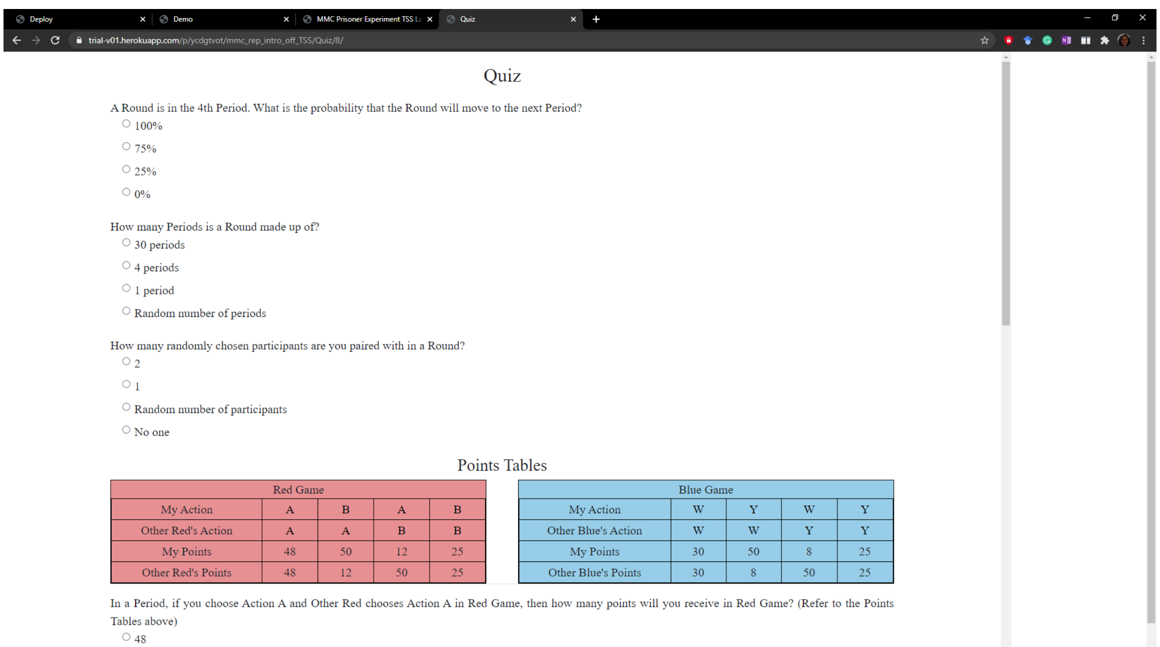
You will be paid in the following way:

- Total Points in a Round = Sum of Points in Red Game over all periods in the round + Sum of Points in Blue Game over all periods in the round
- Total Points in Experiment = Sum of Total Points in every round. (At the end of the experiment, you can see the total points that you earned in the experiment and its dollar equivalent.)
- Total Payment from Session = Participation payment + Quiz payment + Dollar equivalent of total points from experiment
- At the end of the experiment, you will be shown the payment details. Please write down those details in the "Payment Sheet" given to you.

Please press the "Start Quiz" button below to proceed to the Quiz.

Start Quiz

A.3.2 Quiz



Quiz

A Round is in the 4th Period. What is the probability that the Round will move to the next Period?

- 100%
- 75%
- 25%
- 0%

How many Periods is a Round made up of?

- 30 periods
- 4 periods
- 1 period
- Random number of periods

How many randomly chosen participants are you paired with in a Round?

- 2
- 1
- Random number of participants
- No one

Points Tables

Red Game				
My Action	A	B	A	B
Other Red's Action	A	A	B	B
My Points	48	50	12	25
Other Red's Points	48	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other Blue's Action	W	W	Y	Y
My Points	30	50	8	25
Other Blue's Points	30	8	50	25

In a Period, if you choose Action A and Other Red chooses Action A in Red Game, then how many points will you receive in Red Game? (Refer to the Points Tables above)

- 48

Deploy | Demo | MMC Prisoner Experiment TSS L... | Quiz

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○ 12
○ 50
○ 25

In a Period, if you choose Action W and Other Blue chooses Action Y in Blue Game, then how many points will you receive in Blue Game? (Refer to the Points Tables above)

○ 30
○ 8
○ 50
○ 25

History Tables

Period	1	2	3	4	5	6
My Action	A	A	A	B	B	?
Other Red's Action	A	B	B	B	B	?
My Points	48	12	12	25	25	?
Other Red's Points	48	50	50	25	25	?
Number	2	3	2	2	1	

Period	1	2	3	4	5	6
My Action	Y	W	Y	Y	Y	?
Other Blue's Action	W	Y	Y	Y	W	?
My Points	50	8	25	25	50	?
Other Blue's Points	8	50	25	25	8	?
Number	2	3	2	2	1	

In Period 2, how many points did Other Red receive in Red Game? (Refer to the History Tables above)

○ 48
○ 12
○ 50
○ 25

In Period 4, which Action was chosen by Other Blue in Blue Game? (Refer to the History Tables above)

○ Y
○ W
○ A

Deploy | Demo | MMC Prisoner Experiment TSS L... | Quiz

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History Tables

Period	1	2	3	4	5	6
My Action	A	A	A	B	B	?
Other Red's Action	A	B	B	B	B	?
My Points	48	12	12	25	25	?
Other Red's Points	48	50	50	25	25	?
Number	2	3	2	2	1	

Period	1	2	3	4	5	6
My Action	Y	W	Y	Y	Y	?
Other Blue's Action	W	Y	Y	Y	W	?
My Points	50	8	25	25	50	?
Other Blue's Points	8	50	25	25	8	?
Number	2	3	2	2	1	

In Period 2, how many points did Other Red receive in Red Game? (Refer to the History Tables above)

○ 48
○ 12
○ 50
○ 25

In Period 4, which Action was chosen by Other Blue in Blue Game? (Refer to the History Tables above)

○ Y
○ W
○ A
○ B

In Period 3, which Action was chosen by Other Red in Red Game? (Refer to the History Tables above)

○ Y
○ W
○ A
○ B

Submit Answer

Quiz Result

You have correctly answered 1 out of 8 questions.
You will get $0.25 from the quiz.

Questions with Correct and Chosen Answers

A Round is in the 4th Period. What is the probability that the Round will move to the next Period?
Chosen Answer: 100%
Correct Answer: 75%

How many Periods is a Round made up of?
Chosen Answer: 1 period
Correct Answer: Random number of periods

How many randomly chosen participants are you paired with in a Round?
Chosen Answer: 1
Correct Answer: 2

Points Tables

Red Game				
My Action	A	B	A	B
Other Red's Action	A	A	B	B
My Points	48	50	12	25
Other Red's Points	48	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other Blue's Action	W	W	Y	Y
My Points	30	50	8	25
Other Blue's Points	30	8	50	25

In a Period, if you choose Action A and Other Red chooses Action A in Red Game, then how many points will you receive in Red Game? (Refer to the Points Tables above)
Chosen Answer: 12
Correct Answer: 48

Correct Answer: 48

In a Period, if you choose Action W and Other Blue chooses Action Y in Blue Game, then how many points will you receive in Blue Game? (Refer to the Points Tables above)
Chosen Answer: 25
Correct Answer: 8

History Tables

Period	1	2	3	4	5	6
My Action	A	A	A	B	B	?
Other Red's Action	A	B	B	B	B	?
My Points	48	12	12	25	25	?
Other Red's Points	48	50	50	25	25	?
Number	2	3	2	2	1	

Period	1	2	3	4	5	6
My Action	Y	W	Y	Y	Y	?
Other Blue's Action	W	Y	Y	Y	W	?
My Points	50	8	25	25	50	?
Other Blue's Points	8	50	25	25	8	?
Number	2	3	2	2	1	

In Period 2, how many points did Other Red receive in Red Game? (Refer to the History Tables above)
Chosen Answer: 50
Correct Answer: 50

In Period 4, which Action was chosen by Other Blue in Blue Game? (Refer to the History Tables above)
Chosen Answer: B
Correct Answer: Y

In Period 3, which Action was chosen by Other Red in Red Game? (Refer to the History Tables above)
Chosen Answer: Y
Correct Answer: B

Please press the "Start Experiment" button below to proceed to the Experiment.

Start Experiment

Table A.16. Percentage of Questions Subjects got Correct

Treatments	Number of Correct Answers			
	5	6	7	8
SGame	2.08	6.25	18.75	72.92
SRole	2.08	6.25	18.75	72.92
MGame	2.08	6.25	12.5	79.17
MRole		14.58	22.92	62.5

Table A.17. Frequency of Correctness of Each Question

Treatments	Question Number							
	1	2	3	4	5	6	7	8
SGame	0.917	0.813	0.938	1	1	0.958	1	1
SRole	0.875	0.875	0.875	1	1	1	1	1
MGame	0.875	0.854	0.958	1	1	1	1	1
MRole	0.854	0.729	0.917	1	0.979	1	1	1

B. TEAM INNOVATION CONTESTS WITH COGNITIVE DIVERSITY

B.1 Contest Model

Proof. Proposition 2.3.1: The distribution under efficiency level α is given by

$$H(x) = \alpha G(\mathbf{x}) + (1-\alpha)(1-\overline{G}(\mathbf{x}))$$

and that under the efficiency level α' is given by

$$H'(x) = \alpha' G(\mathbf{x}) + (1-\alpha')(1-\overline{G}(\mathbf{x}))$$

with $\alpha' > \alpha$.

A distribution H' is said to first order stochastically dominate another distribution H if $H'(x) \leq H(x)$, for all $x \in \mathbb{R}$. We now show that $H'(x) \succ^{FOSD} H(x)$ by showing that $H'(x) - H(x) \leq 0$ for all $x \in \mathbb{R}$.

$$\begin{aligned} H'(x) - H(x) &= \Big(\alpha' G(\mathbf{x}) + (1-\alpha')(1-\overline{G}(\mathbf{x}))\Big) - \Big(\alpha G(\mathbf{x}) + (1-\alpha)(1-\overline{G}(\mathbf{x}))\Big) \\ &= (\alpha'-\alpha)G(\mathbf{x}) - (\alpha'-\alpha)(1-\overline{G}(\mathbf{x})) \\ &= (\alpha'-\alpha)\Big(G(\mathbf{x}) + \overline{G}(\mathbf{x}) - 1\Big) < 0. \end{aligned}$$

□

Proof. Proposition 2.3.2: Recall that when a joint distribution G is more cognitively diverse that G', then according to definition 2.3.2,

$$\begin{aligned} & C\left(G^1\left(x^1\right), \ldots, G^M\left(x^M\right)\right) \leq C'\left(G^1\left(x^1\right), \ldots, G^M\left(x^M\right)\right) \quad \forall\left(x^1, \ldots, x^M\right) \in \mathbb{I}^M \\ & \quad \Rightarrow G\left(x^1, \ldots, x^M\right) \leq G'\left(x^1, \ldots, x^M\right) \end{aligned}$$

and

$$\bar{C}\left(G^1\left(x^1\right),\ldots,G^M\left(x^M\right)\right) \leq \bar{C}'\left(G^1(x^1),\ldots,G^M(x^M)\right) \quad \forall\left(x^1,\ldots,x^M\right) \in \mathbb{I}^M$$
$$\Rightarrow \overline{G}\left(x^1,\ldots,x^M\right) \leq \overline{G'}\left(x^1,\ldots,x^M\right).$$

The distributions of the team tool effectiveness levels are given by

$$H(x) = \alpha G(\mathbf{x}) + (1-\alpha)(1-\overline{G}(\mathbf{x})) \quad \text{where } \mathbf{x} = (x,\ldots,x)$$

and

$$H'(x) = \alpha G'(\mathbf{x}) + (1-\alpha)(1-\overline{G'}(\mathbf{x})) \quad \text{where } \mathbf{x} = (x,\ldots,x).$$

To find the threshold efficiency level $\hat{\alpha}$ we compare H and H' for all $x \in [0,1]$.

$$\begin{aligned}
H(x) - H'(x) &= \left(\alpha G(\mathbf{x}) + (1-\alpha)\left(1-\overline{G}(\mathbf{x})\right)\right) - \left(\alpha G'(\mathbf{x}) + (1-\alpha)\left(1-\overline{G'}(\mathbf{x})\right)\right) \\
&= \alpha\left(G(\mathbf{x}) - G'(\mathbf{x})\right) + (1-\alpha)\left(\overline{G'}(\mathbf{x}) - \overline{G}(\mathbf{x})\right) \\
&= \alpha\left(\left(G(\mathbf{x}) + \overline{G}(\mathbf{x})\right) - \left(G'(\mathbf{x}) + \overline{G'}(\mathbf{x})\right)\right) - \left(\overline{G}(\mathbf{x}) - \overline{G'}(\mathbf{x})\right).
\end{aligned}$$

The threshold $\alpha^*(\mathbf{x})$ is given by

$$\alpha\left(\left(G(\mathbf{x}) + \overline{G}(\mathbf{x})\right) - \left(G'(\mathbf{x}) + \overline{G'}(\mathbf{x})\right)\right) - \left(\overline{G}(\mathbf{x}) - \overline{G'}(\mathbf{x})\right) \leq 0$$
$$\Rightarrow \alpha \geq \frac{\overline{G}(\mathbf{x}) - \overline{G'}(\mathbf{x})}{\left(G(\mathbf{x}) + \overline{G}(\mathbf{x})\right) - \left(G'(\mathbf{x}) + \overline{G'}(\mathbf{x})\right)} = \alpha^*(\mathbf{x})$$

since $G(\mathbf{x}) < G'(\mathbf{x})$ and $\overline{G}(\mathbf{x}) < \overline{G'}(\mathbf{x})$.

Therefore, H first order stochastically dominates (dominated by) H' if $\alpha \geq \max_{x\in(0,1)} \alpha^*(\mathbf{x}) = \alpha_1(\alpha \leq \min_{x\in(0,1)} \alpha^*(\mathbf{x}) = \alpha_2)$. □

B.2 Limit Contest

Proof. Claim 2.4.1: Let us first represent the sequence $\left\{ \frac{\sum_{n'=1}^{N} G_{n'}(\cdot)}{N} \right\}_{N=1}^{\infty}$ as $\{W_n\}_{N=1}^{\infty}$ and the sequence $\left\{ \frac{\sum_{n'=1}^{N} \overline{G}_{n'}(\cdot)}{N} \right\}_{N=1}^{\infty}$ as $\left\{\overline{W}_n\right\}_{N=1}^{\infty}$. Then the individual functions $G_n(\cdot)$ and $\overline{G}_n(\cdot)$ can be written in terms of $W_n(\cdot)$ and $\overline{W}_n(\cdot)$ respectively.

$$
\begin{aligned}
G_1(\cdot) &= W_1(\cdot) & \overline{G}_1(\cdot) &= \overline{W}_1(\cdot) \\
G_2(\cdot) &= 2W_2(\cdot) - W_1(\cdot) & \overline{G}_2(\cdot) &= 2\overline{W}_2(\cdot) - \overline{W}_1(\cdot) \\
G_n(\cdot) &= nW_n(\cdot) - (n-1)W_{n-1}(\cdot) & \overline{G}_n(\cdot) &= n\overline{W}_n(\cdot) - (n-1)\overline{W}_{n-1}(\cdot)
\end{aligned}
$$

Therefore the weighted sums can be written as following,

$$
\begin{aligned}
\sum_{n=1}^{N} \alpha_n G_n(\cdot) =& \alpha_1 W_1(\cdot) + \alpha_2 \left(2W_2(\cdot) - W_1(\cdot)\right) + \ldots + \alpha_{N-1} \left((N-1)W_{N-1}(\cdot)\right. \\
& \qquad \left. + (N-2)W_{N-2}(\cdot)\right) + \alpha_N \left(NW_N(\cdot) - (N-1)W_{N-1}(\cdot)\right) \\
=& \left(\alpha_1 - \alpha_2\right) W_1 + 2\left(\alpha_2 - \alpha_3\right) W_2 + \ldots + (N-1)(\alpha_{N-1} - \alpha_N) W_{N-1} + N\alpha_N W_N \\
=& \sum_{n=1}^{N} \omega_n W_n
\end{aligned}
$$

with, $\omega_n = n(\alpha_n - \alpha_{n+1})$ for $n = 1, .., N-1$ if $N > 1$, $\omega_N = N\alpha_N$ for $N \geq 1$, and

$$
\sum_{n=1}^{N} \omega_n = (\alpha_1 - \alpha_2) + 2\left(\alpha_2 - \alpha_3\right) + \ldots + (N-1)(\alpha_{N-1} - \alpha_N) + N\alpha_N = \sum_{n=1}^{N} \alpha_n .
$$

Similarly,

$$
\begin{aligned}
\sum_{n=1}^{N} (1 - \alpha_n) \left(1 - \overline{G}_n(\cdot)\right) &= \sum_{n=1}^{N} (1 - \alpha_n) - \sum_{n=1}^{N} (1 - \alpha_n) \overline{G}_n(\cdot) = \sum_{n=1}^{N} \eta_n - \sum_{n=1}^{N} \eta_n \overline{G}_n(\cdot) \\
&= \sum_{n=1}^{N} \overline{\omega}_n - \sum_{n=1}^{N} \overline{\omega}_n \overline{W}_n(\cdot) = \sum_{n=1}^{N} \overline{\omega}_n \left(1 - \overline{W}_n(\cdot)\right)
\end{aligned}
$$

with, $\overline{\omega}_n = n(\eta_n - \eta_{n+1})$ for $n = 1, .., N-1$ if $N > 1$, $\overline{\omega}_N = N\eta_N$ for $N \geq 1$, and

$$\sum_{n=1}^{N} \overline{\omega}_n = (\eta_1 - \eta_2) + 2\,(\eta_2 - \eta_3) + \ldots + (N-1)(\eta_{N-1} - \eta_N) + N\eta_N = \sum_{n=1}^{N} \eta_n = \sum_{n=1}^{N} (1 - \alpha_n).$$

Now we find the limit of $\dfrac{\sum\limits_{n'=1}^{N} H_{n'}(\cdot)}{N}$ as $N \to \infty$.

$$\begin{aligned}
\lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} H_{n'}(\cdot)}{N} = \hat{H}(\cdot) &= \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \alpha_{n'} G_{n'}(\cdot) + (1-\alpha_{n'}) \left(1 - \overline{G}_{n'}(\cdot)\right)}{N} \\
&= \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \alpha_{n'}}{N} \frac{\sum\limits_{n'=1}^{N} \alpha_{n'} G_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \alpha_{n'}} + \frac{\sum\limits_{n'=1}^{N} (1-\alpha_{n'})}{N} \frac{\sum\limits_{n'=1}^{N} (1-\alpha_{n'}) \left(1 - \overline{G}_{n'}(\cdot)\right)}{\sum\limits_{n'=1}^{N} (1-\alpha_{n'})} \\
&= \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \alpha_{n'}}{N} \frac{\sum\limits_{n'=1}^{N} \omega_{n'} W_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \omega_{n'}} + \frac{\sum\limits_{n'=1}^{N} (1-\alpha_{n'})}{N} \frac{\sum\limits_{n'=1}^{N} \overline{\omega}_n \left(1 - \overline{W}_{n'}(\cdot)\right)}{\sum\limits_{n'=1}^{N} \overline{\omega}_n} \\
&= \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \alpha_{n'}}{N} \frac{\sum\limits_{n'=1}^{N} \omega_{n'} W_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \omega_{n'}} + \frac{\sum\limits_{n'=1}^{N} (1-\alpha_{n'})}{N} \left(1 - \frac{\sum\limits_{n'=1}^{N} \overline{\omega}_n \overline{W}_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \overline{\omega}_n}\right) \\
&= \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \alpha_{n'}}{N} \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \omega_{n'} W_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \omega_{n'}} \\
&\quad + \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} (1-\alpha_{n'})}{N} \left(1 - \lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \overline{\omega}_n \overline{W}_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \overline{\omega}_n}\right) \\
&= \hat{\alpha}\hat{G}(\cdot) + (1-\hat{\alpha}) \left(1 - \hat{\overline{G}}(\cdot)\right)
\end{aligned}$$

The equality between the last and the second last expressions is derived by using the Stolz - Cesàro theorem, since $\lim\limits_{N\to\infty} W_N(\cdot) = \hat{G}(\cdot)$, $\lim\limits_{N\to\infty} \overline{W}_N(\cdot) = \hat{\overline{G}}(\cdot)$, $\left\{\sum\limits_{n'=1}^{N} \omega_{n'}\right\}_{N=1}^{\infty}$ and

$\left\{\sum\limits_{n'=1}^{N} \overline{\omega}_{n'}\right\}_{N=1}^{\infty}$ are strictly monotonically increasing and $\lim\limits_{N\to\infty} \sum\limits_{n'=1}^{N} \omega_{n'} = \infty$, $\lim\limits_{N\to\infty} \sum\limits_{n'=1}^{N} \overline{\omega}_{n'} = \infty$. The Stolz - Cesàro theorem gives us the following.

$$\lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \omega_{n'} W_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \omega_{n'}} = \hat{G}(\cdot)$$

and

$$\lim_{N\to\infty} \frac{\sum\limits_{n'=1}^{N} \overline{\omega}_{n'} \overline{W}_{n'}(\cdot)}{\sum\limits_{n'=1}^{N} \overline{\omega}_{n'}} = \hat{\overline{G}}(\cdot).$$

□

B.3 Effect of Diversity and Efficiency

Proof. Theory 2.5.1: Given the ranking distribution of team tool qualities $\hat{H}(\cdot)$, the expected bid of a team member is

$$E[\beta] = \frac{1}{M^2} \int_0^1 \left(\int_0^x \frac{z\hat{h}(z)}{\hat{\Phi}'\left(\hat{\Phi}^{-1}\left(\hat{H}(z)\right)\right)} dz \right) \hat{h}(x) dx.$$

With the substitution $\hat{\Phi}^{-1}\left(\hat{H}(z)\right) = w$ we get

$$E[\beta] = \frac{1}{M^2} \int_0^1 \left(\int_0^{\hat{\Phi}^{-1}\left(\hat{H}(x)\right)} \hat{H}^{-1}\left(\hat{\Phi}(w)\right) dw \right) \hat{h}(x) dx.$$

Finally with the substitution $\hat{H}(x) = r$,

$$E[\beta] = \frac{1}{M^2} \int_0^1 \left(\int_0^{\hat{\Phi}^{-1}(r)} \hat{H}^{-1}\left(\hat{\Phi}(w)\right) dw \right) dr. \tag{B.1}$$

Now if $\hat{H}_1 \succ^{\text{FOSD}} \hat{H}_2$ then by its definition $\hat{H}_1(\cdot) < \hat{H}_2(\cdot)$ which also implies $\hat{H}_1^{-1}(\cdot) > \hat{H}_2^{-1}(\cdot)$. Therefore we have that $E[\beta_1] > E[\beta_2]$. □

Proof. Result 2.5.1 Let us represent the initial joint distribution of team n by $G_n(\cdot)$. As the cognitive diversity of each team weakly increases, the joint distribution of team n becomes $G'_n(\cdot)$ with $G_n(\cdot) \geq G'_n(\cdot)$ and for the corresponding survival functions $\overline{G}_n(\cdot) \geq \overline{G'}_n(\cdot)$ for all n. Corresponding to two joint distributions we get corresponding distribution of highest and lowest team tool effectiveness levels and their contest level averages. The corresponding sequence of contest level expected percentile ranking of tool effectiveness as the number of teams increases are given by

	Highest Effectiveness	Lowest Effectiveness
Initial	$\left\{\frac{\sum_{n'=1}^{N} G_{n'}(\cdot)}{N}\right\}_{N=1}^{\infty} = \{W_N\}_{N=1}^{\infty}$	$\left\{\frac{\sum_{n'=1}^{N}(1-\overline{G}_{n'}(\cdot))}{N}\right\}_{N=1}^{\infty} = \left\{1-\overline{W}_N(\cdot)\right\}_{N=1}^{\infty}$
Final	$\left\{\frac{\sum_{n'=1}^{N} G'_{n'}(\cdot)}{N}\right\}_{N=1}^{\infty} = \{W'_N(\cdot)\}_{N=1}^{\infty}$	$\left\{\frac{\sum_{n'=1}^{N}(1-\overline{G'}_{n'}(\cdot))}{N}\right\}_{N=1}^{\infty} = \left\{1-\overline{W}'_N(\cdot)\right\}_{N=1}^{\infty}$

with $W_N \geq W'_N$ and $\overline{W}_N \geq \overline{W}'_N$. Therefore $\lim_{N\to\infty} W_N = \hat{W} > \hat{W'} = \lim_{N\to\infty} W'_N$ and $\lim_{N\to\infty} \overline{W}_N = \hat{\overline{W}} > \hat{\overline{W'}} = \lim_{N\to\infty} \overline{W'}_N$.

Under the initial set of distributions, the rank distribution of the limit contest is given by

$$\hat{H}(\cdot) = \hat{\alpha}\hat{G}(\cdot) + (1-\hat{\alpha})\left(1-\hat{\overline{G}}(\cdot)\right)$$

and under the final set,

$$\hat{H'}(\cdot) = \hat{\alpha}\hat{G'}(\cdot) + (1-\hat{\alpha})\left(1-\hat{\overline{G'}}(\cdot)\right).$$

From an earlier claim we know that $\hat{H}'(\cdot) \leq \hat{H}(\cdot)$ if $\hat{\alpha} \geq \hat{\alpha}^*(\cdot)$ given by,

$$\hat{\alpha}^*(\cdot) = \frac{\hat{\overline{G}}(\cdot) - \hat{\overline{G'}}(\cdot)}{\left(\hat{G}(\cdot) + \hat{\overline{G}}(\cdot)\right) - \left(\hat{G}'(\cdot) + \hat{\overline{G'}}(\cdot)\right)}.$$

Therefore if $\hat{\alpha} \geq \max_{x \in (0,1)} \hat{\alpha}^*(\cdot)$, then $\hat{H}'$ first order stochastically dominates $\hat{H}$ and the expected individual effective efforts will improve due to the increase in cognitive diversity. Since each team's project value V is an increasing function of the effective efforts of all its members, its expected value also increases with expected effective effort. On the other hand, if $\hat{\alpha} \leq \min_{x \in (0,1)} \hat{\alpha}^*(\cdot)$, then $\hat{H}'$ is first order stochastically dominated by $\hat{H}$ and the expected individual effective effort will decrease due to increase in cognitive diversity. As in the first case, a team's expected project value $\mathbb{E}(V)$ decreases as the expected effective effort falls. But, there remains a region $\hat{\alpha} \in \left(\min_{x \in (0,1)} \hat{\alpha}^*(\cdot), \max_{x \in (0,1)} \hat{\alpha}^*(\cdot) \right)$ for which we can not specify whether increasing cognitive diversity is beneficial or detrimental to the expected team performance.

$\square$

C. TRANSITION RULE TYPE OF INTERACTION IN STOCHASTIC DYNAMIC GAME

C.1 Results

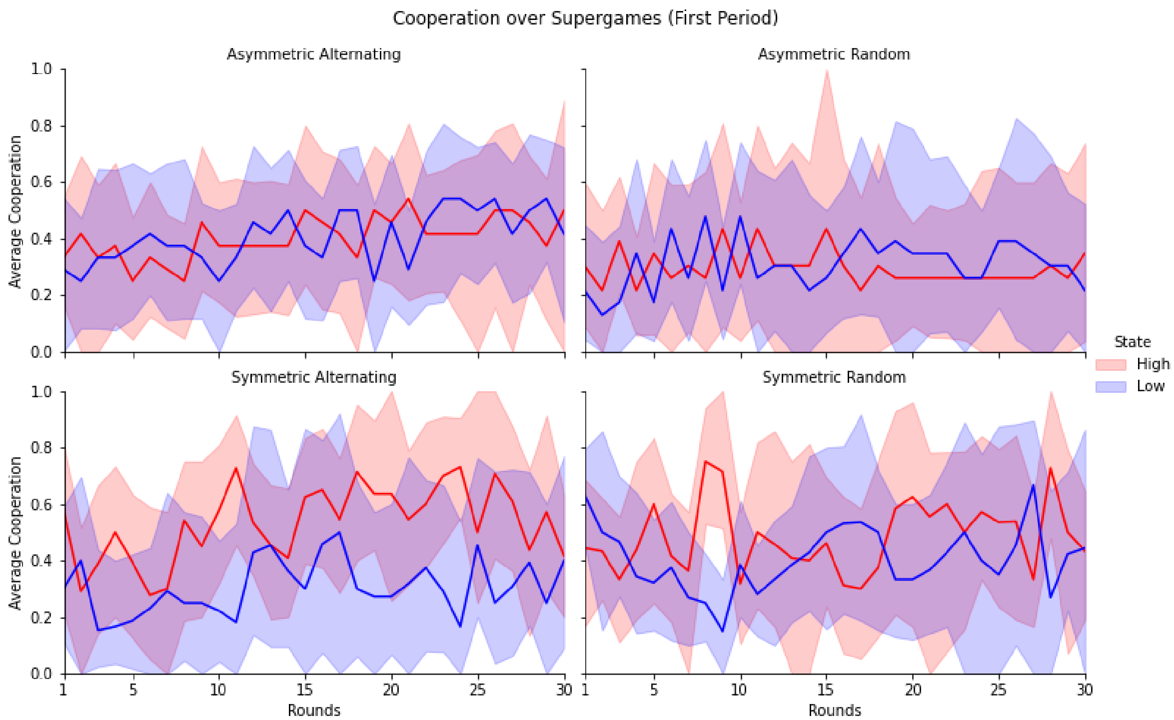

Figure C.1. Average Cooperation rates in Treatments for each Round (First Period)

Notes: The shaded areas are the Two-Stage Clustered Bootstrap 95% Confidence Intervals (clustered at session level, randomized at subject level).

Table C.1. Change in Cooperation Rate over Supergame (All Periods)

	High State				Low State			
	Asym-Alt	Asym-Ran	Sym-Alt	Sym-Ran	Asym-Alt	Asym-Ran	Sym-Alt	Sym-Ran
Supergame	0.007***	0.000	0.005***	0.002	0.007***	0.002	0.005***	0.004**
	(4.92)	(0.42)	(3.67)	(1.35)	(5.23)	(1.21)	(3.88)	(2.53)
Constant	0.246***	0.232***	0.354***	0.374***	0.227***	0.225***	0.219***	0.287***
	(10.50)	(10.09)	(13.88)	(13.95)	(9.8)	(9.81)	(9.47)	(11.47)
# Obs	1286	1143	1168	1154	1286	1143	1174	1190

Notes: This tables shows the coefficients from the OLS regression (robust SE) of average cooperation rate (all periods) on the supergame. t-statistics are in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2. Change in Cooperation Rate over Supergame (First Period)

	High State				Low State			
	Asym-Alt	Asym-Ran	Sym-Alt	Sym-Ran	Asym-Alt	Asym-Ran	Sym-Alt	Sym-Ran
Supergame	0.005**	-0.001	0.007***	0.003	0.007***	0.002	0.004*	0.002
	(2.54)	(-0.65)	(2.95)	(1.19)	(3.21)	(1.24)	(1.82)	(0.8)
Constant	0.321***	0.316***	0.435***	0.446***	0.303***	0.272***	0.249***	0.380***
	(8.77)	(8.8)	(11.00)	(11.08)	(8.33)	(7.85)	(6.97)	(10.55)
# Obs	720	690	662	668	720	690	658	772

Notes: This tables shows the coefficients from the OLS regression (robust SE) of average cooperation rate (first period) on the supergame. t-statistics are in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3. Average Cooperation and Treatment Effects (Last 15 supergames, First Period)

	High State			Low State			All States		
	Asymmetric		Symmetric	Asymmetric		Symmetric	Asymmetric		Symmetric
Alternating	0.472	$\sim$	0.589	0.427	$\sim$	0.335	0.45	$\sim$	0.465
	(0.086)	(0.231)	(0.031)	(0.054)	(0.299)	(0.143)	(0.068)	(0.861)	(0.087)
	$\vee$*		$\wr$	$\wr$		$\wr$	$\vee$*		$\wr$
	(0.061)		(0.518)	(0.153)		(0.276)	(0.098)		(0.946)
Random	0.306	<**	0.527	0.301	$\sim$	0.436	0.304	<**	0.471
	(0.14)	(0.018)	(0.112)	(0.128)	(0.133)	(0.116)	(0.124)	(0.056)	(0.12)

Notes: This table shows the average cooperation in the last 15 supergames of the experiment for first period. Clustered bootstrap S.E. for the cooperation levels are reported in parenthesis below. We also provide treatment effects in terms of greater than, less than or equality. For this we provide the p-values of the two-sided test of comparison of average cooperation levels of two treatments using Non-parametric permutation test in the parenthesis below.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C.2 Experimental Details

Table C.4. Supergame Lengths

Supergame → Sessions ↓	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Session 1	4	5	1	3	1	7	6	10	4	9	1	3	2	12	6	5	2	3	4	1	3	18	1	4	1	2	2	13	7	7
Session 2	2	6	2	1	19	2	8	2	4	1	4	15	1	4	7	4	3	1	4	1	4	3	5	2	12	3	3	4	4	1
Session 3	5	2	4	8	3	2	3	2	2	3	7	1	6	2	2	1	2	1	4	1	6	1	2	4	8	4	14	1	4	3

C.2.1 Otree Application

Instructions

How Matches Work

The experiment is made up of **30 matches**.

At the start of each match you will be randomly paired with another participant in this room.

You will then play a number of periods with that participant (this is what we call a "match").

Each match will last for a random number of **periods**:

- At the end of each period the computer will roll a twelve-sided fair dice.
- If the computer rolls a number less than 10, then the **match continues** for at least one more period (**75% probability**).
- If the computer rolls a 10 or greater, then the **match ends** after the current period (**25% probability**).

To test this procedure, click the 'Test' button below. You will need to test this procedure 10 times.

Period

Dice Roll

Remember that at the end of each period the computer rolls a twelve-sided fair dice. The match ends when the computer rolls 10 or greater.

Test #1

Period Payoffs

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

- In each period you and the participant you are matched with will play either Red Game or Blue Game
  - In Red Game you will select **A** or **B**, and the participant you are matched with will select **A** or **B**
  - In Blue Game you will select **W** or **Y**, and the participant you are matched with will select **W** or **Y**
- At the time of your decision you and the participant you are matched with will know which game you are playing
- Tables above display the payoffs that you and the participant that you are matched with will recieve for each combination of choices
- For example, if in the Red Game you select **B** while the participant you are matched with selects **A**, then you receive **50** while the parcipant you are matched with will receive **12**
- Another example, if in the Blue Game you select **W** while the participant you are matched with selects **W**, then you receive **32** while the parcipant you are matched with will receive **48**

Continue

Which Game Will be Played Next

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

- If you are playing Red Game in the current period, in the next period, you will play Red Game with probability 10.0% and Blue Game with probability 90.0%
- If you are playing Blue Game in the current period, in the next period, you will play Blue Game with probability 10.0% and Red Game with probability 90.0%

Continue

How History Will be Recorded

Period Number	1	2	3	4	5
Game	Red	Blue	Red	Red	Blue
My Action	B	W	B	A	?
Other's Action	A	Y	B	A	?
My Payoff	50	12	25	48	?
Other's Payoff	12	50	25	32	?
Roll	1	9	7	3	?

The history of all variables will be recorded in a history table like the one presented above. In this table you can see an example history of a match in which the computer picked actions at random. The recorded variables include:

- Period Number -- period number
- Game -- which game is played in the period (Red Game or Blue Game)
- My Action -- your choice (either **A** or **B** if the Red Game is played in the period; either **W** or **Y** if the Blue Game is played in the period)
- Other's Action -- the choice by the participant that you are paired with in that match
- My Payoff -- your payoff in that period
- Other's Payoff -- the payoff of the the participant that you are paired with in that match
- Roll -- at the end of each period the computer rolls a twelve-sided fair dice. The match ends when the computer rolls 10 or greater

Reminder, your earnings for the experiment will be the sum of your points across all matches converted into cash at the exchange rate of 180 points = $1. In addition, you will be paid your show-up payment of $5.0.

Continue

Quiz

Quiz

Next, there will be a quiz with 5 questions.

You have to answer each question correctly in order to proceed to the next question.

If you answer a question incorrectly, you will see a hint. At that point you will have an opportunity to answer again.

Begin Quiz

Quiz

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

Period Number	1	2	3	4	5
Game	Red	Blue	Red	Red	Blue
My Action	B	W	A	A	Y
Other's Action	B	Y	B	A	W
My Payoff	25	12	12	48	50
Other's Payoff	25	50	50	32	12
Roll	1	5	3	8	11

Question 1: Which game was played in Period 1?

Red Game Blue Game

Quiz

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

Period Number	1
Game	Blue
My Action	?
Other's Action	?
My Payoff	?
Other's Payoff	?
Roll	?

Question 2: If you choose **W** and the participant you are paired with chooses **W**, what will be your payoff in Period 1?

12 25 32 48 50

Quiz

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

Period Number	1
Game	Red
My Action	A
Other's Action	B
My Payoff	50
Other's Payoff	12
Roll	6

Question 3: In Period 1 Red Game is played and the Match is proceeding to Period 2. What is the probability that Blue Game will be played in Period 2?

10% 25% 50% 75% 90%

Quiz

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

Period Number	1	2
Game	Red	Blue
My Action	B	?
Other's Action	A	?
My Payoff	50	?
Other's Payoff	12	?
Roll	2	?

Question 4: If you choose **W** and the participant you are paired with chooses **Y**, what will be the other participant's payoff in Period 2?

12 **25** **32** **48** **50**

Quiz

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

Period Number	1	2
Game	Red	Blue
My Action	B	W
Other's Action	A	Y
My Payoff	50	12
Other's Payoff	12	50
Roll	2	?

Question 5: What is the probability that the Match will end in the current round? (rounded to the nearest integer)

0 % **17 %** **25 %** **33 %** **50 %** **67 %** **75 %** **83 %** **100 %**

Main Application

Reminders

- At the start of each Match, you will be paired with one other randomly chosen participant who we will refer to as Other.
- Each Match will last for a random number of periods.
- At the end of each period, the match will continue to another period with probability 75% and end with probability 25%.
- In each period you will participate in either Red Game or the Blue Game with Other.
- If you are playing Red Game in the current period, in the next period, you will play Red Game with probability 10.0% and Blue Game with probability 90.0%.
- If you are playing Blue Game in the current period, in the next period, you will play Blue Game with probability 10.0% and Red Game with probability 90.0%.
- In the experiment, you will work with points. Today's exchange rate is 180 Points = $1.

Payoff Tables for the Two Games

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

Start Experiment

Match #1

Red Game				
My Action	A	B	A	B
Other's Action	A	A	B	B
My Points	48	50	12	25
Other's Points	32	12	50	25

Blue Game				
My Action	W	Y	W	Y
Other's Action	W	W	Y	Y
My Points	32	50	12	25
Other's Points	48	12	50	25

History Table

Period Number	1
Game	Blue
My Action	?
Other's Action	?
My Points	?
Other's Points	?
Roll	?

In this period you will play the Blue Game.

Please choose your action.

W Y