Instability in Social Dilemma Games: Experimental Evidence

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ABSTRACT

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Starting from the discovery of "prisoner's dilemma" (originally framed by Merrill Flood and Melvin Dresher in 1950), in more than half a century, a lot of economic researches devoted to study the problem of social dilemma. The social dilemma refers to a situation in which individuals in a group profit from self-interested action unless all group members make the self-interested choices, then which results in the loss of the whole group. In experimental economics, based on the basic game of the prisoner's dilemma, the voluntary contribution mechanism (VCM) and the common-pool resources (CPR) successively have been proposed. Each of them attempts to capture the conflict between the individual interest and the group interest in different situations. Because of the concise of game theory framework, all of those previous studies employed an equilibrium analysis based on the core concept of Nash equilibrium in game theory. However, they overlooked the discussion for the stability of the Nash equilibrium in such games. Once the Nash equilibrium is unstable, the equilibrium analysis is invalid.

Recently, Saijo (2014, 2015) and Saijo et al. (2016) investigated the stability property in both the VCM and the CPR situations. Through a dynamic analysis, the Nash equilibrium is unstable or non-globally stable under some particular conditions. Furthermore, by examining previous experimental studies, he found that a lot of published literature using the equilibrium analysis actually employed an experimental design in which the Nash equilibrium is unstable. This result raises a doubt whether the results from previous experimental studies are valid.

In order to determine the implications of this new theoretical insight in the field of experimental studies, in this thesis, we employ the methodology of experimental economics. Specifically, we design new experiments or reanalyze the data from previous experimental studies to examine the distance between theoretical predictions of Saijo (2014, 2015) and Saijo et al. (2016) and experimental observations.

First, we conduct a new experiment with a homogeneous design to investigate the dynamic pattern of contributing behavior in the VCM with two different quasi-linear payoff functions. The design of this study is based on the theory of Saijo (2014). As the theory predicted, one treatment is stable, and the other one is unstable. Although we have not found a clearly unstable pulsing in the group total contribution from the unstable treatment, we found a significant difference in the dynamic patterns of contributing behavior between the two treatments. The experimental results show that, the system is converging to the interior dominant equilibrium in the stable treatment. The average contribution decreases with

repeated trials and individual contributions converge and become steady. In contrast, in the unstable treatment, although contributions on average are also decreasing in repeated trials with no clearly unstable pulsing in the group's total contribution, individual contributions diverge and continuously change. Since these observations do not support the hypothesis that the system of the unstable treatment is asymptotically stable, it indicates that only a comparative static analysis might not be suitable for the VCM with this setting.

Second, based on the theory of Saijo (2015), we introduce the heterogeneity in benefits from the public good into the design of the unstable treatment in the first study and design four treatments with an identical Nash equilibrium, but with different stability properties. We clearly observe significant differences in the belief formation process, the responding process and the convergence of contributing behavior of subjects across the four treatments. The Nash equilibrium is a good predictor for the two globally stable treatments. However, for the two locally stable treatments, it is not. Furthermore, the non-convergence in the two locally stable treatments does not stem from the local stability, but from the changes in both the belief formation process and the responding process of subjects.

Third, I turn to the instability in the CPR. Based on the theory of Saijo et al. (2016), we reanalyze the data from the previous studies. We make a connection between the new insight of local instability and the unexplained pulsing behavior among players. Moreover, the reanalysis shows that the local instability is also a reason for the inefficiency in experiments summarized by Ostrom et al. (2006).

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Chapter 1

INTRODUCTION

The content of this thesis reaches the experimental investigation for the instability argument in two social dilemma games: the voluntary contribution mechanism (VCM) and the common-pool resources (CPR) game. Chapter 2 investigates the experimental performance for the theoretical argument of instability in the VCM with a homogeneous design. In Chapter 3, we investigate the experimental performance for the theoretical argument of global or non-global stability in the VCM with a heterogeneous design. Finally, in Chapter 4, we investigate the experimental performance for the theoretical argument of instability in the CPR.[1] Therefore, in the introduction part, I successively introduce the basic models of the VCM and the CPR. Then, I clarify the theoretical instability arguments and their implications. Finally, I explain the methodology of experiment economics that I employed to empirically examine the theoretical results.

1.1 Voluntary Contribution Mechanism

The VCM usually is mentioned as a mechanism for privately providing public goods. Therefore, it is also called the public goods game. When a group of people face a situation that a common project needs to be funded and then everyone in the group can benefit from this common project, a simple mechanism could be proposed for the problem, which is the VCM. Each of the group members could voluntarily decide how much he/she want to contribute to the group account from his/her own private account.

Bergstrom et al. (1986) provides a general theoretical discussion for the VCM. Here, I use a simple linear model to illustrate the basic idea of the VCM. In economics, from a simple case, economists always attempt to use a mathematic model to capture the relation between the group members' personal decisions and their outcomes at the end. For example, consider a VCM environment that a group of villagers want to build a road for their village via voluntary contributions. In this game, for a set of players $I = \{1, \dots, \mathrm{n}\}$, each has a differentiable quasi-linear payoff function π_i from consuming a private good (money) x_i and a single public good

[1] Chapter 2 is a joint work with Tatsuyoshi Saijo, Xiangdong Qin and Junyi Shen. An earlier version was published as Feng et al. (2018). Chapter 3 is developed in collaboration with Yoshio Kamijo and Tatsuyoshi Saijo. Chapter 4 is a part of the content in a joint work with Tatsuyoshi Saijo and Yutaka Kobayashi. The full version can be found in Saijo et al. (2017).

(road) S that is the sum of all individual contributions (hours of labor input) denoted by s_i from players.[2] That is $\pi_i(x_i, S) = x_i + t_i(S)$, where $S = \sum_{i=1}^{n} s_i$ and $t_i(S)$ is player i's personal benefits from S. Generally, $t_i(S)$ might be nonlinear functions and different among players. However, most previous studies employ a linear and homogeneous design for them. Here, for simplicity, I also follow the usual design in this introduction but in the below studies, the assumption is changed with the purpose of discussions. Let $t_i(S) = \alpha S$, where α is a positive constant, and E_i denote the endowment of player i such that $E_i = x_i + s_i$. Then, player i faces the following maximization problem.

$$Max_{s_i}\ x_i + \alpha(s_i + S_{-i})\ subject\ to\ E_i = x_i + s_i, \tag{1.1}$$

where $S_{-i} = \sum_{j \neq i} s_j$. Let $\pi_i(E_i - s_i, s_i + S_{-i}) = v_i(s_i, S_{-i})$. A combination of individual contributions $\hat{s} = (\hat{s}_1, \hat{s}_2, \cdots, \hat{s}_n)$ is a Nash equilibrium if for all i, $v_i(\hat{s}_i, \hat{S}_{-i}) \geq v_i(s_i, \hat{S}_{-i})$ for all $s_i \in [0,\ E_i]$, where $\hat{S}_{-i} = \sum_{j \neq i} \hat{s}_j$. Then, we have the following three different cases in which we can get

(1). $\alpha \geq 1$. In this case, since the benefit from contributing the hours of labor to building the road is always larger than keeping it privately, the best choice for player i is contributing all his endowments of hours to build the road. The Nash equilibrium, therefore, is $\hat{s} = (E_1, E_2, \cdots, E_n)$.

(2). $\alpha \leq 1/n$. This case is totally contrasted to the above case. Now, since the benefit from contributing the hours of labor to building the road is always smaller than keeping it privately, the best choice for player i is contributing zero to build the road. The Nash equilibrium, therefore, is $\hat{s} = (0, 0, \cdots, 0)$. Furthermore, since α is so small, even smaller than $1/n$, if all group members still decide to build the road and ask every group member to contribute, the benefit at the end is still dominated by the benefit from not constructing the road.

(3). $1/n < \alpha < 1$. The third case is in the midway of above two cases. First, since $\alpha < 1$, since the benefit from contributing the hours of labor to building the road is always smaller than keeping it privately, the best choice for player i is contributing zero to build the road. The Nash equilibrium, therefore, is also $\hat{s} = (0, 0, \cdots, 0)$. However, since $1/n < \alpha$, if all group members decide to build the road and ask every group member to contribute, the benefit at the end is larger than the benefit from not constructing the road. Thus, for individual group members, the best choice is contribute nothing but for the whole group, the best choice is contribute everything.

Since case (3) captures the conflict between the individual interest and the group interest in the VCM, the design of case (3) always attracts a lot of academic discussions. Therefore, in

[2] Note that, here, I assume that the production function for building the road is $f(x) = x$.

economics, when we talk about the problem of the VCM or the public goods game, we usually refer to the situation of case (3).

1.2 Common-Pool Resources

The common-pool resource refers to an open access resource. The classic example of the common-pool resources is the fishing ground. Consider an example of local fishery with n fishers. Assume that the number of fisher i's fishing hours is x_i and the output y of the fishing ground is a function of the total number of hours of fishing, $\sum_{i=1}^{n} x_i$. That is $y = f(\sum_{i=1}^{n} x_i)$, where $f(.)$ is an increasing, differentiable and strictly concave function. Therefore, the average output for each fishing hour is $f(\sum_{i=1}^{n} x_i)/\sum_{i=1}^{n} x_i$. Then, for fisher i, his/her expected output from his/her fishing hours x_i is $f(\sum_{i=1}^{n} x_i)x_i/\sum_{i=1}^{n} x_i$. Furthermore, assume that the opportunity cost for each fishing hour is a positive constant c and let w_i denote the endowment of fishing hours for fisher i. Then, fisher i faces the following maximization problem.

$$Max_{x_i}\, v_i(x_i, X_{-i}) = c(w_i - x_i) + \frac{x_i}{x_i + X_{-i}} f(x_i + X_{-i}), \tag{1.2}$$

where $X_{-i} = \sum_{j \neq i} x_j$. Then a list of inputs $\hat{x} = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$ is a Nash equilibrium if, for all i, $v_i(\hat{x}_i, \hat{X}_{-i}) \geq v_i(x_i, \hat{X}_{-i})$ for all $x_i \in [0, w_i]$, where $\hat{X}_{-i} = \sum_{j \neq i} \hat{x}_j$. Since all fishers have the symmetric value function v_i, in equilibrium, we get $\hat{x}_1 = \hat{x}_2 = \cdots = \hat{x}_n$. Therefore, from the first-order condition of the maximization problem (1.2), we can get,

$$f'(\hat{x}_i + \hat{X}_{-i}) = nc - (n-1)\frac{f(\hat{x}_i + \hat{X}_{-i})}{\hat{x}_i + \hat{X}_{-i}}, \tag{1.3}$$

An important insight of this model is that each fisher in this situation has a strong incentive to obtain more and more resources, which finally results in an inefficient outcome or overexploitation of the CPR. To see this, we can consider that, if all fishers belong to a fishery company and their working hours is corresponding to the arrangement of the company. Assume that the opportunity cost for each fishing hour is a positive constant c and let w denote the endowment of fishing hours for the company. Then, the fishery company faces the following maximization problem.

$$Max_z\, c(w - z) + f(z). \tag{1.4}$$

We can get the optimal choice $\hat{x}$ from the first-order condition of equation (1.4). It satisfies,

$$f'(\hat{z}) = c, \tag{1.5}$$

Then, we can compare two equations (1.3) and (1.5). Since the function $f(.)$ is a strictly concave function, we have $\hat{z} < \hat{x}_i + \hat{X}_{-i}$ if $n \geq 2$ and $c < \frac{f(\hat{x}_i+\hat{X}_{-i})}{\hat{x}_i+\hat{X}_{-i}}$ which is the participation constraint. Since $\hat{x}$ represents the optimal choice for the group of fishers, it is the efficient outcome. This simple result indicates that if $n \geq 2$, the sum of every fisher's best choice will larger than the optimal choice for the group of fishers, which leads to a overexploitation problem for the CPR. This is called "the tragedy of the commons" (Harding, 1968). Therefore, in this situation, there is also a conflict between the individual interest and the group interest.

1.3 Instability: Theoretical Implications

Instability in games, in particular, in economics, refers to the convergence of an equilibrium, i.e. a Nash equilibrium. For example, when we say that a system is locally asymptotically stable, it indicates that, for an equilibrium of the system, all nearby solutions not only stay nearby but also tend to the equilibrium (see formal discussions and definitions in Chapter 2). Therefore, by contrast, if a system is not locally asymptotically stable, it informally means that all nearby solutions will not tend to the equilibrium. Related formal definitions with respect to different stability properties can be found in each chapter, before we discuss concrete theoretical predictions.

The theoretical argument of instability in the VCM and the CPR consists of three parts, respectively applied to three different settings: the VCM with homogeneous design, the VCM with heterogeneous design and the CPR. A notable difference between the VCM and the CPR is that different players might benefit differently from the common project in the VCM, but usually people benefit identically from the CPR since they can sell the resource in the downstream market. Therefore, the theoretical argument of instability is separately discussed in the homogeneous and heterogeneous designs. In the following, we explain them successively.

First, as I mentioned, in most previous experimental studies, researchers employ a linear payoff function (for a survey, see Ledyard, 1995). However, in most practical situations, the private good is money, hence its marginal return could be assumed as a constant, but the marginal return from a specific public good usually decreases as the level of the public good increases. Some researchers, therefore, pay much attention to this quasilinear payoff function in their investigation (for a survey, see Laury and Holt, 2008). If the payoff function is a homogeneous quasilinear setting that is linear with respect to the private good and nonlinear with respect to the public good, it induces multiple static Nash equilibria.[3] Saijo (2014) argues that all Nash equilibria are not asymptotically stable under the assumption of self-interested players and myopic best response dynamics in which players make best response to the last observation of their opponents' actions. This leads to pulsing of contributions (alternating between contributing nothing and contributing everything).

Second, if the payoff function is a heterogeneous quasilinear setting that different players benefit differently from the public good, the multiple static Nash equilibria are degenerated to a unique Nash equilibrium (Bergstrom et al., 1986; Saijo, 2015). Under the same assumption of self-interested players and myopic best response dynamics, Saijo (2015) argues that, if the number of players exceeds two, there is a necessary and sufficient condition for the global stability of the unique Nash equilibrium in this asymmetric environment. If the setting of the system does not satisfy this condition, the unique Nash equilibrium is non-globally stable which indicates that the sequences start from some initial points will be pulsing after several periods between two contribution levels under the assumption of best response dynamics.

Third, still under the same assumption of self-interested players and myopic best response dynamics, Saijo et al. (2016) argue that, if the number of players exceeds two, there is a necessary and sufficient condition for the local stability of the Nash equilibrium in the system of the CPR. Furthermore, this result indicates that, if the number of players is two, the difference equation system is always locally stable at the Nash equilibrium and if the number of players is at least four, then the difference equation system is always locally unstable at the Nash equilibrium. When $n = 3$, the stability is indeterminate. Moreover, when the system is locally unstable at the Nash equilibrium, the choices of player will be pulsing between two extraction levels.

Overall, all of these theoretical arguments are based on the assumption of self-interested players and best response dynamics. The result is that, if the setting of the system does not satisfy a particular condition, the contributions or the extraction levels will be pulsing, which indicates the Nash equilibrium in these games is not a good predictor for players' decisions. Therefore, an obvious implication is that the Nash equilibrium is not a suitable standard of comparison for the empirical investigations in such the environments with the unstable settings.

However, although the Cournot best response dynamic is useful in the theoretical analysis, it is usually too strict to explain the experimental observations. First, players in the game might not be so myopic and forming their beliefs according to not only the last observation. Second, players might not be so self-interested; they might also care about the difference between

[3] We will explain more details in chapter 2.

his/her own payoff and the other's payoff. Therefore, to examine the assumptions the theoretical arguments that are based on those assumptions, a useful method is the methodology of experimental economics. In the next subsection, I will explain it and introduce some new insights in economics benefited from this methodology.

1.4 Methodology of Experimental Economics

Experimental economics as an empirical method is formally introduced by Vernon L. Smith in 1970s (Plott and Smith, 2008). Due to this contribution, he has been awarded Nobel Prize in 2002. Originally, he wants to investigate the predictions from the basic economic theory, i.e. supply and demand, market structure, using the experiment with human subjects. Since, in the design of lab experiments, experimenters can rule out all other factors that cannot be controlled in reality, the environment of lab experiments becomes a perfect place to test the prediction of economic theories with human subjects.

Since all economic theories are based on various assumptions, experimental method could be looked as a tool to examine the basic assumptions of economic theory. This might be the most important contribution of experimental economics to the economic theory. For example, since nineteenth century, a widely used assumption in various economic theories is the economic man that is a selfish and rational person in the economic environment. Under this widely accepted assumption, economics has achieved great success, especially, the wide use of game theory in economics. However, it also provides a lot of problem, i.e., charitable giving, that economic theory cannot explain. It seems that, although the assumption of economic man is important to economic theories, people in reality are not as selfish and rational as economists assumed. Then, experimental economics, due to its many advantages, provides very clean experimental evidence to show the distance between the theoretical predictions and the real performance of human subjects. Following the introduction of experimental economics, behavioral economics has been established. It changes the norm. The widely used assumption in behavioral economics is no longer the economic man but a social man with bounded rationality and social preferences. Therefore, behavioral economics becomes an inter-discipline interacting with psychology.

However, although the method of experimental economics is much like the method of experimental psychology, there are still some differences between these two disciplines. Let me manifest the methodology of experimental economics.

(i). *Random Assignment*. In experimental economics, likes the experimental psychology, the most important regulation or the basis of the empirical tests is the design of the random assignment in the experiment. This is the key step to control the unspecific factors in the experiment. Through random assigning subjects across treatments, the effects of unspecific factors, i.e. the individual heterogeneity, could be averaged among treatments. Therefore, these unspecific factors cannot becomes an alternative explanation for the experimental results.

(ii). *Anonymity*. It is also like the experimental psychology. The identity of human subjects is classified in the experiments of experimental economics. Since the investigations in experimental economics usually focus on the decision-making in an environment of social interaction, through controlling the identity of subject, we can rule out the complex social intentions in the lab experiments and make clean the experimental data.

(iii). *Incentive Compatibility*. This might be the most important trait. Because of this, experimental economics is different from experimental psychology and surveying method that is the traditional empirical method in economics and sociology. The incentive compatibility indicates that the performance of human subjects should be consistent with the basis of rewards. It is also the basis of trustworthy for the experimental data. Human subjects make decisions in the experiments, because they want to get more and more rewards from the experiments. Therefore, it is a mechanism to ensure every decision could be considered as a true reflection of their intentions. A usual way of rewards is money, since money might be the item with the smallest individual heterogeneity in preference among human subjects. Obviously, if the experimenters can control the individual heterogeneity in the preference, anything could be used as a reward in the experiments. But, usually, in the experiment with student subjects, we use money. The incentive compatibility also indicates that subjects must be voluntarily participating in the experiments. If a subject is not voluntarily participating, the experimenter cannot make sure whether he/she cares about the rewards from the experiment. In other words, the experimental data from his/her decisions also cannot be trusted.

(iv). *Faithfulness*. This is another trait that is different from experimental psychology. The design of experiments in experimental economics requests a faithful formulation. The subjects should not be deceived during the experiments. Since most experimental studies in experimental economics investigate the economic decision-making, a faithful and coherence is necessary for subjects to connect decisions and outcomes during the experimental environment. Especially, for the repeated use of the subject pool and the lab, the reputation of the lab could significantly influence the experimental data of the successive experiments.

After explaining four basic traits in experimental economics, I will manifest the procedure of the experiments. Usually, the lab of experimental economics is equipped with one server and about twenty clients and each client locates in a closed chamber. A local network links all of these computers. The procedure of experimental treatments is programed by a computer software.[4]

[4] Usually, it is Z-tree (see Fischbacher, 2007). Other network software is also useful, for example, the web server with PHP.

When subjects are randomly chosen from the pool and enter the closed chambers, the experimenter should read loudly the instructions of the experiment. When every subject understands the meaning of the instructions, they are requested to answer the control questions. Through the answer of the control questions, the experimenters can identify whether a particular subject understands the rule of the experiment. If a subject does not seem well-understood, more private instructions are suitable. Furthermore, the answer of the control questions could also be a standard to select the experimental data.

The subjects usually are randomly assigned to a group with several persons in order to achieve the anonymity. And, no communication is allowed during the experiment. When the experiment is completed, each subject should be paid the rewards privately. All experimental data and material will be preserved for years.

After the collection of the experimental data, economists usually use the analysis tools from econometrics to analysis the data. It includes not only nonparametric statistic tests that are very common in the data analysis of experimental psychology, but also the regression models or other statistic models. These methods enrich the analysis of the experimental data. It allows the economists not only to identify the treatment effects of the experiment design, but also to investigate the particular reasoning behind the treatment effects. Therefore, experimental studies in experimental economics usually are plenty of insights.

In this thesis, I will employ the methodology of experimental economics to investigate not only the treatment effects but also the economic reasoning based on the theoretical arguments of instability in social dilemma games. The experimental investigations can provide an intuitive understanding of the distance between the theoretical results and the empirical results. Basically, I want to answer the questions how the theoretical reasoning fits the experimental data and whether the assumption behind the theory is suitable for analyzing the experimental data.

1.5 Challenges to the methodology of Experimental Economics

There are two main challenges to the methodology of Experimental Economics nowadays. One comes from the other traditional areas of Economics. The main criticism is that, the researches of Experimental Economics usually are conducted in a virtual environment. Although those unimportant influences could be eliminated in such an environment, there is a certain distance from the realistic economic decision-making environment. For example, a critical difference is that players in a virtual environment usually are unfamiliar with the decision environment they have to take time to understand and make trials in these environments created by economists, but in a realistic economic environment, the decision-makers usually are very familiar with surrounding economic environments, especially, some of them might have years of related experience. Such information or experience can significantly affect subjects' risk attitude (Harrison and List, 2004). This criticism seems very simple. However, it directly points out that the experimental observation in the lab experiments might not reflect the practice in reality, especially, in some researches regarding market structure and industry organization. Recently, an emerging discipline, called Field Experimental Economics, attempts to solve this criticism. The new discipline follows the related methodology of Experimental Economics, but conducts experiments in a more realistic environment. The researchers from this discipline make effort to render their experiments happened in a realistic environment which is very familiar to subjects.

The other challenge comes from natural science, especially, Biology and Neuroscience. For many years, Neuroscience and Psychology are gradually integrated together. The new disciplines, called Cognitive Neuroscience and Social Neuroscience start to investigate the neural basis behind human cognitive activities and social interactions. It is natural to see Neuroscience intrudes into Experimental Economics, since any economic decision is a consequence of brain activity. Without a basis of brain activity, any finding that deviated from the assumption of economic-man cannot be thoroughly understood (Glimcher and Fehr, 2013). Therefore, a new discipline, called Neuroeconomics, has been established recently. It aims to investigate the neuro basis of human economic decision-making with the method of neuroscience. In such a discipline, the methodologies of Experimental Economics and Neuroscience are integrated together.

Instability in the Voluntary Contribution Mechanism with a Quasi-Linear Payoff Function

2.1 Introduction

Experimental economists have investigated the voluntary contribution mechanism (VCM) for many years for the purpose of understanding the public goods provision problem.[5] The linear payoff functions such as $u(x_i, y) = x_i + by$, where x_i is a private good of player i, y is a public good, and b is a positive constant is widely employed by most researchers in this field. However, a number of scholars argue that this setting cannot represent real-world VCM environment because the self-interested choice (Nash equilibrium) and the optimal social choice are located at opposite boundaries of the feasible choice set (see, e.g., Sefton and Steinberg, 1996; Laury and Holt, 2008).

This problem could be mitigated by adopting quasi-linear payoff functions to make interior solutions for the self-interested and optimal social choices. In most real-world situations, the private good x_i is money, the marginal return of which could be assumed to be constant. However, for a specific public good y, its marginal return is nonlinear. Thus, the first quasi-linear payoff function is, $\pi(x_i, y) = x_i + t(y)$ (see Isaac et al., 1985; Isaac and Walker, 1991; Sefton and Steinberg, 1996; Isaac and Walker, 1998; Laury et al., 1999; Hichri and Kirman, 2007). We refer to this as "QL1." Conversely, one might consider a reverse case in which the marginal return of the payoff function is linear with respect to y and nonlinear with respect to x_i. Thus, that is $\pi(x_i, y) = h(x_i) + y$ (see Sefton and Steinberg, 1996; Keser, 1996; Falkinger et al., 2000; Willinger and Ziegelmeyer, 2001; van Dijk et al., 2002; Uler, 2011; Maurice et al., 2013; Cason and Gangadharan, 2014). We refer to this as QL2. This payoff function could be employed to model a relatively rare situation that is the decrease (constant) of the marginal return of the private (public) good.

Different theoretical predictions are presented in these two designs. For the VCM with QL1, multiple static Nash equilibria coexist, which induces a coordination problem. Conversely, for the VCM with QL2, a unique dominant equilibrium exists, which is similar to the VCM with linear payoff functions. A previous study compared contribution levels

[5] See Ledyard (1995) and Chaudhuri (2011) for surveys on experiments regarding the VCM. Bergstrom et al. (1986) discuss the basic theoretical properties of the VCM.

between QL1 and QL2 environments (Sefton and Steinberg, 1996). They use a randomly re-matched group setting to suppress the feedback from the results of previous periods in the experiments. Theoretically, they argue that the presence of the coordination problem should be a reason for the fact that the average of individual contributions is significantly above the Nash equilibrium in their VCM experiment with QL1. However, their experimental results show a slight difference in contribution levels between the two experiments.

Differing from Sefton and Steinberg (1996), this study devotes to investigate the VCM experiments with QL1 and QL2 under a fixed group setting. Because the game is transformed into a super game in the fixed group setting, players might play strategically in the experiment (for details, see the discussions in Sefton and Steinberg, 1996). Moreover, Healy (2006) provides experimental evidence that subjects appear to best respond to recent observations in the VCM experiment with QL1 using a fixed group setting. This indicates that, in the fixed group setting, the feedback from preceding periods contributes to belief formation much more directly in the fixed group setting than it does in the randomly re-matched group setting.

A recent study shows that all Nash equilibria are not asymptotically stable in the difference dynamic system of the VCM with QL1 under the assumptions of self-interested players and myopic best response dynamics (Saijo, 2014).[6] This results in a pulse of contributions (alternating between some particular numbers). This dynamic analysis predicts that the coordination problem will be worsened by the feedback from repeated trials in the VCM with QL1. Furthermore, previous studies show that the symmetric Nash equilibrium is not a good predictor of individual contributions and that mean contributions also vary widely among individuals, even within a single experiment (Laury et al., 1999; Hichri and Kirman, 2007). The experimental observations and the theoretical instability argument suggest a complex interaction among subjects in the VCM experiment with QL1.

The instability arguments are experimentally discussed in the field of industrial organization (see Cox and Walker, 1998; Rassenti et al., 2000; Huck et al., 2002). However, those discussions differ from the current study. Andreoni (1995) points out that, subjects are called upon to generate positive externalities in the VCM environment, whereas they are asked to generate negative externalities in the experiment of oligopoly competition.[7]

[6] An intuitive explanation of asymptotic stability is that an equilibrium $\hat{x}$ is asymptotically stable if all nearby solutions not only stay nearby but also tend to $\hat{x}$ (Hirsch and Smale, 1974, p. 180). We provide the formal definition of asymptotic stability in Section 2.2.

[7] The VCM experiments usually frame the subject's choice as contributing to the provision of public goods, which could benefit other players within the group, whereas the oligopoly experiments

Different effects on cooperation will be induced by the positive and negative framing (see Andreoni, 1995; Sonnemans et al., 1998; Cookson, 2000; Bowles and Polania-Reyes, 2012). Previous researchers have identified that cooperative behavior is widely observed in the VCM experiments (for a survey, see Chaudhuri, 2011). Therefore, the present study might provide an opportunity shedding light on the effect of instability in a cooperative environment.

More importantly, most experimental studies in the field of VCM experiment employ the linear payoff function, which might have failed to capture the real-world instability of the VCM. Therefore, this study aims to investigate that instability and provides dynamic analyses on the convergence of individual contributions in the VCM with QL1 using a fixed group setting. For the purpose of comparison, the results of the VCM experiment with QL2 serve as a reference.

Differing from the observation of a tiny difference between the QL1 and QL2 environments with the randomly re-matched group setting in Sefton and Steinberg (1996), the experimental observations of our study show a significant difference in the convergence of individual contributions between the QL1 and QL2 environments with the fixed group setting. Experimental evidence clearly shows that the decreasing dispersion of individual contributions and the diminishing the absolute changes of individual contributions in the experiment with QL2.[8] These observations indicate the convergence of individual contributions and suggest more and more steady individual contribution. In contrast, in the experiments with QL1, our observations show that the dispersion of individual contributions increases progressively and that individual contributions are still volatile in the experiments' last periods, but we do not find a clearly unstable pulsing in the group's total contribution. This indicates that individual contributions diverge. Therefore, the coordination problem is not alleviated and individual contributions are not converging to any equilibrium in the experiments with QL1. Our main result is that the experimental observations provide supporting evidence for the non-convergence of individual contributions in the QL1 environment using a fixed group setting, but there is still a significant distance between the theoretical instability argument and our experimental observations.

Moreover, our data show considerable cooperation across players in all experiments in line with the findings of previous studies. In each experiment, about 50 percent subjects could be regarded as typical conditional cooperators, and about 20 percent subjects are

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usually frame the subject's choice as providing a product, which will lower the market price and result in a disbenefit to others within the group.

[8] Absolute changes are the absolute values of the first-order differences of individual contributions.

weak free riders.[9] Based on this observation, possible explanations are discussed for the distance between our theoretical predictions and the experimental observations in the conclusion.

The remainder of this chapter is organized as follows. Section 2.2 summarizes several theories concerning the VCM with QL1 and QL2. Section 2.3 presents our experimental design. Section 2.4 reports the experimental observations. Finally, the last section discusses the results and concludes the study.

2.2 Theories of the VCM with QL1 and QL2

2.2.1 VCM with QL1

In an n-player VCM with QL1, all players are homogeneous and have the same payoff function and the same endowment E. Hence, a simple specification of the payoff is as follows:

$$\pi_i = E - s_i + aS - bS^2, \tag{2.1}$$

where a and b are positive constants, s_i denotes the individual contribution of player i, and $S = \sum_{i=1}^{n} s_i$ is the group's total contribution. More precisely, we assume that $1 \leq a \leq 2bnE + 1$, $\frac{a-1}{2nE} \leq b$, and $\frac{a-1}{2bn} \leq E$. For this simple game, a list of individual contributions $\hat{s} = (\hat{s}_1, \hat{s}_2, \cdots, \hat{s}_n)$ is a Nash equilibrium if, for all i, $\pi_i(\hat{s}_i, \hat{S}_{-i}) \geq \pi_i(s_i, \hat{S}_{-i})$ for all $s_i \in [0,\ E]$, where $\hat{S}_{-i} = \sum_{j \neq i} \hat{s}_j$. Therefore, from the first-order condition, the sum of Nash equilibrium contributions is

$$\hat{S} = \frac{a-1}{2b}, \hat{S} \in [0, nE]. \tag{2.2}$$

Hence, any combination of individual contributions constitutes a static Nash equilibrium as long as the total contribution equals $\hat{S}$ (Bergstrom et al., 1986).

[9] Typical conditional cooperators are those players who always try to match the average contribution of others in the previous period and whose contribution is insignificantly different from the average contribution of others. Weak free riders are those whose contribution is significantly below the average contribution of other players in the group and who are affected by the difference between their individual contributions and the average.

Anderson et al. (1998) introduce decision errors into this model. They find an interesting result. Although there is a continuum of Nash equilibria, a unique logit equilibrium exists that is symmetric across players. The equilibrium density is a (truncated at the boundary of the choice set) normal density for the quadratic public goods game (the VCM with QL1).[10] Furthermore, they suggest that this model can easily be generalized to allow for individual differences in error parameters. The equilibrium thus becomes a unique asymmetric logit equilibrium. Moreover, the distribution is truncated by the boundary of the choice set, and the expected contribution of the logit equilibrium, therefore, is also sandwiched between the symmetric Nash equilibrium level and half of the endowment. These findings seem consistent with the experimental observations from Isaac and Walker (1998). The nature of this comparative static analysis is that the feedback from repeated trials will help subjects achieve the equilibrium consistency condition of the logit equilibrium and solve the coordination problem.[11]

However, this comparative static analysis is built on the assumption that the dynamic system of VCM is stable and converging to the unique logit equilibrium. If belief updating process cannot lead players to reach the equilibrium consistency condition of the logit equilibrium, this implies that the system is unstable, and the comparative static analysis might thus not be suitable.

Then, we show the dynamic analysis conducted by Saijo (2014) for exploring the equilibrium in the VCM with QL1. The best response function in the VCM with QL1 is as follows:

$$s_i = min\{max\{-\sum_{j\neq i} s_j + \hat{S}, 0\}, E\}, \tag{2.3}$$

where $\hat{S}$ is the Nash prediction for the aggregate contribution given by equation (2.2) (see Bergstrom et al., 1986). The myopic Cournot best response dynamics indicates that player i's contribution at period t directly responds to the total contribution of others in the group at period t-1. Hence, the best response function (2.3) then becomes

$$s_i^t = min\{max\{-\sum_{j\neq i} s_j^{t-1} + \hat{S}, 0\}, E\}. \tag{2.4}$$

[10] See Proposition 3 in Anderson et al. (1998).

[11] The equilibrium consistency condition is that player i's expectations of other players' actions are equal to the means of the actual equilibrium distributions (Anderson et al., 1998).

Now, let us look at the stability property of this dynamic difference system. In the analysis, we employ the following definition of asymptotic stability.

Definition 2.1. An equilibrium $\hat{x}$ is locally asymptotically stable, if and only if there exists some open neighborhood O of $\hat{x}$ such that, for any $x^t \in O$, x^t converges to $\hat{x}$ as t approaches infinity.

The following property is useful to decide whether the Nash equilibria in the difference equation system of equation (2.4) are asymptotically stable (see Bischi et al., 2009; Saijo, 2014).

Property 2.1. Let k be the slope of the best response function at the Nash equilibrium. The system $s_i^t = r(s_{-i}^{t-1})$, (i = 1, 2, ..., n), is locally asymptotically stable if and only if $|k(n - 1)| < 1$.

Because the slope of equation (2.4) is -1 and n-1≮1 if n≥2, all equilibria are not locally asymptotically stable. This indicates that, under the assumptions of self-interested subjects and myopic best response, contributions will alternate between contributing nothing and contributing everything after a few rounds (if $\hat{S} \geq E$) in a simultaneous difference equation system of the VCM with QL1. The nature of this theoretical result is that the feedback from repeated trials will not alleviate the coordination problem, but worsen it. This insight implies the possibility that the dynamic difference system of a VCM experiment with QL1 is unstable.

2.2.2 VCM with QL2

In an n-player VCM with QL2, a simple quadratic payoff function could be given as follows:

$$\pi_i = c(E - s_i) - d(E - s_i)^2 + S, \tag{2.5}$$

where $1 \leq c \leq 2dE + 1$, $\frac{c-1}{2E} \leq d$, and $\frac{c-1}{2d} \leq E$. Then, from the first-order condition, we can get a dominant Nash equilibrium solution for every player

$$\hat{s} = \frac{1-c}{2d} + E, \hat{s} \in [0, E]. \tag{2.6}$$

Therefore, due to a unique dominant equilibrium, the VCM environment with QL2 is similar to the VCM with linear payoff functions. The only difference is the location of the equilibrium in the choice set. Anderson et al. (1998) also introduce decision errors into the quadratic model of the VCM with QL2. They suggest that the decision error should partially explain excessive giving when the Nash equilibrium is less than half of the endowment, because the distribution of the logit equilibrium is also truncated by the boundary of the choice set. Willinger and Ziegelmeyer (2001) provide experimental evidence supporting this theoretical result.

2.3 Experimental Design and Procedures

We conducted the experiments at the Vernon Smith Experimental Economics Lab at Shanghai Jiaotong University (SJTU) in March 2015 (192 subjects) and March 2017 (96 subjects). The subjects were recruited among SJTU students excluding those from the Department of Economics and Management. Subjects participated voluntarily and had no experience of VCM experiments using nonlinear payoff structures. The experiments consisted of 12 sessions. For each session, we recruited more than 30 subjects. We then used a lottery to select the participants. 24 subjects were selected in each session, and we paid a show-up fee to the rest. We used z-Tree to run the experiments (Fischbacher, 2007).

Table 2.1 summarizes the parameters of our experiments.[12] Four different experiments are implemented. Three of these (QL1N, QL1P, and QL1M) employ payoffs based on QL1, which is linear with respect to the private good and nonlinear with respect to the public good, while QL2N is based on QL2, which is linear in the public good and nonlinear in the private good.

[12] Payoff lists and instructions translated from the Chinese version can be found among the supplementary documents. We also present graphs for the relation between returns and tokens for each account and clearly display which part indicates diminishing marginal returns. This makes our design close to the detailed information (DET) experiments in Laury et al. (1999).

Consistent with the design of Sefton and Steinberg (1996), we set the following consistency conditions for the two experiments with nonlinear designs (QL1N and QL2N):

1. The same (symmetric) equilibrium contribution of two tokens per individual.
2. The same (symmetric) socially optimal contribution of six tokens per individual.
3. The approximately equal reward from (symmetric) equilibrium play.
4. The approximately equal reward from (symmetric) socially optimal play.[13]

Table 2.1 Parameters of the experiments

Experiments	QL1N	QL1P	QL1M	QL2N
Payoff function	QL1N: $(E - s_i) + 1.4484S - 0.0137(S)^2 + 28$			
	QL1P and QL1M: $\begin{cases} 10(E - s_i) + 15S, \ S \leq 16; \\ 10(E - s_i) + 5(S - 16) + 240, \ 16 < S \leq 48; \\ 10(E - s_i) + (S - 48) + 400, \ 48 < S \leq 64. \end{cases}$			
	QL2N: $11.5(E - s_i) - 0.875(E - s_i)^2 + S$			
Endowment (Tokens)	8	8	8	8
Additional payment (E$)	28	0	0	0
(symmetric)				
Nash choice ŝ (Payoff)	2(53.7)	2(300)	2(300)	2(53.5)
(symmetric)				
Socially optimal s^*(Payoff)	6(68)	6(420)	6(420)	6(67.5)
Payment ratio	22:1	110:1	110:1	22:1
Periods	15(Random ending)	30	30	15(Random ending)
Groups/Subjects	12/96	6/48	6/48	12/96

s_i denotes the individual contribution of player i; E represents the endowments; and S denotes the group's total contribution.

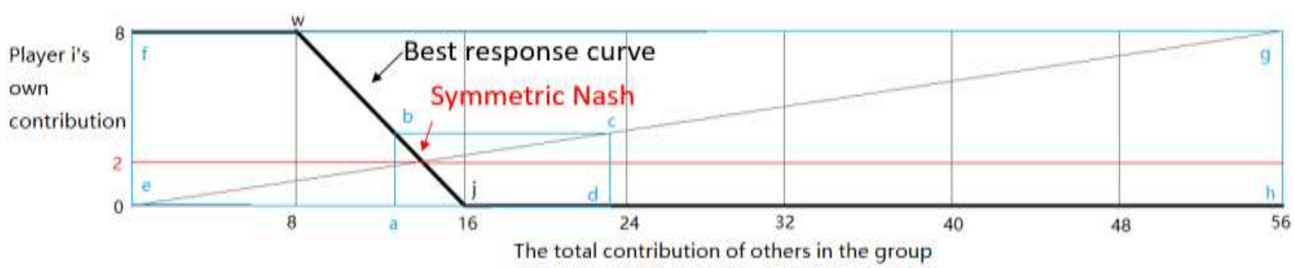
However, our experimental design differs from that of Sefton and Steinberg (1996) in two crucial ways. First, our design employs an eight-player fixed group setting. In the

[13] We set an additional payment to make the rewards from equilibrium play and socially optimal play approximately equal between the two experiments.

design of Sefton and Steinberg (1996), four individuals are randomly allocated to a group at the beginning of each period. We use a relatively large group, following Ostrom et al. (1992), who use an eight-player group setting to study common pool resource environments (see Chapter 4 for more details).

Second, because setting the coefficient of linear returns to be equal to one could be easier for subjects to understand the nonlinear return structure in the payoff table, we do not consider the 5th symmetric condition in Sefton and Steinberg (1996)—the same monetary loss from a one-token unilateral departure from equilibrium play. This design results in the opportunity costs among choices in the QL1N experiment are significantly lower than those in the QL2N experiment. As Smith and Walker (1993) shown, the opportunity costs among choices directly affect the dispersion of individual choices in experiments. Therefore, the relatively small opportunity costs might influence the convergence of choices.[14] To ensure that our experimental observations do not originate from the design of relatively small opportunity costs, we implement the other two experiments (QL1P and QL1M) for robustness checks. The QL1P experiment employs a piecewise linear payoff function as the linear approximation for the nonlinear returns from the public good (similar to the payoff design in Cason and Gangadharan, 2014). The opportunity costs are also increased among choices.[15] The QL1M experiment utilizes the same payoff function as that used in the QL1P experiment but with a different the payoff table in the instructions. The new payoff table uses a matrix to directly connect the choices to the payoffs (see, e.g., the design of payoff tables in Cason et al., 2004).

The experiments with QL1



The QL2N experiment

[14] We thank an anonymous referee for pointing this out.
[15] Different from the QL1N experiment, we remove the fixed payment in each period and boost the magnitude of experimental payoffs by 10 times, but the exchange ratio from experimental dollars to real money increases by only five times (from 22:1 to 110:1) in the QL1P and QL1M experiments. For the choices around the Nash equilibrium, the opportunity cost in the piecewise linear design is significantly greater than is that in the nonlinear design.

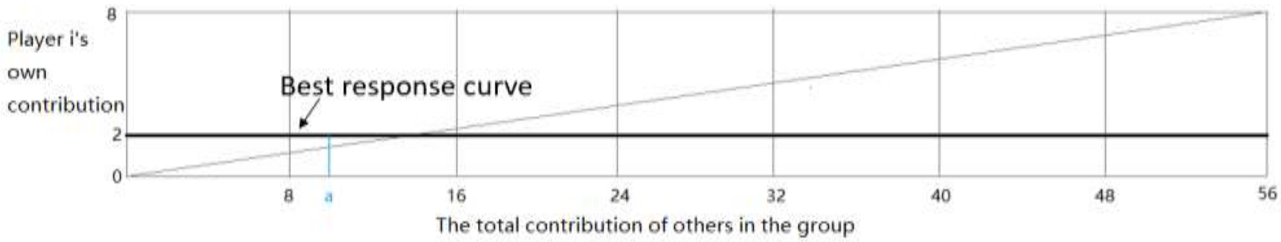


Fig. 2.1 Stability property of the design

We draw the best response curves for the two environments to clearly illustrate the stability property of our design. In Figure 1, the horizontal axis is the total contribution of others in the group, and the vertical axis represents player i's own contribution. For the three experiments with QL1, the myopic Cournot response curve (the bold black line "f-w-j-h") is

$$s_i^t = \min\{\max\{-\textstyle\sum_{j\neq i} s_j^{t-1} + 16,\ 0\},\ 8\}. \tag{2.7}$$

For example, suppose that every player's initial contribution is the same at a/7, which implies that the total contribution of others is initially "a." Obviously, the best response to "a" is point "b." Then, if players are symmetric, the total contribution of others goes to "c." Then, we find the best response to "b" is point "d," that to "d" is point "f," and that to "f" is point "h." Finally, the dynamic difference system will be pulsing between point "f" and point "h." This example shows that, under the assumption of Cournot best response dynamics, the contributions of subjects will be pulsing between 0 and 8 after a few rounds. However, for the QL2N experiment, this curve is derived simply as follows:

$$s_i^t = 2. \tag{2.8}$$

Therefore, the best response to any case is contributing two tokens. Given these theoretical results, we propose the following hypotheses:

Hypothesis 2.1. In the experiment with QL2 (QL2N), individual contributions will converge to the unique Nash equilibrium, which indicates that (*i*) the dispersion of individual contributions decreases and (*ii*) individual contributions become steady with repeated trials.

Hypothesis 2.2. In the experiments with QL1 (QL1N, QL1P, and QL1M), individual contributions will not converge to the symmetric and asymmetric Nash equilibria, which indicates that (*i*) the group's total contribution will be pulsing round after round (the sample autocorrelation statistic should be negative), (*ii*) the dispersion of individual contributions might not decrease because of the intergroup level heterogeneity, and (*iii*) individual contributions will be volatile even in the last periods.

For each session in the QL1N and QL2N experiments, we implement the experiment with a random ending rule. Subjects were certain to participate in the first 15 periods. From the beginning of the 16th period, the experiment would continue with a probability of 0.3. This setting helps to suppress strategic play (e.g., the endgame effect) in a repeated game with the fixed group setting.[16] Data from the first 15 rounds were used for analysis. Furthermore, to show more information regarding the convergence of contributing behavior, the public goods game repeated 30 periods in each session of the QL1P and QL1M experiments. Since these two experiments serve as robustness checks for the observations from QL1N experiments, we have the following third hypothesis.

Hypothesis 2.3. The dynamic patterns of contributions (concerning dispersion and contribution volatility) should not be significantly different among the QL1N, QL1P, and QL1M experiments.

At the beginning of each period, each subject receives eight tokens. They are called upon to allocate these tokens into two accounts: the private account and the public account. All tokens have to be allocated in each period without communication with others, and the feasible choice set is $\{0,1, \ldots ,7,8\}$. Each token in the private account produces a private return to oneself. Each token in the public account produces a public return to each member of the group. The framing of instructions was similar to that of Sefton and Steinberg (1996) and consistent across experiments.

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[16] See Dal B´o (2005). However, other studies find no significant difference between the finite period setting and the random terminated setting (e.g., Selten and Stoecker, 1986; Engle-Warnick and Slonim, 2004).

At the end of each period, the result of that period is reported to each subject. The report consists of three parts: each subject's own decisions, the total tokens in the public account, and his/her own payoff. No subject can observe the individual contributions of other members of the same group. This incomplete information setting is consistent with most studies of the literature on VCM experiments.

The instructions are distributed to each one, at the time when all 24 subjects enter the lab in each session. At the beginning of each session, a native speaking research assistant reads the instruction loudly. Then, control questions are required to be answered correctly to ensure that every subject understands the experimental procedure. At the end of each session, each subject receives his/her payment privately at a preannounced exchange rate of 22 experimental dollars (E$) to 1 Chinese RMB in the QL1N and QL2N experiments and 110 experimental dollars (E$) to 1 Chinese RMB in the QL1P and QL1M experiments. The 192 subjects earn RMB 44.5 (7.5 US dollars) each on average, with a range of RMB 36 to RMB 47 in the QL1N and QL2N experiments and the 96 subjects earn RMB 94 (15 US dollars) each on average, with a range of RMB 80 to RMB 108 in the QL1P and QL1M experiments. Each session lasts about one hour and a half, including the instruction and payment distribution time.

2.4 Results

This section consists of four subsections. The first gives an overview for the experimental data. The second investigates the dispersion of individual contributions. The third shows the dynamics of changes in individual contributions. The final subsection investigates the conditional cooperation in the four experiments and roughly categorizes subjects.

2.4.1 Overview

First, we present an overview of individual contributions. Figure 2.2 shows the average contributions at each period for the four experiments. A decreasing tendency of average contributions is shared by the four experiments. Individual contributions from periods 11 to 15 are significantly lower than those from periods 1 to 5 in both the QL1N and QL2N experiments (p-values = 0.0000 by the Wilcoxon signed-rank tests) and that individual contributions from periods 21 to 30 are significantly lower than those from periods 1 to 10 in both the QL1P (p-value = 0.0171) and QL1M (p-value = 0.0000) experiments.[17]

[17] For all Wilcoxon signed-rank tests in this paper, we first compute two averages across periods 1 to 5 and 11 to 15 for each subject in the QL1N and QL2N experiments and across periods 1 to 10

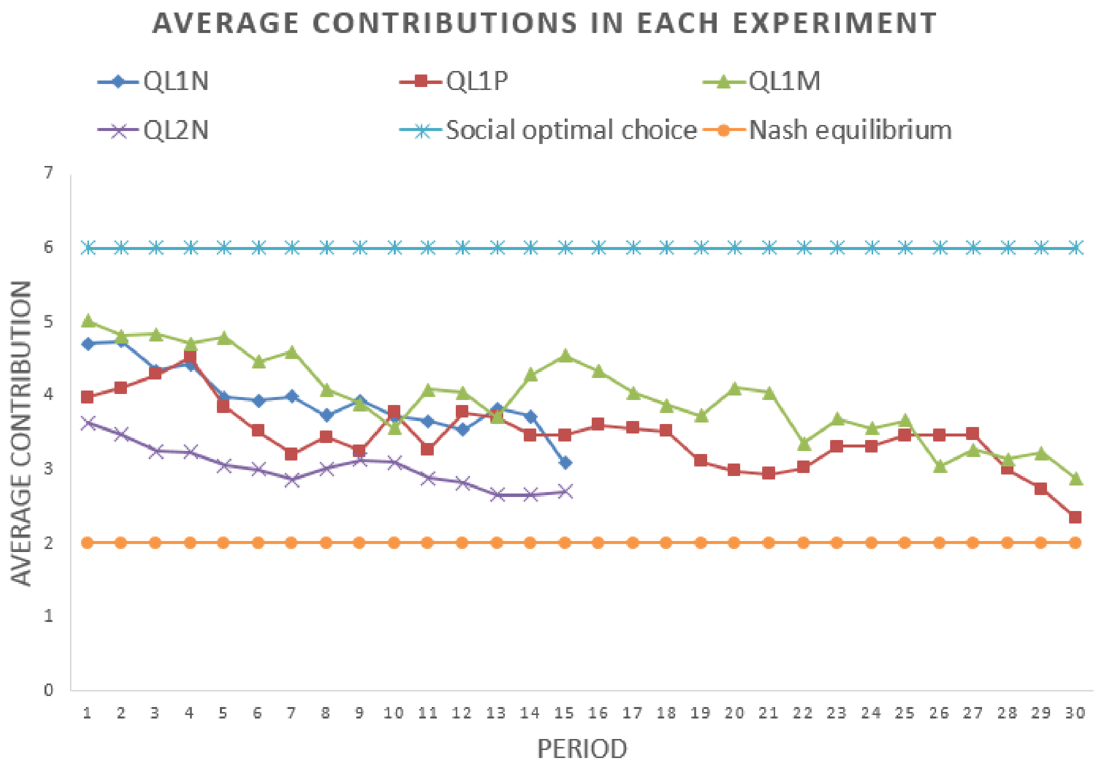
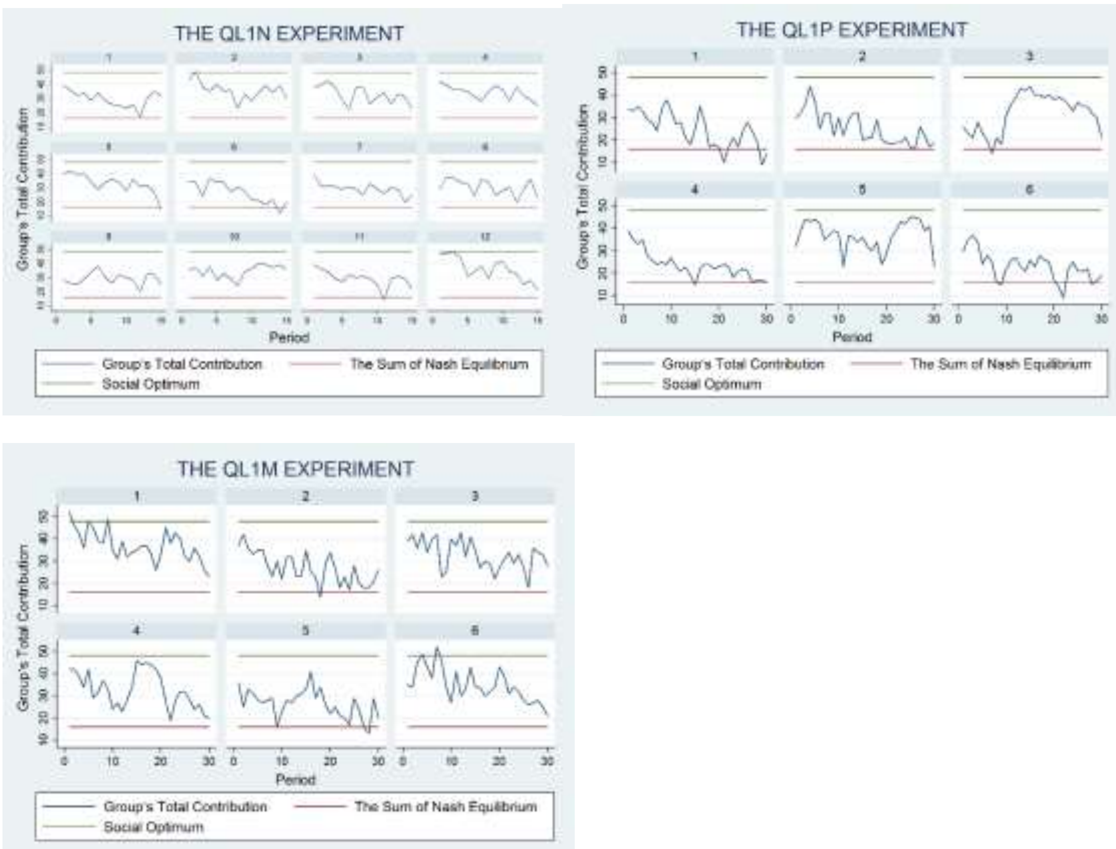


Fig. 2.2 Average contributions in the four experiments

Second, we show an overview of the group's total contributions. Figure 2.3 shows time series plots of the group's total contributions. It clearly shows that the total contributions of all groups are significantly above the Nash prediction. This observation indicates the presence of cooperation. The corresponding sample autocorrelation statistics (α) of each group are reported in Table 2.2. They are positive for all groups. There is a slight difference in autocorrelation statistics between the QL1N and QL2N experiments (p-value = 0.0781 by the Wilcoxon rank-sum test). Figure 2.3 shows that the group's total contribution is pulsing more in some groups in the QL1N experiment than in the QL2N experiment. However, the unstable pulsing seems to have been greatly smoothed compared to the prediction of instability in Saijo (2014). According to the theoretical prediction, serial correlation should be negative in the experiments with QL1. These observations reject the first prediction of hypothesis 2.2.

and 21 to 30 for each subject in the QL1P and QL1M experiments. Then, we conduct the Wilcoxon signed-rank tests over two samples of averages to eliminate correlation across periods.

Panel A: The three experiments with QL1



Panel B: The QL2N experiment

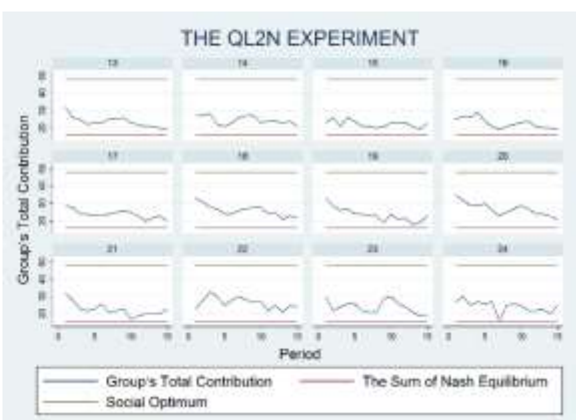


Fig. 2.3 Time series plots of groups' total contributions

Table 2.2 Sample autocorrelation statistics of group's total contributions

The QL1N experiment

Group	1	2	3	4	5	6	7	8	9	10	11	12
α	0.43	0.27	0.21	0.39	0.55	0.27	0.18	0.11	0.03	0.33	0.53	0.34

The QL1P experiment

Group	1	2	3	4	5	6
α	0.68	0.62	0.83	0.71	0.41	0.65

The QL1M experiment

Group	1	2	3	4	5	6
α	0.42	0.47	0.29	0.68	0.35	0.53

The QL2N experiment

Group	1	2	3	4	5	6	7	8	9	10	11	12
α	0.45	0.37	0.10	0.65	0.48	0.56	0.53	0.57	0.45	0.38	0.36	0.09

2.4.2 Dispersion

In this subsection, we show the dynamics of dispersion in the four experiments. A common way to do this in statistics is to use the coefficient of variation to compare dispersion between two samples with different averages. However, in this study, we focus on the dispersion of choices rather than the dispersion of numbers. In this context, each number of contributions represents each position of actions in the choice set. Hence, two contribution samples of {0,0,1,1,2,2,3,3} and {5,5,6,6,7,7,8,8} share an identical dispersion although their averages are different. Therefore, we still use the standard deviation as a measure of dispersion.

Result 2.1 (**Dispersion**): Although average contributions are declining in all four experiments, the standard deviation of individual contributions is ascending in the three experiments with QL1 at the aggregate level, whereas it is descending in the QL2N experiment. The ascending standard deviation of individual contributions at the aggregate level stems from the intragroup level in the three experiments with QL1.

Support: Figure 2.4 shows the dynamic tendency of the standard deviations of individual contributions for the four experiments. The Spearman's rank correlation tests reveal an ascending tendency shared by the three experiments with QL1 ($\rho = 0.7857$, p-value < 0.001 for QL1N; $\rho = 0.7130$, p-value < 0.001 for QL1P; $\rho = 0.7433$, p-value < 0.001 for QL1M), yet a descending tendency appears in the QL2N experiment ($\rho = -0.9464$, p-value < 0.001).

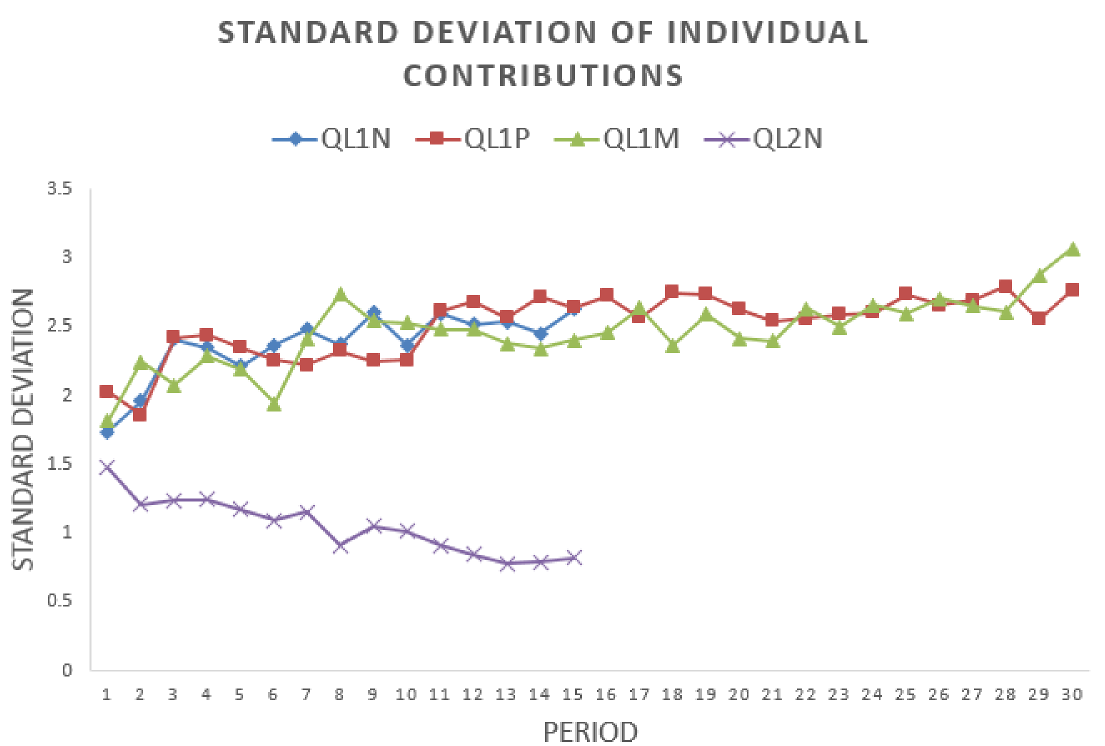
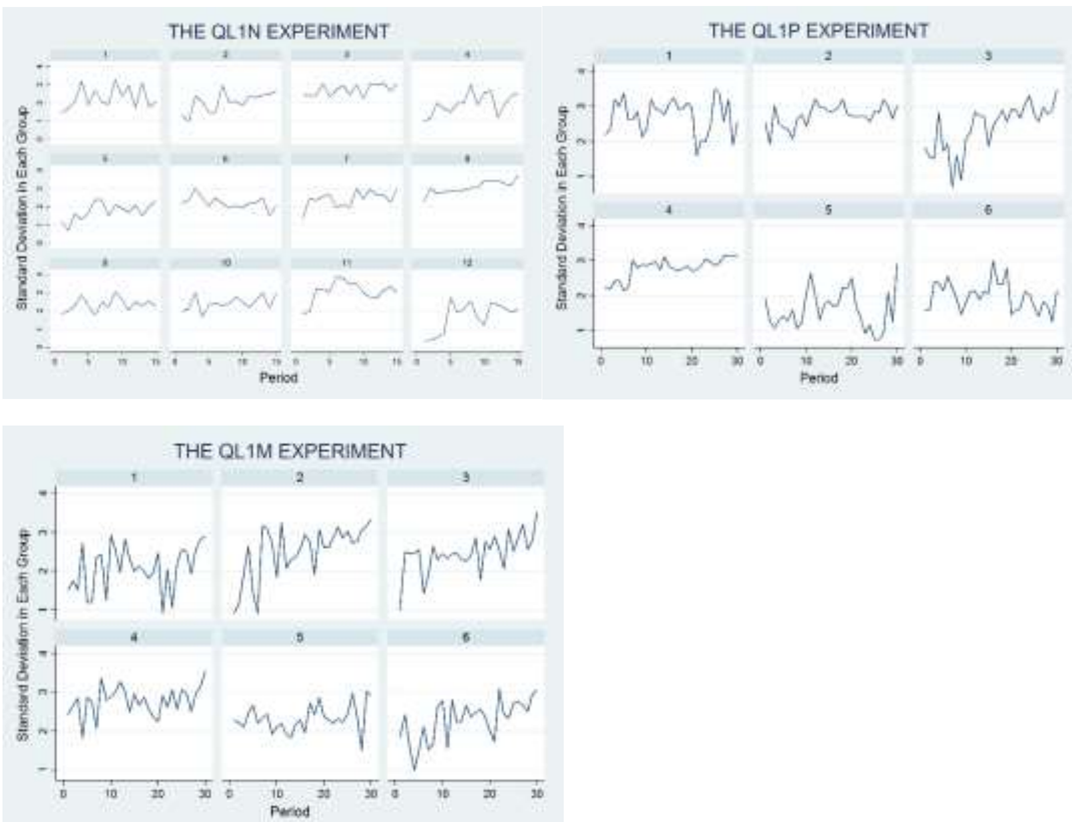


Fig. 2.4 Standard deviation of individual contributions

Figure 2.5 shows time series plots of the standard deviation at the group level in the four experiments. In the three experiments with QL1, eight out of 12 groups from the QL1N experiment, three out of six groups from the QL1P experiment, and five out of six groups from the QL1M experiment share a significantly increasing pattern (p-values < 0.1 for 16 groups; p-values < 0.05 for 11 groups by the Spearman's rank correlation tests); and no group shows a significantly decreasing pattern. By contrast, eight out of 12 groups share a significantly decreasing pattern (p-values < 0.05), and no group shows a significantly increasing pattern in the QL2N experiment.

Panel A: The three experiments with QL1



Panel B: The QL2N experiment

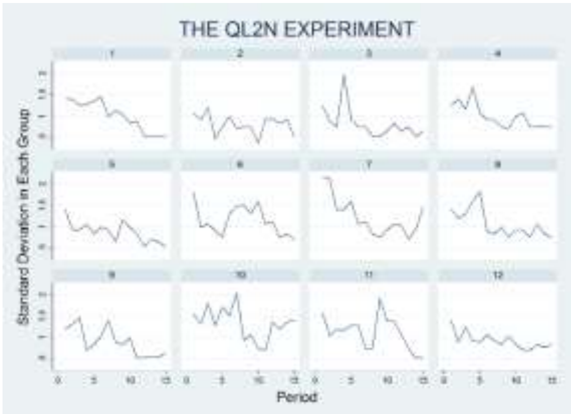


Fig. 2.5 Time series plots of standard deviations in groups

To sum up, the observation that the standard deviation of individual contributions is ascending at the aggregate level emerges from the intragroup level in the three experiments with QL1. This observation does not support that individual contributions are converging to a symmetric equilibrium in the experiments with QL1. However, we also notice that the increasing dispersion at the aggregate level stems mainly from the intragroup level rather than the intergroup level.[18] This observation is inconsistent with the reasoning of the second prediction of hypothesis 2.2.

Therefore, Result 2.1 supports the first prediction of hypothesis 2.1, but rejects the the second prediction of hypothesis 2.2. Furthermore, the observation that all the three experiments with QL1 share similar dynamics of dispersion supports hypothesis 2.3.

2.4.3 Absolute Changes in Individual Contribution

We use the absolute value of the first-order difference of individual contributions ($\left|s_i^t - s_i^{t-1}\right|, t \geq 2$; hereafter "AVFD") to measure the pulsing of individual contributions. If the dynamic system is approaching an equilibrium, the degree of contribution pulsing, the AVFD, on average will diminish.

[18] We also check the dynamical tendency of the standard deviation of the group's total contributions across periods in the four experiments. The Spearman's rank correlation tests show that $\rho = 0.2536$ and p-value = 0.3618 for QL1N, $\rho = 0.5537$ and p-value = 0.0015 for QL1P, $\rho = 0.0007$ and p-value = 0.9972 for QL1M, and $\rho = -0.6643$ and p-value = 0.0069 for QL2N. These results indicate that, in two of the three experiments with QL1, the dispersion at the intergroup level does not increase with repeated trials.

Result 2.2 (**Absolute changes**): The absolute changes on average are diminishing in the QL1P and QL2N experiments. In the QL1N and QL1M experiments, however, they do not decline relative to the beginning of the experiment.

Support: Figure 2.6 shows the dynamic tendency of the average of AVFDs for the four experiments. Comparing sample 1 (the AVFDs from periods 2 to 6) with sample 2 (the AVFDs from periods 11 to 15), the Wilcoxon signed-rank test shows a significant decrease in the QL2N experiment (p-value = 0.0000), but an insignificant result for the QL1N experiment (p-value = 0.1312). Furthermore, for the QL1P and QL1M experiments, comparing sample 1 (the AVFDs from periods 2 to 11) with sample 2 (the AVFDs from periods 21 to 30), the Wilcoxon signed-rank test shows a significant decrease in the QL1P experiment (p-value = 0.0012), yet an insignificant result for the QL1M experiment (p-value = 0.4817). Although there is also a decreasing tendency in the QL1P experiment, the AVFDs in the last 10 periods of the QL1P experiment are still significantly larger than those in the last five periods of the QL2N experiment (p-value = 0.0124, by the Wilcoxon rank-sum test).

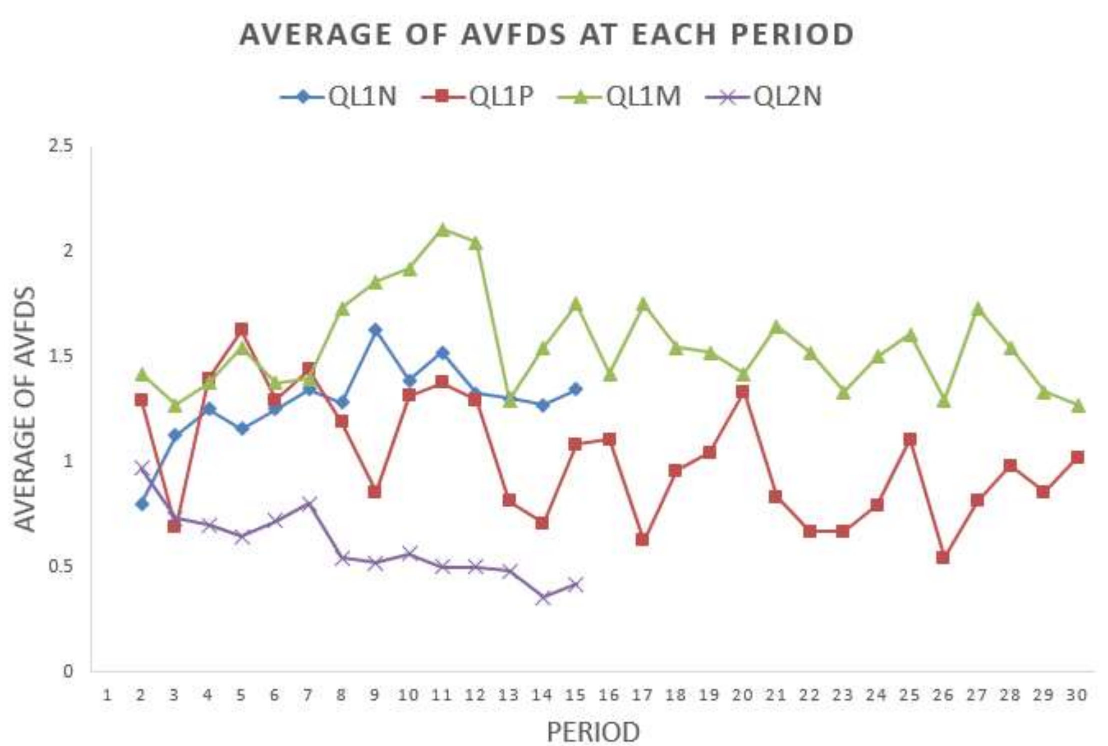


Fig. 2.6 Average of AVFDs at each period

Combined with the observations in the previous subsection, the decreasing AVFDs in the QL2N experiment indicate that the experimental system is converging to the dominant equilibrium, which is symmetric across players. Conversely, the decreasing AVFDs in the QL1P experiment might indicate that some groups in the experiments with QL1 are converging to some asymmetric equilibrium. Therefore, we further check the AVFDs at the group level. Comparing sample 1 with sample 2 in each group of the three experiments with QL1 reveals a significant decrease in four groups (p-value = 0.0138 for group 10 in the QL1N experiment; p-value = 0.0117 for group 2 and p-value = 0.0687 for group 4 in the QL1P experiment; and p-value = 0.0929 for group 1 in the QL1M experiment). However, after checking the individual data in these four groups, we find that the individual contributions of a part of the group members are still volatile in the last periods of the experiment. This is not compatible with the fact that the experimental dynamic system is converging to a static asymmetric equilibrium.

Therefore, Result 2.2 supports the second prediction of hypothesis 2.1 and the group level observations also support the third prediction of hypothesis 2.2. Furthermore, although the observation in the QL1P experiment at the aggregate level is different from those in the other two experiments with QL1, the group level observations show that individual contributions are volatile in the last periods of all the three experiments with QL1. This is consistent with the prediction of hypothesis 2.3.

Overall, our experimental data reveal a clear dynamic pattern showing that contributions are converging to the static equilibrium in the QL2N experiment. By contrast, our observations do not suggest the existence of a process that the dynamic system is approaching a symmetric or asymmetric equilibrium and that the coordination problem is alleviated in the three experiments with QL1. However, we also notice that there are some observations that cannot be explained by our instability theory. For example, there is not a significant pulsing in the group's total contributions in the three experiments with QL1 and the increasing dispersion of individual contribution comes mainly from the intragroup level. Therefore, in the following subsection, we investigate the heterogeneity among individuals in order to generate insights concerning these observations via a categorization of the subjects.

2.4.4 Conditional Cooperation

In the VCM experiments with linear payoff functions, players are often classified into several categories. The three most common categories are free riders, conditional cooperators, and unconditional cooperators. Usually, free riders account for only around 20 percent of the total population. However, conditional cooperators account for around 50 percent (see Fischbacher et al., 2001; Sonnemans et al., 1999; Keser and van Winden, 2000; for a survey, see Chaudhuri, 2011). These findings indicate that the experimental environment is much more complex than the assumption in Saijo (2014) implies. Furthermore, the previous study, Laury et al. (1999), finds that, in the QL1 environment, average contributions varied widely among individuals, even within a single experiment. This might imply that there is a systematic difference in the motivation of cooperation between the experiments with QL1 and QL2.[19] In this subsection, we attempt to investigate the conditional cooperation from a myopic perspective to see whether there is a systematic difference in conditional cooperation across the experiments.

The individual decision rule is assumed to take the following form to isolate the motivation of conditional cooperation.

$$s_i^t - s_i^{t-1} = \alpha_i + \beta_i\left(s_i^{t-1} - \tfrac{1}{7}\textstyle\sum_{j\neq i} s_j^{t-1}\right) + \varepsilon_i, t \geq 2, \tag{2.9}$$

where ε_i is the residual term of player i. Equation (2.9) is estimated using the Seemingly Unrelated Regressions (SUR) for each group of eight players in the four experiments. In this regression (2.9), $-\frac{\alpha_i}{\beta_i}$ approximately denotes the overall distance between player i's contribution and the average contribution of other players in the group. Thus, two aspects of the subjects' contribution behavior could be identified by this regression. First, it shows how many players are reacting to the difference between their own contribution and the average contribution of others (or how many players try to match the average contribution of others in the previous period). Second, It identifies the overall distance between player i's contribution and the average contribution of other players. $\alpha_i > 0$ and $\beta_i < 0$ indicate that subject i's contribution is significantly above the average contribution of other players in the group and is also affected by the difference between his/her contribution and the average. This result means that this subject is a *weak* unconditional cooperator (WUC).[20] In

[19] Here, the term "systematic difference in the motivation for cooperation" is used to indicate the difference in the distribution among different types of subjects.

[20] We call them "*weak* unconditional cooperators" to distinguish them from those unconditional cooperators who always contribute six tokens throughout the experiment.

turn, $\alpha_i < 0$ and $\beta_i < 0$ indicate a *weak* free rider (WFR). A *typical* conditional cooperator (TCC) should have $\alpha_i = 0$ and $\beta_i < 0$, which implies that player i always tries to match the average contribution of others in the previous period and his/her contribution is insignificantly different from the average contribution of others. Moreover, unconditional cooperators (UC) are those who persisted in contributing a fixed number of at least six tokens; conversely, free riders (FR) are those who persisted in contributing a fixed number of no more than two tokens. Hence, through examining α_i and β_i, we can roughly classify all subjects into six categories.[21]

Result 2.3 (**Conditional cooperation**): No systematic difference in conditional cooperation is observed across the four experiments. The individual estimates from the SUR show that around 50 percent of the players could be categorized as typical conditional cooperators; weak free riders and weak unconditional cooperators each account for about 20 percent of the total population in all experiments.

Support: Table 2.3 summarizes the results of the SUR. Briefly, by comparing the number and proportion of subjects of each type, we have not found a systematic difference in conditional cooperation across the four experiments. In all experiments, almost half of the players could be regarded as typical conditional cooperators, while weak free riders and weak unconditional cooperators each account for about 20 percent of the total population. This result is consistent with the previous findings in the linear environment of the VCM experiments. The existence of a considerable proportion of conditional cooperators might be a reason for the smoothed pulsing in the group's total contribution in the experiments with QL1.

Table 2.3 Conditional cooperation

Form	$s_i^t - s_i^{t-1} = \alpha_i + \beta_i\left(s_i^{t-1} - \frac{1}{7}\sum_{j\neq i} s_j^{t-1}\right) + \varepsilon_i, t \geq 2$			
Individual results				
Category	QL1N (96 subjects)	QL1P (48 subjects)	QL1M (48 subjects)	QL2N (96 subjects)

[21] There is one subject from the QL1N experiment who should be classified as $\alpha_i < 0$ and $\beta_i = 0$. Because p-value = 0.049 for $\alpha_i < 0$ and only one observation is considered, we take this observation as an unimportant exception and assign this subject into category $\alpha_i = 0$ and $\beta_i = 0$.

UC	3 (3%)[b]	1 (2%)	2 (4%)	1 (1%)
WUC ($\alpha_i > 0$ and $\beta_i < 0^a$)	19 (20%)	11 (21%)	7 (15%)	17 (18%)
TCC ($\alpha_i = 0$ and $\beta_i < 0$)	40 (42%)	21 (44%)	27 (56%)	48 (50%)
WFR ($\alpha_i < 0$ and $\beta_i < 0$)	21 (22%)	11 (23%)	11 (23%)	20 (21%)
FR	1 (1%)	0 (0%)	0 (0%)	5 (5%)
Unclassified ($\alpha_i = 0$ and $\beta_i = 0$)	12 (12%)	4 (8%)	1 (2%)	5 (5%)

[a] Both α_i and β_i of individual regressions (SUR) are judged by a two-tailed test at the 5% significance level (the null hypotheses are $\alpha_i = 0$ and $\beta_i = 0$).

[b] Percentages of the total population are reported in parentheses.

2.5 Discussion and Conclusion

In this study, we conducted experiments to investigate the dynamic patterns of contributing behavior in the VCM with two quasi-linear payoff functions. We find clear evidence indicating that the system is converging to the dominant equilibrium in the QL2N experiment. Individual contributions decrease and converge with repeated trials, and become steady. By contrast, in the experiments with QL1, although contributions on average are also decreasing with no clearly unstable pulsing in the group's total contributions, individual contributions diverge and change continuously.

These observations do not support that the dynamic system of the VCM with QL1 is converging to an equilibrium, indicating that a comparative static analysis alone might not be suitable for the VCM with QL1 using a fixed group setting. On the other hand, our observation is consistent with the finding of previous studies on the VCM experiments with linear payoff functions. That is, most players in the lab VCM experiment follow the decision rule of conditional cooperators. This might constitute a reason for the growing dispersion we observed in the three experiments with QL1.

Consider a repeated VCM game with two types of players—free riders and conditional cooperators. The decay of the average contribution could be explained by the classical scenario of the interaction between free riders and conditional cooperators if the game has a dominant strategy, such as that of a linear environment. Once the conditional cooperators become frustrated by free riding, they start reducing their contributions. Then, the average contribution becomes close to the dominant equilibrium. Our experimental evidence suggest that this may also be true in the VCM experiment with QL2 in which there is a dominant equilibrium.

In contrast, in the three experiments with QL1, the observations of the dispersion and the absolute changes indirectly suggest another possible interpretation of the interaction between free riders and conditional cooperators in the VCM experiment with QL1. When conditional cooperators become frustrated by free riding, they will reduce their contributions to a certain level. The free riders may then have to increase their contribution to increase their payoffs if they expect that the total contribution of others will become less than the sum of the Nash equilibrium contributions. When the conditional cooperators find that the total contribution is increasing, they will seek to sustain this total contribution level. However, the free riders will then begin to free ride again, and a new round of the decreasing total contribution will begin. We thus conjecture that starting from the dynamic analysis of Saijo (2014) and incorporating the interaction between several different types of players might offer insights into the ascending dispersion we observed in this study.

Finally, two empirical implications of our experimental observations are worth mentioning. First, the growing dispersion indicates that the stability property of the mechanism itself might also be a reason for the diversity of individual contributions, in addition to the social preference heterogeneity among the players. Second, and more importantly, the experimental observation of non-convergence indicates that the Nash equilibrium might not be a suitable theoretical benchmark to use in empirical analyses of the real-world VCM environment if the system is not converging to it.

Supplementary Documents

Instructions and payoff tables in our experiments.

There are four sets of instructions and payoff tables in this supplementary document.

The QL1N experiment, the QL1P experiment, the QL1M experiment, and the QL2N experiment.

(The QL1N experiment)

Instructions

This is an experiment concerning economic decision-making. At the end of today's session, you will be paid in private and in cash. It is essential that you remain silent and do not watch at other people's decisions. Please shut down your cell phone and don’t talk with others. If you have any questions or need assistance of any kind, please raise your hand. If you exclaim out loudly or violate any of the rules explained below, you may be asked to leave and will not be paid. This is necessary for our experiment.

We thank you very much for your cooperation in this regard.

Overview

There will be at least 15 decision-making rounds in this experiment. You will each make a decision in each of these rounds. When the first 15 rounds are finished, the experiment will continue with a probability of 30%. In other words, the experiment will be directly terminated with a probability of 70%. At the end of each round, you will be informed your earnings for that round on the PC screen. The rules are similar in every round.

In the first round, you will be randomly assigned to a group. Each group consists of eight members. The composition of your group will be fixed throughout the experiment. You will not know which of the other people in the lab are in your group in any given round. You will be paid the total of your earnings of all rounds at the end of today's session.

Rules

In each round, you have eight tokens to allocate. You must decide the number of tokens to place into either or both of two accounts: a private account and a group account. All tokens must be placed in one account or the other. Each token you placed in the private account generates a return to you (and to you alone), and each token you placed in the group account generates a return to every member of your group. Returns from the two accounts are listed in the Earning Tables. Everybody has the exact identical Earning Tables. When the experiment begins, you need to enter your decisions in blanks on the screen. Your entries on the blanks must be whole numbers between 0 and 8 and must be summed to be 8.

After everyone has made a decision, the computer will compute the total number of tokens placed in the group account for your group in this round, and prepare a “Report to Subject” for each of you. You can record the number that the computer has reported on the line entitled "Total Number of Tokens Placed By Your Group in Your Group Account was" and compute your earnings. Your earnings in each period are the sum of your earnings from the private account, your earnings from the group account, and an additional fixed payoff 28 E$. To determine your earnings from the private account, you need to find the number from the column headed "Private Account($E - x_i$)” and “Private return (E$)” on the Earning Tables, according to your decisions. To determine your earnings from the group account, you need to find the correct number in the column headed “Group account ($\sum x$)” and “Individual return from the group account (E$)” on the Earning Tables. This part reports the amount you will earn from the group account. Your total payoff will be reported on the PC screen corresponding to the number of tokens you have placed in your private account and your group has placed in the group account in that round.

Next, you should check to see if your calculation is consistent with the computer’s report on the screen. It is extremely important that we both make this calculation and the results are consistent. If your calculation differs from the computer’s or if you are unsure on how to compute your earnings in any round, please raise your hand. When all things are correct, the next round will begin.

Finally, at the end of experiment, the earnings you have gotten in today’s session will be exchanged for Chinese yuan at an exchange rate of 22:1.

Final Remarks

(1) All subjects have the same Earning Tables.

(2) This session will comprise of at least 15 rounds. From 16th round, the experiment will continue with a probability of 30%.

(3) In each round, you and other members of your group will each have 8 tokens to allocate.

(4) In each round, you should decide the number of tokens to place in your private account and the number of tokens to place in your group account. You must distribute all 8 tokens in each round.

(5) Your earnings from the private account depend only on your decision (the number of tokens that you placed in the account).

(6) Your earnings from the group account depend upon the total number of tokens your group placed in this account.

(7) The members in your group will be fixed throughout the experiment.

(8) The exchange rate from experimental dollars to Chinese yuan is 22:1.

(9) Do not discuss your decisions with other subjects.

Are there any questions?

If all things are clear, please click “next” on your screen and finish those questions. Note that the purpose of those questions is only to make you understand the instructions and your answers will not affect your earnings in the experiment.

Appendix

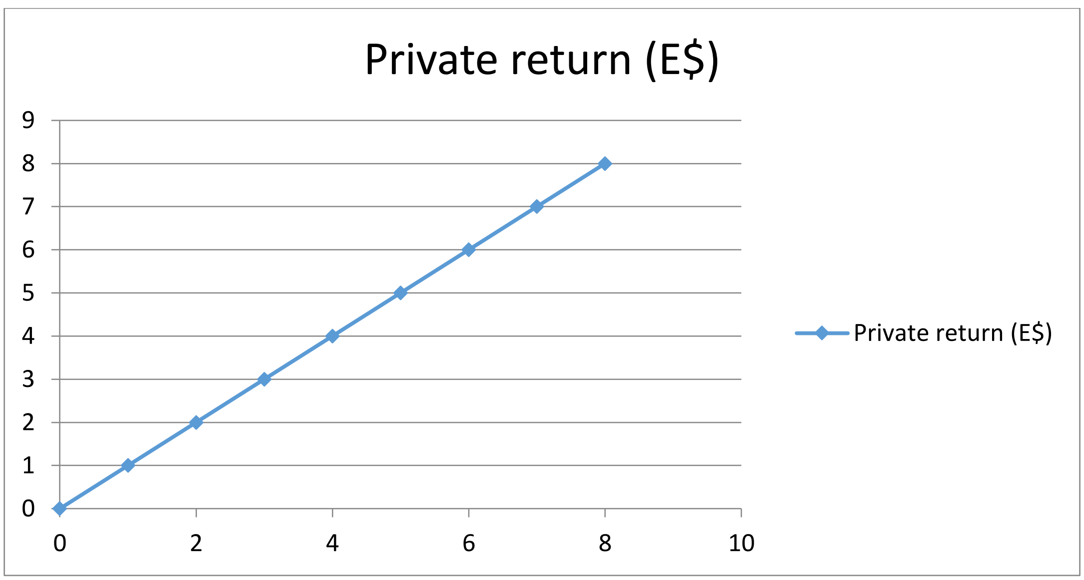
Earning Tables:

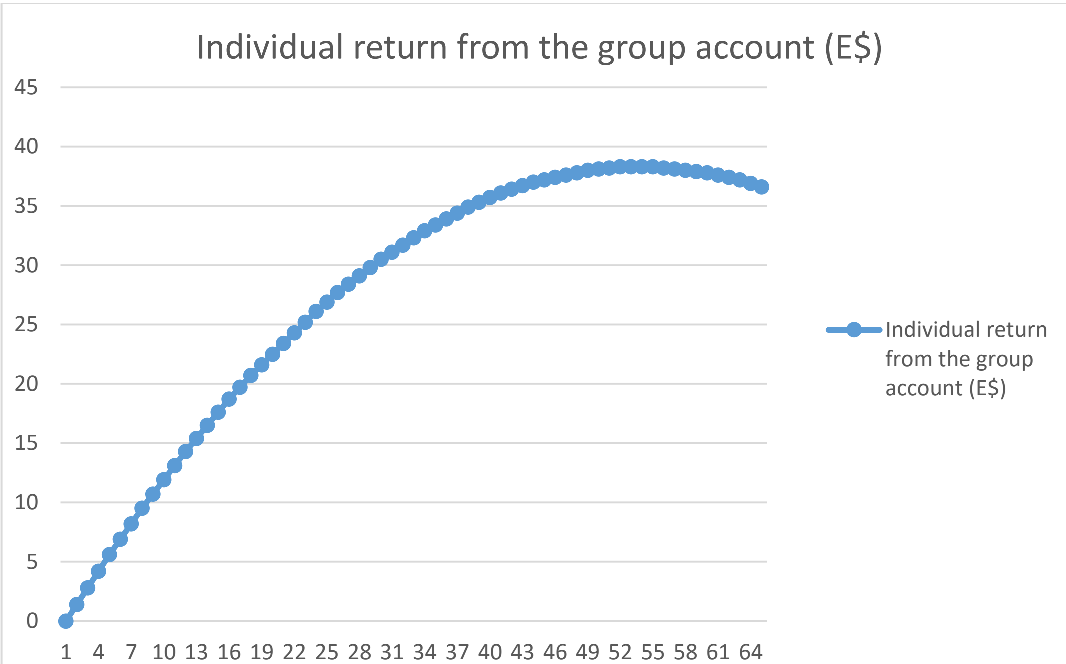
Total payoff = Private return + Individual return from the group account+28

Private account ($E - x_i$)	Private return (E$)	Group account ($\sum x$)	Individual return from the group account (E$)	Group account ($\sum x$)	Individual return from the group account (E$)
0	0	0	0	33	32.9
1	1	1	1.4	34	33.4
2	2	2	2.8	35	33.9
3	3	3	4.2	36	34.4
4	4	4	5.6	37	34.9
5	5	5	6.9	38	35.3
6	6	6	8.2	39	35.7
7	7	7	9.5	40	36.1
8	8	8	10.7	41	36.4
		9	11.9	42	36.7
		10	13.1	43	37
		11	14.3	44	37.2
		12	15.4	45	37.4
		13	16.5	46	37.6
		14	17.6	47	37.8
		15	18.7	48	38
		16	19.7	49	38.1
		17	20.7	50	38.2
		18	21.6	51	38.3
		19	22.5	52	38.3
		20	23.4	53	38.3
		21	24.3	54	38.3
		22	25.2	55	38.2

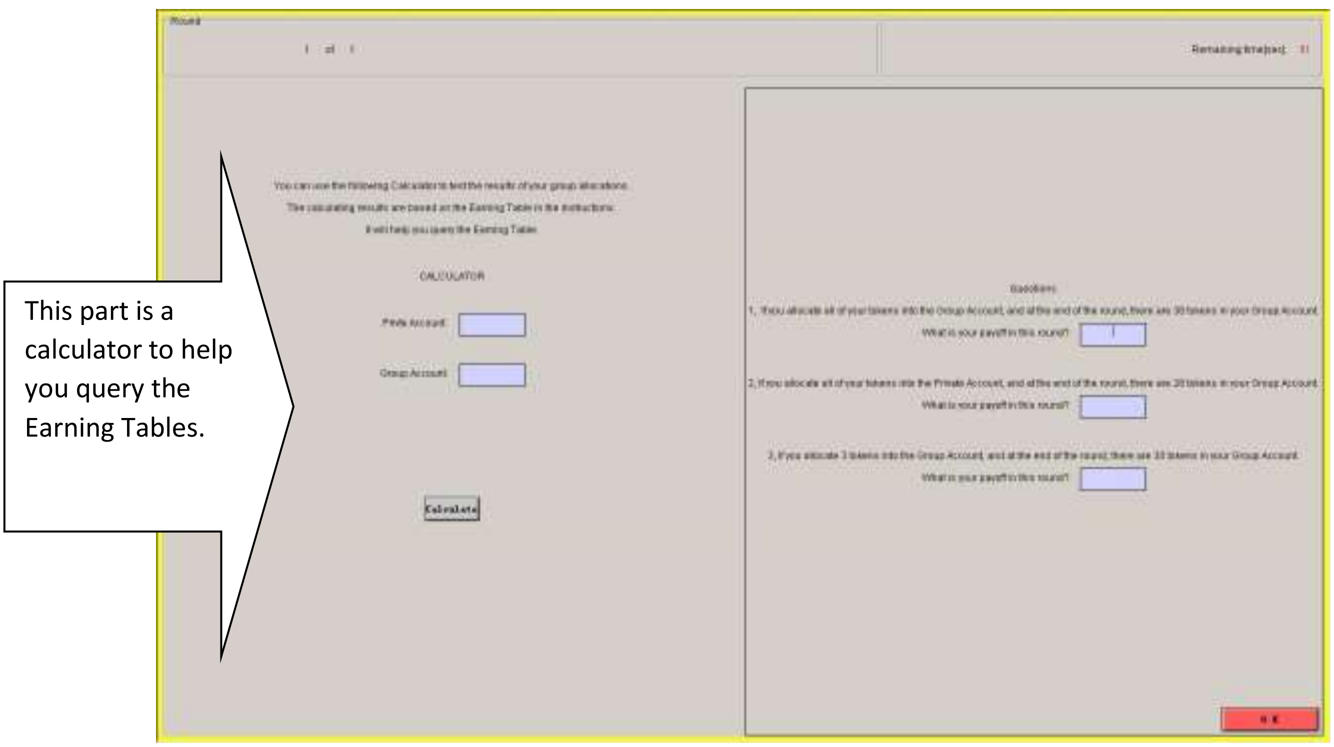
	23	26.1	56	38.1
	24	26.9	57	38
	25	27.7	58	37.9
	26	28.4	59	37.8
	27	29.1	60	37.6
	28	29.8	61	37.4
	29	30.5	62	37.2
	30	31.1	63	36.9
	31	31.7	64	36.6
	32	32.3		

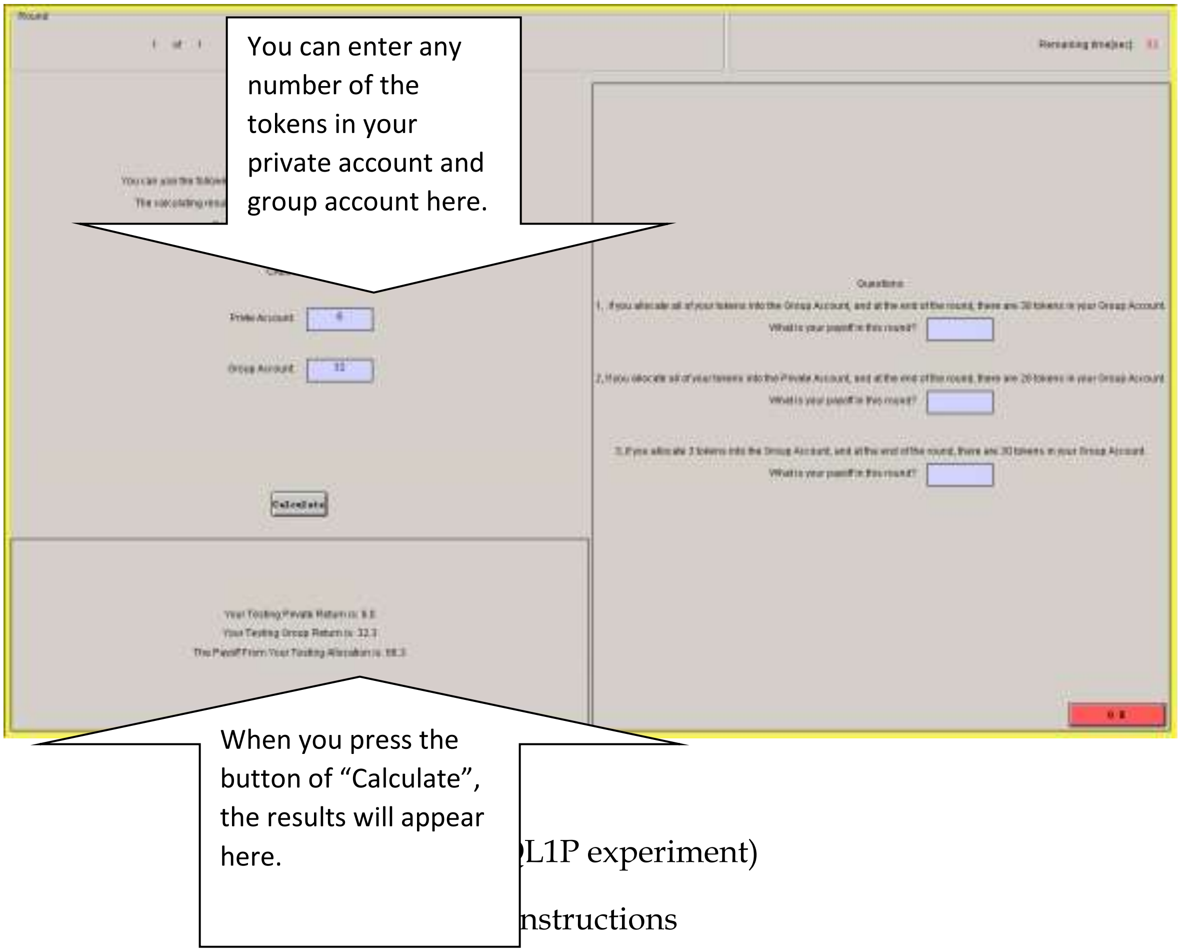
Tables of two kinds of return





Explanation for the calculator





L1P experiment)

nstructions

This is an experiment concerning economic decision-making. At the end of today's session, you will be paid in private and in cash. It is important that you remain silent and do not watch at other people's decisions. Please shut down your cell phone and don't talk with others. If you have any questions or need assistance of any kind, please raise your hand. If you exclaim out loudly or violate any of the rules explained below, you may be asked to leave and will not be paid. This is necessary for our experiment.

We thank you very much for your cooperation in this regard.

Overview

There will be 30 decision-making rounds in this experiment. You will each make a decision in each of these rounds. At the end of each round, you will be informed your earnings for that round on the PC screen. The rules are similar in every round.

In the first round, you will be randomly assigned to a group. Each group consists of eight members. The composition of your group will be fixed throughout the experiment. You will not know which of the other people in the lab are in your group in any given round. You will be paid the total of your earnings of all rounds at the end of today's session.

Rules

In each round, you have eight tokens to allocate. You must decide the number of tokens to place into either or both of two accounts: a private account and a group account. All tokens must be placed in one account or the other. Each token you placed in the private account generates a return to you (and to you alone), and each token you placed in the group account generates a return to every member of your group. Returns from the two accounts are listed in the Earning Tables. Everybody has the exact identical Earning Tables. When the experiment begins, you need to enter your decisions in the blanks on the screen. Your entries on the blanks must be whole numbers between 0 and 8 and must be summed to be 8.

After everyone has made a decision, the computer will compute the total number of tokens placed in the group account by your group in this round, and prepare a “Report to Subject” for each of you. You can record the number that the computer has reported on the line entitled "Total Number of Tokens Placed By Your Group in Your Group Account was" and compute your earnings. Your earnings in each period are the sum of your earnings from both the private account and the group account. To determine your earnings from the private account, you need to find the number from the column headed "Private Account($E - x_i$)” and “Private return (E$)” on the Earning Tables, according to your decision. To determine your earnings from the group account, you need to find the correct number in the column headed “Group account ($\sum x$)” and “Individual return from the group account (E$)” on the Earning Tables. This part reports the amount you will earn from the group account. Your total payoff will be reported on the PC screen corresponding to the number of tokens you have placed in your private account and your group has placed in the group account in that round.

Next, you should check to see if your calculation is consistent with the computer’s report on the screen. It is extremely important that we both make this calculation and the results are consistent. If your calculation differs from the computer’s or if you are unsure on how to compute your earnings in any round, please raise your hand. When all things are correct, the next round will begin.

Finally, at the end of experiment, the earnings you have gotten in today's session will be exchanged for Chinese yuan at an exchange rate of 110:1.

Final Remarks

(1) All subjects have the same Earning Tables.

(2) This session will last 30 rounds.

(3) In each round, you and other members of your group will each have 8 tokens to allocate.

(4) In each round, you need to decide the number of tokens to place in your private account and the number of tokens to place in your group account. You must distribute all 8 tokens in each round.

(5) Your earnings from the private account depend only on your decision (the number of tokens that you placed in the account).

(6) Your earnings from the group account depend upon the total number of tokens your group placed in this account.

(7) The members in your group will be fixed in each round.

(8) The exchange rate from experimental dollars to Chinese yuan is 110:1

(9) Do not discuss your decisions with other subjects.

Are there any questions?

If all things are clear, please click "next" on your screen and finish those questions. Note that the purpose of those questions is only to make you understand the instructions and your answers will not affect your earnings in the experiment.

Appendix

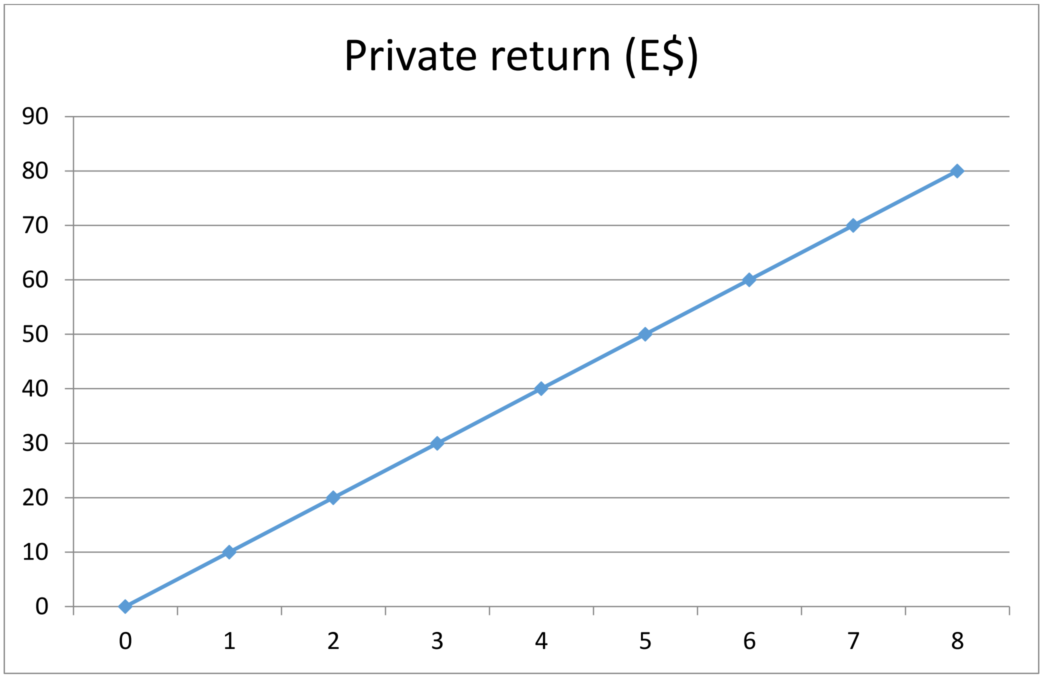
Earning Tables:

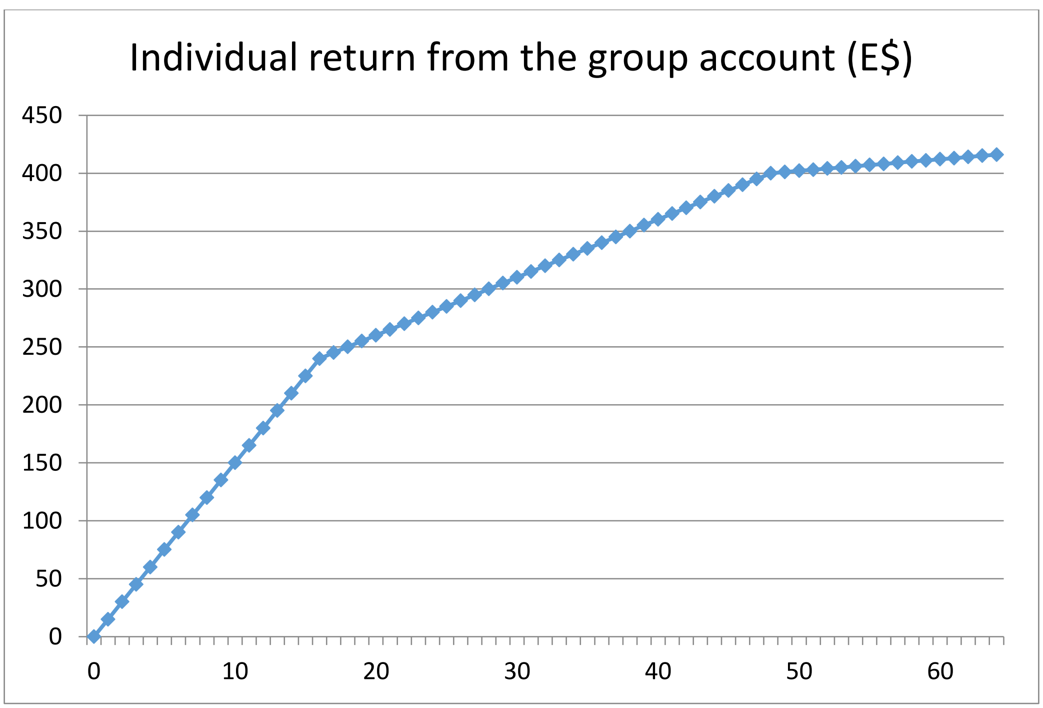
Total payoff = Private return + Individual return from the group account

Private	Private return	Group	Individual	Group	Individual

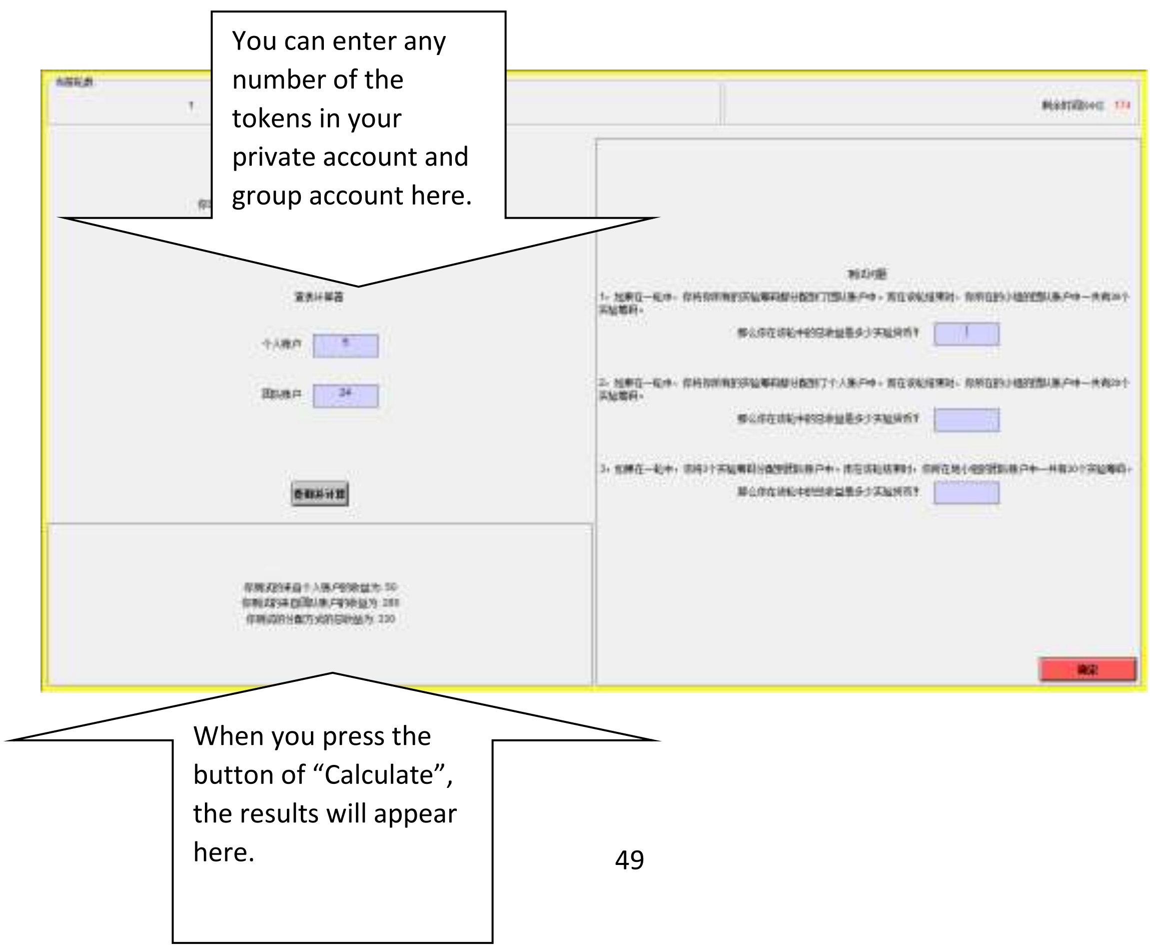
account $(E - x_i)$	(E$)	account $(\sum x)$	return from the group account (E$)	account $(\sum x)$	return from the group account (E$)
0	0	0	0	33	325
1	10	1	15	34	330
2	20	2	30	35	335
3	30	3	45	36	340
4	40	4	60	37	345
5	50	5	75	38	350
6	60	6	90	39	355
7	70	7	105	40	360
8	80	8	120	41	365
		9	135	42	370
		10	150	43	375
		11	165	44	380
		12	180	45	385
		13	195	46	390
		14	210	47	395
		15	225	48	400
		16	240	49	401
		17	245	50	402
		18	250	51	403
		19	255	52	404
		20	260	53	405
		21	265	54	406
		22	270	55	407
		23	275	56	408
		24	280	57	409
		25	285	58	410
		26	290	59	411
		27	295	60	412
		28	300	61	413
		29	305	62	414
		30	310	63	415
		31	315	64	416
		32	320		

Tables of two kinds of return





Explanation for the calculator



(The QL1M experiment)

Instructions

This is an experiment concerning economic decision-making. At the end of today's session, you will be paid in private and in cash. It is important that you remain silent and do not watch at other people's decisions. Please shut down your cell phone and don't talk with others. If you have any questions or need assistance of any kind, please raise your hand. If you exclaim out loudly or violate any of the rules explained below, you may be asked to leave and will not be paid. This is necessary for our experiment.

We thank you very much for your cooperation in this regard.

Overview

There will be 30 decision-making rounds in this experiment. You will each make a decision in each of these rounds. At the end of each round, you will be informed your earnings for that round on the PC screen. The rules are similar in every round.

In the first round, you will be randomly assigned to a group. Each group consists of eight members. The composition of your group will be fixed throughout the experiment. You will not know which of the other people in the lab are in your group in any given round. You will be paid the total of your earnings for all rounds at the end of today's session.

Rules

In each round, you have eight tokens to allocate. You must decide the number of tokens to place into either or both of two accounts: a private account and a group account. All tokens must be placed in one account or the other. Your earnings are listed in the Earning Table. Everybody has the exact same Earning Tables. When the experiment begins, you need to enter your decisions in the blanks on the screen. Your entries on the blanks must be whole numbers between 0 and 8 and must be summed to be 8.

After everyone has made a decision, the computer will compute the total number of tokens placed in the group account by the other members in your group in this round, and prepare a "Report to Subject" for each of you. You can record the number that the computer has reported on the line entitled "Total Number of Tokens Placed By the Other Members of Your Group in Your Group Account was" and compute your earnings. In each round, your earnings depend on the tokens placed by your own and the total tokens placed by the other seven group members into the group account. In the Earning Table, you can find the column corresponding to the number of tokens placed to the group account by you own and the line corresponding to the total number of tokens placed to the group account by the other seven group members. The number at the intersection of the line and the column is your earning in that round. Your earnings will be reported on the PC screen corresponding to the tokens you have placed in the group account and the total tokens that the other seven members of your group have placed in the group account in that round.

Next, you should check to see if your calculation is consistent with the computer's report on the screen. It is extremely important that we both make this calculation and the results are consistent. If your calculation differs from the computer's or if you are unsure on how to compute your earnings in any round, please raise your hand. When all things are correct, the next round will begin.

Finally, at the end of experiment, the earnings you have gotten in today's session will be exchanged for Chinese yuan at an exchange rate of 110:1.

Final Remarks

(1) All subjects have the same Earning Table.

(2) This session will last 30 rounds.

(3) In each round, you and other members of your group will each have 8 tokens to distribute.

(4) In each round, you need to decide the number of tokens to place in your private account and the number of tokens to place in your group account. You must allocate all 8 tokens in each round.

(5) Your earnings depend on the tokens that you have placed in the group account and the total tokens that the other seven members of your group have placed in the group account.

(6) The members in your group will be fixed in each round.

(7) The exchange rate from experimental dollars to Chinese yuan is 110:1

(8) Do not discuss your decisions with other subjects.

Are there any questions?

If all things are clear, please click "next" on your screen and finish those questions. Note that the purpose of those questions is only to make you understand the instructions and your answers will not affect your earnings in the experiment.

Appendix

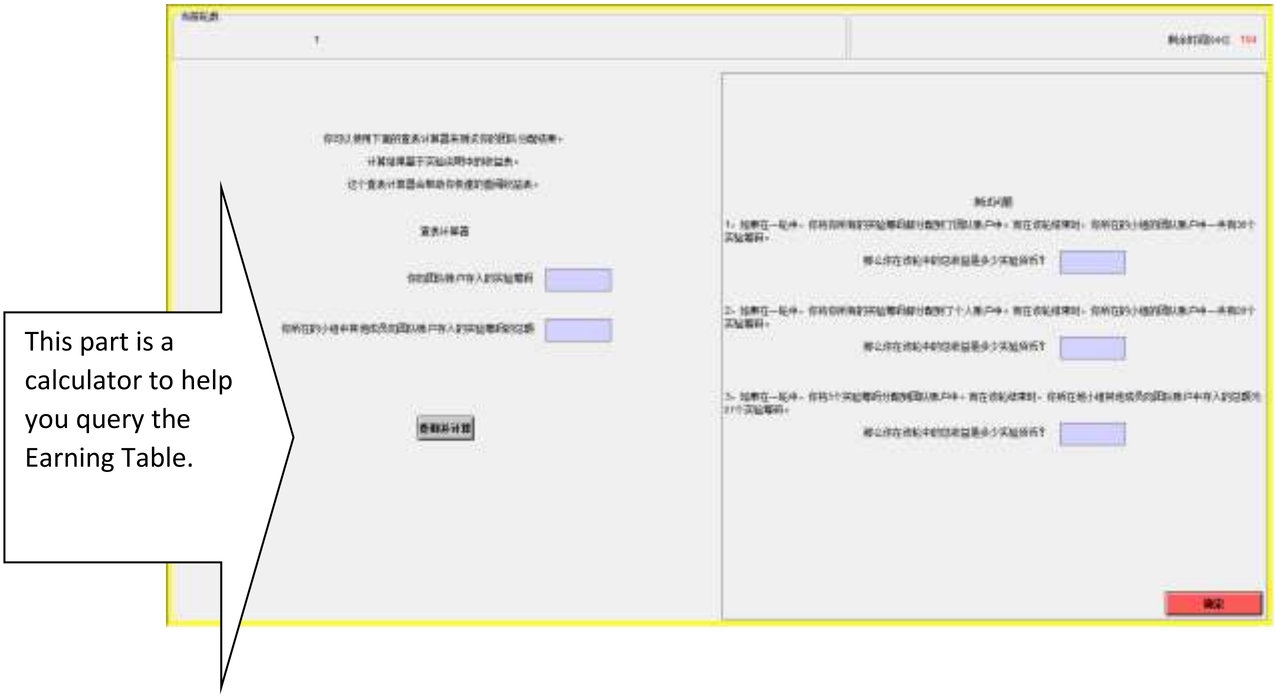
Earning Table:

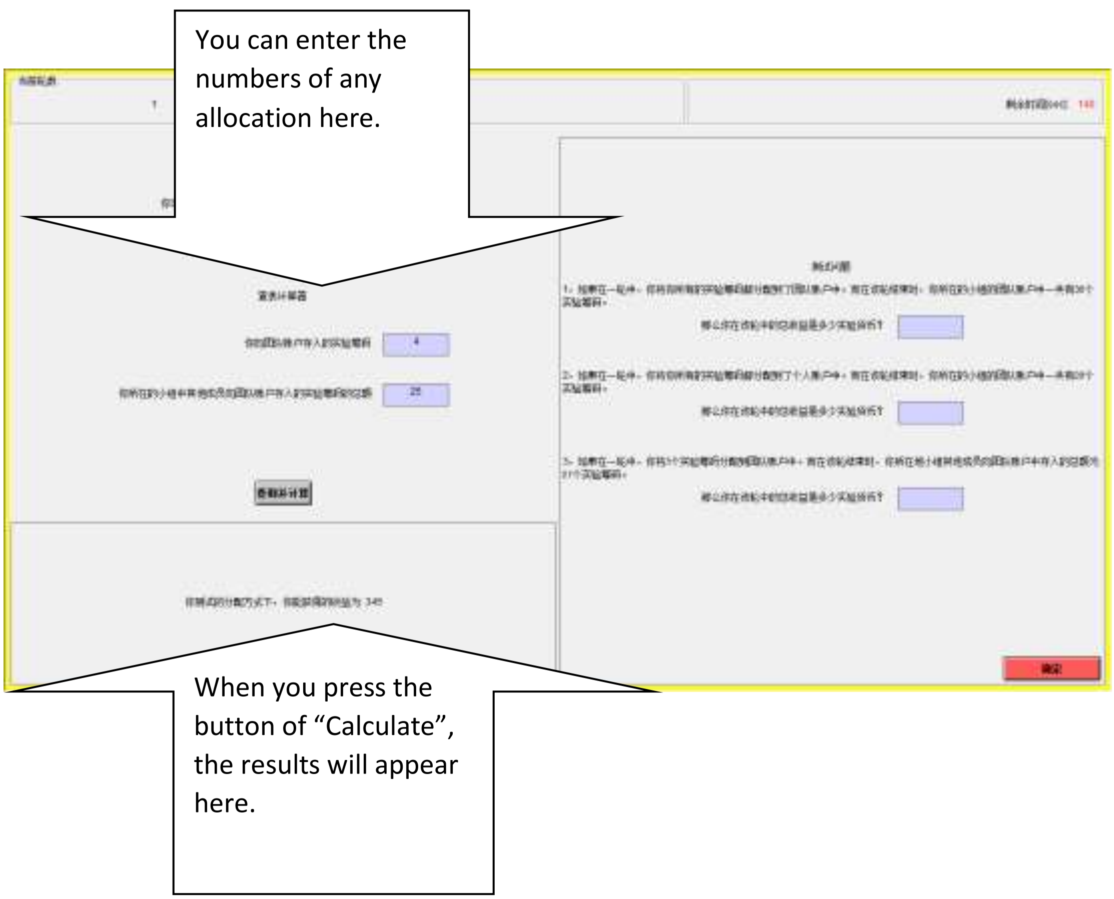
The tokens that you have placed in the group account / The total tokens that the other seven members of your group has placed in the group account.	0	1	2	3	4	5	6	7	8
0	80	85	90	95	100	105	110	115	120
1	95	100	105	110	115	120	125	130	135
2	110	115	120	125	130	135	140	145	150
3	125	130	135	140	145	150	155	160	165
4	140	145	150	155	160	165	170	175	180
5	155	160	165	170	175	180	185	190	195
6	170	175	180	185	190	195	200	205	210
7	185	190	195	200	205	210	215	220	225
8	200	205	210	215	220	225	230	235	240
9	215	220	225	230	235	240	245	250	245
10	230	235	240	245	250	255	260	255	250

11	245	250	255	260	265	270	265	260	255
12	260	265	270	275	280	275	270	265	260
13	275	280	285	290	285	280	275	270	265
14	290	295	300	295	290	285	280	275	270
15	305	310	305	300	295	290	285	280	275
16	320	315	310	305	300	295	290	285	280
17	325	320	315	310	305	300	295	290	285
18	330	325	320	315	310	305	300	295	290
19	335	330	325	320	315	310	305	300	295
20	340	335	330	325	320	315	310	305	300
21	345	340	335	330	325	320	315	310	305
22	350	345	340	335	330	325	320	315	310
23	355	350	345	340	335	330	325	320	315
24	360	355	350	345	340	335	330	325	320
25	365	360	355	350	345	340	335	330	325
26	370	365	360	355	350	345	340	335	330
27	375	370	365	360	355	350	345	340	335
28	380	375	370	365	360	355	350	345	340
29	385	380	375	370	365	360	355	350	345
30	390	385	380	375	370	365	360	355	350
31	395	390	385	380	375	370	365	360	355
32	400	395	390	385	380	375	370	365	360
33	405	400	395	390	385	380	375	370	365
34	410	405	400	395	390	385	380	375	370
35	415	410	405	400	395	390	385	380	375

36	420	415	410	405	400	395	390	385	380
37	425	420	415	410	405	400	395	390	385
38	430	425	420	415	410	405	400	395	390
39	435	430	425	420	415	410	405	400	395
40	440	435	430	425	420	415	410	405	400
41	445	440	435	430	425	420	415	410	401
42	450	445	440	435	430	425	420	411	402
43	455	450	445	440	435	430	421	412	403
44	460	455	450	445	440	431	422	413	404
45	465	460	455	450	441	432	423	414	405
46	470	465	460	451	442	433	424	415	406
47	475	470	461	452	443	434	425	416	407
48	480	471	462	453	444	435	426	417	408
49	481	472	463	454	445	436	427	418	409
50	482	473	464	455	446	437	428	419	410
51	483	474	465	456	447	438	429	420	411
52	484	475	466	457	448	439	430	421	412
53	485	476	467	458	449	440	431	422	413
54	486	477	468	459	450	441	432	423	414
55	487	478	469	460	451	442	433	424	415
56	488	479	470	461	452	443	434	425	416

Explanation for the calculator


This part is a calculator to help you query the Earning Table.


You can enter the numbers of any allocation here.
When you press the button of "Calculate", the results will appear here.

(The QL2N experiment)

Instructions

This is an experiment concerning economic decision-making. At the end of today's session, you will be paid in private and in cash. It is important that you remain silent and do not watch at other people's decisions. Please shut down your cell phone and don't talk with others. If you have any questions or need assistance of any kind, please raise your hand. If you exclaim out loudly or violate any of the rules explained below, you may be asked to leave and will not be paid. This is necessary for our experiment.

We thank you very much for your cooperation in this regard.

Overview

There will be at least 15 decision-making rounds in this experiment. You will each make a decision in each of these rounds. When the first 15 rounds are finished, the experiment will continue with a probability of 30%. In other words, the experiment will be directly terminated with a probability of 70%. At the end of each round, you will be informed your earnings for that round on the PC screen. The rules are similar in every round.

In the first round, you will be randomly assigned to a group. Each group consists of eight members. The composition of your group will be fixed throughout the experiment. You will not know which of the other people in the lab are in your group in any given round. You will be paid the total of your earnings for all rounds at the end of today's session.

Rules

In each round, you have eight tokens to allocate. You must decide the number of tokens to place into either or both of two accounts: a private account and a group account. All tokens must be placed in one account or the other. Each token you placed in the private account generates a return to you (and to you alone), and each token you placed in the group account generates a return to every member of your group. Returns from the two accounts are listed in the 'Earning Tables'. Everybody has the same Earning Tables. When the experiment begins, you need to enter your decisions in the blanks on the screen. Your entries on the blanks must be whole numbers between 0 and 8 and must be summed to be 8.

After everyone has made a decision, the computer will compute the total number of tokens placed in the group account by your group in this round, and prepare a "Report to Subject" for each of you. You can record the number that the computer has reported on the line entitled "Total Number of Tokens Placed By Your Group in Your Group Account was" and compute your earnings. Your earnings in each period are the sum of your earnings from both the private account and the group account. To determine your earnings from the private account, you need to find the number from the column headed "Private Account($E - x_i$)" and "Private return (E$)" on the Earning Tables according to your decisions. To determine your earnings from the group account, you need to find the correct number in the column headed "Group account ($\sum x$)" and "Individual return from the group account (E$)" on the Earning Tables. This part reports the amount you will earn from the group account. Your total payoff will be reported on the PC screen corresponding to the number of tokens you have placed in your private account and your group has placed in the group account in that round.

Next, you should check to see if your calculation is consistent with the computer's report on the screen. It is extremely important that we both make this calculation and the results are consistent. If your calculation differs from the computer's or if you are unsure on how to compute your earnings in any round, please raise your hand. When all things are correct, the next round will begin.

Finally, at the end of experiment, the earnings you have gotten in today's session will be exchanged for Chinese yuan at an exchange rate of 22:1.

Final Remarks

(1) All subjects have the same Earning Tables.

(2) This session will consist of at least 15 rounds. From 16th round, the experiment will continue with a probability of 30%.

(3) In each round, you and other members of your group will each have 8 tokens to distribute.

(4) In each round, you need to decide the number of tokens to place in your private account and the number of tokens to place in your group account. You must allocate all 8 tokens in each round.

(5) Your earnings from the private account depend only on your decision (the number of tokens that you placed in the account).

(6) Your earnings from the group account depend upon the total number of tokens your group placed in this account.

(7) The members in your group will be fixed in each round.

(8) The exchange rate from experimental dollars to Chinese yuan is 22:1

(9) Do not discuss your decisions with other subjects.

Are there any questions?

If all things are clear, please click "next" on your screen and finish those questions. Note that the purpose of those questions is only to make you understand the instructions and your answers will not affect your earnings in the experiment.

Appendix

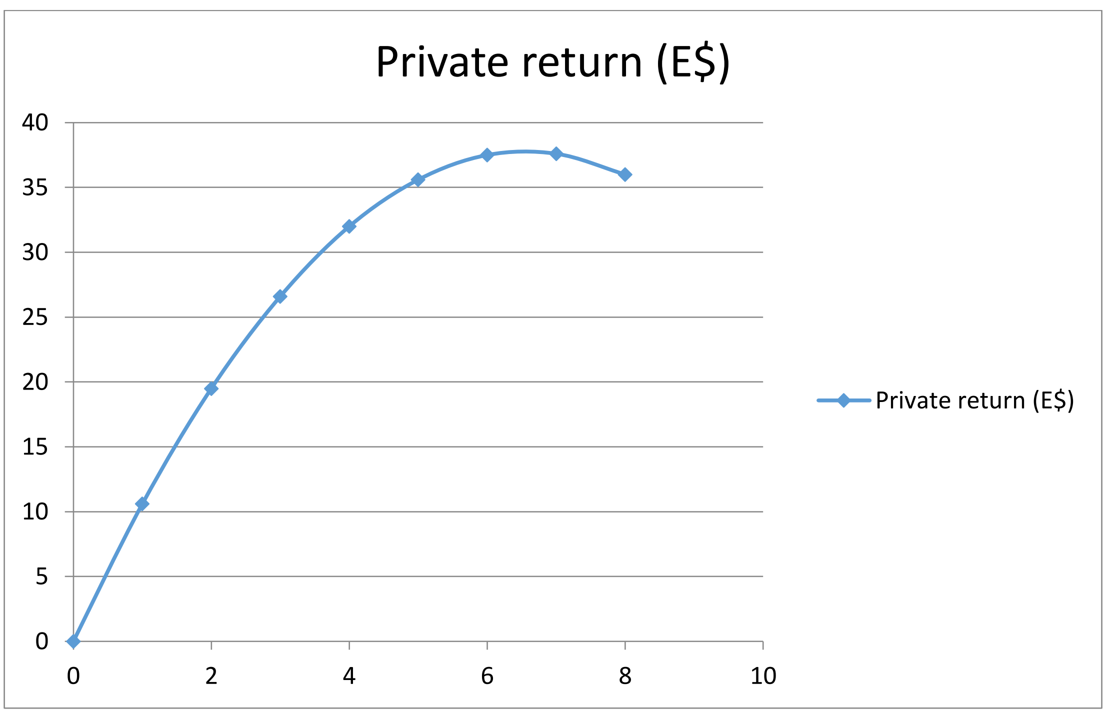
Earning Tables:

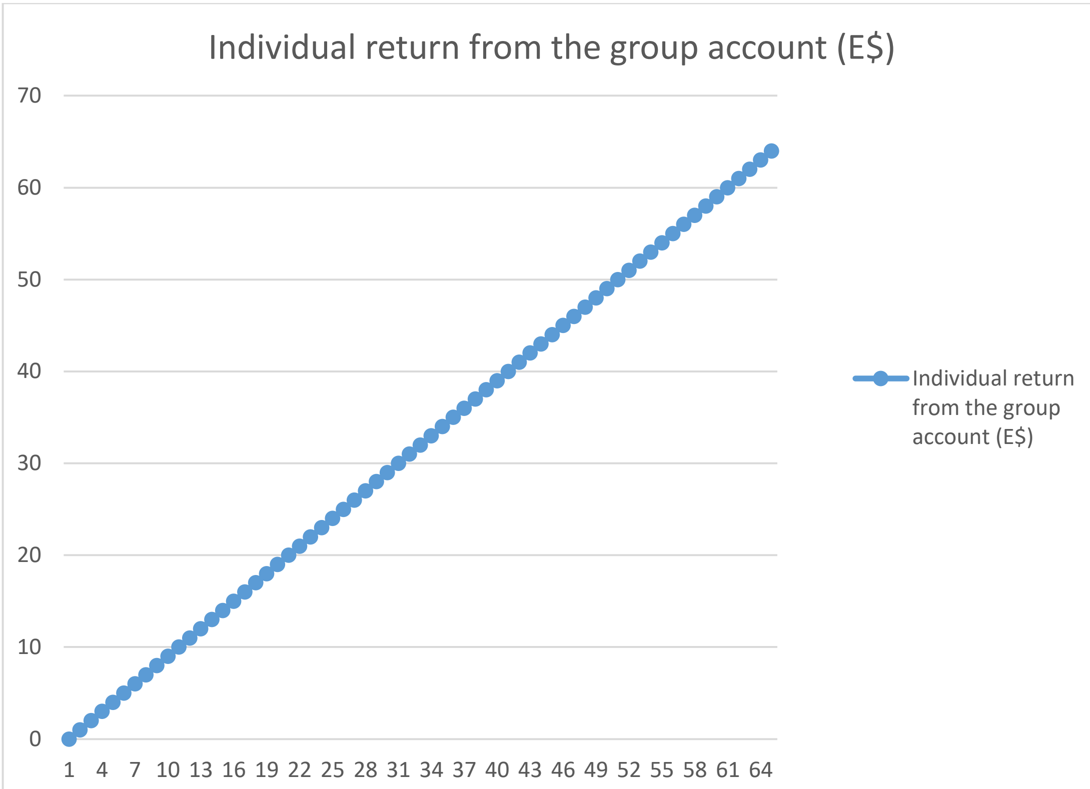
Total payoff = Private return + Individual return from the group account

Private account $(E - x_i)$	Private return (E$)	Group account ($\sum x$)	Individual return from the group account (E$)	Group account ($\sum x$)	Individual return from the group account (E$)
0	0	0	0	33	33
1	10.6	1	1	34	34
2	19.5	2	2	35	35
3	26.6	3	3	36	36
4	32	4	4	37	37
5	35.6	5	5	38	38
6	37.5	6	6	39	39
7	37.6	7	7	40	40
8	36	8	8	41	41
		9	9	42	42
		10	10	43	43
		11	11	44	44
		12	12	45	45
		13	13	46	46

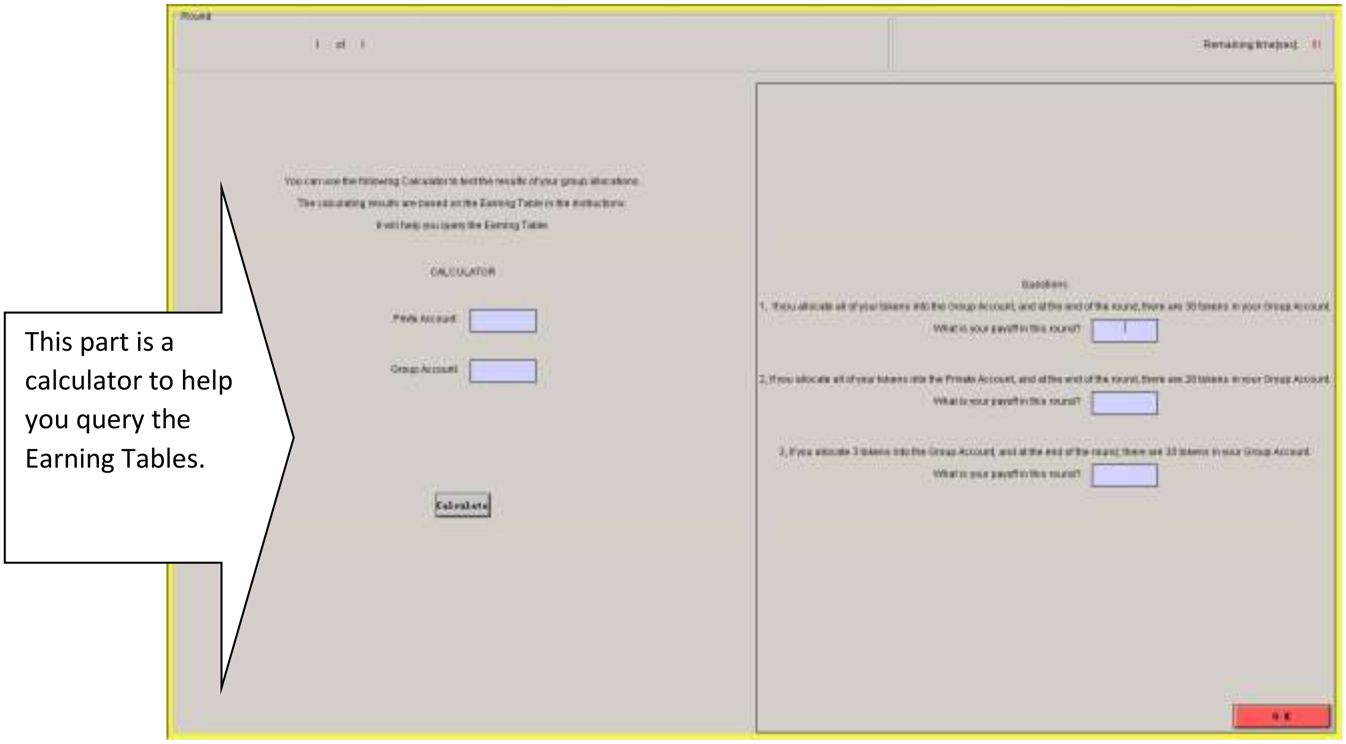
	14	14	47	47
	15	15	48	48
	16	16	49	49
	17	17	50	50
	18	18	51	51
	19	19	52	52
	20	20	53	53
	21	21	54	54
	22	22	55	55
	23	23	56	56
	24	24	57	57
	25	25	58	58
	26	26	59	59
	27	27	60	60
	28	28	61	61
	29	29	62	62
	30	30	63	63
	31	31	64	64
	32	32		

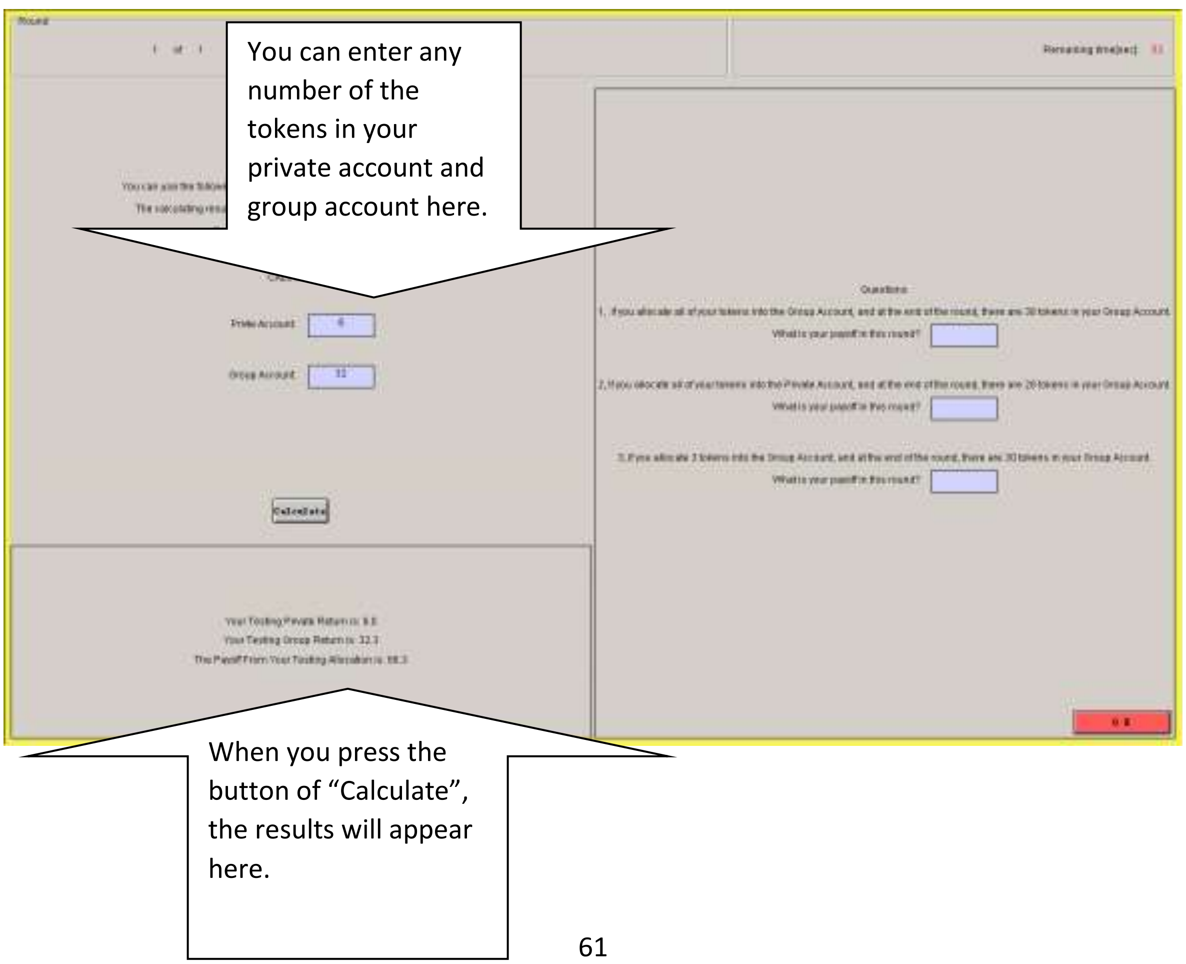
Tables of two kinds of return





Explanation for the calculator


This part is a calculator to help you query the Earning Tables.


You can enter any number of the tokens in your private account and group account here.
When you press the button of “Calculate”, the results will appear here.

Chapter 3

Belief formation, Response, and Convergence in the Voluntary Contribution Mechanism with Heterogeneous Quasi-Linear Payoff Functions

3.1 Introduction

In many situations, the equilibrium analysis plays a central role in economic studies. Most of these studies take an implicit assumption that the dynamic system they concerned eventually converges to the equilibrium benchmark used in the studies. However, if a dynamic system is not locally or globally stable at the equilibrium, only a static equilibrium analysis is not sufficed. For a long time, the empirical investigations regarding stability properties of the Nash equilibrium have attracted a lot of attention in the field of oligopoly competition (i.e. Cox and Walker 1998; Rassenti et al. 2000; Huck et al. 2002). By contrast, most of the experimental studies on the voluntary contribution mechanism (VCM) ignore this problem because they employ a design of linear environments in which there always exists a dominant equilibrium. This might fail to capture the problem of different stability properties of the Nash equilibrium in the real-world VCM scenarios (Saijo 2014; Feng et al. 2018).

In this study, we are interested in the quasi-linear VCM environment. In most practical cases of providing public goods using the VCM, the private good is money. Hence, the marginal return of the private good could be assumed to be a constant. However, the marginal return of a specific public good usually decreases as the level of the public good increases. Therefore, a quasi-linear VCM environment could be used to model these scenarios. In a homogeneous setting of this environment, there are multiple locally unstable Nash equilibria (Saijo 2014). Feng et al. (2018) have further empirically demonstrated the non-convergence of individual contributions although there still exists a distance between experimental observations and the instability argument of Saijo (2014). As an extension of their study, the current study devotes to investigating the heterogeneous setting of the quasi-linear VCM environment because participators usually benefit in different ways from the public good in the real-world scenarios. After including benefit heterogeneity in this environment, a unique static Nash equilibrium exists in the game (Bergstrom et al. 1986; Saijo 2015). Furthermore, based on the assumption of Cournot best-response dynamics in which players simultaneously make a self-interested best response to their last observations of their opponents' actions, Saijo (2015) shows a necessary and sufficient condition for global stability at the unique Nash equilibrium in this asymmetric environment.

This theoretical result implies that different heterogeneous settings induce different stability properties for the unique Nash equilibrium and, thus, the contribution behavior might also differ among these settings in the quasi-linear VCM experiments. However, previous studies focus only on comparing experimental observations between treatments with a heterogeneous design and those with a homogeneous design (for linear VCM environments, see Ledyard (1995); for nonlinear VCM environments, see Chan et al. (1999, 2012); McGinty and Milam (2013)). In other words, in order to better understand the effects of heterogeneous benefits, the theoretical results of Saijo (2015) deserve further experimental investigation. To the best of our knowledge, this is the first study that aims to provide experimental comparisons of contributions across different heterogeneous designs in a quasi-linear VCM environment.

On the basis of previous experimental observations, although the Cournot best-response dynamic is useful in theoretical analyses, its assumptions of the myopic belief formation process and the self-interested best response process are usually too strict to explain experimental observations in the VCM experiments. The challenges come from empirical evidence of both the belief formation process and the response process.

Regarding the belief formation process, Healy (2006) provides a theoretical discussion and experimental evidence based on a k-period average learning model, which assumes players form their beliefs in the current period from their observations of the previous k periods, in a quasi-linear VCM environment with a heterogeneous design. Fischbacher and Gächter (2010) further provide experimental evidence showing that belief formation in a linear VCM environment can be regarded as a weighted average of the belief and the observation of the previous period.

Regarding the response process, many studies on VCM experiments suggest that most players are conditional cooperators who always want to match the (average) contributions of others (Chaudhuri 2011). Several different motivations of conditional cooperation are well documented in the literature. For example, it can be explained by theoretical models with assumptions of inequity aversion and/or reciprocity. Fehr and Schmidt (2006) provide a survey of these other-regarding utility models. In particular, in the linear VCM environment, the observed conditional cooperation is closely related to the marginal per capita return (MPCR) (Goeree et al. 2002; Ledyard 1995). This is because different MPCRs of a VCM environment induce different opportunity costs among choices. A high MPCR has a strong positive impact on conditional cooperation because the opportunity cost of matching beliefs is relatively low.

However, in the quasi-linear VCM environment, the previous study, Healy (2006), finds that players seem to make the best response to the average of observations in previous up to seven periods. In addition, in the neighbor field of common-pool resources, Saijo et al. (2017) empirically show that subjects are relatively myopic and very close to the best-response behavior using the experimental data from Walker et al. (1990). Therefore, the current study still takes the predictions of the Cournot best-response dynamics from Saijo (2015) as a theoretical benchmark. We intend to empirically investigate decision processes employed by subjects in a lab experiment and to show the distance between experimental observations and theoretical predictions.

Our analysis investigates the belief formation process, the response process, and their effects on convergence. To this end, for simplicity, we choose a three-player group setting, with two levels of benefits from the public good. Four treatments with different heterogeneous settings are designed to share an identical Nash equilibrium, but with different stability properties. Two treatments in our design are globally stable, while the other two are non-globally stable, following the theoretical prediction of Saijo (2015).[22] Moreover, in contrast to previous studies, we investigate the decision-making processes of players by eliciting their beliefs about individual contributions of the other group members, rather than about the average contributions of others, in the experiment. Therefore, the overall decision-making process in the experiment is divided into two parts: a belief-formation process and a response process.

Our data show significant differences in the belief-formation processes, the response processes, and the convergence of subjects' contribution behavior across the four treatments. The Nash equilibrium is a good predictor for the two globally stable treatments, but not for the two non-globally stable treatments. However, even though the convergence of contributions differs among the four treatments, the groups' total contributions are not significantly different in the last 10 periods of the experiments. Furthermore, in order to determine why the convergence in each of the four treatments differs, we use a simulation to compare the outcomes under several different counterfactual assumptions. Our main result is that the theoretical predictions are well supported by the experimental evidence in the two globally stable treatments, but that the non-convergence in the two non-globally stable treatments stems from changes in the decision-making processes of subjects, rather than from the non-global stability of the Cournot best-response dynamics.

The remainder of the paper is structured as follows. In section 3.2, we describe the environment and the theoretical results of Saijo (2015). Section 3.3 presents our experimental design and procedure, and then we report our findings in section 3.4. In section 3.5, we conduct a simulation using a 2 × 2 design to investigate the isolated effect on the convergence of the belief-formation process and the response process. The final section concludes the paper.

3.2 Environment and Theoretical Results

Consider a voluntary contribution mechanism (VCM) environment. There are n players. For the set of players $I = \{1, \dots, n\}$, each i has differentiable quasi-linear payoff functions from consuming private goods x_i and the single public good S, which is the sum of all players'

[22] In this study, we say a dynamic system is non-globally stable at an equilibrium unless the dynamic sequences starting from all initial points in the feasible strategy space converge to the equilibrium. We provide a formal definition of the global stability in Section 3.2.

contributions $(s_1, \ldots, s_n)$. That is $\pi_i(x_i, S) = x_i + t_i(S)$, where $S = \sum_{i=1}^{n} s_i$ and $t_i(S)$ is increasing and strictly concave in S. Let E_i denote the endowment of player *i*. Then, player *i* faces the following maximization problem:

$$Max_{s_i}\ \pi_i(x_i, s_i + s_{-i}), \tag{3.1}$$

subject to $E_i = x_i + s_i$, where $s_{-i} = \sum_{j \neq i} s_j$. In such a maximization problem, it is well known that the best response function is as follows:

$$s_i = Min\{Max\{-\sum_{j \neq i} s_j + a_i, 0\}, E_i\}, \tag{3.2}$$

where $a_i = t_i'^{-1}(1)$, which is the intercept (Bergstrom et al. 1986; Saijo 2015). Let $\pi_i(E_i - s_i, s_i + s_{-i}) = v_i(s_i, s_{-i})$. In such an environment, a list of individual contributions $\hat{s} = (\hat{s}_1, \hat{s}_2, \cdots, \hat{s}_n)$ is a Nash equilibrium if, for all i, $v_i(\hat{s}_i, \hat{s}_{-i}) \geq v_i(s_i, \hat{s}_{-i})$ for all $s_i \in [0, E_i]$, where $\hat{s}_{-i} = \sum_{j \neq i} \hat{s}_j$. For simplicity, let a_1 denote the intercept of the player with the largest intercept, and a_j be the intercept of the best-response curve of player *j*. Then, the following proposition from Saijo (2015) shows the uniqueness of the Nash equilibrium.

Proposition 3.1. Suppose that $a_1 > a_j \geq 0$ for all j $\neq 1$, and $E_i \geq a_i$ for all i. Then the unique Nash equilibrium is $(a_1, 0, \ldots, 0)$.

Proposition 3.1 states that, in equilibrium, the player with the largest intercept contributes an amount equal to his/her own intercept, while all other group members contribute nothing.

Before we discuss the stability property of this unique Nash equilibrium, it is necessary to define several concepts with regard to the stability property. In this study, the stability property of an equilibrium refers only to the asymptotical stability of the Cournot best-response dynamics. The Cournot best-response dynamics indicate that the best-response function of equation (3.2) becomes

$$s_{i,t} = Min\{Max\{-\sum_{j \neq i} s_{j,t-1} + a_i, 0\}, E_i\}, \tag{3.3}$$

where $s_{i,t}$ indicates the contribution of player *i* at period *t*. An intuitive interpretation of the asymptotical stability is that if an equilibrium is asymptotically stable, all nearby solutions not only stay nearby but also tend to the equilibrium (see, Hirsch and Smale 1974). Hence, we refer to this stability property as the Cournot stability, where a system is globally stable if and only if the sequences starting from every possible initial point in the dynamic system converge to some equilibrium with Cournot best-response dynamics.[23] Formally, we employ the following definition of global stability.

Definition 3.1. Let $O = \prod_{i \in I}[0, E_i]$ denote the feasible strategy space of system (3.3). The system is globally asymptotically stable at an equilibrium $\hat{s}$, if and only if, for any $s_t = (s_{1,t}, \dots, s_{n,t}) \in O$, s_t converges to $\hat{s}$ as t approaches infinity.

Since Proposition 3.1 shows that the Nash equilibrium is unique, global stability indicates that sequences starting from every feasible initial point converge to the unique Nash equilibrium. Based on the assumption of Cournot best-response dynamics, the following proposition from Saijo (2015) shows the necessary and sufficient condition for the global stability of the Nash equilibrium.

Proposition 3.2. Suppose that $a_1 > a_j \geq 0$ for all j $\neq 1$, and $E_i \geq a_i$ for all i. Then, the system is globally stable at the unique Nash equilibrium if and only if $a_1 > \sum_{j=2}^{n} a_j$.

Proposition 3.2 indicates that if the largest intercept is sufficiently large (larger than the sum of the other intercepts), then the system is globally stable at the unique Nash equilibrium; otherwise, it is non-globally stable at the unique Nash equilibrium. The non-global stability indicates that sequences starting from some initial points will not converge to Nash equilibrium and will be pulsing between some particular points after a few periods. This implies that contributions might become unstable (repeatedly alternate between some numbers). For details, see discussions in the next section.

Based on these two propositions of Saijo (2015), we design four treatments with an identical Nash equilibrium, but with different stability properties. For each of global stability and non-global stability, we design two treatments to serve as a robustness check for the experimental observations. In the next section, we explain our experimental design and procedure.

3.3 Experimental Design and Procedure

The experiments were conducted at the Vernon Smith Experimental Economics Lab at Shanghai Jiao Tong University (SJTU) in March 2016. We designed four treatments of three-player repeated public goods games. Each treatment consists of four sessions. In each session,

[23] Here, "all possible initial points" means all possible combinations of the initial play of every player.

there are 21 or 24 voluntary subjects. Subjects were recruited from among the SJTU students via an Internet recruiting system. The experiment was run on a local area network using a program called z-Tree (Fischbacher 2007).

At the beginning of the experiment, subjects are assigned randomly to a three-person group ($n = 3$). The composition of the groups remains the same throughout the session. Then, each player in a group is randomly assigned an investor number (1, 2, or 3). These investor numbers also remain fixed for subjects throughout the session. In each session, the public goods game is repeated for 25 periods.

At the beginning of each period, every player receives an endowment of 12 tokens and then decides on the number of tokens that he/she intends to contribute to a common project. The feasible choice set is $s_i \in \{0,1,\dots,12\}$. Contributing to the common project generates a payoff to every player in the group, given by the following payoff function:

$$\pi_i = 10[12 - s_i + (a_i + 1)\, ln(S + 1)]\,;\; i = 1, 2, \text{or } 3, \tag{3.4}$$

where s_i denotes the individual contribution of player i, S is the group's total contribution, and a_i is a positive constant.[24] In this formula, $10(12 - s_i)$ denotes the income from the remained tokens and $10[(a_i + 1)\, ln(S + 1)]$ denotes the income from the common project. In each group, the three players are divided into two different experimental roles, each with different a_i. The player with investor number = 1 obtains an outstanding benefit from the public good, while the other two players obtain a relatively lower, but identical benefit from the public good. Hence, in our experiment, we assume $a_1 > a_2 = a_3$. In each session, there are two different payoff tables, both of which are given to every subject.[25]

Table 3.1 shows the parameters and theoretical predictions for our experiments. For all treatments, the unique Nash equilibrium is (10, 0, 0). This theoretical result indicates that, in Nash equilibrium, the player with investor number = 1 contributes 10 tokens, while the other two players contribute nothing. Furthermore, the system is globally stable at the unique Nash equilibrium in treatments (10, 2, 2) and (10, 4, 4). However, in the other two treatments, the system is non-globally stable.

Table 3.1 Parameters and theoretical predictions

Treatments (a_1, a_2, a_3)	(10,2,2)	(10,4,4)	(10,6,6)	(10,8,8)

[24] Note that, a_i is the intercept of player i's (self-interested) best-response curve for this payoff function.

[25] See Section 1 in the supplementary documents for the instructions and payoff tables translated from Chinese. In the experiment, we also design a calculator to help subjects quickly compare the possible outcomes.

Endowment	12	12	12	12
Unique Nash equilibrium (s_1^*, s_2^*, s_3^*)	(10,0,0)	(10,0,0)	(10,0,0)	(10,0,0)
Cournot stability	globally	globally	non-globally	non-globally
Optimal social outcome (group's total contribution)	16	20	24	28
Average MPCR	6.43	7.95	9.46	10.98
Sessions	4	4	4	4
Groups/subjects	30/90	31/93	32/96	31/93
Total period	25	25	25	25

Because the theory predicts that the sequences starting from some initial points will not converge to the Nash equilibrium but from some other points will converge in such non-globally stable situations, we conducted simulations to check the convergence of sequences starting from every possible initial point in the two non-globally stable treatments. The simulations show that sequences starting from 526 and 136 of 2197 (13^3) possible initial points converge to the unique Nash equilibrium with Cournot best-response dynamics in treatments (10, 6, 6) and (10, 8, 8), respectively. Figure 3.1 shows the positions of these stable initial points in a three-dimensional graph, where "Player *i*" denotes the initial contribution of the player with investor number *i* = 1, 2, or 3. The shapes of the stable regions in treatments (10, 6, 6) and (10, 8, 8) are irregular. Some initial points (e.g., (0, 0, 12)), are relatively far away from the Nash equilibrium but are still stable. Sequences starting from the unstable region pulse after several periods between (0, 0, 0) and (10, 6, 6) or between (2, 0, 0) and (10, 4, 4) in treatment (10, 6, 6), and between (0, 0, 0) and (10, 8, 8) or between (6, 0, 0) and (10, 2, 2) in treatment (10, 8, 8).

Panel A: Treatment (10,6,6)

Panel B: Treatment (10,8,8)

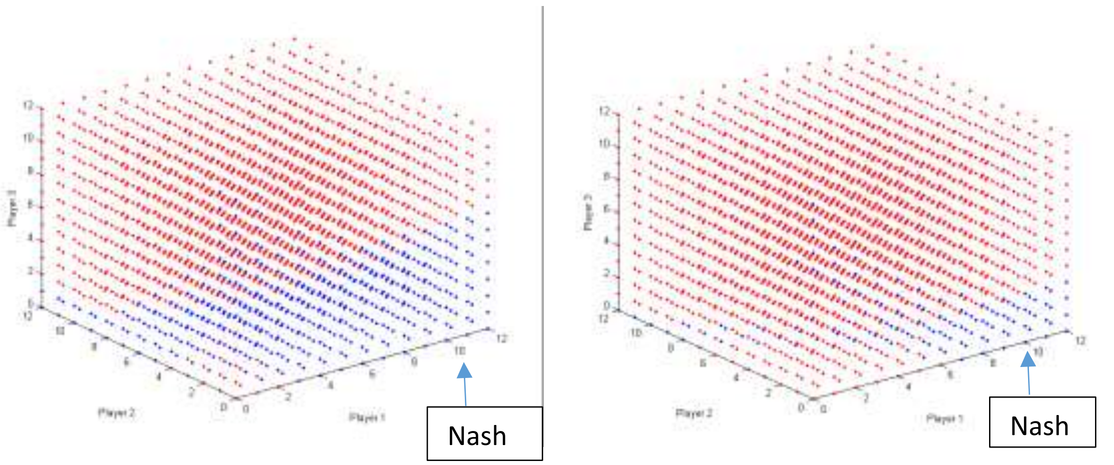


Fig. 3.1 Stable initial points (blue) versus unstable initial points (red) in treatments (10,6,6) and (10,8,8)

The optimal social outcomes are calculated with the Samuelson condition.[26] In our design, although the marginal per capita return (MPCR) varies with the group's total contribution, we still have a general ranking for the average MPCR of the two experimental roles across the four treatments.[27] The average MPCR reported in Table 3.1 is increased continuously from treatment (10, 2, 2) to treatment (10, 8, 8). Note that, the MPCR of low benefit players (investors 2 and 3) are different across treatments but, for those high benefit players (investor 1), it is identical. Thus, our experimental design also serves as an investigation of the behavioral changes of investor 1, when the external MPCR (the MPCR of other players) varies.

In addition to the choices of contributions, we also elicited each subject's beliefs about the individual contributions of the other two group members.[28] This is incentivized. We follow the design in Gächter and Renner (2010) and set the payoff function y_{ij} for the belief elicitation task as follows[29]:

---

[26] The Samuelson condition refers to a condition for the efficient provision of public goods (Samuelson 1954). In our experiment, the Samuelson condition requires that the social optimum of the group's total contribution be equal to $a_1 + a_2 + a_3 + 2$.

[27] The MPCR refers to the individual benefit of the public good from one additional contribution to the public good. In our experiment, it is $10[\frac{a_i+1}{S+1}]$. Because the payoff function is quasi-linear, the MPCR varies with the group's total contribution, S. Therefore, we calculate the average of all possible MPCR of the three players for the comparisons across treatments, which is $\frac{1}{111}\sum_{i=1}^{3}\sum_{S=0}^{36} 10[\frac{a_i+1}{S+1}]$.

[28] Since each group consists of three players, each player should make two predictions in each period. The payoffs from the two predictions are calculated separately and then summed in each period.

[29] Note that, in this payoff design, the penalty increases when the distance from being correct becomes small, which is different from other designs (i.e. quadratic scoring rule). The main justification is that we intend to give higher incentive to making an exactly correct prediction.

$$y_{ij} = \begin{cases} 150, \; if \; B_{ij} = s_j \\ \frac{100}{|B_{ij} - s_j|}, \; if \; B_{ij} \neq s_j \end{cases}; \;\; i, j = 1,2, or \; 3, i \neq j, \tag{3.5}$$

where B_{ij} is player i's stated belief about player j's contribution, and s_j is the observed contribution of player j. This payoff function indicates that, if player i's prediction is exactly equal to player j's choice, player i can get 150 experimental dollars, otherwise, the prediction payoff is equal to 100 divided by the absolute difference between player i's prediction and player j's choice.

In the payment procedure, following Blanco et al. (2010), we employ a special design to eliminate the hedging problem.[30] At the end of the experiment, the real payments of all subjects in each session depend on either the total payoff from the contribution task or the total payoff from the prediction task, based on a random mechanism. Therefore, the scale of the payoffs in equation (3.5) is designed to be comparable to the income from the VCM. Blanco et al. (2010) set an equal probability (1/2 versus 1/2) for the payoff from each of the two tasks. Differing slightly from their design, we set different probabilities for the payoff from each of the two tasks. For all treatments, the real payments of players depend on the total payoff from the contribution task, with probability 5/6, or on the total payoff from the prediction task, with probability 1/6.

We also conducted two additional sessions with the settings of treatment (10, 8, 8) but using equal probabilities (1/2 versus 1/2) (see Section 2 of the supplementary documents for the report on these two additional sessions). The results show that the contributions from investors 2 and 3 are significantly higher in the experiment with the equal probability design than in the experiment with the different probability design. Therefore, we suggest that, in addition to the hedging problem, a high-incentivized design of belief elicitation still induces a significant change in contributions, compared to a low-incentivized design. Because we intend to make the influence stemming from the belief elicitation as small as possible (but not completely remove the incentivized design), we employ the design which assigns a high probability to the payoff of the contribution task and a low probability to the payoff of the prediction task.

At the end of each period, each player receives feedback on the experimental results in that period. This includes his/her own payoffs from contribution and prediction tasks, and the individual contributions and investor numbers of group members. However, it

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Because the choices and predictions are the whole numbers in a continuous interval, [0, 12], players might choose a middle number to hedge between several different predictions. This payoff design eliminates these hedging motives.

[30] The hedging problem in the experiments with belief elicitation refers to the fact that a risk-averse subject might act according to an optimistic belief, but report a pessimistic belief in order to hedge against the possible loss from the action. For details, see Blanco et al. (2010).

excludes the individual predictions of the other group members. Therefore, the experimental design is complete information for the VCM. Every player knows the payoff structure of each player, as well as the individual contribution and investor number of each group member. However, although the design provides complete information, subjects cannot link an experimental role to a real person, because they make decisions in a closed chamber and are not allowed to communicate with other subjects.

Subjects receive instructions at the beginning of each session when entering the lab. A native speaking research assistant reads the instructions loudly. Then, all subjects are required to answer control questions correctly. At the end of each session, each subject receives his/her payment privately at a pre-announced exchange rate of 130 experimental dollars to 1 Chinese RMB. The 372 subjects earned RMB 60 (8.8 US dollars) each, on average, including a participation fee, with a range of RMB 45-RMB 75. Each session lasts about one hour and a half, including providing the instructions and making the necessary payments.

3.4 Results

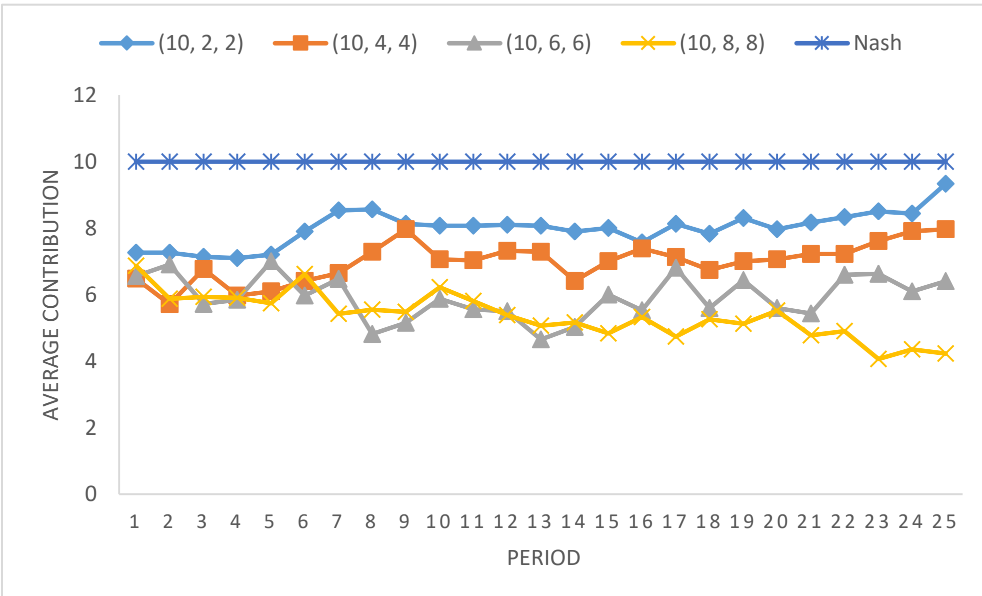
In this section, we discuss the experimental data from three aspects. In the first subsection, we provide observations with regard to the convergence of the contribution behavior. The second subsection analyzes the belief-formation process. Then, we investigate the response process in the third subsection.

3.4.1 Contributions and Nash Equilibrium Benchmark

Result 3.1: (**Contributions and Nash Equilibrium**) Individual contributions in the final 10 periods are much closer to the Nash equilibrium in the two globally stable treatments than in the two non-globally stable treatments, for both roles of players. However, no significant differences are observed in the groups' total contributions across the four treatments in the final 10 periods.

Support: In each group, subjects play two roles, each with different payoff structures. Thus, the average contributions are calculated separately. Figure 3.2 shows the average contributions over time for the two roles in the four treatments. Panel A displays the average contributions of players with investor number = 1. Here, the average contributions from the two globally stable treatments are much closer to the Nash prediction than those from the two non-globally stable treatments are. Panel B of Figure 2 displays the average contributions for players with investor number = 2 or 3. The graph clearly shows a reverse ordering of average contributions for the four treatments. Moreover, for both roles, the Kruskal–Wallis test shows a significant difference among the four treatments in the final 10 periods (d.f. = 3, p-values < 0.001).[31] The p-values of Dunn's tests are presented in Table 3.2 in order to compare the individual contributions in the final 10 periods across the four treatments. Overall, the average contribution from treatment (10, 2, 2) is closest to the Nash prediction in the final 10 periods among the averages of the four treatments.

Panel A: Players with investor number =1



Panel B: players with investor number = 2 or 3

[31] For all Kruskal–Wallis tests in this paper, we first calculate the average over periods for each individual in order to eliminate autocorrelation among periods. Then, we conduct the Kruskal–Wallis test over the samples of averages. Moreover, because there are four treatments in our experiment, we use Dunn's test with the Bonferroni correction to conduct pairwise comparisons when the null hypothesis in the Kruskal–Wallis test is rejected (Dunn 1964).

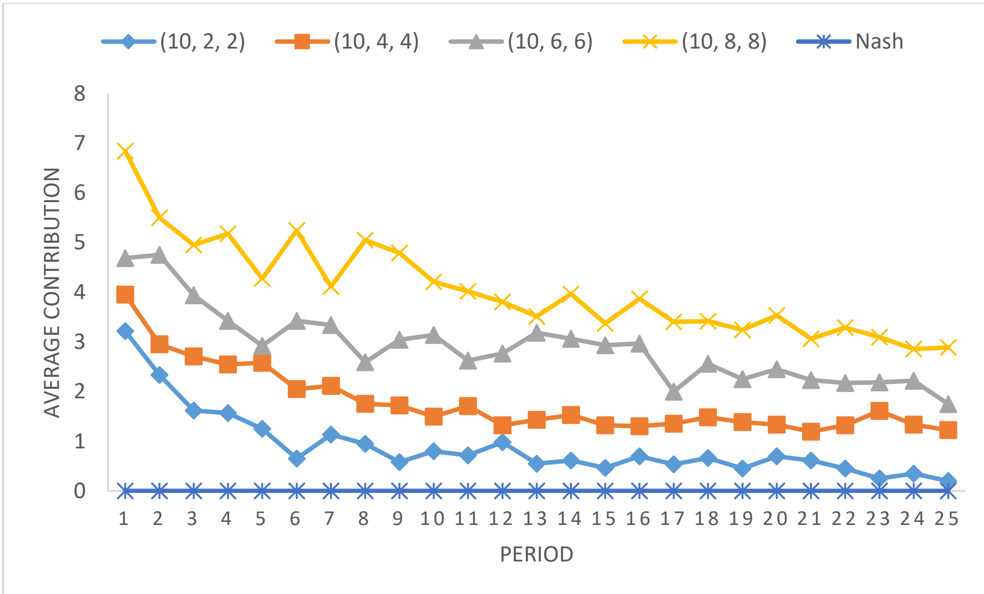
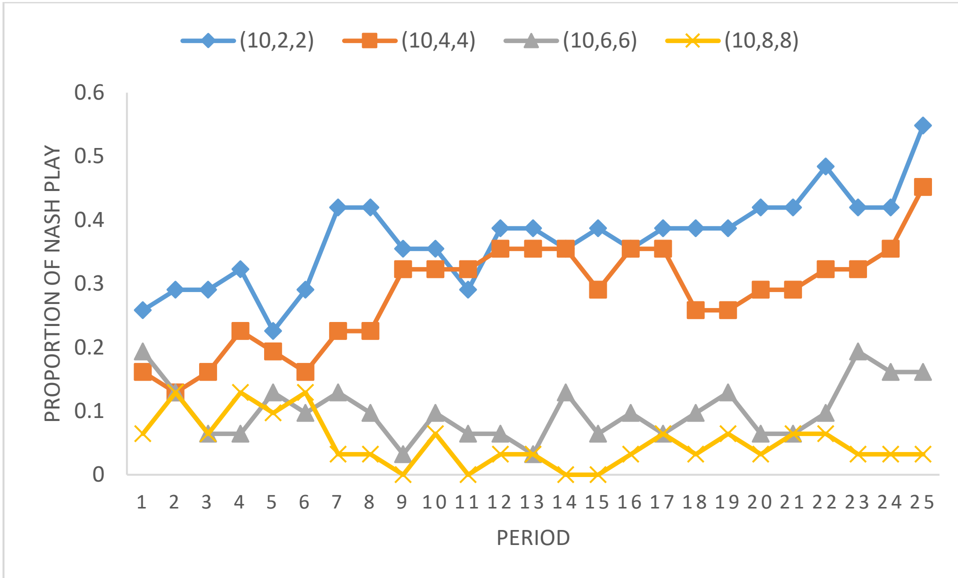


Fig. 3.2 The average contribution per period for two roles of subjects

Table 3.2 Pairwise comparisons for contributions in the final 10 periods (Dunn's test with the Bonferroni correction)

Players with investor number = 1			
Treatments	(10,2,2)	(10,4,4)	(10,6,6)
(10,4,4)	0.5262		
(10,6,6)	0.0066	0.2623	
(10,8,8)	0.0000	0.0010	0.1735
Players with investor number = 2 or 3			
Treatments	(10,2,2)	(10,4,4)	(10,6,6)
(10,4,4)	0.0426		
(10,6,6)	0.0000	0.0325	
(10,8,8)	0.0000	0.0000	0.0097

Panel A: Players with investor number =1



Panel B: players with investor number = 2 or 3

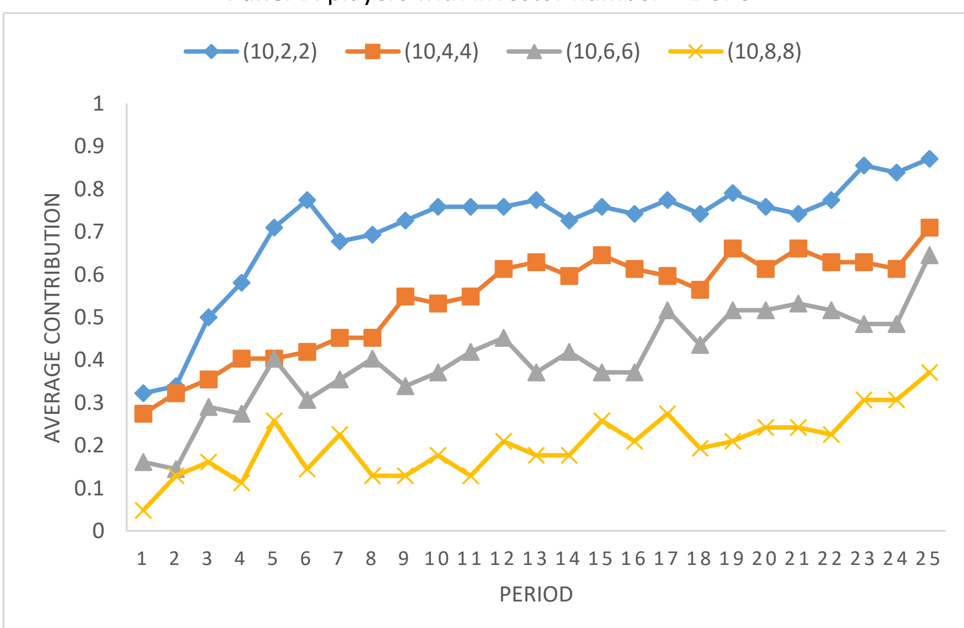


Fig. 3.3 The proportion of the Nash play in each period

To see the convergence of individual contributions, Figure 3.3 shows the proportion of players who played their part of the unique Nash equilibrium in each period. Each line depicts a treatment in each graph. Panel A shows that, in the final periods, the proportions almost reach the 50 percent level in treatments (10, 2, 2) and (10, 4, 4), but in treatments (10, 6, 6) and (10, 8, 8), they remain at a relatively low level. In Panel B, despite the fact that there is an ascending tendency shared by all treatments, the proportions are relatively lower in treatments (10, 6, 6) and (10, 8, 8) than those in treatments (10, 2, 2) and (10, 4, 4). At the group level, there are 11 groups in treatment (10, 2, 2), seven groups in treatment (10, 4, 4), one group in treatment (10, 6, 6), and one group in treatment (10, 8, 8) in which contributions converge to the unique Nash equilibrium, (10, 0, 0), when the experiment progresses to the last five periods.

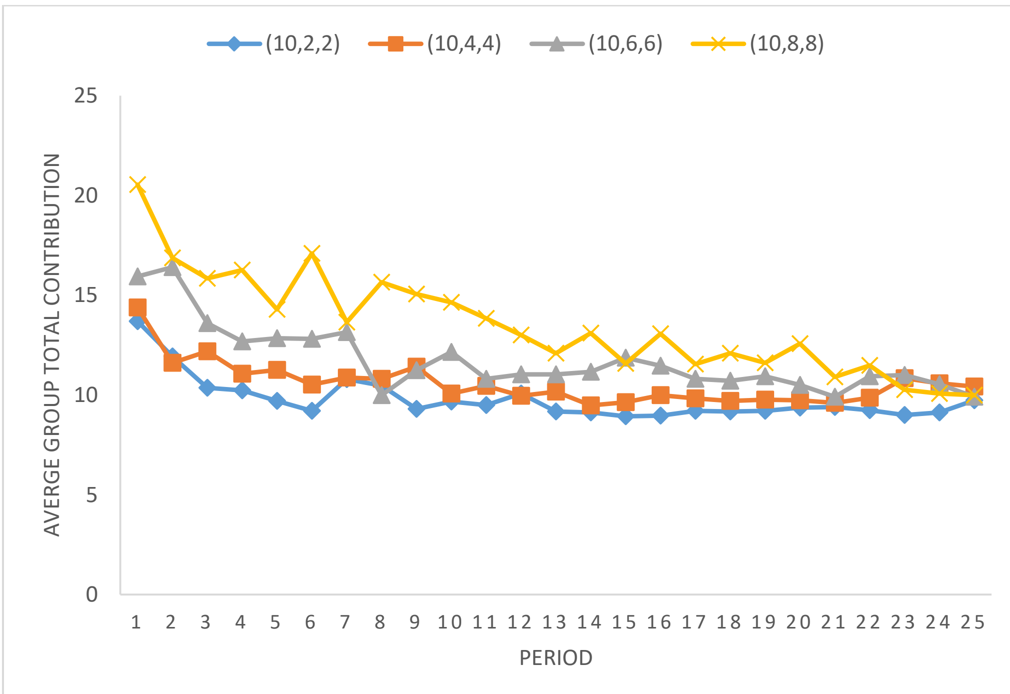


Fig. 3.4 The average of group total contributions per period

Figure 3.4 reports the averages of the groups' total contributions at each period, for all treatments. The Kruskal–Wallis test shows that, in the first 10 periods, the groups' total contributions from the four treatments are significantly different (d.f. = 3, p-value = 0.0001). Dunn's test further shows that the groups' total contributions from treatment (10, 8, 8) are significantly higher than those from the other three treatments (p-values < 0.001 for the comparison with treatments (10, 2, 2) and (10, 4, 4), and p-value = 0.0387 for the comparison with treatment (10, 6, 6)). In addition, the groups' total contributions from treatment (10, 6, 6) are higher than those from treatments (10, 2, 2) (p-value = 0.0130) and (10, 4, 4) (p-value = 0.0906), but there is no significant difference between treatments (10, 2, 2) and (10, 4, 4) (p-value = 1.0). However, in the final 10 periods, there is no longer a significant difference in the groups' total contributions across the four treatments (p-value = 0.459 by the Kruskal–Wallis test).

In summary, we observe a clear trend that indicates convergence to a unique Nash equilibrium in the two globally stable treatments. In contrast, the individual contributions are still far from the Nash prediction in the final 10 periods in treatments (10, 6, 6) and (10, 8, 8). These results seem consistent with the theoretical prediction of Saijo (2015). However, we find that sample autocorrelations of groups' total contributions are positive for most groups in treatments (10, 6, 6) and (10, 8, 8).[32] The Kruskal–Wallis test further shows a slight difference over the sample autocorrelations across the four treatments (d.f. = 3, p-value = 0.0520), but Dunn's test shows that the only significant difference is between treatment (10, 2, 2) and treatment (10, 8, 8). The sample autocorrelations in treatment (10, 8, 8) are significantly larger than those in treatment (10, 2, 2) (p-value = 0.0241). These results are inconsistent with the theoretical prediction that the Cournot best-response dynamics will induce pulsing contributions in some groups for treatments (10, 6, 6) and (10, 8, 8).[33] Therefore, to examine the reasons behind the differences in convergence, we release the assumption of Cournot best-response dynamics, and empirically investigate players' belief-formation processes and response processes respectively in the following two subsections.

3.4.2 Belief Formation Process

First, we report the belief accuracy in the four treatments. Figure 3.5 shows the average absolute differences between stated beliefs and real choices in each period for the four treatments. The accuracy becomes higher and higher with repeated trials in all treatments (p-values < 0.001 by comparing the observations from the first 10 periods with those from the final 10 periods in each treatment with the Wilcoxon signed-rank test). Moreover, there is a significant distinction between the two globally stable treatments and the two non-globally stable treatments in the final 10 periods. The accuracy of stated beliefs in the two globally stable treatments is significantly higher than that in the two non-globally stable treatments (p-values < 0.001 by the Dunn's tests), but there are no significant differences between the two globally stable treatments (p-value = 0.1185) and between the two non-globally stable treatments (p-value = 0.2263).

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[32] One might think that the sample autocorrelation of individual contributions is also a way to check for the pulsing behavior. However, if players within the same group are not synchronized, the pulsing behavior of each subject is not related to the non-globally stable argument. Thus, we check only the sample autocorrelation of the group's total contributions.

[33] The pulsing contributions will induce negative sample autocorrelations for the groups' total contributions in some groups. Thus, the sample autocorrelations in treatments (10, 6, 6) and (10, 8, 8) should be smaller than those in treatments (10, 2, 2) and (10, 4, 4).

The non-global stability suggests that, if subjects follow the Cournot best-response dynamics, the distance between beliefs and choices will become larger and larger in the non-converged groups. To verify this, we checked dynamics of belief accuracy in each group. The Spearman's rank correlation tests show that the average difference at the group level significantly increases in only one group from treatment (10, 6, 6) (Spearman's rho = 0.4214, p-value = 0.0359) and two groups from treatment (10, 8, 8) (Spearman's rho = 0.5661 and 0.4661, p-values < 0.05).

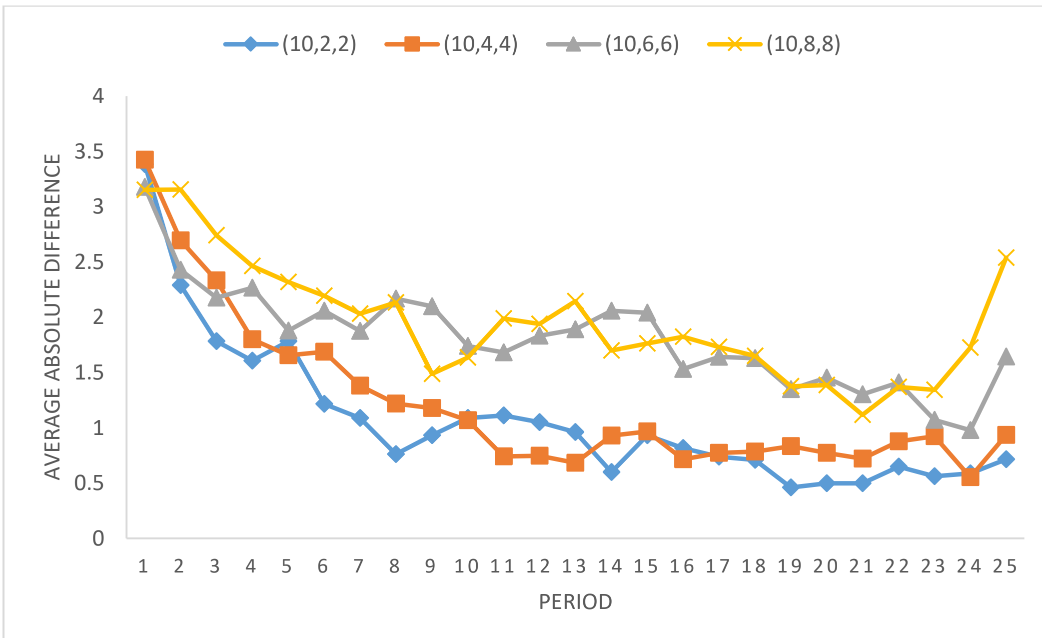

Fig. 3.5 Average absolute differences between stated beliefs and real choices at each period

Then, we release the assumption of myopic Cournot learning and empirically investigate the belief formation processes of subjects.[34] Fischbacher and Gächter (2010) suggest that belief formation in a linear VCM environment can be regarded as a weighted average of the belief and the observation of the previous period.[35] Since this weighted average could be expressed

[34] The term "myopic Cournot learning," also called naive learning (e.g., Fischbacher and Gächter 2010), means players' beliefs are equal to the most recent observation.

[35] Fischbacher and Gächter (2010) also provide an intuitive interpretation for this argument. "In period 1 a subject can only rely on his or her intuitive ('home-grown') beliefs about others' contributions. In period 2, he or she also makes an observation about others' actual contribution in period 1. A subject may therefore update his or her period 2 belief on the basis of his or her period 1

as a weighted average of all previous observations and the prior belief, we introduce a model to estimate the belief formation process, using the argument of Fischbacher and Gächter (2010) as an assumption.[36] The model is expressed as follows:

$$b_{ij,t+1} = \frac{s_{j,t} + \sum_{u=1}^{t-1} \gamma_i^u s_{j,t-u} + \frac{\gamma_i^t}{1-\gamma_i} B_{ij,1}}{1 + \sum_{u=1}^{t-1} \gamma_i^u + \frac{\gamma_i^t}{1-\gamma_i}}, \tag{3.6}$$

where $b_{ij,t+1}$ is player *i*'s belief about the contribution of player *j* at period $t + 1$, $s_{j,t}$ is the contribution of player *j* at period t, γ_i^u is the weight given to the observation of $s_{j,t-u}$ at period $t - u$, and $B_{ij,1}$ is the stated belief about the contribution of player *j* at period 1.[37]

However, although the rewarding structure for eliciting beliefs in our design is similar to that of Fischbacher and Gächter (2010), we elicit beliefs about individual contributions. In contrast, Fischbacher and Gächter (2010) elicit beliefs about the average contributions of other group members. Therefore, an alternative model that can explain the belief-formation process in our experimental data is the smoothed (or noisy) γ-weighted fictitious play model (see Cheung and Friedman 1997; Fudenberg and Levine 1998). To distinguish between these two models, we conduct a model selection procedure. The results indicate that the argument of Fischbacher and Gächter (2010) outperforms the smoothed γ-weighted fictitious play model in explaining the belief-formation process at the aggregate level.[38]

Then, we extend the analysis to the individual level. Define $\gamma_i^* \in [0, 1)$ for player i, which minimizes the sum of the squared errors (SSE) between the stated beliefs and the beliefs suggested by equation (3.6).[39] That is,

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beliefs and the observed period 1 contributions by others. A similar logic might hold in all remaining periods" (Fischbacher and Gächter 2010, p. 548).

[36] We also conduct regressions of three models to check the lag length of the information used by players. The first is the same as Model 3 in Fischbacher and Gächter (2010), which includes "belief (t – 1)" and "other's contribution (t – 1)". The second and third models include additional lagged variables. The results show that the argument of Fischbacher and Gächter (2010) is a reasonable assumption to explain the belief-formation process in our experiment. See Section 3 of the supplementary documents for details.

[37] See the appendix for the derivation of this model.

[38] See Section 4 of the supplementary documents for details.

[39] As Cheung and Friedman (1997) suggested, γ_i^* might also be located outside the range [0, 1). Such cases are relatively counter-intuitive. Here, $\gamma_i^* > 1$ indicates that player *i* pays more attention to old information than to recent information, and the effect of the prior belief is negative. Then, $\gamma_i^* < 0$ indicates that the effect of past information changes sign in each period. However, in our empirical analysis, since we are only interested how subjects form their stated beliefs based on the weighted average over all previous observations and their prior beliefs, we omit the discussion on those

$$\gamma_i^* = \arg min_{0 \le \gamma_i < 1} \{\sum_{t=2}^{25} \left(B_{ij,t} - b_{ij,t}\right)^2\}, \tag{3.7}$$

where $B_{ij,t}$ is player *i*'s stated belief on player *j*'s contribution at period t, and $b_{ij,t}$ is the constructed belief at period *t* given by equation (3.6). Here, γ_i^* should be equal to 0 when player *i* exactly follows the myopic Cournot learning process. In contrast, γ_i^* is close to 1 if player *i* pay much attention to previous observations and his/her prior belief. In this sense, this model is close to the k-period average model of Healy (2006) but assigns a high weight to the prior belief. Briefly, the empirical model of equation (3.6) can be regarded as a time-weighted average model, including the prior belief. Equation (3.7) is calculated twice for each individual because, in each period, each subject states two beliefs about the individual contributions of the other two players in the group.[40]

Result 3.2: (**Belief formation**) The belief-formation processes of subjects are significantly more myopic in the two globally stable treatments than they are in treatment (10, 8, 8). Furthermore, the minimal SSE in the two non-globally stable treatments are significantly larger than those in the two globally stable treatments.

Support: Penal A of Figure 3.6 shows the distributions of γ_i^* in the four treatments. The left-most bar decreases continuously from treatment (10, 2, 2) to treatment (10, 8, 8). This decrease has a significant impact on the distribution in treatment (10, 8, 8), which is significantly different to the distributions in treatments (10, 2, 2) (p-value = 0.006) and (10, 4, 4) (p-value = 0.008), based on the two-sample Kolmogorov-Smirnov tests. The Kruskal–Wallis test also shows a significant difference in the distributions of γ_i^* among the four treatments (d.f. = 3, p-value = 0.0121). Furthermore, Dunn's test shows that γ_i^* in treatment (10, 8, 8) is significantly larger than that in treatments (10, 2, 2) (p-value = 0.0246) and (10, 4, 4) (p-value = 0.0082). Comparing minimal SSE from the four treatments, the Kruskal-Wallis test also shows a significant difference (d.f. = 3, p-value = 0.0001), and Dunn's test further shows that the minimal SSE from treatments (10, 2, 2) and (10, 4, 4) are significantly smaller than those from treatments (10, 6, 6) and (10, 8, 8) (p-values < 0.01).

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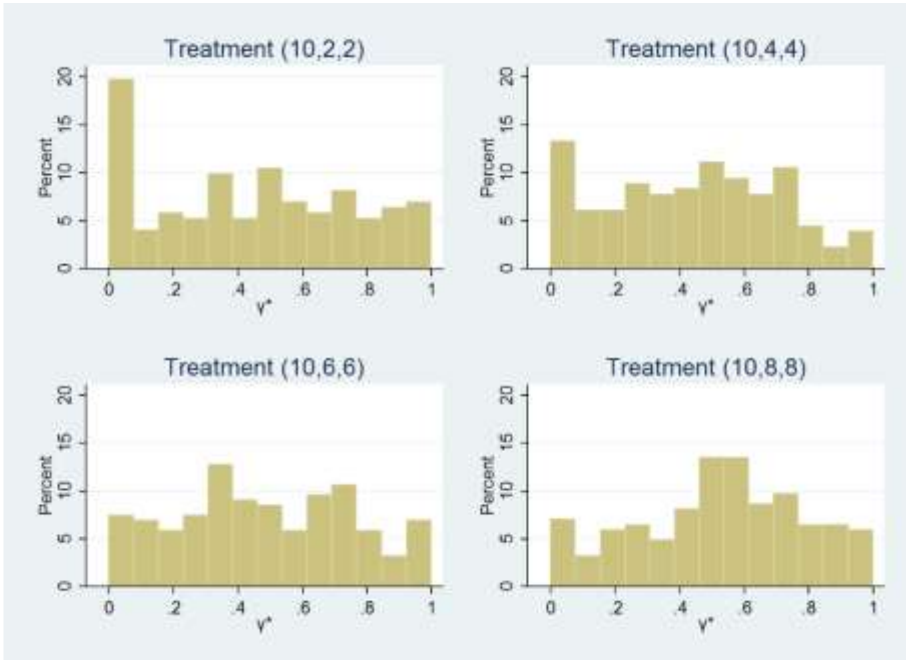
counter-intuitive situations. This design can also be found in the analysis of the belief-formation process in Hyndman et al. (2012).

[40] In 19 cases (eight cases in treatment (10, 2, 2), six cases in treatment (10, 4, 4), four cases in treatment (10, 6, 6), and one case in treatment (10, 8, 8)), players' prior beliefs were equal to their group members' contributions, and their group members did not change their contributions during the experiment. In such cases, since γ_i is canceled out in equation (3.6), we eliminate these data. The calculations were carried out 725 times.

Penal A: Periods 2-25



Penal B: Periods 2-11

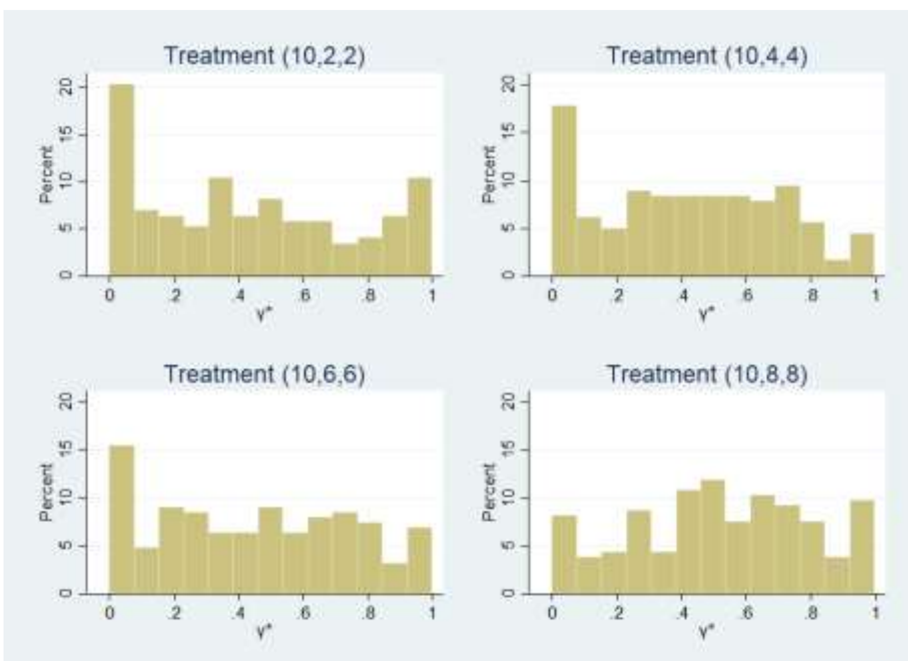


Fig. 3.6 Distributions of γ_i^* in the four treatments

Moreover, note that, for the two globally stable games, many groups converge to the Nash equilibrium, which means that beliefs will converge too. This might make γ_i^* a bit bias to zero. To rule out this problem, we conduct the estimations with the data from periods 2-11 as a double check. The results are shown in Penal B of Figure 3.6. These graphs are very similar to those in Penal A. Actually, the Wilcoxon signed-rank test shows that players in treatment (10, 6, 6) are significantly more myopic in periods 2-11 than they are in periods 2-25 (p-value = 0.0295), and it shows insignificant results in the other three treatments (p-value = 0.8096 for treatment (10, 2, 2), p-value = 0.2452 for treatment (10, 4, 4), and p-value = 0.7410 for treatment (10, 8, 8)). More importantly, the Dunn's tests show that, in periods 2-11, the differences in γ_i^* and minimal SSE between the two globally stable treatments and treatment (10, 8, 8) are consistent with the above results (p-values < 0.05).

Result 3.2 is rather interesting. It could indicate that when the system could approach equilibrium using the myopic Cournot learning process, subjects might be willing to follow this process because it incurs less of a cognitive cost than that of processing information from previous periods. However, when the system cannot approach equilibrium with the myopic Cournot learning process, subjects might have to process more previous information and, thus, incur greater cognitive costs.[41] We consider this interpretation in the simulation section to show whether this change in the belief-formation process improves the stability of the system. In addition, the difference in the minimal SSEs across treatments might be the result of a higher number of decision errors in treatments (10, 6, 6) and (10, 8, 8) than in treatments (10, 2, 2) and (10, 4, 4). However, the difference might also suggest that subjects employ more information beyond those of historical observations on choices in the two non-globally stable treatments.[42]

3.4.3 Responding Process

In this subsection, we release the assumption that players make self-interested maximization choices and empirically investigate subjects' response processes. Since many experimental studies suggest that most players are conditional cooperators who always want to match the (average) contributions of other players (see Chaudhuri 2011), we incorporate this behavioral pattern into our empirical analysis.

Our experimental design includes three players and two roles in each group. Players with investor number = 1 might match the average of beliefs about the contributions of investor 2 or 3 because the latter two players have the same payoff table. However, players with investor

[41] Theoretically, when subjects take more previous observations into consideration, i.e. the fictitious play or best response to the average of all previous observations, the global stability at the Nash equilibrium will generally be improved (e.g., Thorlund-Petersen 1990; Hofbauser and Sandholm 2002).

[42] See Milgrom and Roberts (1991) for a discussion on the different learning processes.

number = 2 or 3 may match the two beliefs separately because the other two players have different payoff tables.

Therefore, we assume different response processes for the two roles. Specifically, we assume that players with investor number = 1 adjust their contributions as follows:

$$s_{i,t} - s_{i,t-1} = \alpha + \beta_1\left(R_{i,t} - s_{i,t-1}\right) + \beta_2\left(\bar{B}_{i,t} - s_{i,t-1}\right) + \varepsilon, \tag{3.8}$$

where $R_{i,t}$ is player i's self-interested best response to his/her own stated beliefs at period t, and $\bar{B}_{i,t}$ is the average of the two beliefs held by player i about the contributions of the other two players. Then, investors 2 or 3 adjust their contributions as follows:

$$s_{i,t} - s_{i,t-1} = \alpha + \beta_1\left(R_{i,t} - s_{i,t-1}\right) + \beta_2\left(B_{i,t}^{1} - s_{i,t-1}\right) + \beta_3\left(B_{i,t}^{23} - s_{i,t-1}\right) + \varepsilon, \tag{3.9}$$

where $R_{i,t}$ is again player i's self-interested best response to his/her own stated beliefs at period t, $B_{i,t}^{1}$ is player i's stated belief about the contribution of investor 1, and $B_{i,t}^{23}$ is player i's stated belief about the contribution of the other player with investor number = 2 or 3.

We employ difference forms in the regressions, which are inconsistent with previous studies (i.e. Fischbacher and Gächter (2010)). The main justification is about multicollinearity. Note that beliefs enter the calculations of best responses and, particularly for investors 2 and 3, beliefs about the other same-role player's contributions could be correlated with their own best response. Via making a difference form, we intend to reduce the correlation between independent variables in models (3.8) and (3.9). For the two independent variables of model (3.8), all the absolute values of Spearman's rho are not larger than 0.36 and all the variance inflation factors are not larger than 1.12 in the four treatments. For the three independent variables in model (3.9), the maximum of the absolute values of Spearman's rho is 0.6215 and the maximum of the variance inflation factors is 2.1186 among the four treatments. Therefore, all the variance inflation factors in our two models are smaller than the critical value of 10 (Gujarati 2003).

These two regressions show the relative importance of the two behavioral patterns, namely self-interested maximization and matching beliefs, when players adjust their contributions.

Results 3.3: (**Response**) The behavioral pattern of self-interested maximization accounts for a significantly larger proportion than that of matching beliefs does in the two globally stable treatments for players with investor number = 1 and in treatment (10, 2, 2) for players with investor number = 2 or 3. However, this is not the case in the two non-globally stable treatments for both roles.

Support: Table 3.3 shows the results of the above regressions.[43] In each treatment, we compare the estimate of β_1 to the estimate of β_2 for players with investor number = 1 and compare the estimate of β_1 to the sum of the estimates of β_2 and β_3 for players with investor number = 2 or 3 (p-values are also reported in Table 3.3). Our results indicate that the behavioral pattern of self-interested maximization is significantly more common than that of matching beliefs in the two globally stable treatments for players with investor number = 1 and in treatment (10, 2, 2) for players with investor number = 2 or 3. However, this is not the case in the two non-globally stable treatments. Conversely, for players with investor number = 2 or 3 in treatment (10, 8, 8), the sum of the estimates of β_2 and β_3 is significantly larger than the estimate of β_1.

Table 3.3 Fixed-effects regressions for the response process

Players with investor number = 1				
Dependent variable: $s_{i,t} - s_{i,t-1}$				
	Treatment (10,2,2)	Treatment (10,4,4)	Treatment (10,6,6)	Treatment (10,8,8)
β_1	0.466***	0.389***	0.475***	0.260***
	(0.071)	(0.051)	(0.096)	(0.060)
β_2	0.238***	0.215***	0.399***	0.398***
	(0.076)	(0.044)	(0.067)	(0.061)
α	1.627***	1.315***	1.692***	1.004***
	(0.530)	(0.217)	(0.218)	(0.144)
P-value (H_0: $\beta_1 = \beta_2$)	0.013	0.024	0.529	0.158
Subjects/Groups	30/30	31/31	32/32	31/31
Observations	720	744	768	744
R-squared	0.24	0.21	0.34	0.26
Players with investor number = 2 or 3				
Dependent variable: $s_{i,t} - s_{i,t-1}$				
	Treatment (10,2,2)	Treatment (10,4,4)	Treatment (10,6,6)	Treatment (10,8,8)
β_1	0.583***	0.450***	0.375***	0.261***
	(0.118)	(0.093)	(0.061)	(0.031)
β_2	0.023	0.007	0.080*	0.214***

[43] The regressions are conducted using a fixed-effects model with clustered groups to isolate unspecified individual traits and to control for unspecified intragroup influence.

	(0.027)	(0.034)	(0.040)	(0.030)
β_3	0.194***	0.312***	0.289***	0.285***
	(0.052)	(0.042)	(0.065)	(0.039)
α	0.203	0.604**	0.508**	0.283***
	(0.276)	(0.292)	(0.235)	(0.096)
P-value (H_0: $\beta_1 = \beta_2 + \beta_3$)	0.035	0.202	0.952	0.000
Subjects/Groups	60/30	62/31	64/32	62/31
Observations	1440	1488	1536	1488
R-squared	0.34	0.27	0.26	0.27

Clustered standard errors are shown in parentheses. Significantly different from zero at $*$ 10% level, $**$ 5% level, $***$ 1% level (all two-tailed tests).

Furthermore, we conduct pairwise tests of the equivalence of the estimates of β_2 across the four treatments with the seemingly unrelated regression. For players with investor number = 1, the estimates of β_2 are not statistically significantly different between treatments (10, 2, 2) and (10, 6, 6) (p-value = 0.112), are slightly different between treatments (10, 2, 2) and (10, 8, 8) (p-value = 0.098), and are significantly different between treatments (10, 4, 4) and (10, 6, 6) (p-value = 0.022) and between treatments (10, 4, 4) and (10, 8, 8) (p-value = 0.015). For players with investor number = 2 or 3, only the estimate of β_2 in treatment (10, 8, 8) is significantly larger than that in the other three treatments (p-values < 0.01). These results suggest that players are less likely to match their beliefs about the contributions of players with different roles in the two globally stable treatments than they are in the two non-globally stable treatments.

For players with investor number = 1, the difference in conditional cooperation across the four treatments might stem from inequity aversion. As Fehr and Schmidt (1999) assumed in their inequity-aversion utility model, players suffer more from inequity that is to their disadvantage than they do from inequity that is to their advantage. If checking the payoff tables in the supplementary documents, we can find that, in treatments (10, 2, 2) and (10, 4, 4), the payoff of investor 1 increases much faster than the payoffs of the other two players when he/she unilaterally increases his/her own contribution. In contrast, in treatments (10, 6, 6) and (10, 8, 8), and especially in treatment (10, 8, 8), when investor 1 unilaterally increases his/her own contribution to 10 tokens, his/her own payoff becomes less than the payoffs of the other two players. Given this fact, investor 1 might be willing to contribute much more than investor 2 or 3 do in the two globally stable treatments, but might not be willing to do so in the two non-globally stable treatments.

For players with investor number = 2 or 3, note that their MPCR varies between the four treatments. The difference in conditional cooperation, in particular, the difference in β_2, across the four treatments might stem from different magnitudes of opportunity costs when making contributions, in addition to social preferences. Because the benefits from keeping tokens for oneself are identical across the four treatments, the opportunity costs of contributions are continuously reduced from treatment (10, 2, 2) to treatment (10, 8, 8). Therefore, matching beliefs in treatment (10, 8, 8) induces lower costs than it does in treatment (10, 2, 2).

In the next section, we apply our empirical findings on the belief formation and response processes to the theory. We conduct a series of simulations to show whether the changes in the belief formation improve stability, to show how conditional cooperation affects convergence, and to explain our observations of the differences in the convergence of the contributions across the four treatments.

3.5 Simulation

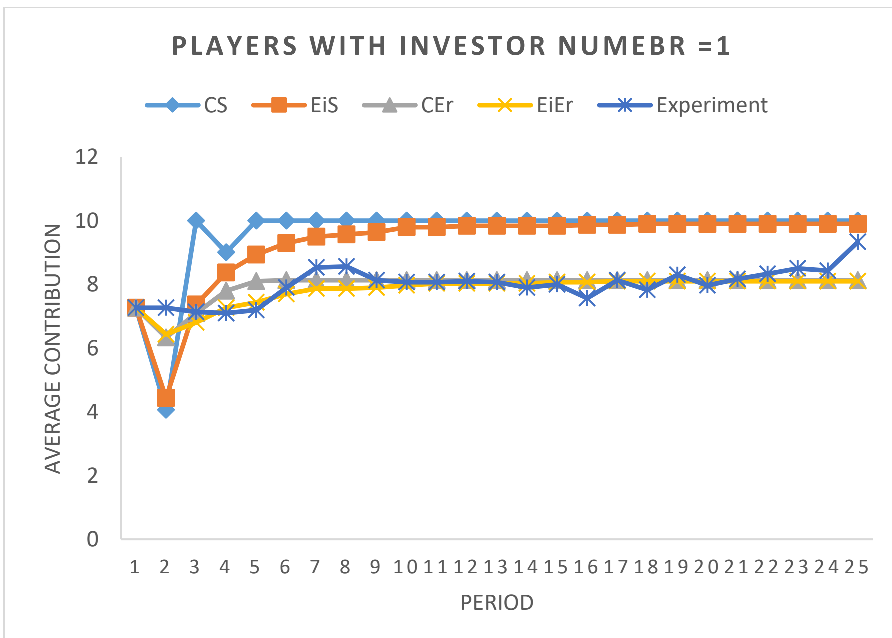
We employ the simulation method because it allows us to compare the outcomes generated by different counterfactual assumptions. This method was also used by Fischbacher and Gächter (2010). We use a 2 × 2 simulation design to investigate the individual effects of the belief-formation process and the response process. Table 4 summaries the simulation design. All simulations are conducted using the initial contributions of the subjects in our experiments.

Table 3.4 2x2 Design of the simulation

Treatments	Belief formation	
Responding process	Myopic Cournot learning	Empirical learning(each individual)
Self-interested best response	CS (baseline)	EiS
Empirical Responding process(each role)	CEr	EiEr

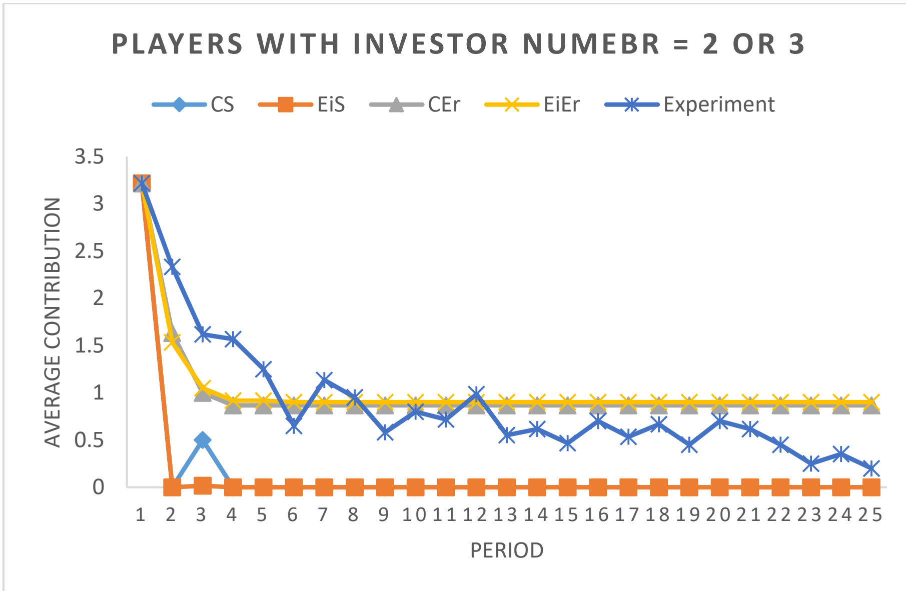
As shown in Table 3.4, the baseline treatment combines the myopic Cournot learning with the self-interested best response. We, therefore, refer to it as the CS treatment. It checks the theoretical predictions against the initial contributions in each group. By replacing myopic Cournot learning with the empirical estimates (periods 2-25) at the individual level in section 3.4.2, but keeping the assumption of the self-interested best response, we get the EiS treatment.[44] By comparing the outcomes of the CS treatment and the EiS treatment, we isolate the effect of the empirical belief-formation process.[45] Furthermore, by replacing the self-interested best response with the empirical response process shown in Table 3.3, but keeping the assumption of myopic Cournot learning, we get the CEr treatment. Similarly, comparing the outcomes of the CS treatment and the CEr treatment, we isolate the effect of the empirical response process. Then, by comparing the EiEr treatment to the other three treatments, we can observe the joint effect of the empirical belief-formation process and the empirical response process. Finally, since we do not have individual response processes, the experimental observations will serve as a treatment for both the empirical belief-formation process and the empirical response process at the individual level.

Penal: Treatment (10, 2, 2)

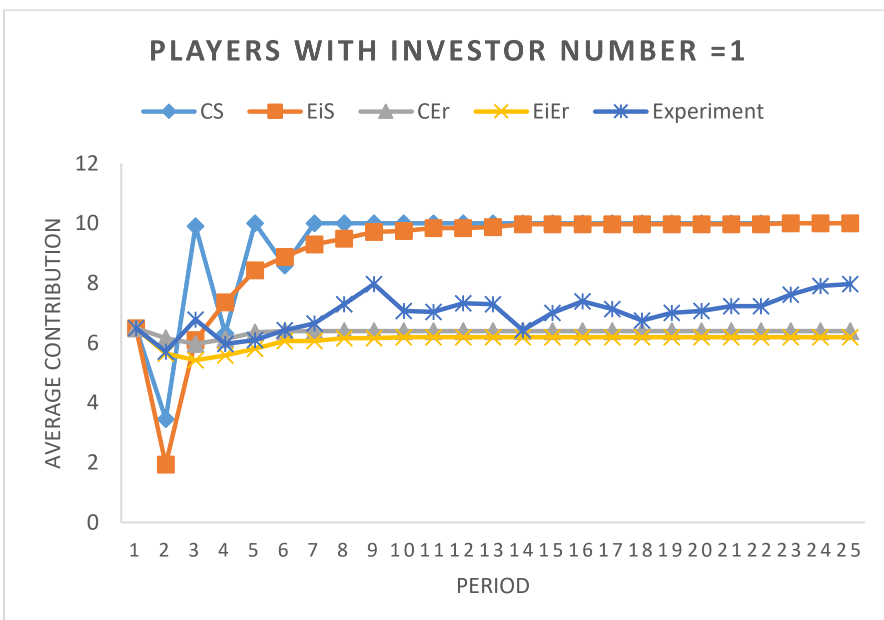


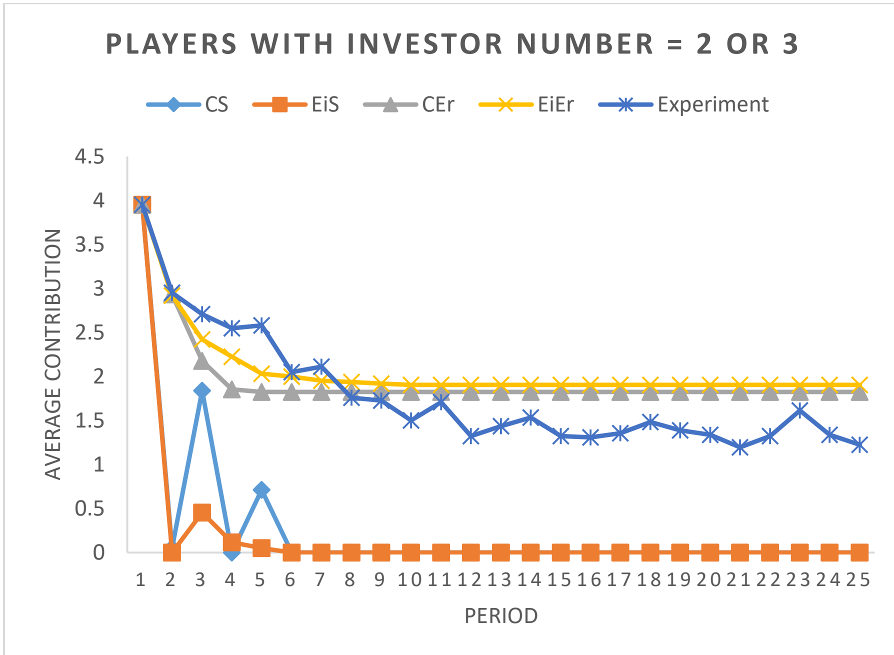
[44] The empirical belief formation process indicates the equation (3.6) with estimates of γ_i^* for each individual. Similarly, the empirical response process indicates models (3.8) and (3.9) with the estimates shown in Table 3.3 for each role.

[45] Recall that we do not have estimates for 19 cases of our experimental data. Since each subject needs to predict twice in our experiment, for those who have only one estimate, we simply use the estimate for both belief formation processes. Furthermore, for those subjects who do not have both estimates available, we keep the assumption of myopic Cournot learning.

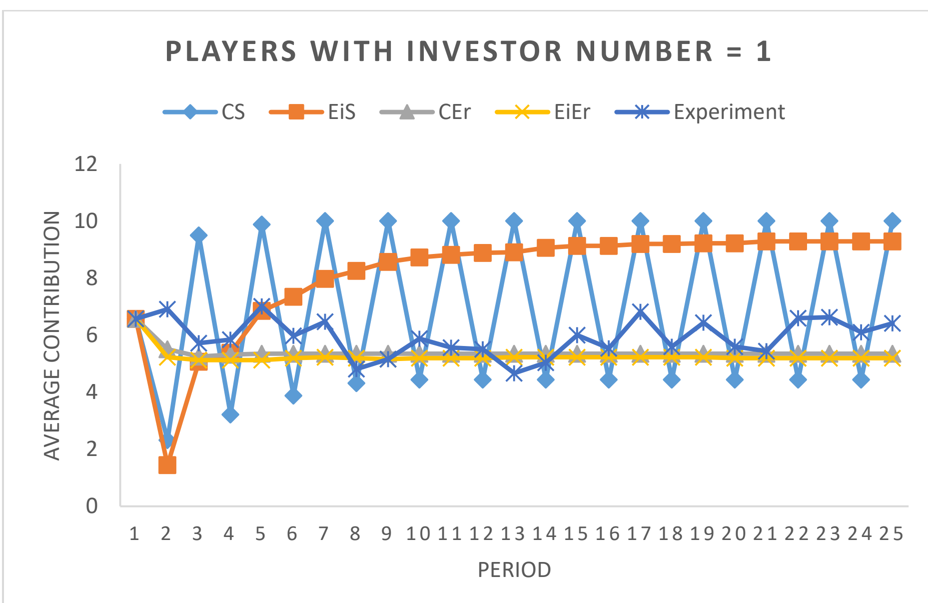


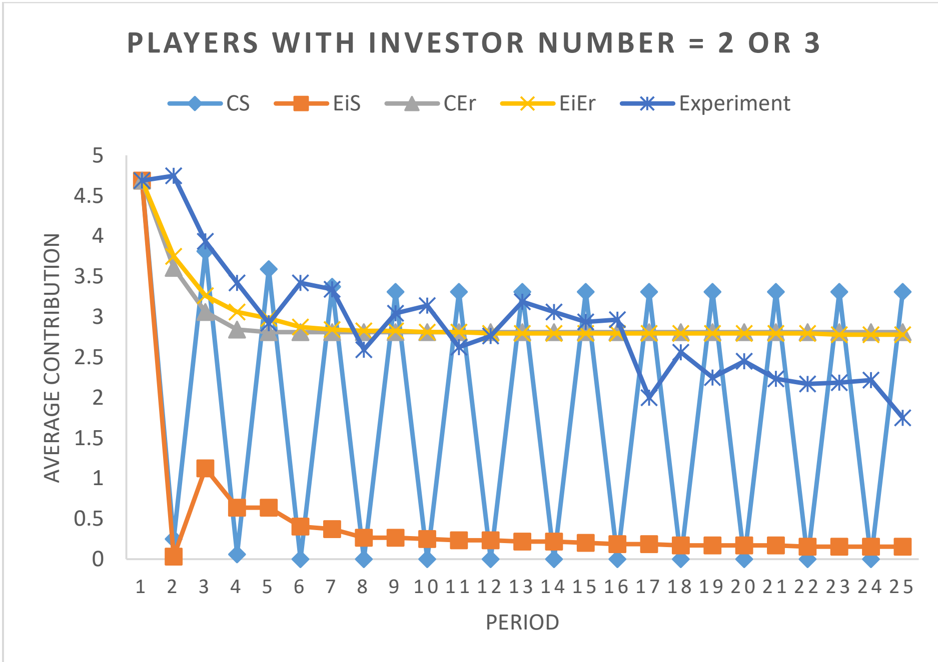
Penal B: Treatment (10, 4, 4)



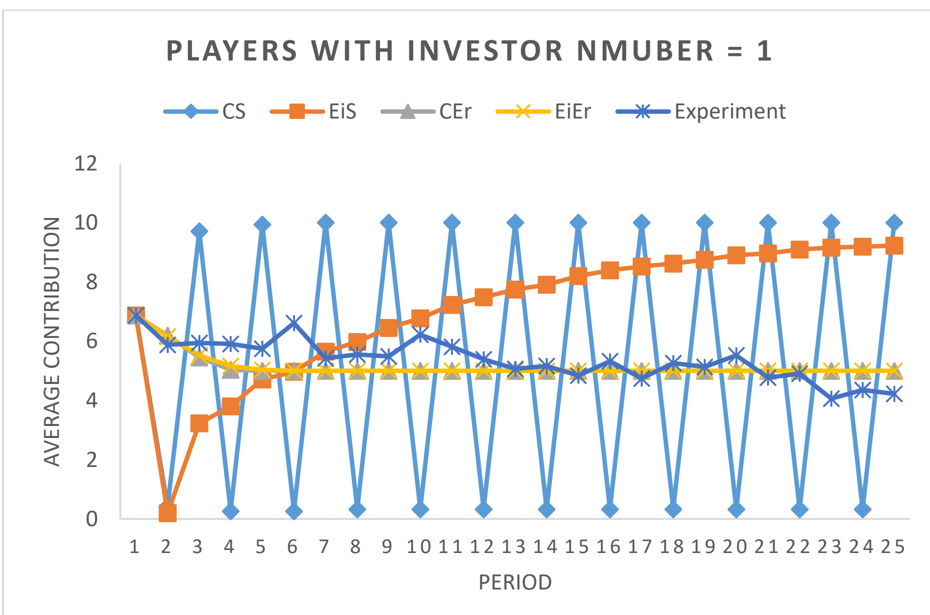


Penal C: Treatment (10, 6, 6)





Penal D: Treatment (10, 8, 8)



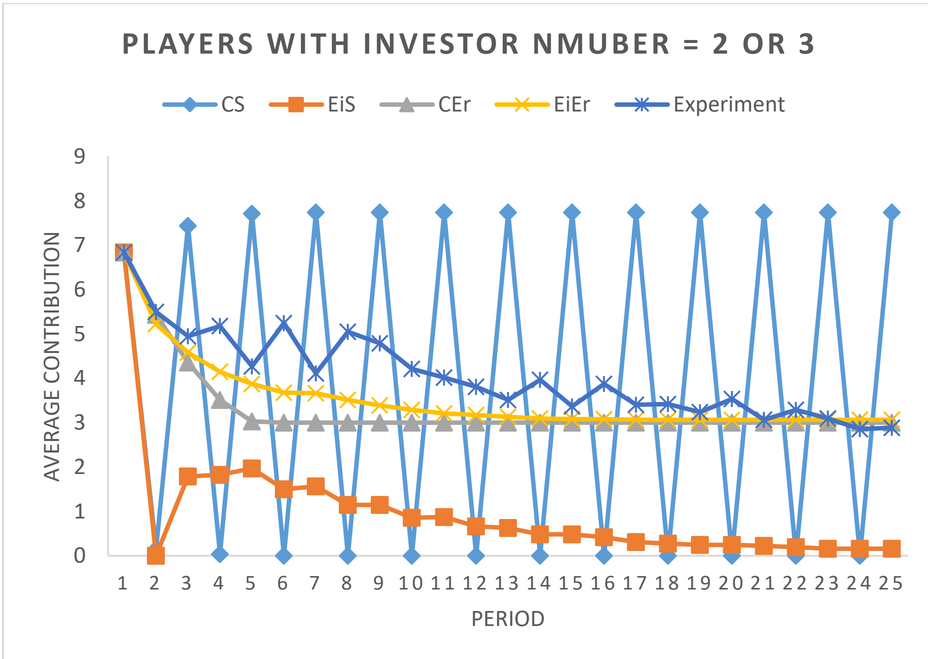


Fig. 3.7 Average contribution per period of simulation results for each role of players in four treatments

Figure 3.7 shows the average contribution in each period for each role, generated from these simulations and the experimental observations. First, the simulation results between the CS treatment and the EiS treatment are very similar in treatments (10, 2, 2) and (10, 4, 4). However, they are quite different in treatments (10, 6, 6) and (10, 8, 8). As predicted by Saijo (2015), at the group level, the simulation results show that 18 of 32 groups in treatment (10, 6, 6) and 30 of 31 groups in treatment (10, 8, 8) begin unstable pulsing in the CS treatment. Thus, we see significant pulsing in the averages. However, in the EiS treatment, no group enters unstable pulsing.[46] Therefore, we conclude that the adaptive change in the belief-formation process improves the stability of the system in treatments (10, 6, 6) and (10, 8, 8).

Second, to compare the prediction power of these simulations, we calculate the prediction errors for each subject at each period.[47] By comparing the prediction errors across these simulation treatments, the Wilcoxon signed-rank tests show that the simulation results from the CEr treatment and the EiEr treatment are quite similar in treatments (10, 2, 2) (p-value = 0.8673) and (10, 4, 4) (p-value = 0.6966). However, the simulation results from the EiEr

[46] Even though there is no unstable pulsing, four groups in treatment (10, 6, 6) and seven groups in treatment (10, 8, 8) still do not reach the unique Nash equilibrium within 25 periods in the simulation of the EiS treatment.

[47] The prediction error is the absolute difference ($|p_i^t - s_i^t|$) between the simulation result (p_i^t) and the experimental observation (s_i^t) for subject i at period t (similar to the analysis in Healy (2006)).

treatment are more accurate than those from the CEr treatment in treatments (10, 6, 6) (p-value < 0.001) and (10, 8, 8) (p-value < 0.001), although Figure 7 shows that their averages are similar. Furthermore, the simulation results from the CEr and EiEr treatments are more accurate than those from the other two simulation treatments (CS and EiS) in all experimental treatments (all p-values < 0.001, by the Wilcoxon signed-rank tests). Briefly, the simulation results from the EiEr treatment are closest to the experimental observations among these simulation treatments. These results confirm that the empirical belief-formation processes are close to myopic Cournot learning in the two globally stable treatments, and indicate that the differences in both the belief-formation and response processes contribute to the difference in the convergence of contributions across the four experimental treatments.

3.6 Conclusion

We have investigated the convergence of contribution behavior in VCM experiments with heterogeneous quasi-linear payoff functions. Four experimental treatments with different heterogeneous settings are designed to share an identical Nash equilibrium, but with different stability properties. We clearly observe a significant difference in the convergence of contributions across the four treatments. The Nash equilibrium is a good predictor for the two globally stable treatments, but not for the two non-globally stable treatments. In the two non-globally stable treatments, the players that benefit more from the public good contribute far less than the Nash prediction, while the players that benefit less contribute much more than the Nash prediction. The overall result is that the groups' total contributions from the four treatments with different average marginal per capita returns are not significantly different in the final 10 periods.

By estimating subject's belief-formation and response processes, we find significant differences in both of them across treatments. Our experimental results indicate that the decision-making processes of subjects are closer to the assumption of Cournot best-response dynamics in the two globally stable treatments than they are in the two non-globally stable treatments. Moreover, using simulations, we find that the changes in the belief-formation process improve the stability of the system in the two non-globally stable treatments and that the differences across treatments in the convergence of the contributions come from the differences in both the belief-formation and response processes.

Our experimental findings might give some insights for the observation that the contribution from some particular individual/company accounts for more than 90% of the total contribution in a practical VCM situation, for example, the voluntary contributions to build anti-tsunami embankments at Hamamatsu city in Japan (Saijo, 2015). However, note that, in most real situations, the condition, $a_1 > \sum_{j=2}^{n} a_j$, in Proposition 2 is not satisfied, which indicates the unique Nash equilibrium is not a good predictor in those situations. Our experimental results show that, in the two non-globally stable treatments, although the contributions are not converging to the Nash equilibrium, they are also not pulsing. These experimental results might imply that they converge to some other equilibria (such as some inequity-averse equilibria).

Although two treatments in our experiment are non-globally stable based on the theory of Saijo (2015), our experimental results suggest that subjects' belief-formation and response processes are, to a large extent, inconsistent with the Cournot best-response dynamics. Our observations of differences in the belief-formation process across treatments might indicate that the cognitive ability of human subjects can proactively choose the range of information used and employ different learning processes in situations with different stability properties. However, in the two non-globally stable treatments, because of the presence of conditional cooperation in the response process, the source of these adaptive changes in the belief-formation process still needs further studies. This finding also raises a new question, can these adaptive changes maintain the stability of the system in an asymmetric quasi-linear VCM environment, if the number of players increases?

In our VCM experiment with quasi-linear payoff functions, we find that the argument of Fischbacher and Gächter (2010) explains the belief-formation process quite well. Therefore, we adopt their argument as an assumption and extend the analysis of the belief-formation process to the individual level. We suggest that this model is similar to the γ-weighted fictitious play model in Cheung and Friedman (1997), applied when players are more likely to be forming their beliefs using the average of historical observations rather than using the probability distribution.

Finally, Ledyard (1995) surveys the literature on VCM experiments with heterogeneous benefits in a linear environment, and conjectures that heterogeneous benefits have a negative effect on contributions and, thus, calls for additional research. Although our study is conducted in a quasi-linear environment, we find an interesting result. The decision-making processes of players are significantly different across different heterogeneous designs, but the groups' total contributions are not statistically different in the final 10 periods of the experiment. This observation is also related to the convergence of contributions in the two non-globally stable treatment. Related issues still need further studies.

Appendix

The derivation of equation (3.6). We begin with the argument of Fischbacher and Gächter (2010). The belief at period t can be expressed as the weighted average of the last observation and the belief in period t – 1. That is,

$$b_{ij,t} = (1-\gamma_i)s_{j,t-1} + \gamma_i b_{ij,t-1},$$

where $\gamma_i \in [0,1)$ is the weighting factor. Then, we have the following series of equations:

$$b_{ij,t-1} = (1-\gamma_i)s_{j,t-2} + \gamma_i b_{ij,t-2},$$

$$b_{ij,t-2} = (1-\gamma_i)s_{j,t-3} + \gamma_i b_{ij,t-3},$$

$$\ldots\ldots$$

$$b_{ij,2} = (1-\gamma_i)s_{j,1} + \gamma_i b_{ij,1}.$$

After substituting all equations into the first equation, we have,

$$\begin{aligned} b_{ij,t} &= (1-\gamma_i)s_{j,t-1} + \gamma_i(1-\gamma_i)s_{j,t-2} + \gamma_i^2(1-\gamma_i)s_{j,t-3} + \cdots + \gamma_i^{t-2}(1-\gamma_i)s_{j,1} + \gamma_i^{t-1}b_{ij,1} \\ &= (1-\gamma_i)[s_{j,t-1} + \gamma_i s_{j,t-2} + \gamma_i^2 s_{j,t-3} + \cdots + \gamma_i^{t-2}s_{j,1} + \frac{\gamma_i^{t-1}}{1-\gamma_i}b_{ij,1}] \\ &= \frac{s_{j,t-1} + \sum_{u=1}^{t-2}\gamma_i^u s_{j,t-1-u} + \frac{\gamma_i^{t-1}}{1-\gamma_i}b_{ij,1}}{\frac{1}{1-\gamma_i}}. \end{aligned} \tag{A3.1}$$

Since $\frac{1}{1-\gamma_i} = 1 + \sum_{u=1}^{t-2}\gamma_i^u + \frac{\gamma_i^{t-1}}{1-\gamma_i}$, equation (A3.1) is exactly equation (3.6).

Supplementary Documents

1. Instructions and payoff tables in our experiments.

There are one instruction and five payoff tables in this supplementary document. All treatments use the same instructions but different payoff tables in the experiment.

Instructions

This is an experiment in the economics of decision-making. At the end of today's session you will be paid in private and in cash. It is important that you remain silent and do not look at other people's work. Please turn off your cell phone and don't talk with others. If you have any questions or need assistance of any kind, please raise your hand. If you exclaim out loud or violate any of the rules explained below, you may be asked to leave and will not be paid.

We thank you for your cooperation in this regard.

Overview

There will be 25 decision-making rounds in this experiment. You will each complete two tasks in each of these rounds. At the end of each round you will be informed your earnings for that round on the PC screen. The rules are identical in every round.

In the first round you will be randomly assigned to a group. Each group consists of 3 members. When groups are created, each of you will be randomly given an Investor Number (1, 2 or 3). These numbers and the composition of your group will be fixed in every round. You will not know which of the other people in the experiment are in your group in any given round.

At the end of the session, one of two tasks will be randomly drawn. You will be paid the total of your earnings from the chosen task for the 25 rounds.

Rules

In each round you and your group members each have 12 tokens to allocate. Each of you must decide how many tokens you want to invest in a project. Returns for all possible allocations are listed in the 'Earnings Tables'. There are two Earnings Tables (table 1 and table 2) with different payoff structures in the appendix. The player whose investor number is 1, is corresponding to table 1. All other two players are corresponding to table 2. When the experiment begins, you should enter your decisions in the blanks on the screen. Your entries on the blanks must be whole numbers between 0 and 12. At the same time, you also need make a prediction regarding the individual investments of the other two members in your group.

After everyone has made the decision and prediction, the computer will display the decisions of other two players in your group. You can record the entries that the computer has reported and compute your earnings according to the Earning Tables. The following illustrations show how to use the payoff table to compute your incomes from the investment task. In each round, you investment income depends on your own investment and the total investments from the other two group members. You can find the line corresponding to your own investment and the column corresponding to the total investment of other two group members. The number at the intersection of the line and the column is your payoff in that round.

You also will gain an additional income from your prediction (since there are two other members in your group, the prediction incomes will be computed separately and summed together). The formula of this additional income is,

$$\pi_i^{rb} = \begin{cases} 150, \ if\ s_j^b = s_j^r \\ \frac{100}{\left|s_j^b - s_j^r\right|}, \ \ if\ s_j^b \neq s_j^r \end{cases}, \ i,j = 1,2,3, i \neq j \ ,$$

where s_j^b is your prediction about the investment from the group member j and s_j^r is the observed investment from group member j. This formula means that if your prediction about player j's investment is exactly equal to his/her investment, you will get 150 experimental dollars. If they are different, you will get 100 divided by the difference.

Next, you will check to see if your calculation is consistent with the reported on the screen. It is very important that we both make this calculation and consistence. If your calculation differs from the computer's or if you are unsure about how to compute your earnings in any round, please raise your hand. When all things are correct, the next round will begin.

Finally, at the end of today's session, the experimenter will invite three subjects to decide the incomes from which task will be set as the basis of your earnings for today's experiment. Six cards (5 cards with numbers and one card with pictures) will be presented. Three subjects discuss and draw one card from these six cards. If the drawn card is the card with numbers, the incomes from the investment task will be the basis of the earnings of today's experiment. In contrast, if the drawn card is the card with pictures, the incomes from the prediction task will be the basis of the earnings of today's experiment. The exchange rate is 130 experimental dollars to 1 Chinese yuan.

Final Remarks

(1) Two Earnings Tables. Subject with investor number 1 is using table 1. Other two players are using table 2.

(2) This session will consist of 25 rounds.

(3) In each round, you and every other member of your group will each have 12 tokens to allocate.

(4) In each round, you will decide how many tokens to invest in the project. The decision must be an integer and within the range of [0, 12].

(5) In each round, you will predict the individual investments from other two players. The prediction must be an integer and within the range of [0, 12].

(6) Your earnings from the investment depend on your decision and the total investment from other two players.

(7) Your earnings from the prediction depend on the distance between the prediction value and the observed value.

(8) The members in your group will be fixed in each round.

(9) The total income from one task (investment task or prediction task) will be randomly chosen as the basis of the earnings of today's experiment. The exchange rate is 130 experimental dollars to 1 Chinese yuan.

(10) Do not discuss your decisions with other subjects.

Are there any questions?

If all things are clear, please click “next” on your screen and finish those questions. Note that the purpose of those questions is only to make you understand the instructions and your answers will not affect your earnings in the experiment.

Payoff tables

In each treatment, two payoff tables will be presented. For example, in treatment (10,2,2), the payoff tables with $a_i = 10$ and $a_i = 2$ will be presented to subjects. The yellow color blocks show the best response line in each payoff table, but is not presented during the experiment.

1. $a_i = 10$

your contribution / the total contribution of others	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
0	120.0	196.2	240.8	272.5	297.0	317.1	334.1	348.7	361.7	373.3	383.8	393.3	402.1	410.3	417.9	425.0	431.7	437.9	443.9	449.5	454.9	460.0	464.9	469.6	474.1
1	186.2	230.8	262.5	287.0	307.1	324.1	338.7	351.7	363.3	373.8	383.3	392.1	400.3	407.9	415.0	421.7	427.9	433.9	439.5	444.9	450.0	454.9	459.6	464.1	468.4
2	220.8	252.5	277.0	297.1	314.1	328.7	341.7	353.3	363.8	373.3	382.1	390.3	397.9	405.0	411.7	417.9	423.9	429.5	434.9	440.0	444.9	449.6	454.1	458.4	462.5
3	242.5	267.0	287.1	304.1	318.7	331.7	343.3	353.8	363.3	372.1	380.3	387.9	395.0	401.7	407.9	413.9	419.5	424.9	430.0	434.9	439.6	444.1	448.4	452.5	456.5
4	257.0	277.1	294.1	308.7	321.7	333.3	343.8	353.3	362.1	370.3	377.9	385.0	391.7	397.9	403.9	409.5	414.9	420.0	424.9	429.6	434.1	438.4	442.5	446.5	450.4
5	267.1	284.1	298.7	311.7	323.3	333.8	343.3	352.1	360.3	367.9	375.0	381.7	387.9	393.9	399.5	404.9	410.0	414.9	419.6	424.1	428.4	432.5	436.5	440.4	444.1
6	274.1	288.7	301.7	313.3	323.8	333.3	342.1	350.3	357.9	365.0	371.7	377.9	383.9	389.5	394.9	400.0	404.9	409.6	414.1	418.4	422.5	426.5	430.4	434.1	437.7
7	278.7	291.7	303.3	313.8	323.3	332.1	340.3	347.9	355.0	361.7	367.9	373.9	379.5	384.9	390.0	394.9	399.6	404.1	408.4	412.5	416.5	420.4	424.1	427.7	431.2
8	281.7	293.3	303.8	313.3	322.1	330.3	337.9	345.0	351.7	357.9	363.9	369.5	374.9	380.0	384.9	389.6	394.1	398.4	402.5	406.5	410.4	414.1	417.7	421.2	424.6
9	283.3	293.8	303.3	312.1	320.3	327.9	335.0	341.7	347.9	353.9	359.5	364.9	370.0	374.9	379.6	384.1	388.4	392.5	396.5	400.4	404.1	407.7	411.2	414.6	417.9
10	283.8	293.3	302.1	310.3	317.9	325.0	331.7	337.9	343.9	349.5	354.9	360.0	364.9	369.6	374.1	378.4	382.5	386.5	390.4	394.1	397.7	401.2	404.6	407.9	411.1
11	283.3	292.1	300.3	307.9	315.0	321.7	327.9	333.9	339.5	344.9	350.0	354.9	359.6	364.1	368.4	372.5	376.5	380.4	384.1	387.7	391.2	394.6	397.9	401.1	404.2
12	282.1	290.3	297.9	305.0	311.7	317.9	323.9	329.5	334.9	340.0	344.9	349.6	354.1	358.4	362.5	366.5	370.4	374.1	377.7	381.2	384.6	387.9	391.1	394.2	397.2

2. $a_i = 8$

your contribution / the total contribution of others	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
0	120.0	182.4	218.9	244.8	264.8	281.3	295.1	307.1	317.8	327.2	335.8	343.6	350.8	357.5	363.7	369.5	375.0	380.1	385.0	389.6	394.0	398.2	402.2	406.0	409.7
1	172.4	208.9	234.8	254.8	271.3	285.1	297.1	307.8	317.2	325.8	333.6	340.8	347.5	353.7	359.5	365.0	370.1	375.0	379.6	384.0	388.2	392.2	396.0	399.7	403.2
2	198.9	224.8	244.8	261.3	275.1	287.1	297.8	307.2	315.8	323.6	330.8	337.5	343.7	349.5	355.0	360.1	365.0	369.6	374.0	378.2	382.2	386.0	389.7	393.2	396.6
3	214.8	234.8	251.3	265.1	277.1	287.8	297.2	305.8	313.6	320.8	327.5	333.7	339.5	345.0	350.1	355.0	359.6	364.0	368.2	372.2	376.0	379.7	383.2	386.6	389.9
4	224.8	241.3	255.1	267.1	277.8	287.2	295.8	303.6	310.8	317.5	323.7	329.5	335.0	340.1	345.0	349.6	354.0	358.2	362.2	366.0	369.7	373.2	376.6	379.9	383.1
5	231.3	245.1	257.1	267.8	277.2	285.8	293.6	300.8	307.5	313.7	319.5	325.0	330.1	335.0	339.6	344.0	348.2	352.2	356.0	359.7	363.2	366.6	369.9	373.1	376.1
6	235.1	247.1	257.8	267.2	275.8	283.6	290.8	297.5	303.7	309.5	315.0	320.1	325.0	329.6	334.0	338.2	342.2	346.0	349.7	353.2	356.6	359.9	363.1	366.1	369.1
7	237.1	247.8	257.2	265.8	273.6	280.8	287.5	293.7	299.5	305.0	310.1	315.0	319.6	324.0	328.2	332.2	336.0	339.7	343.2	346.6	349.9	353.1	356.1	359.1	361.9
8	237.8	247.2	255.8	263.6	270.8	277.5	283.7	289.5	295.0	300.1	305.0	309.6	314.0	318.2	322.2	326.0	329.7	333.2	336.6	339.9	343.1	346.1	349.1	351.9	354.7
9	237.2	245.8	253.6	260.8	267.5	273.7	279.5	285.0	290.1	295.0	299.6	304.0	308.2	312.2	316.0	319.7	323.2	326.6	329.9	333.1	336.1	339.1	341.9	344.7	347.4
10	235.8	243.6	250.8	257.5	263.7	269.5	275.0	280.1	285.0	289.6	294.0	298.2	302.2	306.0	309.7	313.2	316.6	319.9	323.1	326.1	329.1	331.9	334.7	337.4	340.0
11	233.6	240.8	247.5	253.7	259.5	265.0	270.1	275.0	279.6	284.0	288.2	292.2	296.0	299.7	303.2	306.6	309.9	313.1	316.1	319.1	321.9	324.7	327.4	330.0	332.5

12	230.8	237.5	243.7	249.5	255.0	260.1	265.0	269.6	274.0	278.2	282.2	286.0	289.7	293.2	296.6	299.9	303.1	306.1	309.1	311.9	314.7	317.4	320.0	322.5	325.0

3. $a_i = 6$

your contribution / the total contribution of others	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
0	120.0	168.5	196.9	217.0	232.7	245.4	256.2	265.6	273.8	281.2	287.9	293.9	299.5	304.7	309.6	314.1	318.3	322.3	326.1	329.7	333.1	336.4	339.5	342.5	345.3
1	158.5	186.9	207.0	222.7	235.4	246.2	255.6	263.8	271.2	277.9	283.9	289.5	294.7	299.6	304.1	308.3	312.3	316.1	319.7	323.1	326.4	329.5	332.5	335.3	338.1
2	176.9	197.0	212.7	225.4	236.2	245.6	253.8	261.2	267.9	273.9	279.5	284.7	289.6	294.1	298.3	302.3	306.1	309.7	313.1	316.4	319.5	322.5	325.3	328.1	330.7
3	187.0	202.7	215.4	226.2	235.6	243.8	251.2	257.9	263.9	269.5	274.7	279.6	284.1	288.3	292.3	296.1	299.7	303.1	306.4	309.5	312.5	315.3	318.1	320.7	323.3
4	192.7	205.4	216.2	225.6	233.8	241.2	247.9	253.9	259.5	264.7	269.6	274.1	278.3	282.3	286.1	289.7	293.1	296.4	299.5	302.5	305.3	308.1	310.7	313.3	315.7
5	195.4	206.2	215.6	223.8	231.2	237.9	243.9	249.5	254.7	259.6	264.1	268.3	272.3	276.1	279.7	283.1	286.4	289.5	292.5	295.3	298.1	300.7	303.3	305.7	308.1
6	196.2	205.6	213.8	221.2	227.9	233.9	239.5	244.7	249.6	254.1	258.3	262.3	266.1	269.7	273.1	276.4	279.5	282.5	285.3	288.1	290.7	293.3	295.7	298.1	300.4
7	195.6	203.8	211.2	217.9	223.9	229.5	234.7	239.6	244.1	248.3	252.3	256.1	259.7	263.1	266.4	269.5	272.5	275.3	278.1	280.7	283.3	285.7	288.1	290.4	292.6
8	193.8	201.2	207.9	213.9	219.5	224.7	229.6	234.1	238.3	242.3	246.1	249.7	253.1	256.4	259.5	262.5	265.3	268.1	270.7	273.3	275.7	278.1	280.4	282.6	284.8
9	191.2	197.9	203.9	209.5	214.7	219.6	224.1	228.3	232.3	236.1	239.7	243.1	246.4	249.5	252.5	255.3	258.1	260.7	263.3	265.7	268.1	270.4	272.6	274.8	276.8
10	187.9	193.9	199.5	204.7	209.6	214.1	218.3	222.3	226.1	229.7	233.1	236.4	239.5	242.5	245.3	248.1	250.7	253.3	255.7	258.1	260.4	262.6	264.8	266.8	268.9
11	183.9	189.5	194.7	199.6	204.1	208.3	212.3	216.1	219.7	223.1	226.4	229.5	232.5	235.3	238.1	240.7	243.3	245.7	248.1	250.4	252.6	254.8	256.8	258.9	260.8
12	179.5	184.7	189.6	194.1	198.3	202.3	206.1	209.7	213.1	216.4	219.5	222.5	225.3	228.1	230.7	233.3	235.7	238.1	240.4	242.6	244.8	246.8	248.9	250.8	252.8

4. $a_i = 4$

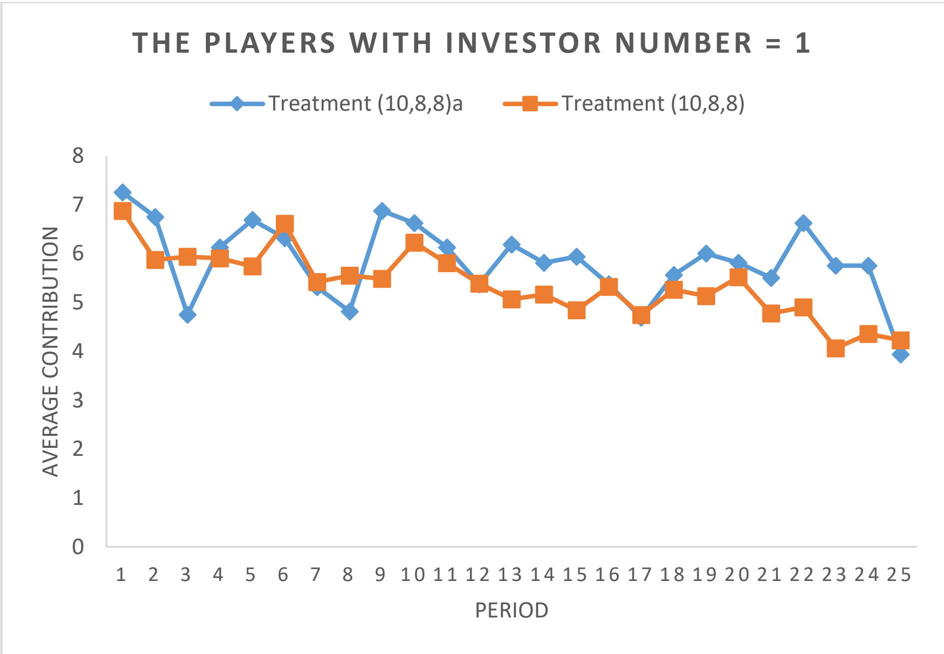
your contribution / the total contribution of others	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
0	120.0	154.7	174.9	189.3	200.5	209.6	217.3	224.0	229.9	235.1	239.9	244.2	248.2	252.0	255.4	258.6	261.7	264.5	267.2	269.8	272.2	274.6	276.8	278.9	280.9
1	144.7	164.9	179.3	190.5	199.6	207.3	214.0	219.9	225.1	229.9	234.2	238.2	242.0	245.4	248.6	251.7	254.5	257.2	259.8	262.2	264.6	266.8	268.9	270.9	272.9
2	154.9	169.3	180.5	189.6	197.3	204.0	209.9	215.1	219.9	224.2	228.2	232.0	235.4	238.6	241.7	244.5	247.2	249.8	252.2	254.6	256.8	258.9	260.9	262.9	264.8
3	159.3	170.5	179.6	187.3	194.0	199.9	205.1	209.9	214.2	218.2	222.0	225.4	228.6	231.7	234.5	237.2	239.8	242.2	244.6	246.8	248.9	250.9	252.9	254.8	256.6
4	160.5	169.6	177.3	184.0	189.9	195.1	199.9	204.2	208.2	212.0	215.4	218.6	221.7	224.5	227.2	229.8	232.2	234.6	236.8	238.9	240.9	242.9	244.8	246.6	248.4
5	159.6	167.3	174.0	179.9	185.1	189.9	194.2	198.2	202.0	205.4	208.6	211.7	214.5	217.2	219.8	222.2	224.6	226.8	228.9	230.9	232.9	234.8	236.6	238.4	240.1
6	157.3	164.0	169.9	175.1	179.9	184.2	188.2	192.0	195.4	198.6	201.7	204.5	207.2	209.8	212.2	214.6	216.8	218.9	220.9	222.9	224.8	226.6	228.4	230.1	231.7
7	154.0	159.9	165.1	169.9	174.2	178.2	182.0	185.4	188.6	191.7	194.5	197.2	199.8	202.2	204.6	206.8	208.9	210.9	212.9	214.8	216.6	218.4	220.1	221.7	223.3
8	149.9	155.1	159.9	164.2	168.2	172.0	175.4	178.6	181.7	184.5	187.2	189.8	192.2	194.6	196.8	198.9	200.9	202.9	204.8	206.6	208.4	210.1	211.7	213.3	214.8
9	145.1	149.9	154.2	158.2	162.0	165.4	168.6	171.7	174.5	177.2	179.8	182.2	184.6	186.8	188.9	190.9	192.9	194.8	196.6	198.4	200.1	201.7	203.3	204.8	206.3
10	139.9	144.2	148.2	152.0	155.4	158.6	161.7	164.5	167.2	169.8	172.2	174.6	176.8	178.9	180.9	182.9	184.8	186.6	188.4	190.1	191.7	193.3	194.8	196.3	197.8
11	134.2	138.2	142.0	145.4	148.6	151.7	154.5	157.2	159.8	162.2	164.6	166.8	168.9	170.9	172.9	174.8	176.6	178.4	180.1	181.7	183.3	184.8	186.3	187.8	189.2
12	128.2	132.0	135.4	138.6	141.7	144.5	147.2	149.8	152.2	154.6	156.8	158.9	160.9	162.9	164.8	166.6	168.4	170.1	171.7	173.3	174.8	176.3	177.8	179.2	180.5

5. $a_i = 2$

your contribution / the total contribution of others	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
0	120.0	140.8	153.0	161.6	168.3	173.8	178.4	182.4	185.9	189.1	191.9	194.5	196.9	199.2	201.2	203.2	205.0	206.7	208.3	209.9	211.3	212.7	214.1	215.3	216.6
1	130.8	143.0	151.6	158.3	163.8	168.4	172.4	175.9	179.1	181.9	184.5	186.9	189.2	191.2	193.2	195.0	196.7	198.3	199.9	201.3	202.7	204.1	205.3	206.6	207.7
2	133.0	141.6	148.3	153.8	158.4	162.4	165.9	169.1	171.9	174.5	176.9	179.2	181.2	183.2	185.0	186.7	188.3	189.9	191.3	192.7	194.1	195.3	196.6	197.7	198.9
3	131.6	138.3	143.8	148.4	152.4	155.9	159.1	161.9	164.5	166.9	169.2	171.2	173.2	175.0	176.7	178.3	179.9	181.3	182.7	184.1	185.3	186.6	187.7	188.9	190.0
4	128.3	133.8	138.4	142.4	145.9	149.1	151.9	154.5	156.9	159.2	161.2	163.2	165.0	166.7	168.3	169.9	171.3	172.7	174.1	175.3	176.6	177.7	178.9	180.0	181.0
5	123.8	128.4	132.4	135.9	139.1	141.9	144.5	146.9	149.2	151.2	153.2	155.0	156.7	158.3	159.9	161.3	162.7	164.1	165.3	166.6	167.7	168.9	170.0	171.0	172.0
6	118.4	122.4	125.9	129.1	131.9	134.5	136.9	139.2	141.2	143.2	145.0	146.7	148.3	149.9	151.3	152.7	154.1	155.3	156.6	157.7	158.9	160.0	161.0	162.0	163.0
7	112.4	115.9	119.1	121.9	124.5	126.9	129.2	131.2	133.2	135.0	136.7	138.3	139.9	141.3	142.7	144.1	145.3	146.6	147.7	148.9	150.0	151.0	152.0	153.0	154.0
8	105.9	109.1	111.9	114.5	116.9	119.2	121.2	123.2	125.0	126.7	128.3	129.9	131.3	132.7	134.1	135.3	136.6	137.7	138.9	140.0	141.0	142.0	143.0	144.0	144.9
9	99.1	101.9	104.5	106.9	109.2	111.2	113.2	115.0	116.7	118.3	119.9	121.3	122.7	124.1	125.3	126.6	127.7	128.9	130.0	131.0	132.0	133.0	134.0	134.9	135.8
10	91.9	94.5	96.9	99.2	101.2	103.2	105.0	106.7	108.3	109.9	111.3	112.7	114.1	115.3	116.6	117.7	118.9	120.0	121.0	122.0	123.0	124.0	124.9	125.8	126.7
11	84.5	86.9	89.2	91.2	93.2	95.0	96.7	98.3	99.9	101.3	102.7	104.1	105.3	106.6	107.7	108.9	110.0	111.0	112.0	113.0	114.0	114.9	115.8	116.7	117.5
12	76.9	79.2	81.2	83.2	85.0	86.7	88.3	89.9	91.3	92.7	94.1	95.3	96.6	97.7	98.9	100.0	101.0	102.0	103.0	104.0	104.9	105.8	106.7	107.5	108.3

2. Experimental observations from two additional sessions.

Since we conducted our experiments with a special design that we set different probabilities for the incomes from two tasks, which is different from the original design in Blanco et al. (2010), we also conducted two additional sessions (24 subjects for each, 48 subjects in total) with the setting of treatment (10,8,8) using the equal probabilities for the incomes from two tasks. We call this two additional sessions as treatment (10,8,8)a. In this document, we report the experimental observations from treatment (10,8,8)a and compare it with the experimental observations from treatment (10,8,8).



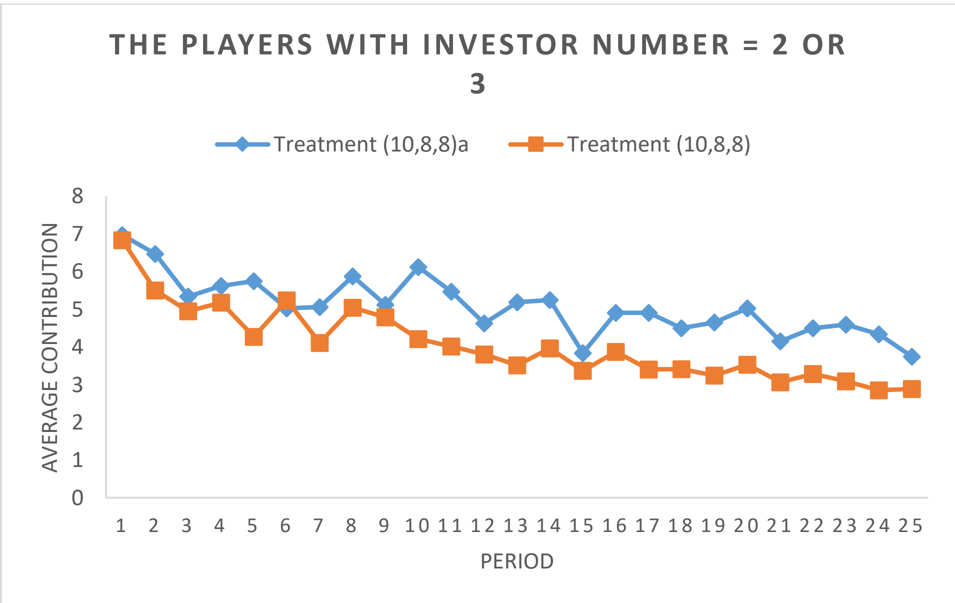


Fig. S1 Average contribution at each period

Figure S1 shows the average contribution at each period for both experimental roles of players in treatments (10,8,8)a and (10,8,8). The Wilcoxon rank-sum tests show that the contributions from the players with investor number =1 in treatment (10,8,8)a are not significantly different from that in treatment (10,8,8) (p-value = 0.4586). However, for the players with investor number = 2 or 3, the contributions are significantly larger in treatment (10,8,8)a than in treatment (10,8,8) (p-value = 0.0202).

The only difference between the two treatments is the design of equal or different probabilities for the incomes from two tasks. Compared to treatment (10,8,8)a, the structure changes stem from the design of belief elicitation is relatively smaller in treatment (10,8,8). Therefore, the difference in contributions comes from the difference in structure changes between the two treatments. This experiment observation shows a consistent result with the experimental observation in Gächter and Renner (2010). They find that the structure changes generated from the belief elicitation with payment incentives increases the contributions in a linear VCM environment with a homogeneous design.

3. The lag length of information used by players

Three models are discussed to check the lag length of information used by players. The first one is the same as Model 3 in Fischbacher and Gächter (2010), which includes "belief (t-1)" and "other's contribution (t-1)". The second and third models include additional lagged variables. The regressions are conducted over the pooled data of each treatment using the OLS model with clustered groups to control unspecified influence within the group.[48]

Table S1 OLS regressions for belief formation

Dependent variable: Belief (t)

Model 1

Variable	Treatment (10,2,2)	Treatment (10,4,4)	Treatment (10,6,6)	Treatment (10,8,8)

[48] Similar to the analysis in Fischbacher and Gächter (2010), we also conduct these regressions with the random effect model, the fixed effect model and the Tobit model. All these regressions produce quite significant estimates for the coefficients in Model 1 and Model 2, but some of the estimates become insignificant in Model 3. These models also produce pretty high values for the R-squared (> 0.8 for treatments (10,2,2) and (10,4,4), > 0.6 for treatments (10,6,6) and (10,8,8)), except the Tobit model (around 0.35 for treatments (10,2,2) and (10,4,4) and around 0.2 for treatments (10,6,6) and (10,8,8)).

Belief (t-1)	0.472***	0.425***	0.409***	0.396***
	(0.038)	(0.025)	(0.029)	(0.027)
Contribution (t-1)	0.504***	0.548***	0.451***	0.484***
	(0.040)	(0.021)	(0.060)	(0.023)
Constant	0.083*	0.173**	0.585**	0.516***
	(0.044)	(0.075)	(0.265)	(0.103)
Obs.	4320	4464	4608	4464
R-squared	0.87	0.83	0.61	0.62
P-value (= 1)	0.052	0.217	0.042	0.000

Dependent variable: Belief (t)

Model 2

Variable	Treatment (10,2,2)	Treatment (10,4,4)	Treatment (10,6,6)	Treatment (10,8,8)
Belief (t-1)	0.292***	0.243***	0.142*	0.240***
	(0.061)	(0.060)	(0.082)	(0.037)
Contribution(t-1)	0.413***	0.457***	0.373***	0.446***
	(0.044)	(0.034)	(0.082)	(0.030)
Belief (t-2)	0.173***	0.110***	0.200***	0.141***
	(0.035)	(0.021)	(0.053)	(0.019)
Investment (t-2)	0.123**	0.190**	0.246**	0.110*
	(0.060)	(0.073)	(0.097)	(0.040)
Constant	-0.002	0.070*	0.166**	0.231**
	(0.026)	(0.041)	(0.065)	(0.080)
Obs.	4140	4278	4416	4278
R-squared	0.89	0.85	0.68	0.65
P-value (= 1)	0.977	0.957	0.046	0.001

Dependent variable: Belief (t)

Model 3

Variable	Treatment (10,2,2)	Treatment (10,4,4)	Treatment (10,6,6)	Treatment (10,8,8)
Belief (t-1)	0.275***	0.224**	0.133**	0.231***
	(0.066)	(0.071)	(0.072)	(0.042)
Contribution (t-1)	0.402***	0.443***	0.359***	0.435***

	(0.053)	(0.040)	(0.075)	(0.031)
Belief (t-2)	0.173***	0.070**	0.188**	0.108***
	(0.053)	(0.034)	(0.080)	(0.024)
Contribution (t-2)	0.123**	0.196**	0.250**	0.105*
	(0.054)	(0.071)	(0.098)	(0.039)
Belief (t-3)	0.085***	0.094***	0.082***	0.076***
	(0.020)	(0.027)	(0.027)	(0.015)
Contribution (t-3)	-0.053	-0.018	-0.041	0.004
	(0.058)	(0.035)	(0.051)	(0.016)
Constant	-0.012	0.024	0.095	0.120
	(0.022)	(0.031)	(0.066)	(0.070)
Obs.	3960	4092	4224	4092
R-squared	0.90	0.86	0.68	0.65
P-value (= 1)	0.384	0.225	0.137	0.004

Clustered standard errors are shown in parentheses. Significantly different from zero at * 10% level, ** 5% level, *** 1% level (all two-tailed tests).

Table S1 shows the results of these regressions. All regressions produce a pretty high R-squared (> 0.8 for treatments (10,2,2) and (10,4,4) and > 0.6 for treatments (10,6,6) and (10,8,8)). Moreover, in all treatments, the estimates of the coefficient of the lagged variable "other's contribution (t-3)" are not significant, which indicates that the weighted observations should be limited within the previous two periods. We also report the p-values in the table for testing whether the sum of the estimated coefficients is equal to one for each regression.[49] It is accepted by all models in treatment (10,4,4) but rejected by all models in treatment (10,8,8). This result indicates that there is a systematic difference in the belief-formation process across the four treatments. Given these observations, we suggest that the argument from Fischbacher and Gächter (2010) also gives a reasonable explanation for the belief-formation process in our experiment.

4. A model selection procedure for the belief-formation process

In this document, we conduct a model selection procedure to compare the performance of two models in explaining the belief-formation process at the aggregate level in our experiment.

[49] If the sum of coefficients is equal to one and the constant of the regression is insignificantly different from zero, it gives a perfect support for the argument of Fischbacher and Gächter (2010).

Model 1: The weighted average model

Fischbacher and Gächter (2010) claim a weighted averaging process in the belief-formation process of subjects in the experiment of a public goods game. That is equation (3.6) in the paper. Subject's belief-formation process is a weighted average over all previous observations and his/her priori belief. That is,

$$b_{ij,t+1} = \frac{s_{j,t} + \sum_{u=1}^{t-1} \gamma_i^u s_{j,t-u} + \frac{\gamma_i^t}{1-\gamma_i} B_{ij,1}}{1 + \sum_{u=1}^{t-1} \gamma_i^u + \frac{\gamma_i^t}{1-\gamma_i}}, \tag{s1}$$

where $b_{ij,t+1}$ is player i's belief about the contribution of player j at period t+1, $s_{j,t}$ is the contribution of player j at period t, γ_i^u is a weight given to the observation of $s_{j,t-u}$ at period t-u, and $B_{ij,1}$ is the prior stated belief about the contribution of player j at period 1. Define γ_i^* for the representative player that minimizes the sum of the squared errors (SSE) between the stated beliefs and the beliefs suggested by equation (s1). That is,

$$\gamma_i^* = \arg min \{\sum_{i=1}^{N} \sum_{t=2}^{25} \left(B_{ij,t} - b_{ij,t}\right)^2\}, \tag{s2}$$

where $B_{ij,t}$ is player i's stated belief about player j's contribution at period t, and $b_{ij,t}$ is the constructed belief at period t given by equation (s1).

Model 2: The smoothed γ-weighted fictitious play model

A usual way to explain the belief-formation process in a normal form game is based on a distribution of historical observations (for example, the fictitious play). Cheung and Friedman (1997) introduce the time decay into the fictitious play model, which is referred to as the γ-weighted fictitious play model. Furthermore, Fudenberg and Levine (1998) propose the smoothed fictitious play model to incorporate decision errors into the fictitious play. Therefore, in our experiment, the process of belief elicitation could be modeled by the smoothed γ-weighted fictitious play model. That is, players follow the γ-weighted fictitious play to form their underlying beliefs, and then report their stated beliefs via a stochastic response process. Therefore, the underlying belief is,

$$b_{i,t+1}^k = \frac{1_t(a^k) + \sum_{u=1}^{t-1} \beta_i^u 1_{t-u}(a^k)}{1 + \sum_{u=1}^{t-1} \beta_i^u}, \tag{s3}$$

Where $b_{i,t+1}^{k}$ is player i's belief about the possibility that his/her opponent will choose action a^k at period t+1, $1_t(a^k)$ is an indicator that equals to 1 if action a^k is chosen at period t and 0 otherwise, and β_i^u is a weight given to the observation of a^k at period t-u. Then, based on this underlying belief, player i will form an expected payoff for each choice in the guessing task at period t. That is,

$$\bar{v}_i^t(B_{i,t}) = \sum_{k=0}^{12} b_{i,t}^{k}\,\pi_i(B_{i,t}, k)\ , \qquad \text{(s4)}$$

where k denotes a contribution of k tokens, $B_{i,t}$ is player i's stated belief at period t, $b_{i,t}^{k}$ is the constructed belief given by equation (s3), and $\pi_i(B_{i,t}, k)$ is the payoff from the guessing task, which is 150 when $B_{i,t} = k$ or $100/|B_i^t - k|$ when $B_{i,t} \neq k$. This expected payoff function is maximized when player i report the choice with the highest probability he/she believes. Based on these expected payoffs, we assume subjects stated his/her belief via a stochastic response rule at period t. That is,

$$r\big(B_{i,t}\big|b_{i,t}(\beta_i), \lambda_i\big) = \frac{\exp(\lambda_i\,\bar{v}_i^t(B_{i,t}))}{\sum_{s=0}^{12}\exp(\lambda_i\,\bar{v}_i^t(s))}, \qquad \text{(s5)}$$

where λ_i denotes player i's sensitivity to the difference in payoffs between choices. When $\lambda_i \rightarrow 0$, this distribution will assign equal probability to all feasible choices. Whereas, when $\lambda_i \rightarrow \infty$, player i always chooses to report the belief that generates highest expected payoff. We maximize the following log-likelihood function to find estimates for the representative player in each treatment.[50]

$$\ln L(\beta_i, \lambda_i) = \sum_{i=1}^{N}\sum_{t=2}^{25} ln\big(\, r\big(B_{i,t}\big|b_{i,t}(\beta_i), \lambda_i\big)\big)\ . \qquad \text{(s6)}$$

Model Selection

We estimate both the models over the data of the four treatments, and compute the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), respectively.

For Model 1, $\mathrm{AIC} = 2\mathrm{k} + \mathrm{n}\ln\left(\frac{\mathrm{RSS}}{\mathrm{n}}\right) + \mathrm{n}\ln(2\pi) + \mathrm{n}$,

$\mathrm{BIC} = \mathrm{k}\ln(\mathrm{n}) + \mathrm{n}\ln\left(\frac{\mathrm{RSS}}{\mathrm{n}}\right) + \mathrm{n}\ln(2\pi) + \mathrm{n}$,

[50] In the estimation, the computation starts from period 1. We omitted any beliefs prior to period 1.

For Model 2, $\mathrm{AIC} = 2\mathrm{k} - 2\mathrm{lnL}$,

$$\mathrm{BIC} = \mathrm{kln(n)} - 2\mathrm{lnL},$$

where k is the number of parameters, n is the number of observations, RSS is the residual sum of squares, and lnL is the maximum of the log-likelihood function. Table s2 summarizes these results.

Table S2 Estimation results

Model 1				
Treatment	(10,2,2)	(10,4,4)	(10,6,6)	(10,8,8)
γ_i	0.516	0.492	0.597	0.567
Obs.	2160	2232	2304	2232
RSS	10275.66	11730.18	20280.44	16524.26
AIC	9500.70	10039.63	11551.69	10804.45
BIC	9506.38	10045.34	11557.43	10810.16
Model 2				
Treatment	(10,2,2)	(10,4,4)	(10,6,6)	(10,8,8)
β_i	0.659	0.613	0.706	0.672
λ_i	0.043	0.043	0.039	0.037
Obs.	2160	2232	2304	2232
lnL	-5064.29	-5470.02	-7497.74	-7578.21
AIC	10132.58	10944.04	14999.48	15160.42
BIC	10143.94	10955.46	15010.96	15171.84

The results in table S2 show that both the AIC and BIC of Model 2 are close to those of Model 1 in the two globally stable treatments, but quite larger than those of model 1 in the two non-globally stable treatments. It seems that both the models have almost equal explanatory power in the two globally stable treatments. However, in the two non-globally stable treatments, the explanatory power of Model 1 is stronger than that of Model 2.

Overall, these results indicate that Model 1 outperforms Mode 2 in explaining the belief-formation process of subjects in our experiment.

Chapter 4

Analyzing Instability in Common-Pool Resources Games

4.1 Introduction

A problem of common-pool resource (CPR) refers to the overexploitation to an open access resource, i.e. a fishing ground, which is called "the tragedy of the commons" (Harding, 1968). Usually, to understand the appropriation dilemma in the analysis is using the Nash equilibrium concept in which the labor input of each appropriator is a strategy. This simple analysis shows that the Nash equilibrium labor inputs for production results in overexploitation (see, for example, Gordon (1954), Gould (1972), Dasgupta and Heal (1979), and Falk, Fehr and Fischbacher (2001)).

However, this standard equilibrium analysis implicitly assumes that the equilibrium in the system is stable. Here, we say that an equilibrium of a game is stable if it is asymptotically stable in a dynamic version of the game. Thus, the stability of an equilibrium depends on the decision-making processes of players in a repeated game. In the theoretical analysis of Saijo and Kobayashi (2016), they focus upon the so-called best-response dynamics, i.e., each discrete time step each player makes the best response to other players' decisions in the previous time step. This is due to recent observations by Healy (2006), and Healy and Mathevet (2012) who confirmed that subjects appeared to best respond to recent observations in five public goods mechanisms including the voluntary contribution mechanism. The results show that the equilibria of CPR systems tend to be unstable under reasonable settings.

Thus, the theoretical foundations of the tragedy of the commons based on static analysis might no longer be reliable. In fact, the theoretical analysis in Saijo and Kobayashi (2016) reveals that the instability is likely to bring additional inefficiency to the system, meaning that previous authors underestimated the level of inefficiency. This implies that dynamical instability is a practical problem for management of CPR and deserves detailed mathematical and empirical investigations.

With the data from the experiments by Walker, Gardner and Ostrom (hereafter, WGO) (1990), we focus on estimating the response functions of players.[51] In the estimation, we consider three key aspects in players' decision-making processes: belief formation, other-regarding preference and decision errors. In the modeling of belief formation, the main purpose is to investigate to what extent players are myopic in an experiment. In the modeling of other-regarding preference, we want to show how large the difference from the self-interested assumption in the experiments. Furthermore, the modeling of decision

[51] We thank Professor James Walker who provided us the individual data in WGO (1990).

errors shows to what extent the experimental environment is different from a deterministic system. Overall, our purpose in this paper is to show how large the distance between the theoretical analysis in Saijo and Kobayashi (2016) and the experimental data of WGO (1990).

4.2 Theoretical results and Implications for the observations in WGO (1990)

In this section, we briefly explain the theoretical results in Saijo and Kobayashi (2016). First, we describe the CPR problem with a general setting. Second, we introduce the two main theoretical propositions of Saijo and Kobayashi (2016). Finally, we interpret the implications for the observations in WGO (1990).

Consider a local society with n (≥2) appropriators. Assume that the output y of the fishing ground is a function of the total number of hours of fishing $\sum_{i=1}^{n} x_i$. That is $y = f(\sum_{i=1}^{n} x_i)$, where $f(.)$ is an increasing, differentiable and strictly concave function. Therefore, the average output for each fishing hour is $f(\sum_{i=1}^{n} x_i)/\sum_{i=1}^{n} x_i$. Then, for fisher i, his/her expected output from his/her fishing hours x_i is $f(\sum_{i=1}^{n} x_i)x_i/\sum_{i=1}^{n} x_i$. Furthermore, assume that the opportunity cost for each fishing hour is a positive constant p and let w_i denote the endowment of fishing hours for fisher i. Then, appropriator i's income or payoff is defined by

$$m_i(x_i, x_{-i}) = p(w_i - x_i) + \frac{x_i}{x_i + x_{-i}} f(x_i + x_{-i}), \tag{4.1}$$

where $x_{-i} = \sum_{j \neq i} x_j$. Each appropriator faces a decision problem of how to divide her endowment between catching fish and personal leisure time to maximize $m_i(x_i, x_{-i})$ subject to $0 \leq x_i \leq w_i$ given x_{-i}.

Assume that the endowment of each appropriator is large enough to ensure that all Nash equilibria are interior points. Suppose that the production function is concave, that is, $f''(x) < 0$. Furthermore, assume that $f(0) = 0$ and $f(x) > 0$ if $x > 0$. Suppose that appropriator i chooses $r(x_{-i}^t)$ at time $t + 1$, where $t = 1,2,\ldots$. Then, the system

$$x_i^{t+1} = r(x_{-i}^t) \quad (i = 1,2,\cdots,n) \tag{4.2}$$

is locally stable at Nash equilibrium $\hat{x}$ if the linear approximation of the system (4.2) is stable at the Nash equilibrium $\hat{x}$. Then we have the following proposition from Saijo and Kobayashi (2016) shows the necessary and sufficient condition for the local stability.

Proposition 4.1. The system (4.2) is locally stable at the Nash equilibrium $\hat{x}$ if and only if

$$f''(\hat{x})(n-2) + \frac{1}{\hat{x}}\left(f'(\hat{x}) - \frac{f(\hat{x})}{\hat{x}}\right)(n-1)(n-4) > 0.$$

Then, based on simple interpretations of Proposition 4.1, the following proposition from Saijo and Kobayashi (2016) shows the stability properties corresponding to the number of players.

Proposition 4.2. (*i*) If the number of appropriators is two, then system (4.2) is locally stable at the Nash equilibrium.
(*ii*) If the number of appropriators is at least four, then the system is locally unstable at the Nash equilibrium.

Therefore, according to proposition 4.2, the system of the design in WGO (1990) is locally unstable.The theoretical result from Saijo and Kobayashi (2016) indicates that the choice of players will be pulsing after several periods between 1 and 10 in the experiment with w_i = 10 or between 0 and 25 in the experiment with w_i = 25. This could be a plausible answer to "some unexplained pulsing behavior" in Ostrom (2006), although it is not fully consistent. Furthermore, the theoretical analysis indicates that the behavior pulsing that stems from instability tends to reduce efficiency even compared with the Nash equilibrium due the concavity of the payoff function.

Given these theoretical implications from Saijo and Kobayashi (2016), in the next section, I empirically estimate the response function of players with the data from WGO (1990) and connect the observations of pulsing behavior with the estimation results. Furthermore, I also provide an empirical investigation for the inefficiency stems from the pulsing.

4.3 Reanalysis of the data from WGO (1990)

4.3.1 The empirical model

The model consists of three parts in the decision-making. They are the belief formation process, the other-regarding preference and the stochastic best response. The purpose of this model is to determine the distance between the myopic best response and the actual decision-making process of players.

(*i*). The belief formation process. Since players might take serval previous observations into account, in the empirical analysis of the belief formation, the key part is to determine the lag length of the information used by players in the experiment. Healy (2006) provides the experimental evidence to support a *k*-period average model that assume players form their beliefs at the current period based on the observations in previous *k* periods. Here, we slightly modify his idea of the average over the fixed *k* periods, but use a time-weighted average to model the belief formation.[52] More precisely, it is,

[52] The idea is borrowed from Cheung and Friedman (1997) in which they introduced a γ-weighted fictitious play model.

$$b_{i,t+1} = \frac{s_{-i,t} + \sum_{u=1}^{t-1} \gamma_i^u s_{-i,t-u}}{1 + \sum_{u=1}^{t-1} \gamma_i^u}, \tag{4.3}$$

where $b_{i,t+1}$ is player i's belief about the total choices of other players in the group at period t+1, $s_{-i,t}$ is the observed total choices of other players at period t and γ_i^u is a time-dependent weighting factor assigned to the observation at period u. If $\gamma_i = 0$, the belief is exactly the observation at the previous period. In contrast, if $\gamma_i = 1$, the belief is the average of all previous observations.[53] In this sense, the amount of γ_i will determine the lag length of the information used by player i. Therefore, this model is an analogue of the k-period average model. Note that, the summation starts from period 1. So, this model omitted any beliefs prior to period 1.

(*ii*). The other-regarding preference. To empirically capture players' concerns about other group members' payoffs, following the design of Cox et al. (2007), we simply assume the utility function of player i as follows:

$$u_i(y_i, \bar{y}_{-i}) = y_i + \beta_i \bar{y}_{-i} \tag{4.4}$$

where y_i is the material payoff of player i, $\bar{y}_{-i}$ is the average material payoff of other group members and β_i captures the other-regarding concerns. If $\beta_i = 0$, player i is self-interested. If $\beta_i > 0$, player i is altruistic or positive reciprocal. If $\beta_i < 0$, player i is spiteful or negative reciprocal.

(*iii*). Stochastic best response. With the utility given by equation (4.4), we assume subjects make decisions with a stochastic best response dynamic (see Fudenberg and Levine, 1998). That is,

$$p\left(s_{i,t+1} \middle| \gamma_i, \lambda_i, \beta_i, s_{-i,t}, \dots, s_{-i,1}\right) = \frac{\exp(\lambda_i u_{i,t+1}(s_{i,t+1} | \gamma_i, \beta_i, s_{-i,t}, \dots, s_{-i,1}))}{\sum_{k=0}^{w_i} \exp(\lambda_i\, u_{i,t+1}(k | \gamma_i, \beta_i, s_{-i,t}, \dots, s_{-i,1}))}, \tag{4.5}$$

where $s_{i,t+1}$ is the observed choice of player i at period t+1, $u_{i,t+1}$ is the utility of player i at period t+1, w_i is the endowment of player i and $\lambda_i > 0$ is a factor that captures the decision errors of player i. Equation (4.5) defines the probability that player i chooses $s_{i,t+1}$ at period t+1 given $s_{-i,t}, s_{-i,t-1}, \dots, s_{-i,1}$. If $\lambda_i \to 0$, all choices for player i have equal probability,

[53] As Cheung and Friedman (1997) suggested, γ_i also might locate at outside of the range [0, 1]. In such cases, it is relatively counter-intuitive. γ_i>1 indicates player i pays more attention to the old information than the recent information. γ_i<0 indicates the effect from past information changes sign in each period.

which means that player i randomly makes decisions. As λ_i becomes large, player i becomes more sensitive to the difference in utility between different choices; in particular, when $\lambda_i \to \infty$, player i chooses the best strategies (i.e. the strategies resulting in the maximum utility) with probability one. We maximize the following log-likelihood function to find estimates for the representative player.

$$lnL(\gamma_i, \lambda_i, \beta_i) = \sum_{i=1}^{N} \sum_{t=1}^{T-1} ln(\, p(s_{i,t+1} | \gamma_i, \lambda_i, \beta_i, s_{-i,t}, \dots, s_{-i,1})) \,, \quad (4.6)$$

4.3.2 Estimation results

Table 4.1 summaries the estimation results. The estimation is separately conducted over two samples: the data from the beginning half periods and the data from the latter half periods.

Table 4.1 Estimation results

	Experiments			
	w=10		*w*=25	
	Periods 2-16	Periods 16-30	Periods 2-11	Periods 11-20
γ_i	0.410	0.653	0.833	0.641
	(0.007)	(0.003)	(0.009)	(0.003)
β_i	-1.581	-0.491	-0.998	-0.290
	(0.055)	(0.011)	(0.016)	(0.010)
λ_i	0.095	0.340	0.045	0.082
	(0.002)	(0.005)	(0.001)	(0.001)
Obs.	360	360	240	240
*ln*L	-677.80	-631.11	-718.50	-681.30

Jackknifed standard errors are shown in parentheses.

Based on the meanings of parameters, it is clear that players are exactly following the best response dynamics when $\gamma_i \to 0$, $\beta_i \to 0$, and $\lambda_i \to \infty$. Now, let us interpret the estimation results. Basically, we think the model captures the decision-making process quite well. First, in both the experiments, λ_i becomes larger with period progress, which indicates the decision errors become fewer ($\chi^2(1)$ = 24.98 for the experiment with w=10, and

$\chi^2(1)$ = 9.52 for the experiment with w=25 by the likelihood ratio tests). We also notice that it is larger in the experiment with w=10 than in the experiment with w=25. This result is intuitive, since the number of possible choices are much fewer in the experiment with w=10 than that in the experiment with w=25.

Second, we turn to see the estimates of β_i. All estimates are negative. This result is intuitive, since the environment of common pool resource (CPR) is competitive. An interesting finding is that, in both the experiments, the estimates of β_i become closer to zero when periods progress ($\chi^2(1)$ = 13.14 for the experiment with w=10, and $\chi^2(1)$ = 8.44 for the experiment with w=25 by the likelihood ratio tests). It indicates that, players are feeling worse when other group members increase their working hours in the beginning half of the experiment than they do when it happens in the latter half of the experiment. This result implicates that, subjects become more self-interested with repeated trials in both the experiments.

Final, the interpretation for estimates of γ_i is not very obvious. It seems players becomes more myopic in the latter half of the experiment with w=25 than in the beginning half. However, it appears that the opposite is the case, i.e. players are more myopic in the beginning than in the latter half in the experiment with w=10.

Result 4.1: The estimation results support that, decision errors become fewer and players become more self-interested over time. Therefore, subjects become closer to making best response to previous observations (not only the last observation) with repeated trials in both the experiments.

4.4 Connection between estimation results and pulsing behavior

Our estimation results suggest that players' decisions become closer to the best responses to previous observations with periods. Therefore, given our theoretical results that best response dynamics will induce some pulsing behavior, we can make a hypothesis.

Hypothesis 4.1: The group sum will be pulsing more in the latter half of the experiment than it does in the beginning half of the experiment.

To test this hypothesis, we computed the sample autocorrelation for the group sum in each group.[54] Table 4.2 summarizes the results.

[54] The sample autocorrelation is also used in Rassenti et al. (2000) as a measure of the pulsing behavior. The sample autocorrelation of individual choices is also a way to check the pulsing behavior. However, if players within the same group are not increasing and reducing their

Table 4.2 The sample autocorrelations

	Experiments			
	w=10		*w*=25	
Group	Periods 2-16	Periods 16-30	Periods 2-11	Periods 11-20
1	-0.133	-0.137	-0.131	-0.366
2	-0.005	-0.344	0.025	-0.210
3	0.086	-0.279	0.140	-0.221

These results support our hypothesis quite well. All groups generate a negative sample autocorrelation in the latter half of the experiment, which indicates pulsing. However, 3 out of 6 groups have a positive sample autocorrelation in the beginning half of the experiment.

Result 4.2: The sample autocorrelations of all groups in the latter half of the experiment are negative and less than those in the beginning half of the experiment.

Now, let us consider whether pulsing caused inefficiency in the experiments. As Table 5.2 (page 117) and Figure 5.4 (page 119) in OGW (1994) show, the low efficiency in the experiment with w=25 mainly stems from the beginning half of the experiment. However, we should not use the data from the beginning half of the experiments because players' behaviors are in a transient phase. I therefore use the data from the latter half of the experiments. Table 4.3 shows some statistics to test the hypothesis that pulsing caused inefficiency.

Table 4.3 Statistics

	Experiments	
	w=10, Periods 16-30	w=25,Periods 11-20
Centile (25%)	62	60
Centile (75%)	68	71
Interquartile range	6	11

working hours simultaneously, the pulsing might not be related to our theoretical analysis. In this sense, I only check the sample autocorrelation for the group sum.

Average payoff (standard deviation)	63.81 (8.16)	133.56 (22.87)
Predicted payoff, Nash	66	141
T-statistic*	-2.12	-3.59

*We first compute the average across periods for each individual, and then conduct the t-test over the sample of those averages.

We use the interquartile range to measure the amplitude of the pulsing in the group sum. It shows the amplitude of the pulsing is larger in the experiment with w=25 than in the experiment with w=10. Second, we report the statistics of individual payoffs and compare them with the Nash prediction. The t-tests reject the null hypothesis that the average payoff equals the predicted payoff of the Nash equilibrium for both the experiments at 5% level. This result supports our theoretical analysis that the pulsing around the Nash equilibrium will results in a lower payoff. Furthermore, we also compared the efficiency between the two experiments to see whether the larger pulsing amplitude will induce a lower efficiency.[55] The Wilcoxon rank-sum test shows that the efficiency in the experiment with w=10 is significantly higher than in the experiment with w=25 (p-value = 0.0259).[56] Given these findings, we suggest that WGO's (1990) result is consistent with the theory of Saijo and Kobayashi (2016) regarding the efficiency.

4.5 Conclusion

In this paper, we conducted some statistical analyses to test the hypothesis that the pulsing behavior in labor inputs observed in WGO's (1990) experiment is due to myopic best-response behavior. The result shows that individuals were resorting to fairly myopic and rather deterministic decision rules. The analyses also revealed that the labor inputs are indeed pulsing (negative autocorrelation was found between labor inputs in succeeding periods) rather than in an equilibrium in the latter half of the experiments. Furthermore, our statistical analyses support the hypothesis that the difference in efficiency between the two experiments by WGO (1990), which are different in initial endowment, is partially due to pulsing. Given these empirical facts, the empirical result provides a support for the theoretical analysis in Saijo and Kobayashi (2016).

55 We use the same index of the efficiency as used in WGO (1990).

56 Similar to the t-test, we also compute the average across periods for each individual to eliminate the time series autocorrelation, and then conduct the Wilcoxon rank-sum test over the sample of those averages.

Chapter 5

CONCLUSION

The goal of this thesis is to examine the three theoretical arguments of instability in social dilemma games. They are, the instability in the VCM with homogeneous design, the global and non-global stability in the VCM with heterogeneous design, and the instability in the CPR game. With the empirical method of experimental economics, the experimental results reflect some distance to the theoretical predictions.

In the first study, the group total contributions are not pulsing as much as the theoretical prediction. However, the experimental results show an increasing dispersion among individual contributions. The main source of this observation might be due to the presence of conditional cooperators. However, without a precise theoretical background for the interaction among players with several different other-regarding preferences in an unstable VCM environment, this conjecture is hard to be tested. But, on the theoretical basis, our observation regarding the increasing dispersion still indicates that the experimental system is not asymptotical stable. In other words, we are missing the theoretical connection between this observation and the theoretical results of instability. This remains as an open question in our study.

In the second study, the experimental results basically rejected the non-global stable argument from the theory in the environment with the particular experimental design. The main reason is that human subjects changed their strategical thinking in the belief formation process and the responding process in the non-globally stable treatments. This adaptive change makes the experimental system more stable than the theoretical prediction. As we pointed out in the conclusion of chapter 3, since our experiments chose the simplest design, whether this adaptive change can keep the stability for the system still remains unknown in the experimental design with more than three players in the group.

In the third study, the analysis of the experimental data from WGO (1990) supports that subjects become closer to making best response to previous observations. Therefore, the argument of instability can at least partially explain the pulsing behavior in the group sum. Furthermore, we clearly show that the pulsing behavior induces additional inefficiency in the CPR.

Overall, via the experimental studies, we find some consistent results corresponding to the theoretical predictions. More importantly, the inconsistent results reflect some flaws in the theoretical assumptions. First, these observations point the way for the refinement of assumptions in the next step. Especially, it is necessary to build up a theory regarding the interaction of several different social oriented players in a nonlinear VCM environment.

Second, the experimental evidence show that some theoretical predictions, i.e. unequal payoff distributions among players and inefficiency from the pulsing, point out new problems in social dilemma games, which stem from the instability. These new findings deserve more theoretical and empirical investigations in the future. Third, generally speaking, the uncertainty to decision-makers is greater in an unstable game environment than in a stable game environment. Our finding indicates that human subjects are willing to take more cognitive costs in an unstable game environment. This interesting finding in the second study sheds some new lights in the field of cognition and decision in uncertainty environment.

Finally, based on the insight of instability, these studies firstly reveal some more profound understanding regarding the social dilemma games than previous studies. However, they also show that the related works are still at the initial stage.

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My interest in the theories of economics was little when I was an undergraduate. The reason is that I think it is a discipline far away from science. Because of the complex of human society, all the theories in economics can be used to partially explain the economic phenomena, but none of them can be used to precisely predict the economic phenomena.

However, after working for six years, I felt that the problems in economics are so important, but I knew so few about the principles behind those economic phenomena. Therefore, I chose to resign my job and came back to the school for learning more about the theories in economics. Fortunately, I came into contact with experimental economics. It gave me a sense that economics could become a discipline of science.

To pursue more knowledge, I came to KUT. My time at KUT was so comfortable. Every day, I had a lot of time to enjoy thinking and reading alone. Although I did not make a lot of friends here due to I had to concentrate on the questions I studied, I learned a lot of things from professors and classmates. Especially, it is the luck in my life that I can accept the academic training from professor Saijo. I am so grateful for his patience in teaching me academic writing. Sentence by sentence and word by word, I learned so many details from his instructions. I also owed a debt of thanks to professor Kamijo. Without his very helpful suggestions, I cannot finish the entire researches in these three years. In addition to this, I also want to express thanks to a senior, Miss. Lingling Wang. Thanks to her help, I can quickly adapt to live in Japan.

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