Università
Ca'Foscari
Venezia

Università Ca' Foscari Venezia

Scuola Superiore di Economia SSE

Dottorato di ricerca in Economia, XXIII ciclo

(A.A. 2007/2008 - A.A. 2010/2011)

Three Essays on Leadership and Cooperation in Public Good Games

SETTORE SCIENTIFICO-DISCIPLINARE DI AFFERENZA: SECS-P/01

Tesi di dottorato di Laura Concina, matricola 955404

Coordinatore del dottorato

Prof. Agar Brugiavini

Tutore del Dottorando

Prof. Michele Bernasconi

The undersigned Laura Concina, in her quality of doctoral candidate for a Ph.D. degree in Economics granted by the *Università Ca' Foscari Venezia* and the *Scuola Superiore di Economia* attests that the research exposed in this dissertation is original and that it has not been and it will not be used to pursue or attain any other academic degree of any level at any other academic institution, be it foreign or Italian.

Acknowledgments

It is a pleasure to thank the many people who made this thesis possible. During the last four years, I have come across so many persons in my private and academic life who rendered invaluable help and support. For these reasons, I want to thank them personally.

I have been deeply indebted in the preparation of this thesis to my supervisor, Michele Bernasconi. His guidance and his infinite patience, as well as his academic experience, have been invaluable to me. I consider myself fortunate for being able to meet him and to work with him. I am thankful to Agar Brugiavini (the director of this Ph.D. programme), for the financial help, for providing funds for the experiment and for letting me to complete the Ph.D. programme. I also want to show my gratitude to Marco Li Calzi, Massimo Warglien and Paola Ferretti for taking their precious time to consider my work. I am deeply grateful to my undergraduate and master professors, Clara Graziano, Marji Lines and Alfredo Medio, without whom I would have never started this incredible journey. They showed me passion for research, love for education and they taught me how to appreciate honesty. I would like to thank all Ph.D. colleagues that I have met during these years, with whom I shared pains and hopes: Oktay, Elena, Umberto, Engin, Carmen, Theresa, Hao, Siddharth, Gine, Racha, Rasha, Kyri, Aks, Matija, Breno, Caterina, Ender, Valentina, Aditi, Novella, Gaetano, Sergio, Giovanna, Paulo. I would like particularly to acknowledge Christiana who tried to make this thesis readable. I would like to thank Giuseppe Attanasi who encouraged me to carry on with the project that have become part of my thesis and who gave me the opportunity to continue to do research in the place I need to be.

All my gratitude to the friends that have been there from the beginning and to those that I met during the journey. Without you, all this would have no sense. Corrado, my brother, for making me laugh of my failings, for keeping my feet on the ground and for being there for me, no matter what. Rò, for your courage, for your patience and for always being honest with me. Giorgia, for the power and confidence that you exude. Racha, for your faith and for the love for life that we share. Furthermore, I would like to thank all other friends for assisting me in many different ways. In no particular order: Becky and Paolo, Devis, Marco, Maxime, Nico, Flavia and Antonio, Simone, Andrea and Valentina, Marzio, Marchetto, Maurice, Omar, Fabio, Johnny, Beatrice, Antonia, Federico and Giammaria, Angela, Paola, Andrea, Roberta, Alessio and Martina, Alessandro, Tommaso, Mich and many others.

Finally, my family. I would like to thank my grandmas and my grandpa for being proud of me - although two of them had passed away many years ago. My aunt Marilisa and my cousin Antonella for all discussions and laughs, and for reminding me of my roots. No words can express my gratitude to my mother. Her unconditional love has been there for me ever since. You have always supported me, emotionally and morally. You have showed me the beauty of life in all its forms. You have been there when I was lost, strict but fair. From you, I have learned to be conscientious and trustworthy, but to enjoy everything I do, every moment, because life is short and we all need a smile.

Last, but not least, Samuele. For your love, your immense patience, your constant encouragement ("forza, coccola, forza!"), for your faith in me when I had none, and for your enormous help with research. In the last three years, nothing has been easy for us, notwithstanding, we are now sharing the most everyday. Thank you.

Contents

Introduction to the Dissertation

The issue explored in this thesis concerns public good games. We tackle the topic from different prospectives focusing in particular on leadership and cooperation.

Both in economics and psychology, social dilemma as public good problems have extensively been studied. These are situations where the self-interest of individuals usually prevents the rise of a cooperative behaviour in groups. Cooperative behaviour is socially preferable. However, the public goods characteristics of non-rivalry and non-excludability encourage free riding.

In the last decades, economic literature has departed from the rationality paradigm that characterized early studies on the topic. Theoretical approaches (e.g. Bergstrom et al. (1986)) have been revised to combine findings of applied fields and of experimental economics. The need to inquire the topic from a different prospective has generated a huge literature on public good experiments (see, for example, Keser (2000)). Many real situations and experiments have highlighted a multitude of different behaviours. Some individuals are, indeed, found to be free riders. However, this is only one of the possible strategies that subjects may follow in public good frameworks. Although a large amount of individuals do cooperate (at different levels) to the common project, cooperation arises because of different motives. To explain these reasons, a behavioural approach to rethink individual actions in public good games has been presented (see, for example, introduction in Ashley et al. (2010)).

A special attention has always been paid to redirect the efforts of the individuals towards cooperation. On the one hand, the free ride prediction makes clear the necessity of policies that enforce the collection of resources for the provision of the public good. On the other hand, a broader part of the literature has focused the attention on the voluntary contribution. As a matter of fact, understanding motives that lead some agents to contribute can help discern among those devices that can encourage cooperation, not by forcing it. A prominent finding is that a large majority of individuals is willing to contribute as the others do so. They are commonly referred to as conditional cooperators. Economists and psychologists have suggested motives for this behaviour as, e.g., other-regarding preferences, strategic interactions and pro-social attitudes.

In the first chapter of the present thesis, we suggest an additional possible motive for some subjects to condition their contribution to others. We theoretically explore contributions to the public good of agents who incorporate Tversky and Kahneman's prospect theory in their utility functions. There exists a large evidence that subjects frame situations according to a reference point. In public good games, an important variable that determines the behaviour is the contribution of other subjects. In a two-players public good game, we assume that a reference dependent agent frames his space of actions with respect to the other agent's contribution. Moreover, we investigate diversity in subjects' behaviours by studying interaction among two different types: standard agents, who only care about the private good and the total provision of public good; and reference dependent agents, who, in addition, frame according to their reference point. We analyse the attitudes in two different contexts: simultaneous and sequential games. The former consists in a game where subjects contribute simultaneously to the public good. In the latter, one agent contributes first to the public good and the other observes the contribution and makes his own. The first mover is called the leader, the second the follower. Chapters one and two of this thesis contribute to the so called literature of leading-by-example (named by Hermalin (1998)), where the leader sets the example by contributing before others.

The second chapter is a joint paper with Samuele Centorrino. It studies a repeated sequential public good experiment where subjects can self-select themselves to achieve the role of leader. In the spirit of trying to select mechanisms to foster cooperation, we focus on the selection of a "good leader", namely a subject who gives the good example with high donations to the public good. We introduce a competitive preliminary stage in which subjects can bid for the right to move first. The higher bidder within a group becomes the leader and pays the second highest bid. Leadership is, thus, voluntary. Subjects can choose to give up competition by selecting a bid equal to zero. We compare behaviour in the repeated public good game with respect to the case where a leader is selected randomly. This is in order to observe different types of leaderships and followers' reactions to first movers' contributions. Moreover, we want to link the heterogeneity that emerges with different bids to personal traits of subjects (by means of a questionnaire given at the end of the experiment). The scope is to determine if there are specific characteristics of individuals that can explain their willingness to pay for the leadership and their contributing behaviour in the repeated public good game.

In the last chapter, we contribute to the public good literature in a different way with respect to the first two chapters. The paper is a re-analysis of cooperation in two well-known simultaneous repeated public good games (Andreoni (1995); Fischbacher and Gächter (2010)) by means of non-parametric statistics and a recent semi-parametric model (Li et al. (2011)). A great debate about the use of econometrics in experimental economics analyses has recently captured the attention of researchers. Besides, a new field, that elaborates new econometric tools, is usually referred to as *experimetrics* or *behavioural econometrics*. In this chapter, we want to show how it is possible to perform a better analysis of public good experiments with already existing statistical tools. We depart from the fully parametric approach that is, sometimes, misused and we employ non-parametric regressions to have a preliminary idea of the form of data for the choice of variables. Then, we use Li et al. (2011) semi-parametric model to perform the analyses. The second aim of the paper is to divide subjects into groups of homogeneous behaviour. Using findings of previous literature on types in public good games, we separate unconditional players from other subjects. A central contribution of this work is that the combination of these two approaches allows to answer additional research questions not only on types behaviour, but also on treatment and session effects.

Chapter 1

Leadership in Public Good Games when Preferences are Reference Dependent

Abstract This paper examines the effect of incorporating prospect theory in simultaneous and sequential public good games. Moreover, we allow for interactions among agents with standard utility function and agents who care about a reference point. An agent who sets others' contributions as a reference point free rides less than predicted by the standard utility theory; when matched with standard agents, he also modifies their reply contributions; and he has effects on the total provision of public good. We find that this setting gives a better understanding of many experimental results.
JEL Codes: D03, H41, Z13.
Keywords: Public good, Leadership, Reference Dependence, Prospect Theory, Sequential, Simultaneous.

1.1 Introduction

The idea that economic agents compare their choices to a reference point is well known in the literature and it has been observed in many economic fields. Prospect theory of Kahneman and Tversky grasps the main psychological insights into how behaviour can actually change whether individuals incur in losses or in gains and how these would give predictions different from a standard utility function theory.

In this paper, we want to incorporate a reference dependence theory in simultaneous and sequential public good games in order to have a theory more in line with experimental evidence: strong prediction on free riding outcomes is in many cases rejected to give place to a more cooperative behaviour. Moreover, we stress the importance of heterogeneity in types and how equilibria could completely reverse when interaction among types takes place.

The fact that it is complicated to determine a reference point in complex situations objectively makes the topic difficult to design in terms of theory. In this paper, we propose two different ways of framing public good games to explain out of equilibria experimental results. Tversky and Kahneman (1991) stress the importance of status quo in determining behaviour in choices that could modify the current situation. In a typical public good game, individual are endowed with some income that they can use to buy private or public good. When matched in groups, other players' contributions is perceived as additional wealth. Since exogeneity is given by those two features, namely endowment and others' contribution to public good, we suggest that individuals frame situations according to these two variables.

Moreover, we address the issue of heterogeneity among subjects which is usually observed in experimental literature. We will proceed by making our reference agent interact with a standard one in order to understand possible implications of different preferences. It is commonly found that many types of agents coexist and play together in public good games. For example, in their early work on conditional cooperation, Fischbacher et al. (2001), via strategy methods, estimates that nearly 30% of experimental subjects behave selfishly and 50% as conditional cooperators (namely with a positive reaction function). Similar results are found in Kurzban and Houser (2005): 20% free riders; 63% subjects who condition their contribution to other group members; and 13% unconditional cooperators. They give support to two fundamental hypotheses usually implicit in analyses of type: "(1) subjects' types are persistent over an experiment; and (2) the types of subjects included in a group affects a group's ability to sustain cooperation".

Many attempts to explain conditional cooperation have been made in the latter decades, among the most important, we can find warm glow, inequality aversion, reciprocity[1]. Nevertheless, testing these theories strictly depends on the design of the experiment, namely on the way experimentalists frame the game, and, thus, influence the frame of subjects. We propose a reference dependent theory to explain experimental results which count for interaction with standard agents.

The paper which is closest to ours is Bernasconi (1996). He discusses the psychological approach of Tversky and Kahneman (1991) applied to public good frameworks at depth. In his work, he explains the failure of strong free riding predictions by means of reference dependence, in particular opposed to the more widespread warm glow approach (Andreoni, 1989). Bernasconi's work focuses on the underlying condition of reference behaviour and he offers a preliminary study of the subject. He observes that "usually the reference state corresponds to the person's exogenous endowment of the different goods". Since the two goods at which an agent refers to are the private and the total public good, he argues that the most convenient choice is to have two reference points, one for each good - the private good and the public good. Initial private good provision is zero, while initial public good provision is given by others' contributions. In this framework, Bernasconi's main result is to observe that a reference dependent agent free rides less than a standard utility maximizer agent. Although warm glow theories find similar results, the importance lies in the motives which lead an agent to reduce his free riding. As far as we know, it is the only work who incorporates prospect theory in public good games.

In our paper, we consider, not only a more general application of prospect theory to public good games, but also the interaction among different agents, and the possibility of changing the timing of the game by introducing sequentiality in contributions. Although the Nash assumption in games with common knowledge is based on the fact that in equilibrium agents take as given other players' contributions, the idea of "setting the reference" is more clear in games where there is actually sequentiality in contributions.

In reality, there are many cases where we can observe public good situations that occur sequentially: donations to charity (e.g. telethon), team works. Hermalin (1998)

[1]For a discussion on motives for giving in public good games, see, for example, Ashley et al. (2010).

identifies a class of sequential games which he calls leading-by-example. The first mover, by showing her contribution, is actually setting the example to those who come after. When asymmetric information makes a leader more informed than her followers, Hermalin shows that the leader would signal the good state of nature when she can influence other group members. The idea that sequentiality influences second movers is kept also in Cartwright and Patel (2010), once more in asymmetric information contexts but, in this case, with the assumption of heterogeneity of types. They suggest that payoff maximizing agents, instead of free riding, might want to contribute to influence followers if first movers believe that there are conditional cooperators among second movers. Their analysis is based on the intuition of Bardsley and Moffatt (2007). In an *ad hoc* experiment to detect types, they find evidence of utility maximiser agents, named strategists. Strategists are those contributing early in a sequence, but free riding if they are the later movers.

In the papers just described, it is shown how important it is for a leader to be a reference. We want to show that in fact the reference is important in a context where agents frame the situation according to gains and losses. Thus, a first mover that sets the reference point makes the sequential an interesting case to study. Imagine a pay-off maximizer who has the possibility of investing, or committing to invest, before others. Clearly, those who observe the investment would find a guideline to which their future choices refer. The revelation of the leader's action becomes a strategic starting point not only in the case it discloses information when there is uncertainty, but also when there is the possibility of directly inciting others, for example, to cooperate. Whenever followers set as reference point the leader's contribution, they frame the situation with respect to her action. A positive initial contribution/investment can be perceived as a gain in the context of prospect theory and, as we will see in the paper, it can crowd in contributions of those who come after.

A basic result of standard sequential public good games with common knowledge is that a first mover's contribution crowds out the contribution of followers. The most cited and important theoretical contribution on the topic which bases its prediction on the standard utility function theory is Varian (1994). He finds that the total contribution in a one shot sequential game is never higher than in a simultaneous game, because of the second mover's downward sloping reaction function and the first mover's advantage. Thus, the free riding advantage of a first mover is at the root of the theoretical results. However, this is not what happens in experiments. Evidence has pointed out that the leader does not always have a free riding behaviour and can sometimes have a large influence on followers contributions (e.g. Arbak and Villeval (2008), Rivas and Sutter (2008)).

The lack of leader's free riding behaviour is explained by warm glow in Romano and Yildirim (2001). They use a more general utility function to analyse sequentiality against simultaneity in public good games. In particular, they claim that players may have additional motives to contribute which might include warm glow (Andreoni, 1989) and status concerns.

Departing from previous literature, with the exception of Cartwright and Patel, we want to show the importance of interaction among heterogeneous agents. Conditional cooperation, reciprocity, inequality aversion are all possible motives which modify standard preferences. In this context, we propose a different prospective of reference dependence.

On reference dependent theory

In this paragraph, we briefly describe the reference dependent model proposed by Tversky and Kahneman (1991). The analysis applies in context with riskless choices, as the public good game that we are considering, where all informations are common knowledge of players. The characteristics that Tversky and Kahneman consider are: *reference dependence*, gains and losses are evaluated with respect to a reference point; *loss aversion*, "losses loom larger than corresponding gains"; and *diminishing sensitivity*, both marginal value of gains and of losses of a good decreases in distance from its reference point.

Reference dependence implies that the utility function not only depends on two goods, in general let's say x and y, but also on the reference points for each good, respectively r_x and r_y,. Thus, $U(x, y; r_x, r_y)$.

Loss aversion requires the marginal rate of substitution[2] to be different if the agent

[2] $MRS_{xy} = \frac{\partial U(x,y;r_x,r_y)/\partial x}{\partial U(x,y;r_x,r_y)/\partial y}$

incurs in losses, namely at the left of the reference point, or if agent obtains gains, namely at the right of the reference point:

$$\lim_{x \to r_x^-} [MRS_{x,y}(x, y; r_x, r_y)] > \lim_{x \to r_x^+} [MRS_{xy}(x, y; r_x, r_y)] \tag{1.1}$$

Diminishing sensitivity implies that the marginal rate of substitution increases with respect to the reference point when we are in the gains domain and decreases in the losses domain:

$$\frac{\partial MRS_{xy}(x, y; r_x, r_y)}{\partial r_x} = \begin{cases} \geq 0 & \text{for } x \geq r_x \\ < 0 & \text{for } x < r_x \end{cases} \tag{1.2}$$

Basically, a reference dependent agent separates the space into two subsets: losses, those alternatives that are below a given threshold, named reference point, and gains, those alternatives that are above it. In doing so, he perceives the same alternative in a different way depending on the reference point that he is facing.

In Figure (1.1), we can observe the implications of the mentioned hypotheses for the choice of two goods x and y. Suppose the reference point for good y is normalized to zero, namely $r_y = 0$, so that we concentrate on the shape of a utility function in the presence of a reference dependence for good x. If the reference point is $(r_0, 0)$, points A and B lie in the gain domain for the x dimension (i.e. $x_B > x_A > x_0$). However, if the reference point changes to $(r_x, 0)$, A is now seen as a loss because the quantity of good x in the alternative A is lower than the one in the reference point (i.e. $r_x > x_A$). On the contrary, since the alternative B has a larger quantity of x, it is recognized as a gain (i.e. $x_B > r_x$).

After having framed the space of alternatives in gains and losses, a reference dependent agent applies different rules to choose among alternatives, whether they belong to one subset or another. The idea of loss aversion is, in fact, of applying a different behaviour if the reference dependent agent incurs in a loss or in a gain. A loss needs to be compensated with a larger amount of the other good, with respect to a gain of the same entity. Moreover, diminishing sensitivity implies that these effects are larger for gains, the higher the reference point, but lower for losses. Let's clarify with an example, in Figure (1.1). Let $U_0(x, y; r_0, r_y = 0)$ and $U_r(x, y : r_x, r_y = 0)$ be two indif-

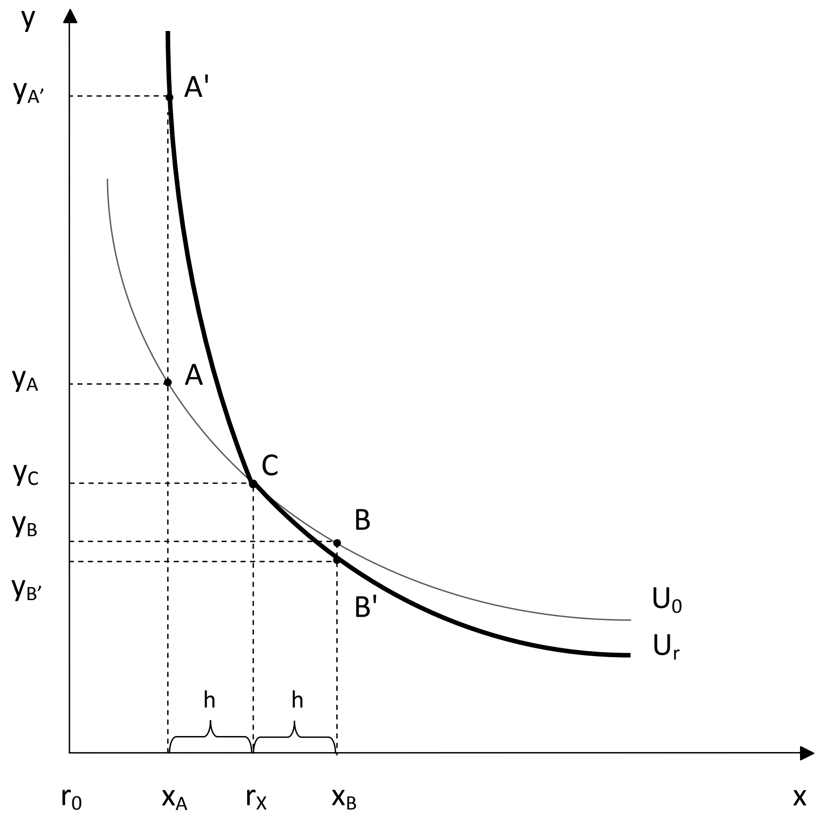

Figure 1.1: Reference dependent agent's utilities with respect to two reference points.

ference curves that pass through C when the agent has a reference point, respectively, $(r_0, 0)$ and $(r_x, 0)$. Loss aversion implies that the indifference curve U_r is kinked at the reference point. On the one hand, the need to compensate more for a loss turns into a higher marginal rate of substitution at the left of the reference point. On the other, gains are less worthy so the marginal rate of substitution is lower at the right side. This is clear when we observe reactions to losses and gains of the same magnitude. Diminishing sensitivity entails that the higher the reference point (namely, moving from $(r_0, 0)$ to $(r_x, 0)$) the higher is the marginal rate of substitution when the agent incurs in gains (see MRS at points B and B'). However, by switching to a lower reference point (from $(r_x, 0)$ to $(r_0, 0)$), the agents are still encountering gains with respect to $(r_0, 0)$, thus the marginal rate of substitution is decreasing (see MRS at points A' and A).

A gain of h from the reference $(r_x, 0)$ demands a lower decrease of good y to maintain the same utility of C, than a loss h (that is $|y_{A'} - y_C| > |y_{B'} - y_C|$). This is the loss aversion effect. Moreover, since the reference point $(r_0, 0)$ is far from these two gains and losses, the effect is less pronounced than for the closer reference point $(r_x, 0)$ (that is $|y_{B'} - y_C| > |y_B - y_C|$ and $|y_{A'} - y_C| > |y_A - y_C|$). The effect of the reference point diminishes farther from it.

With these features in mind, we incorporate reference dependent theory in simultaneous and sequential public good games.

1.2 The Simultaneous Game

1.2.1 The Model

The model consists of a common public good game with two utility maximizer agents. A generic agent i has an initial endowment, I^i, that can be kept for the consumption of a private good x or can be used to contribute to the public good y.

We consider two different games: the simultaneous; and the sequential. In the simultaneous game, the two agents select, at the same time, the level of contribution to the public good that they want to provide. In the sequential game, there are two stages. In the first stage, one player settles a level of contribution to the public good. In the second stage, the other agent, first, observes the contribution fixed by the player and, second, he decides his level of provision to the public good.

Moreover, we consider heterogeneity of types. In both games, agents can have different types: they can be standard agents (represented by s) or reference dependent agents (represented by r). The former has preferences which depend on his consumption of private and public good; in addition to standard agent's preferences, the latter cares also whether he incurs in gains or losses with respect to an initial status. Depending on the context, an agent i ($i = r, s$) can play with another standard agent or a reference dependent agent, thus, we refer to the opponent as agent j. We assume that initial endowment and preferences of players are common knowledge.

We will proceed as follows: first, we describe the standard agent in more detail and the maximization problem that he faces with simultaneous games; then, we will introduce a reference dependent agent. After having completed the simultaneous framework, we will analyse the implications in sequential games.

The Standard Agent

We call a *standard agent* s, an agent who solves the standard public good problem, as commonly described in literature (e.g. Bergstrom et al. (1986)). Agent s preferences depend on his private consumption, x^s, and on the total provision of public good, Y. The utility function $U^s(x^s, Y)$ describing his preferences is twice differentiable; strictly quasiconcave; and strictly increasing in both two arguments, namely the private consumption and the total provision of public good, $Y = y^s + y^j$ (where y^s denotes standard agent's contribution to the public good and y^j is other agent's contribution). The agent has an income I^s which is divided between the private and the public good, $I^s = x^s + y^s$. By Nash assumption, standard agent s takes as given other's contribution (namely, y^j), thus, his simultaneous-move problem is:

$$\max_{x^s, y^s} U^s = (x^s, Y) \tag{1.3}$$

$$\begin{aligned} \text{s.t. } & x^s + y^s = I^s \\ & y^s + y^j = Y \\ & x^s, y^s \geq 0 \end{aligned}$$

Following Bergstrom et al. (1986), let $\phi^s(W)$ be standard agent's demand function for public good when total wealth is W. Since agents can not draw other's contribution from the public good, this implies $Y \geq y^j$. Nevertheless, if we ignore the latter constraint, the total wealth of a maximizing agent is $W^s = I^s + y^j$. Taking these two arguments into account, we can, thus, write agent s total demand for public good as:

$$Y = \max\{\phi(I^s + y^j), y^j\}$$

By subtracting y^j from both sides of the equation, we obtain the standard agent's best reply function:

$$f^s(y^j) = \max\{\phi(I^s + y^j) - y^j, 0\}$$

An equivalent formulation of problem 1.3 can be derived by substituting x^s and Y with constraints to get a utility function of one variable. Thus, yhe agent's problem can be stated as:

$$\max_{y^s \in (0, I^s)} U^s = (I^s - y^s, y^s + y^j) \tag{1.4}$$

and using assumptions made on U^s, we can solve it as a quasiconcave programming problem. First and second order conditions are:

$$\text{FOC}\ {}^s_{sim} - U^s_1 + U^s_2 = 0 \tag{1.5}$$

$$\text{SOC}\ {}^s_{sim} H^s = U^s_{11} - 2U^s_{12} + U^s_{22} < 0 \tag{1.6}$$

The existence of a solution to the maximization problem is guaranteed when we assume both public and private good to be normal goods[3]. The normality assumption of the public good can be formalized as $\frac{\partial \phi^s(W^s)}{\partial W^s} \in (0, 1)$ and implies that in an interior solution of the maximization problem the best reply function has a negative derivative: $\frac{\partial f^s(y^j)}{\partial y^j} \in (-1, 0)$.

From FOC ${}^s_{sim}$, we can write the slope of the best reply function as:

$$\frac{\partial f^s}{\partial y^j} = -\frac{1}{H^s}[-U^s_{12} + U^s_{22}] = -\frac{1}{H^s}\left[\frac{\mathrm{d}U^s_2}{\mathrm{d}y^s}\right] \tag{1.7}$$

As we have seen, by normality assumption, the slope of the reply function is always negative; this is confirmed by marginal returns for the public good which are decreasing in the contribution of agent s $\left(\frac{\mathrm{d}U^s_2}{\mathrm{d}y^s} < 0\right)$ and by the quasiconcavity assumption on SOC ${}^s_{sim}$ $(H^s < 0)$.

Assume that a simultaneous game is played by two general agents i and j. A *Nash equilibrium* is a pair of contributions $(\bar{y}^i, \bar{y}^j)$ which solves the maximization problems of, respectively, the two agents i and j. Underneath *Nash assumption* is that a maximizing agent takes as given the contribution of his opponent; the existence of the equilibrium is guaranteed by the normality assumption of goods x and y.

[3]For existence and uniqueness of equilibrium, we refer to Bergstrom et al. (1986)

Before moving onward with the analysis of the game, we distinguish between two possible equilibria outcomes. For *interior equilibrium*, we mean an equilibrium where both agents contribute strictly positive amounts to the public good, (namely, $\bar{y}^i > 0$ and $\bar{y}^j > 0$). Although, in some cases, we will consider corner solutions where only one agent gives a strictly positive contribution[4]. To better understand the agent's behaviour, we consider the case where only one of the two players is contributing a positive amount to the public good and the other is totally free riding on him (e.g., $\bar{y}^i > 0$ and $\bar{y}^j = 0$). We, thus, define the following concept:

Definition 1. *A* ***standalone contribution*** $\tilde{y}^i$ *is the contribution which maximizes agent i's problem, when player j contributes zero to the public good* ($y^j = 0$)*.*

Note that the standalone contribution is not only the best response to total free riding of the opponent, but also the contribution that a player would choose if he were not playing with anyone else. We can then refer to an agent with his standalone contribution because it would characterize an important feature of his preferences.

Definition 2. *Two agents i and j are* ***standalone similar*** *whenever* $I^i = I^j$ *and* $\tilde{y}^i = \tilde{y}^j$*.*

So far, we have solved the simultaneous problem from the point of view of a *standard agent* whose preferences depend exclusively on private consumption and on total contributions of public good. We will now introduce a second type of agent.

The Reference Dependent Agent

To describe a *reference dependent agent* r, we need to change assumptions on the utility function.

As presented in Bergstrom et al. (1986), each agent has a total wealth that is the sum of the individual income I^i and the other agent's contribution y^j. These are the exogenous variables to which a reference dependent agent can refer. Let r_i be the reference point of good i, the utility function of a reference dependent agent can be

[4] To pursue the analysis of the model, unless otherwise stated, we concentrate the analysis on the interior equilibria.

written as $U^r(I^r - y^r, y^r + y^j; r_I, r_Y)$, where r_I and r_Y are, respectively, reference points for the income and the public good.

A reference point for the public good, r_Y, can be thought as the part of the public good that is not directly provided by the reference agent, r. In our model with two players, it seems natural to set the other player's contribution, y^j, as the reference point. Indeed, the Nash assumption requires one to take the other's action as given and, in equilibrium, conjectures about rival's actions are correctly forecasted. Thus, while taking his decision, agent r knows the contribution of the opponent and frames the situation according to that.

Regarding the reference point on income, r_I, the framing can depend on the initial status quo of agent r. The income is exogenously given to each agent at the beginning of the game, thus the initial amount of income I^r would set the point at which r could distinguish between losses and gains.

To sum up, in the context of public good, we can refer to the reference dependent agent r's utility function as $U^r(I^r - y^r, y^r + y^j; I^r, y^j)$, where last two arguments of the function are, respectively, the reference point for income and the one for the public good. In this paper, we will restrict our attention on those cases where the income is exogenously given[5].

Thus, we can simplify the notation of the utility function in $U^r(x^r, Y; y^j)$. As regards constraints, there are the same restrictions as for standard agents: income is divided between private and public good, $I^r = x^r + y^r$; private consumption and own contribution to public good have to be non negative, $x^r, y^r \geq 0$; and the opponent's contribution can not be used to purchase private good, $Y \geq y^j$.

To begin, recall that an agent who makes a standalone contribution is facing a free riding opponent. Since a reference dependent agent models his preferences with respect to the other player's contribution, there is no reason why he would frame the situation differently than a standard agent.

[5]In general, we consider frames where the reference point of the public good is active, in the sense that the opponent, by contributing a positive amount, sets the reference. Hence, we exclude the framing with respect to income variations: income is given and can not be modified during the game. Namely, we do not treat all those possible circumstances that might shift subjects' incomes (e.g. taxes, subsidies, money transfers among agents).

Assumption 1. *Two agents s and r with the same income, $I^s = I^r$, are* ***standalone similar****.*

In other words, Assumption (1) claims that when r is the only contributor to the public good the reference point is null, he behaves as a standard agent s with same exogenously given income. This implies that for every level of income, the heterogeneity between agents rises only when the reference point comes into play. It is important to understand that we do not depart completely from the standard theory, but we introduce framing effects that modify behaviour when interaction with other subjects in the public good influences the perception of a reference dependent agent.

In addition to the standard utility function, assumptions that follow directly from Tversky and Kahneman (1991) are *loss aversion* and *diminishing sensitivity* with respect to the reference point y^j. Moreover, we add a new assumption, namely the presence of *increasing reference effects*.

A utility function exhibits an *increasing reference effect* when it has increasing marginal returns with respect to the reference point. Recall that the reference point is also the other agent's contribution to the public good. The reference dependent agent gets utility directly for being matched with higher contributors and this is reflected by a higher reference point. He is enjoying more when the public good is provided by others. Thus, the higher is the benchmark he is referring at, the higher is the level of public good provided by the other. An increasing reference effect translates into $U_3^r > 0$.

Loss aversion entails that $\lim_{y^j \to R^-} MRS_{2,1}(x^r, Y; R) > \lim_{y^j \to R^+} MRS_{2,1}(x^r, Y; R)$, where R is the reference point. Since by the Nash assumption (i.e. $Y \geq y^j$) the total contribution can never be below the reference point, agent r is always in the domain of gains. Although the utility function is kinked at the reference point, it does not imply discontinuity. In fact, whether we approach the reference point from the gain or the loss domain, the function reaches the same value, $\lim_{y^j \to R^-} U^r(x^r, Y; R) = \lim_{y^j \to R^+} U^r(x^r, Y; R)$. Note that, since the reference point counts as the "zero" of the reference dependent function, it is easy to observe the foundation of Assumption (1). It can be restated in the following way: the reference dependent utility function shrinks into a standard utility function when the other agent is not contributing to the public good. Since the reference point is the other player's contribution, r is in a neutral framework while contributing the standalone amount, $\tilde{y}^r$. Thus, whenever the two incomes of the two agents r and s are equal (i.e. $I^s = I^r$), Assumption (1) says that they have the same standalone contribution. Thus, we can write $\lim_{y^j \to 0} U^r(x^r, y^r + y^j; y^j) = U^r(x^r, \tilde{y}^r; 0) = U^s(x^s, \tilde{y}^s)$.

The assumption of *diminishing sensitivity* implies that in the gains domain, namely when $Y \geq y^j$, the marginal rate of substitution between the private and the public good is increasing in the reference point: $\frac{\partial MRS_{x^r,Y}(x^r,Y,y^j)}{\partial y^j} \geq 0$. As we will see, by introducing a reference dependent theory, diminishing sensitivity implies that the higher the reference point, the larger the effect of the public good provision in the domain of the gains. This translates in a lower reduction of the private good as the reference point increases.

In short, this formulation of the reference dependant's utility function has many advantages. First, all assumptions and hypotheses concerning the standard model are maintained (i.e. normality assumption of goods and differentiability, monotonicity and quasiconcavity of the utility function). Moreover, it allows to have a more general utility function which has, as a particular case, the standard utility when agents are *standalone similar*. Despite all similarities, incorporating the reference dependent model in public good games helps shed light on many irregularities found in experimental results.

The maximization problem for the reference dependent agent can be stated in the following way:

$$\max_{y^r \in (0, I^r)} U^r = (I^r - y^r, y^r + y^j; y^j) \tag{1.8}$$

and using assumptions made on U^r, we can solve it as a quasiconcave programming problem. First and second order conditions are:

$$\text{FOC}\,^r_{sim} - U_1^r + U_2^r = 0 \tag{1.9}$$

$$\text{SOC}\,^r_{sim} H^r = U_{11}^r - 2U_{12}^r + U_{22}^r < 0 \tag{1.10}$$

As we can observe, the fact that a reference dependent agent maximizes his utility with respect to his own contribution to the public good implies FOC^r_{sim} and SOC^r_{sim}

similar to a standard agent FOC^s_{sim} (1.5) and SOC^s_{sim} (1.6). However, what really does distinguish one agent from the other is the interaction with another player.

Since the utility function of r depends twice on the contribution of player j, as quantity in the public good provision and as reference point, his best reply function is:

$$\frac{\partial f^r}{\partial y^j} = -\frac{1}{H^r}[-U^r_{12} + U^r_{22}] - \frac{1}{H^r}[-U^r_{13} + U^r_{23}] = -\frac{1}{H^r}\left[\frac{\mathrm{d}U^r_2}{\mathrm{d}y^r} + \frac{\mathrm{d}U^r_3}{\mathrm{d}y^r}\right] \tag{1.11}$$

It is worth noticing that the unique difference between the best reply functions of standard and reference agents lies in the second term in parenthesis of equation (1.11), namely the total differential of the marginal utility of the reference point with respect to the public good provision.

1.2.2 Results

We can state the first result that follows directly from the comparison between the best reply functions of two types of agents.

Proposition 1. *If two agents, a standard agent s and a reference dependent r, are standalone similar ($\tilde{y}^s = \tilde{y}^r$), for any strictly positive contribution of an opponent j (y^j), their reply contributions would differ. Moreover, for any y^j, we have that $f^r(y^j) > f^s(y^j)$.*

Proof for Proposition 1. Let $y^j > 0$ be opponent's contribution of a standard agent s and a reference dependent agent r.

Comparing best reply functions of agent s and agent (equations (1.7) and (1.11)), the difference consists in the additional term $-\frac{1}{H^r}(-U^r_{13} + U^r_{23})$.

Since a reference dependent agent when $y^j > 0$ is in the gains domain, by definition of *diminishing sensitivity*:

$$\frac{\partial MRS_{21}(x^r, Y; y^j)}{\partial y^j} > 0$$

Thus:

$$\frac{\partial MRS_{21}(x^r, Y; y^j)}{\partial y^j} > 0$$
$$\frac{\partial\left(-U_1^r/U_2^r\right)}{\partial y^j} > 0$$
$$-\frac{(U_2^r U_{13}^r - U_1^r U_{23}^r)}{(U_2^r)^2} > 0$$

since by assumption $U_1^r > 0$ and by FOCs $U_1^r = U_2^r$, we have that:

$$\frac{(U_1^r)(-U_{13}^r + U_{23}^r)}{(U_2^r)^2} > 0$$
$$\frac{\mathrm{d}U_3^r}{\mathrm{d}y^r} > 0$$

Thus, $\left.\frac{\partial f^r}{\partial y^j}\right|_{y^j} > \left.\frac{\partial f^s}{\partial y^j}\right|_{y^j}$.

$\square$

This first Proposition claims that a reference dependent agent's best reply is to always contribute more than a standard agent at any positive contribution of the other player. In Figure (1.2), we plot the implications of Proposition (1) for downward sloping reaction functions.

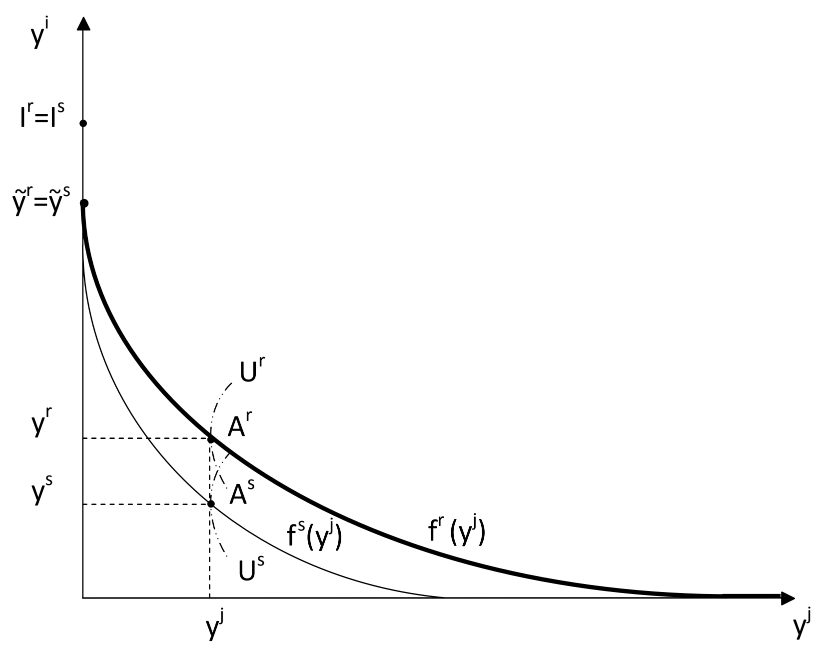

Figure 1.2: Best reply functions for standalone similar standard and reference dependent agents.

Contributions y^r and y^s are, respectively, the best reply contributions to y^j for the reference agent r and the standard agent s. The assumption of diminishing sensitivity is at the basis of the result. When $y^j = 0$, both agents contribute the standalone, however when y^j increases, it produces two effects on players. Both agents are affected by the normality assumption of both goods which, as already explained, produces a decrease of the reaction functions (each unit of additional public good provided by j is devoted, in part, to the private good, in part, to the public good). Recall that the higher the reference point, the higher the marginal rate of substitution between the private good and the public good. Thus, the reference dependent agent perceives the private good as less valuable. This second effect entails that he is willing to contribute more to the public good in order to get a higher utility.

The most evident implication is that, if the reference dependent agent takes other players' contributions as given (as for example in case that his contribution is so little that does not affect others' replies), the free riding effect is less marked than can be predicted by standard theory.

Furthermore, a high diminishing sensitivity effect can translate into an increasing reaction function for the reference dependent agent ($\frac{\partial f^r}{\partial yj} > 0$). In fact, the diminishing sensitivity effect can be so large as to overcome the normality assumption (whenever $\left|\frac{\mathrm{d}U_3^r}{\mathrm{d}y^r}\right| > \left|\frac{\mathrm{d}U_2^r}{\mathrm{d}y^r}\right|$). This implies that a reference dependent agent is not only free riding less than expected, but he can behave as a reciprocator, in the sense that the higher his opponent's contribution, the higher he is willing to contribute to the public good.

As discussed in the introduction, experimental evidence shows that many economic agents are conditional cooperators which exactly reflects the fact that they have increasing reaction functions. In this context, the idea is that other agents' contributions set the reference point for some economic agents, who are prone to increasing their contribution as the others do so.

However, increasing one's contribution might create higher levels of free riding for standard agents whose reply function is decreasing. So the aggregate effect on the total public good provision, in presence of heterogeneous agents (i.e. standard and referent dependent), has to be investigated in more detail.

On Simultaneous Interaction Among Heterogeneous Agents

The next result gives some insight into total contribution with heterogeneity of types. We are interested not only in understanding what are the implications of others' contributions on the reference dependent agent, but also how a standard agent reacts when encountering other types.

Proposition 2. *Suppose there are two agents contributing to a simultaneous public good. If at least one of the two is a reference dependent, the total amount of public good contributed can never be lower than the total amount provided by two standard agents with, respectively, the same standalone contributions.*

Proof. See Appendix. □

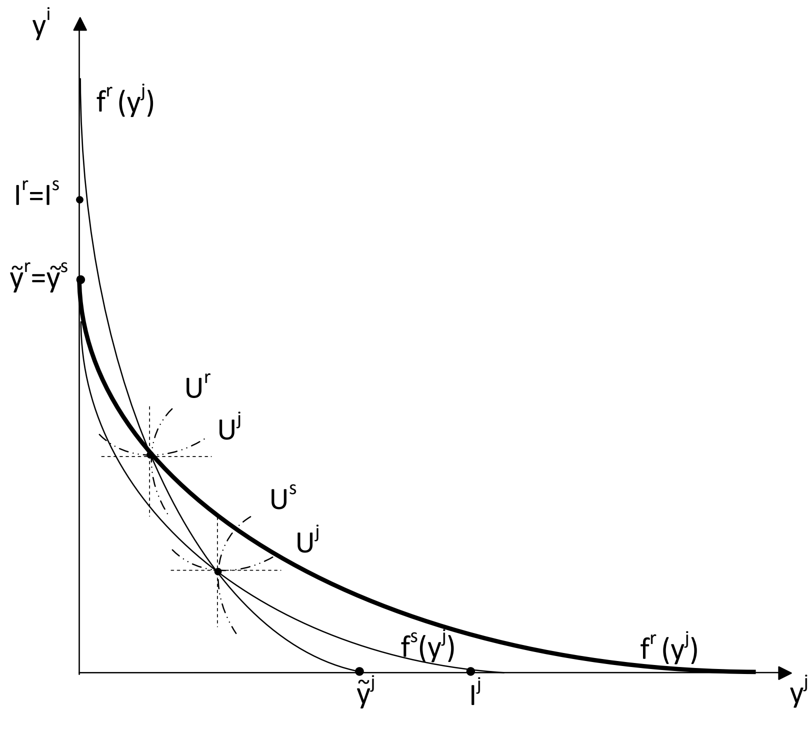

Figure 1.3: Simultaneous equilibria with downward sloping reaction functions.

Proposition 2 sheds light on equilibrium outcomes in simultaneous games with standard agents and reference dependent agents. The total provision of public good is at the lower level when both agents are standard. On the contrary, reference dependent agents' contributions are affected by opponents and they turn into lower free riding than the one of the corresponding standard agents. This reduction of free riding is exploited by standard agents who take into account their benchmark role. Thus, the burden of contributing shifts to the reference dependent agent. This is clear in Figure (1.3).

Agents r and s are standalone similar with downward sloping reaction functions, respectively, $f^r(y^j)$ and $f^s(y^j)$. Knowing that a reference dependent agent contributes more than a standard one, an opponent j with a downward sloping reaction function, $f^j(y^i)$ (where $i = r, s$), responds with a lower contribution. Improvement of the total contribution is only achieved because the reference dependent agent contributes more. The crowding out effect is present because both private and public goods are normal. Only when two reference agents whose reference dependence is high enough to produce increasing reaction functions we can find a crowding in effect.

1.3 The Sequential Game

In this section, we describe results for sequential games. In the spirit of Stackelberg, we will call *leader* the agent who moves first in the sequential game; and *follower*, the second mover. Similarly to previous analyses, we will concentrate on the interaction among the two different agents, *reference dependent* and *standard* agent. Moreover, we compare sequential outcomes with simultaneous ones.

In simultaneous games, the Nash assumption states that in equilibrium, the prediction on the other agent's contribution is correctly satisfied. This implies that the reference point is known before the act of contributing to the public good game takes place. An interesting case to analyse is when contributions occur sequentially and there is actually an agent that contributes first. Whenever an agent moves first, clearly, she is setting the reference point, that is because she is showing followers at which level of contribution she is located (or at which level she is committed to). A leader that internalizes the follower's behaviour has to be aware of the role she holds.

As we have already seen, a reference dependent agent can have a positive upward reaction function and he can improve the total contribution in simultaneous games.

This kind of behaviour is also found in the sequential game. Andreoni et al. (2002) study, for example, the difference between simultaneous and sequential games. They found that "a small increase in the initial contribution ... causes an immediate reaction [on second player's response] in the sequential game". It is the leader that, by taking the opportunity to conduce, influences the follower who observes her as a benchmark.

Nevertheless, also when the reference dependent agent is the first mover, she correctly predicts which will be the subgame perfect contribution of the follower. So, as we have assumed in the simultaneous game, the reference point for a reference dependent leader will be the follower's contribution.

Let's first introduce the model and then the results for the sequential game with heterogeneous players.

1.3.1 The Model

Let G_0 and G_i refer to, respectively, the simultaneous game and the sequential game when the first mover is agent i. As we have discussed in previous paragraphs, a simultaneous-move game G_0 requires both agents in equilibrium to be on their best-reply functions, namely agents i and j would contribute $y^i = f^i(y^j)$ and $y^j = f^j(y^i)$.

In a subgame perfect equilibrium of the game G_i, the second mover j is on his best-reply function $f^j(y^i)$ as in G_0. Moreover, the leader has the advantage of moving first thus she will contribute out of her reaction function[6]. Let's distinguish between reference dependent r and standard agent s when they are first movers. The standard leader's maximization problem and first order conditions are:

$$\max_{y^s \in (0, I^s)} U^s(I^s - y^s, y^s + f^j(y^s)) \tag{1.12}$$

$$\text{FOC}\ {}^{s}_{seq} - U_1^s + U_2^s \left(1 + \frac{\partial f^j}{\partial y^s}\right) = 0 \tag{1.13}$$

The maximization problem and first order conditions of a reference dependent leader are:

$$\max_{y^r \in (0, I^r)} U^r(I^r - y^r, y^r + f^j(y^r); f^j(y^r)) \tag{1.14}$$

[6]Note that the worst a leader can do is to contribute as in a simultaneous game. Since she has the right to move first and her contribution is increasing in the contribution of the other player ($\frac{\partial U^i}{y^j} > 0$), she can modify her contribution to achieve higher utility.

$$\text{FOC}\ {}^{r}_{seq} - U_1^r + U_2^r \left(1 + \frac{\partial f^j}{\partial y^r}\right) + U_3^r \frac{\partial f^j}{\partial y^r} = 0 \tag{1.15}$$

To simplify the analysis, unless otherwise stated, we assume interior solutions. Given assumptions described regarding strictly quasi-concavity of the function, monotonicity in arguments and linear constraints, as we assume an interior solution to the quasi-concave programming problem, the solution exists and is unique.

1.3.2 Results

By backward induction, followers are on their best reply functions as in simultaneous games, while a leader maximizes by anticipating the follower's response. The standard (reference dependent) leader solves problem (1.12) (problem (1.14)).

With standard utility function, leaders and followers have downward sloping reaction functions. Thus, by observing first order conditions of a sequential game, (1.13), and first order conditions in the simultaneous game, (1.5), of a standard agent, we can conclude that the interaction among two standard agents makes the first mover decrease her contribution. A leader knows that any one dollar increase in her contribution would actually crowd out follower's one. This occurs because of the normality assumption (that gives the shape of the reaction function): a follower who observes an increase in the contribution of the leader will perceive an increase in wealth of one dollar. Thus, he would devote a part of the dollar to the consumption of the private good and a part to the public good. This crowding out behaviour is anticipated by the leader who applies the opposite mechanism: by being the first to free ride, she will increase her utility by exploiting second mover. The latter would respond to a decrease in the leader's contribution by increasing his own.

However, in many experimental results, we observe that the leader, instead of free riding on followers, contributes more than expected. In the light of rationality of agents, this behaviour of the first mover can be rational only if it crowds in contributions of the followers.

We will start to analyse the leader' and follower's contributions and the total provision of public good in sequential games by comparing their behaviour in simultaneous games. Our main interest is to clarify what might be the reasons for creating a crowd in effect and improving the social outcome. We, thus, give a general result and a discussion of possible interactions among heterogeneous agents. Finally, we try to address the issue of identifying Pareto superior outcomes.

Let's state the main result regarding sequential games:

Proposition 3. *(A) Whenever the second mover is a standard agent or is a reference dependent agent with a downward sloping reaction function, in equilibrium the total contribution to the public good is lower in the sequential game than in the simultaneous one. Moreover, the first (second) mover is contributing less (more) to the public good than in the simultaneous one.*

(B) Whenever the second mover is a reference dependent agent with upward reaction function, in equilibrium the total contribution is higher in the sequential game than in the simultaneous one. Moreover, both first and second movers contribute more to the public good than in the simultaneous one.

Proof. See Appendix. □

Proposition (3) distinguishes among two different possible outcomes in comparing simultaneous versus sequential public good games. It includes all possible combinations of standard agents (with downward sloping reaction functions) and/or reference dependent agents (who can have both downward or upward sloping reaction functions depending on how powerful the diminishing sensitivity effect is).

Independently of their preferences, the driving element of the results in Proposition (3) is given by second mover's reaction function. In the part (A) of the result, by committing to low contributions, the leader anticipates a second mover's crowding in behaviour and exploits it. One example is the case presented in Figure (1.4). When agent i moves first, she is acquiring a higher utility by decreasing her contribution with respect to the simultaneous game. The equilibrium of game G_i lies on best reply function of second mover, namely on $f^j(y^i)$. This latter agent can only increase his contribution with respect to what he does in the simultaneous game. The same happens when agent i is the first mover. This result is basically Varian's case where agents who only care about the total provision of public good exploit the first mover advantage.

Whenever a reference dependent agent is present in a sequential public good, we

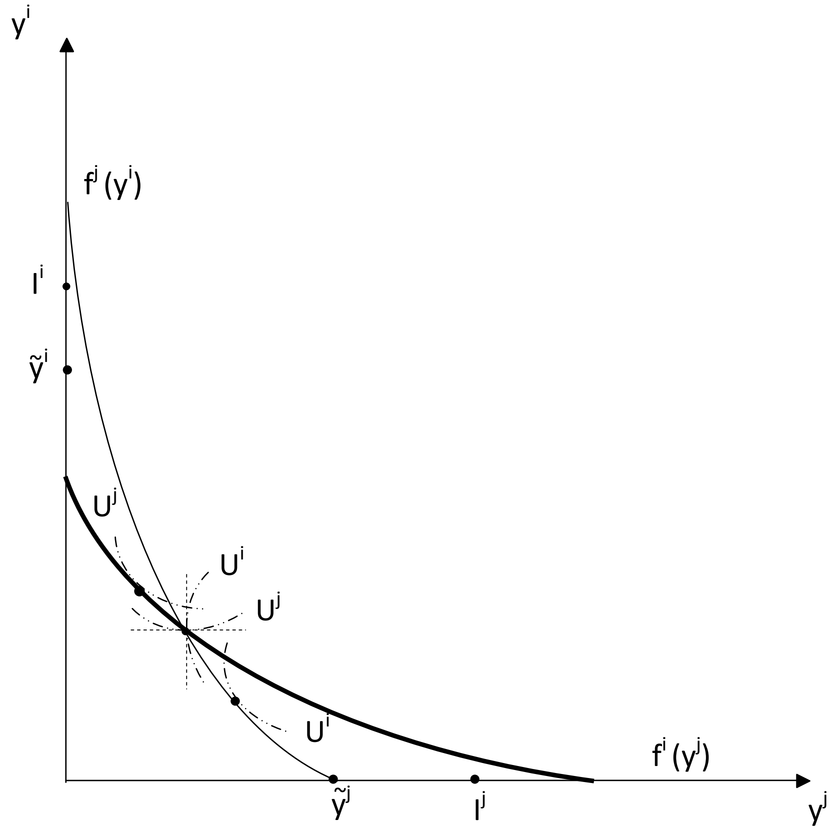

Figure 1.4: Simultaneous and sequential equilibria with downward sloping reaction functions.

might have expected the total provision of public good to be always higher. That is because, as we have seen in the simultaneous case (Propositions (1) and (2)), the reference dependent agent is free riding less than a standard agent in simultaneous games. On the contrary, in Proposition (3) part (A), even if a leader sets the benchmark to which a reference dependent agent refers, the total contribution in the sequential game is lower if his reaction function is downward sloping. When the diminishing sensitivity effect is too low to compensate the normality assumption effect, the leader takes advantage, contributes less and the reference dependent follower does not counterbalance enough to enhance total contributions.

Part (B) of Proposition (3) demonstrates that the provision of public good can increase if we allow players to move sequentially in the public good game. Three cases can occur: both agents are reference dependent with an upward sloping reaction function; a reference dependent second mover facing a standard leader or a downward sloping reference dependent first mover.

Clearly, when two reference agents have upward reaction functions, both are better off by contributing higher amounts in the sequential game. The leader is the first one that is willing to contribute more if the other does the same. By committing to a high contribution, she is actually setting an example for a follower who reciprocates. In Figure (1.5), we can observe that the total provision of public good is always higher than in the simultaneous game, no matter who the leader is. Note that subjects are both better off by moving sequentially to the public good game even if their individual contribution is higher. Since the second mover does not free ride on the leader, she can increase her utility by showing a cooperative behaviour.

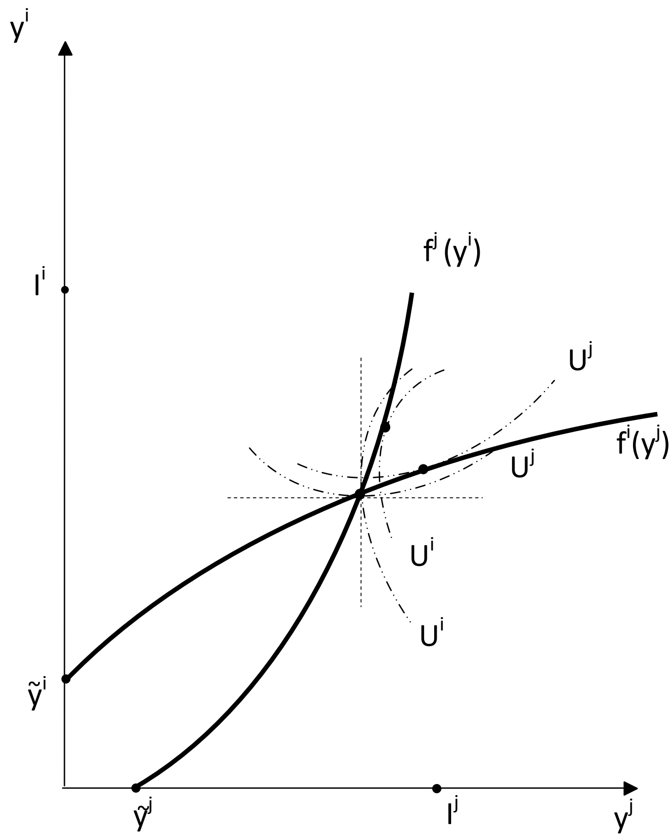

Figure 1.5: Simultaneous and sequential equilibria with upward sloping reaction functions.

A natural question that arises is if this type of result is maintained also in the presence of heterogeneous agents. A leader who meets a reciprocator is induced to cooperate to augment the overall public good provision. This happens only when second movers have upward reaction functions (see Figure (1.6)). In this case, the first mover takes advantage of her role by not free riding as usual, but by contributing to the public good more than that is expected even in a simultaneous game. In our context, the leader (whether she is a standard agent or a reference dependent) knows that she would set the reference point for second movers. She has to take into account her influence on the follower when choosing her contribution.

Besides, if we have the possibility of imposing roles in the sequential game, we might want to know how to improve the social outcome. However, when the two players have both downward reaction functions, it is not simple to understand which of the two it would be better to force to move first. Even if one agent is a reference dependent and the other is a standard agent, it is not clear. On the one hand, a standard first mover, when facing a reference dependent agent, would free ride less because she observes more cooperation from the second mover. Nevertheless, given the assumption of increasing reference effect, reference dependent agents with downward sloping reaction functions would reduce her contribution as leader more than expected. If she reduces her contribution, the standard follower would increase his own. This latter result has a double effect on the reference dependent leader: on the one hand, it would enter positively in her utility function through the public good increase; on the other hand, higher contributions of followers have marginal positive effects on her utility by being matched with higher contributors. Thus, her contribution would decrease more than expected. To conclude, we fail to state a general result in presence of heterogeneity of subjects with downward sloping reaction functions. On the contrary, when a reciprocator behaviour appears in the reference dependent agent, we can draw a more clear picture.

Suppose now that we have a standard agent and a reference dependent with upward reaction function. Corollary (1) states our last result:

Corollary 1. *Suppose there are two agents, a standard and a reference dependent. If the latter has an upward sloping reaction function, then the equilibrium is Pareto superior whenever the leader is the standard agent with respect to the simultaneous game and with respect to the sequential game where the leader is the reference dependent agent.*

Proof. See Appendix. □

Corollary (1) states what is clear from Figure (1.6). When r is the first mover, her utility's gain is achieved by free riding on the standard second mover. Once more, only the leader is better off to the detriment of the other. On the contrary, the rise of a cooperative behaviour when the reference dependent is a second mover increases the utility of both agents with respect to the simultaneous game (and, thus, also when r is leader).

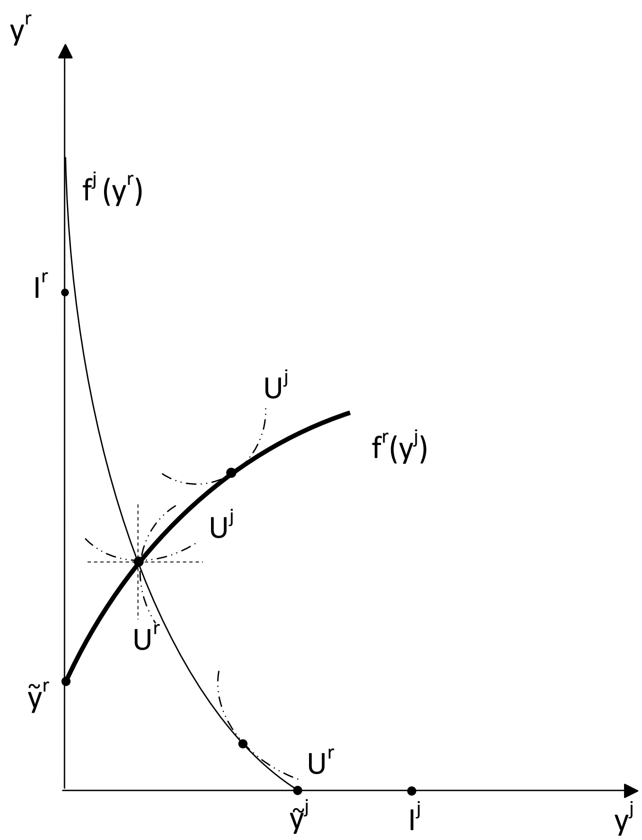

Figure 1.6: Simultaneous and sequential equilibria with upward and downward sloping reaction functions.

1.4 Discussion

As far we have discussed predictions of incorporating reference dependent theory in public good simultaneous and sequential games. We want now to give some intuition on the motives that underlies our results.

It has been largely proved that people are motivated by concerns other than pure self-interest[7] (in this context, represented by the standard agents' behaviour). Free riding prediction might be correct in some games, however, there is evidence that in public good settings (both experimental conditions and real life situations) this can not explain all individuals behaviour. Society is composed by many different types of agents and this heterogeneity is at the basis of strategic interaction among people. Interaction among agents with different or opposed preferences can, however, end up in unexpected behaviour that depends on the particular interchange that occurs (e.g. a selfish subject can cooperate instead of free riding in certain conditions).

Although a large literature on other regarding preferences (e.g. fairness, altruism) has emerged in the last decades[8], we propose another approach that differs because the motives underlying subjects' choices depart from concerns about others. It is well known in psychology (Tversky and Kahneman, 1991) that the behaviour of subjects is conditioned by situations, environments, others' actions. We focus on the idea that the latter influence some agents by setting a reference point for them. In social dilemmas, as the public good game, interaction matters. Thus, we suggest that subjects might have a tendency to a pro-social behaviour both because of a sort of learning to cooperate in a group or because of some bounded rationality that prevents them to make correct choices and refer to others' contributions. The former can, however, become an advantage when they imitate or reciprocate even with selfish agents, which might cooperate too (as we have seen in the sequential case). The reference point given by others might reduce the overall free riding in general or turn into conditional cooperative behaviour.

1.5 Conclusions

In this paper, we provide an alternative explanation to describe deviations from the equilibrium outcomes usually observed in public good contexts with rational agents. The latter's behaviour is independent of the frame of the game and relies only on abso-

[7]Andreoni (1990); Rabin (1993); Fehr and Schmidt (1999)

[8]For example, Fehr and Schmidt (2000) argue that "many people are not only maximizing their own material payoffs, but that they are also concerned about social comparisons, fairness, and the desire to reciprocate".

lute monetary payoffs. However, many studies (both in psychology and in economics) suggest that the cognitive process that guides choices induces people to simplify the space of action according to some reference points. People, therefore, make choices depending on the distance from these reference points. We argue that some subjects may frame the public good game considering others' contributions as a benchmark to which refer.

We find that reference dependent subjects free ride less than standard agents. This failure in giving a high weight to self-incentives can turn into reciprocity, which can explain part of the conditional cooperation behaviour largely observed in public good games. However, if we consider games where strong free riders and reference dependent agents play together, we analytically prove that the former can exploit this sort of "bounded rational" behaviour. This, not only, always occurs in simultaneous games, but also in sequential games when the first movers reduce contributions to shift the burden of the public good provision to the second movers. However, when the reference dependent agent is a reciprocator, a leader acquires an important role in setting the example. The usual first mover advantage does not turn into a free riding behaviour but in a cooperative one, even if the leader is a standard agent. This important result is in line with Cartwright and Patel (2010), although in their paper reciprocating behaviour is not motivated. In our work, we instead show that, on the one hand, reciprocity might be consistent with a reference dependent agent theory, on the other, a strategic behaviour of standard agents can increase the production of public good in sequential frameworks.

1.6 Appendix

Lemma 1. *If an interior equilibrium exists for two standard agents and if at least one of them is replaced by a standalone similar reference dependent agent, the equilibrium is still an interior equilibrium.*

Proof. Suppose that two standard agents s and s' have stand-alone contributions, respectively, $\tilde{y}^s$ and $\tilde{y}^{s'}$. Suppose both standard agents contribute in equilibrium positive amounts $(\bar{y}^s, \bar{y}^{s'})$.

Without loss of generality, suppose a reference dependent agent r is standalone similar to s', that is $\tilde{y}^r = \tilde{y}^{s'}$, and he replaces agent s' in the contribution to the public good.

To establish that the equilibrium is an interior solution, let's prove that a corner solution it is not feasible. By Proposition 1, a reference dependent agent contributes always more than a standard agent with same stand-alone contribution. Since standard agent s has decreasing reply function, the only possible corner solution would be $(\tilde{y}^r, 0)$. But since $\tilde{y}^r = \tilde{y}^{s'}$, this would imply that also the equilibrium with the two standard agent s and s' is a corner solution. Thus, the equilibrium has to be interior. $\square$

Proof of Proposition 2. Let's first consider the case with only one reference dependent agent. Suppose that two standard agents s and s' have stand-alone contributions, respectively, $\tilde{y}^s$ and $\tilde{y}^{s'}$. Without loss of generality, suppose a reference dependent agent r has same stand-alone contribution as s': $\tilde{y}^r = \tilde{y}^{s'}$. We can consider two cases: when both contribute to the public good and when only one is providing the all contribution.

Suppose both standard agents contribute in equilibrium positive amounts $(\bar{y}^s, \bar{y}^{s'})$. Moreover, suppose that reference dependent agent r substitutes agent s' in the contribution to the public good.

By Lemma 1, the equilibrium is still an interior equilibrium, thus both s and r contribute positive amounts. Since by diminishing sensitivity (1), whenever agent s contributes $\bar{y}^s$ to the public good, agent r would contribute $\bar{y}^r > \bar{y}^{s'}$. Thus, s is no more in equilibrium. Since his perceived wealth is increased by $\Delta\bar{y} = (\bar{y}^r - \bar{y}^{s'})$, by normality assumption (namely, the fact that $\frac{\partial f^s}{\partial y^r} \in (-1, 0)$), he would decrease his contribution but less than $\Delta \bar{y}$. We can iterate this reasoning until reaching the equilibrium, which is, by Lemma 1, an interior solution.

Thus, total contribution to the public good is higher.

Suppose that only one agent contributes the total provision of public good. We can have two cases.

i) Suppose that agent s is the only contributor. Thus, the equilibrium quantities provided are the stand-alone equilibrium for s and zero for s': $(\tilde{y}^s, 0)$. Again, by diminishing sensitivity, since $\tilde{y}^s > 0$ and $\bar{y}^{s'} = 0$, then $\bar{y}^r \geq 0$. If r would continue to complete free ride on s, then the total provision of public good is the same. In contrast, if r starts contributing positive amounts, similarly to proof of Lemma 1, the increase in contribution of r will provoke a lower decrease in standard agent's contribution. Thus, higher provision of public good would be provided.

ii) Suppose that agent s' is the only contributor. Thus, the equilibrium quantities provided by agent s and agent s' are, respectively, $(0, \tilde{y}^{s'})$. Since by assumption, $\tilde{y}^r = \tilde{y}^{s'}$), then the total provision of public good is the same.

When both standard agents are substituted by reference dependent agents, trivially results are the same when at least one agent has a downward sloping reaction function.

If both reference dependent agents have upward reaction functions, by Proposition 1, both would contribute more to the public good, respect to standard agents with same stand-alone equilibrium. Thus, total provision of public good is always higher. $\square$

Proposition 3 can be restated as follows:

Proposition 3. *Suppose A is the first mover and B the second mover.*
(A) Whenever $\frac{\partial f^B}{\partial y^A} < 0$*, in equilibrium* $Y\big|_{G_0} > Y\big|_{G_A}$.
Moreover, we have that $y^A\big|_{G_A} < y^A\big|_{G_0}$ *and* $y^B\big|_{G_A} > y^B\big|_{G_0}$.
(B) Whenever $\frac{\partial f^B}{\partial y^A} > 0$*, in equilibrium* $Y\big|_{G_0} < Y\big|_{G_A}$.
Moreover, we have that $y^A\big|_{G_A} > y^A\big|_{G_0}$ *and* $y^B\big|_{G_A} > y^B\big|_{G_0}$.

Proof of Proposition 3. Leader's FOC for standard and reference dependent agents can also be written as:

$$\text{FOC}_s \quad -U_1^s + U_2^s + \frac{\mathrm{d}U^s}{\mathrm{d}y^j}\frac{\partial f^j}{\partial y^s} = 0$$

$$\left(\text{where } \frac{\mathrm{d}U^s}{\mathrm{d}y^j} = U_2^s > 0\right)$$

$$\text{FOC}_r \quad -U_1^r + U_2^r + \frac{\mathrm{d}U^r}{\mathrm{d}y^j}\frac{\partial f^j}{\partial y^r} = 0$$

$$\left(\text{where } \frac{\mathrm{d}U^r}{\mathrm{d}y^j} = U_2^r + U_3^r > 0\right)$$

Suppose $\frac{\partial f^j}{\partial y^i} < 0$, with $i = r, s$.

For both types of agents we have that $\frac{\mathrm{d}U^i}{\mathrm{d}y^j} > 0$.

(A) By comparing sequential and simultaneous FOC, whenever $\frac{\partial f^j}{\partial y^i} < 0$, then in equilibrium $\left(y^i\big|_{G_0} > y^i\big|_{G_i}\right)$. By normality assumption, every decrease of first mover contribution in the sequential game respect to the simultaneous one, will be compensate by an increase of second mover's contribution, $\left(y^j\big|_{G_0} > y^j\big|_{G_i}\right)$. Since second mover is always on his best reply function, the increase will be less that one-to-one, thus, $\left(Y\big|_{G_0} > Y\big|_{G_i}\right)$.

(B) Suppose now that $\frac{\partial f^j}{\partial y^r} > 0$, with $i = r, s$. Namely, suppose that second mover is a reference dependent agent with upward sloping reaction function. Then, by comparing FOC in sequential and simultaneous, first mover is always better off by increasing her contribution to the public good, $\left(y^i\big|_{G_0} < y^i\big|_{G_i}\right)$. Then, since $\left(\frac{\partial f^j}{\partial y^i} > 0\right)$, $\left(y^j\big|_{G_0} < y^j\big|_{G_i}\right)$. Finally, $\left(Y\big|_{G_0} < Y\big|_{G_i}\right)$. □

Proof of Corollary 2. It follows directly from Proposition (3) that when second mover has an increasing reaction function, than both agents are better off by contributing more than in simultaneous games. The standard leader is better off because she has the first mover advantage. Reference dependent second mover is gaining higher utility both because of the higher provision of public good and because his not the only contributor. □

Chapter 2

A Competitive Approach to Leadership in Public Good Games

with Samuele Centorrino[1]

Abstract We show that introducing a competitive preliminary stage in a sequential public good game helps select one of the more cooperative leaders in the group. Using a modified second price auction, we find that bids have a strong positive predictive power on individual contributions. Moreover, there is evidence that trust can explain voluntary and cooperative leadership. Nevertheless, followers reaction to voluntary leaders may rise free riding behaviour, with uncertain effect on total public good provision.

JEL Codes: A13, C72, C92, H41.

Keywords: Public good experiment, Leadership, Self-selection, Cooperation, Trust, Public good provision.

2.1 Introduction

In many economic situations, subjects are asked to contribute to a common project: fundraising, team work and outcomes, environmental frameworks, etc. In the baseline case, all agents choose simultaneously and independently how much effort to put into the project. For instance, in teamworks, it may be decided to split a given task and

[1]GREMAQ/Toulouse School of Economics.

each person would autonomously decide how much time to spend on his obligation.

However, in many real cases, it has been shown that setting a benchmark can increase the total effort in the project. Charities often update their receipts in real time so that people are pushed to offer their help as others have already done so (e.g. Telethon). This raises the question on whether we can increase the total provision of a public good by choosing an actor, which is often referred to as the leader, who is asked to set a good example for others (so called followers). In this case, the choice is not simultaneous any more but sequential: followers observe the leader's choice before making theirs.

Leadership can take different forms. For instance, leaders might be able to gather more information with respect to followers on the task for/return to public good; or they might be able to observe contributions of each single group member. However, as it has already been stressed by Hermalin (1998), leadership is an informal authority. Other agents do not follow the leader because they are obliged to, but because they have some interest in doing so.

The next question to ask is therefore: who will be a good leader? The answer to this question is of fundamental importance, as the leader is the one who followers trust and pursue.

A part of the experimental literature on sequential public good games focuses on selection mechanisms that aim at increasing the total contribution. Among these works, our mainstream is toward those devices that are not costly for the group (but may be for individuals) and are directed to voluntary leadership, without coercive power (e.g. punishment, reward, ostracism). The effect of sequentiality in these no enforcement frameworks has been studied both theoretically and experimentally.

Our contribution is related precisely to the mechanism used to select a good leader. We argue that subjects should make an effort to become leaders; and this effort should be individually costly.

In our framework, the leader is selected as the highest bidder in a modified second-price auction. We claim that, with respect to other selection mechanisms, where leadership is voluntary, bids allow us to observe a competitive process to select the leader and to establish a measure of the willingness to lead. This last result permits to capture heterogeneity among agents. It also helps us link the effort to obtain leadership to cooperative behaviour in the public good game. We, thus, run a sequential public good game with two separate treatments: in the *exogenous treatment*, the leader is randomly chosen within the group; in the *endogenous treatment*, the leader is the highest bidder in her group.

The most cited and important theoretical contribution on the topic which bases its prediction on the standard utility function theory is Varian (1994). He finds that the total contribution in a one shot sequential game is never higher than in a simultaneous game, because of the second mover's downward sloping reaction function and the first mover's advantage. Given first mover advantage, he considers auctioning off the right to move first. When players have heterogeneous preferences for the public good, the player with the lowest valuation is willing to bid for the right to contribute first. She can, in fact, free-ride on the second mover, who, having a higher valuation for the public good, contributes a higher amount.

Another theoretical, but behaviourally founded approach can be found in Romano and Yildirim (2001). They use a more general utility function to analyse sequentiality against simultaneity in public good games. In particular, they claim players may have additional motives to contribute which might include warm glow (Andreoni, 1989) and status concerns. They find that a player "will either not decrease his contribution as much as dictated by income effect, or will increase his contribution". For example, total provision of public good is larger than with simultaneous moves, whenever a follower has an upward sloping reaction function. The leader anticipates this response from the follower and sets higher contributions. An alternative specification of Romano and Yildirim (2001) accounts for status concerns, where players care about the relative contribution to public good. The leader, instead of free riding on the second player as in Varian's standard case, would contribute more to increase her prestige and to induce a reduction of follower's contribution. Despite the leader giving more, total provision of public good may decrease, if follower gives up competition for status.

A different approach is given in Cartwright and Patel (2010). They assume heterogeneity of agents in a sequential public good game, where subjects contribute, one after the other, in an exogenous sequence. Agents differ with respect to their behaviour:

imitators contribute according to earlier provision of public good (e.g., mimics, reciprocators, conformists); *independents* do not condition their contributions to others (e.g., total free riders, total cooperators, automata); finally, *strategists* maximize their expected profits. Cartwright and Patel (2010) find that, when a certain number of imitators are expected, a strategist contributes only if he is early enough in the sequence to influence followers.

Finally, some interesting results in theoretical literature with asymmetric information about the return of the public good are given by Hermalin (1998). He questions "how a leader induces rational agents to follow her in situations when the leader has incentives to mislead them". When the leader has private information about the public good, Hermalin assumes that she has two possible ways to signal to followers an eventual good state of nature. She can either give the example by contributing before others (*leading-by-example*), therefore a sequential game takes place; or sacrifice part of her endowment to signal possible future gains (*leading-by-sacrifice*) and then playing a simultaneous game with the other group members. In both cases, when the signal can not be misinterpreted, followers contribute and the leader does not mislead.

Experimental literature on sequentiality has studied many different issues related to first mover selection and the impact on the outcome of a public good experiment, e.g. asymmetric information, leader status (Eckel et al., 2010), coercive power of leader as punishment or reward (Rivas and Sutter, 2008) etc.

Several experimental papers test for Varian (1994) theory on sequential public goods. For example, Andreoni et al. (2002) observe outcomes in a two-player sequential public good game with interior solution and compare them with those obtained in the simultaneous game. Players have different returns to public good, with the first mover having a higher valuation. They find that, despite equilibrium predictions, total contributions to public good are similar in both simultaneous and sequential game. Although the leader contributes less in the sequential game than in the simultaneous one, her contributions are much higher than predicted by Varian's result of free-riding behaviour. Second mover contributions are similar in the two games. In the sequential framework, he either punishes low contributions by first mover, or he decreases his contributions as the first mover increases hers.

Gächter et al. (2010a) use a similar framework. They allow preferences for the public good to be different, but with larger asymmetries than Andreoni et al. (2002). Furthermore they consider both cases when the first mover has either a lower or a higher valuation. Wider asymmetries should entail that, in equilibrium, players with low valuation would always free ride, and high valuation players would bear all the provision of public good, whatever is their role in the game. In spite of these predictions, they find that high valuation players contribute less than expected and, vice versa, low valuation players contribute more than zero to the public account. However, Varian's statement about overall contributions is fulfilled as total provision of public good is lower in a sequential framework than in a simultaneous one. This is partially due to the fact that an early contribution to public good crowds-out follower's one.

In the framework where the leader has private information, many attempts to test Hermalin's theory have been proposed. Meidinger and Villeval (2002) tackle both *leading-by-example*, where the leader has the right to move first, and *leading-by-sacrifice*, where the leader tries to signal the state of nature by transferring money to followers or burning them. In the latter case, followers believe in the signal only when money is burned and not transferred to them from the leader. When the leader moves first, she might give up her signalling power, if the signal can not be easily interpreted. Thus, she coordinates the group towards the free-ride equilibrium.

Potters et al. (2001, 2005, 2007) find that sequentiality increases total provision of public good in presence of asymmetric information. They argue this is due to signalling rather than reciprocity: privately informed leaders anticipate followers positive reaction to their contribution.

Our paper follows the stream of literature that deals with voluntary leadership. Experimental results have pointed out that, even without monetary incentives, a significant percentage of subjects wants to lead. Leadership is fleeting both when the leader is chosen as the fastest contributor in the group (Rivas and Sutter, 2008), and when she is randomly selected among the voluntary contributors in a preliminary stage (Arbak and Villeval, 2008). In fact, leaders could change at every period. Differently, our setting allows the voluntary leader to be in charge for the entire game and for the same group, favouring a more stable and complex strategy in leading as well as in the decision to lead.

In Rivas and Sutter (2008), at each period, endogenous leaders self-select themselves by contributing to public good faster than other group members. They found that leaders - either voluntary or imposed - contribute more than followers. Follower behaviour is unchanged in the two treatments[2].

The closest in spirit to our work is Arbak and Villeval (2008). Their endogenous selection mechanism consists in asking subjects at each period, if they want to move first. They select leaders among these volunteers. They are, therefore, able to class players in three categories: *actual leaders* - those who volunteer for leadership and move first ; *self-selected followers* - those that do not want to become leader; and *eliminated leaders* - those that volunteer for leadership, but were not randomly selected. Their main finding is that volunteers are more cooperative. Actual leaders contribute more than imposed leaders. Moreover, eliminated leaders, who were voluntary but move later on in the game, cooperate more than other followers. Followers behaviour is different with respect to Rivas and Sutter (2008): followers react to voluntary leadership with a higher tendency to free-ride. On the one hand, early high provision of leaders crowds-out contributions of second movers; on the other hand, in the imposed leader setting, followers do not have the chance to self-select to be leader, thus, there might be cooperative players among them.

A different example of a sequential public good game can be found in Levati and Neugebauer (2004). Agents in each team are synchronized by means of a clock which presents ascending contributions (from zero to total endowment). When an agent makes his contribution decision, it is instantaneously transmitted to his partners. Individual decisions have a double effect: not only setting the personal choice, but also signal level of contribution to other group members. Indeed, authors find evidence of reverse leadership: the first group member who stops contributing, namely the one who free rides first, induces others to do the same. Moreover, leadership fleets, i.e. it is not always the same subject who stops contributing first. Finally, they do not detect

[2]In a separate treatment, leaders are endowed with exclusive or reward power. The leader remains in charge for all periods and her coercive power leads to higher contributions with respect to the simultaneous game and to the sequential game without reward power.

a significant decline in contributions over time. However, their framework entails a greater variance in between group contributions, with some groups coordinating on the subgame perfect equilibrium and some others on the social optimum. They argue that all these features of their game come from conditional cooperators who react to the person who contributes the least.

In our opinion, some natural questions arise: if many subjects volunteer for leadership in a group, is there place for competition? Are leaders who emerge through a competitive process more cooperative and do they set good examples for followers? What are their personal characteristics? Are they able to maintain cooperation in a group with respect to randomly chosen leaders?

To become leaders, in our experiment, subjects participate in a modified second price auction and pay a cost, if they win. Since theoretical insights on second price auctions predict that bids elicitate the subjects' true valuation, we expect the bid to be a good predictor of the "willingness to lead". Thus, our main claim is that subjects who value leadership the most, bid higher values, even if it is costly and there is no (direct) monetary incentive to lead.

While there has already been evidence that voluntary leadership selects good leaders, we expect our mechanism of competition to give a better understanding of how much these "volunteers" are willing to renounce to in order to achieve leadership, namely to capture heterogeneity among agents. Moreover, since the bid is a more accurate measure than a binary response (as in Arbak and Villeval, 2008), we can try to link bids to subjects' characteristics and to their behaviour in guiding team-mates.

Why would someone pay for leadership, when there is no direct incentive? As we have seen in the literature, there may be many reasons to lead a group. Leadership can be referable to concerns for status, signalling issues, set an example or implement strategic behaviour. First of all, returns to public good are common knowledge, therefore, no additional information is given to the leader and she is not signalling the quality of the public good as in other contexts. Second, the cost paid by the winner is private information, thus, we rule out the possibility of showing other group members the amount, using Hermalin's terminology, *sacrificed* by the leader. Finally, we can exclude status concerns[3]: status requires that subjects show off the role achieved or ostentate the amount paid for leadership, whereas our setting accounts for anonymity of players and private information about bids.

We argue that the most plausible explanation for the willingness to lead is related to a strategic behaviour of the leader. If a subject believes that his guidance would reduce free riding and increase his payoffs, then it is rational for him to bid positively at the auction stage and to pay a cost if he wins.

As a matter of fact, if many subjects behave as strategists, our main hypothesis is that they would compete for the role of leader by bidding their own value.

The paper is organized as follows: in section 2, we describe the experimental design, in section 3, we outline the results. First of all, we analyse behaviour in the auction stage, section 3.1, then we move to the discussion of the public good game, section 3.2, and section 3.3. In section 4, we provide some conclusions.

2.2 Experimental Design

Our experiment is a 10 periods sequential linear public good game: the leader moves first; then followers observe her contribution and they take their decisions. Subjects are randomly matched in groups of four and keep their role until the end of the game. At the end of each period, subjects are informed about their own earnings and total contribution of the group.

We use standard linear pay-off function that is equal for each player i:

$$\Pi_i(x_i, \sum_{j=1}^{n} g_j) = \alpha x_i + \beta \sum_{j=1}^{n} g_j$$

where x_i is the private contribution, n is the number of subjects in a group and $G = \sum_{j=1}^{n} g_j$ is the total contribution to the public good. To obtain an equilibrium with zero contribution, as in our design, the constraints on the coefficients are $\alpha > \beta$ and $n\beta > \alpha$ with the endowment $w_i = x_i + g_i$. Players have fixed endowment of 30 tokens to be allocated either in a private account (x_i) or in a common project (g_i). Each token

[3] For status concerns in public good and leadership see Eckel et al. (2010) and Kumru and Vesterlund (2010).

allocated in the common project doubles and it is equally redistributed to the group members. Therefore, the marginal per capita return is 0.5 for the common project (β) and 1 for the private account (α). The subgame perfect equilibrium for the followers is to free ride on the leader's contribution. The leader rationally anticipates the free rider behaviour and contributes nothing to the public good.

Subjects who participate in the *endogenous treatment* can use an initial income of 120 tokens in a modified second price sealed-bid auction to compete for leadership. Since there is no monetary incentive for leadership, rational subjects should bid zero. To keep constant income per treatment, also subjects in the *exogenous treatment* receive the same amount of income (120 tokens) independently of their actions.

In the *exogenous treatment* ($X - Treatment$), a leader is randomly chosen within each group.

In the *endogenous treatment* ($N - Treatment$), all subjects participate with the initial income to a modified second price sealed-bid auction with an ascending clock mechanism to compete for leadership. We are aware that auctions might be an imperfect mechanism for unexperienced subjects, who tend to over-bid[4]. To observe if subjects regret their initial bids, we introduced an unknown stage where they can slightly modify their preliminary choice. As far as we know, this particular framework has not been studied yet in the literature, but it gives us a better understanding of players' choices.

We model the auction as follows. For each group, the winner of the auction becomes the leader and pays the second highest bid. The auction phase has two stages (subjects are unaware of the second one): a preliminary auction stage and a refinement stage. The first stage lasts 2 minutes. Starting from 0, each 10 seconds, the price increases by 10 tokens. When the suited amount is reached, the subject will *drop* the auction. However, they will not leave the auction stage till the time expires. That is the reason we refer to our mechanism as a sealed-bid auction. In the subsequent refinement stage, subjects are asked to revisit their bid by choosing any amount in the interval $\{bid - 10, bid + 10\}$ (e.g., if a subject has bid 40 tokens, he can revisit his bid within

[4] Auction literature proved that it is due mainly to inexperience of subjects and/or risk loving attitudes (see, e.g., Kagel, 1993).

the interval $\{30, 50\}$). Namely, they can alter previous decisions and/or correct errors upwards and downwards[5]. Should a tie occur, a subject is randomly drawn among those with the highest bid. All subjects are then informed about their role and their own earnings: followers keep initial income; and leaders pay the group second highest bid[6].

The experiment took place at the Ca' Foscari University of Venice in June 2010. We ran 4 computerized sessions with 96 subjects overall (6 groups per session) using the software $Z-Tree$ (Fischbacher, 2007). Subjects played in two of the sessions the $X-Treatment$ followed by a $N-Treatment$; in the remaining sessions, the order was reversed[7]. This mechanism helps identify learning and order effects that may arise during the game. As a result, we have 12 unexperienced (experienced) leaders and 36 unexperienced (experienced) followers for both treatments.

Instructions (see Appendix) are read aloud at the beginning of each treatment. Subjects answered a short questionnaire to ensure they understood the game[8]. The accumulated tokens were converted at a rate of 2.50 Euro per 100 tokens (average payment 14.13 Euro; average session length 60 minutes).

In the end, subjects were administered a 10 minutes questionnaire. We collected general information about the subject to assess the general traits of players that could shed lights on the role they chose in the game[9].

2.3 Results

In this section, we discuss the main results of our experiment. We first tackle the outcome of the auction played in the endogenous treatment. Then, we compare the contribution behaviour in the two treatments of unexperienced and experienced subjects.

For the sake of clarity, we refer to players with different roles in the endogenous leader treatment and in the analysis as follows:

[5]Trivially, players on the lower (upper) bound can only increase (decrease) their contributions.

[6]The money paid is burned.

[7]Subjects knew that only one treatment would have been randomly paid.

[8]Questions were answered privately.

[9]A detailed description of the questionnaire is given in the Appendix.

(i) *Endogenous leaders* are those who obtain the role of leader in the public good game.

(ii) *Potential leaders* are those who have made a bid on strictly positive amounts in the auction, no matter if they are subsequently selected as leaders or not.

(iii) *Eliminated leaders* are those who submit a strictly positive bid, but do not win the auction.

(iv) *Self-selected followers* are those who give in to competition by bidding zero tokens[10].

2.3.1 The Auction Stage and Endogenous Leadership

To present our results about the endogenous selection of leaders, we first show that a large share of subjects is willing to bid a positive amount. Then, we link the amount bid in the auction to the first contribution in the public good game, to prove the positive relationship existing between the two. Finally, we tackle the motives for being leaders: we argue trust is the main driver of players bidding in the auction stage.

The Analysis of Competitive Leadership

Result 1. *Despite the lack of monetary incentives, subjects bid positively to compete for the role of leader. Moreover, distribution of bids is robust to experience on the sequential public good game.*

Competition for leadership arises, although a full rationality assumption would imply that no agent bids a strictly positive amount, as long as the subgame perfect equilibrium of the public good is to free ride.

A considerable percentage of subjects made positive offers to become leader: 66.66% for the unexperienced subjects and 68.75% for the experienced ones. The two distributions of bids, whose frequencies are plotted in Figure 2.1, are not significantly different: the mean bid for unexperienced subjects is 19.94 and the one for experienced is 24.50

[10]Many results of the paper are similar when, instead of considering subjects who bid exactly zero, we define self-selected followers as those subjects whose bids are lower than 10 tokens (e.g. in case of subjects' mistakes for low amount).

(p-value of 0.44 of a Mann-Whitney-U test[11]). The auction, therefore, elicits preferences for leadership in the same way whether there exists or not previous experience on the repeated sequential public good game.

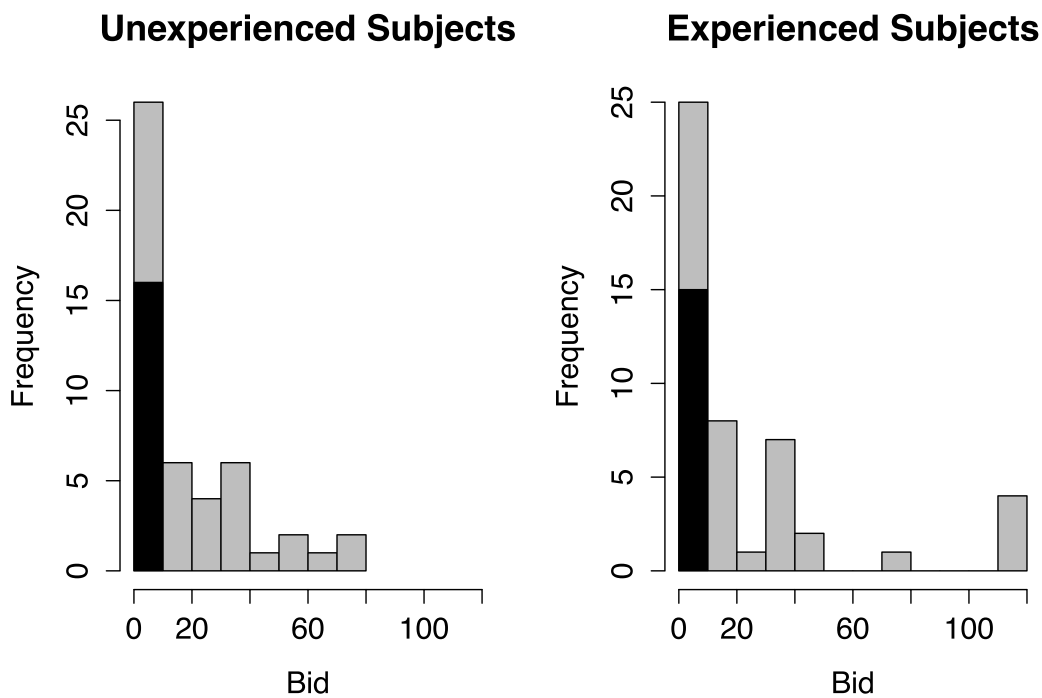

Figure 2.1: Frequency of Bids for Unexperienced and Experienced Subjects in the Endogenous treatment. The thick black line indicates the number of subjects bidding zero.

As far as the refinement stage is concerned, a large share of participants did not modify its previous choice: 72% of subjects confirmed their preliminary bid, 3% reduced it and the remaining 25% increased it. The mean bid refinement is 5.30: 6.83 tokens for those who refined the bid above and -7 for those who refined it below. In particular, the refinement stage left unaffected bids for 82% of "preliminary" *self-selected followers*. This result confirms the powerful prediction of the auction: a large fraction of those subjects which are not willing to undertake competition for leadership, if asked to increase their bid (they could change any ones in the interval $\{0, 10\}$), leave it unchanged.

Therefore, by contrast with equilibrium prediction, subjects are willing to bear a

[11]Unless otherwise stated, all test are Mann-Whitney non-parametric tests.

cost to achieve the role of leader. Individuals do not only volunteer for leadership, but also elicit with different bids heterogeneous preferences for the role of leader. This result integrates findings of previous literature that has already proved voluntary (costless) leadership to be common among subjects[12]. Our setting helps go further and the great variability in bids allows us to have a more detailed measure for the preference on voluntary leadership.

Why do people compete (or do not compete) to become a leader? Despite the fact that leaders *sacrifice* part of their initial endowment, there is neither status nor reward effect in our experimental design. Leaders can not signal either their ability in winning the auction or the quality of their future leadership, because followers never observe their bids. Moreover, we can also exclude that our auction mechanism selects unconditional cooperators, i.e. those subjects whose contribution to the public account is independent of team-mates behaviour. As a matter of fact, these players would not have any incentive to lead the group and waste part of their income in the auction, as long as their behaviour is not affected by the role they cover in the game.

We argue, instead, that *potential leaders* may be strategists and expect their leadership to compensate the loss incurred in the auction stage.

When setting their bids, subjects are unaware of other group members' characteristics[13], thus, they can only rely on their own beliefs[14]. A strategist is a subject that, given his beliefs, maximizes his expected payoff. If a strategist thinks there are subjects that will imitate contributions of first mover and he assumes that without

[12]Existing literature has focused mainly on the behaviour of leader and on follower's response to leadership, with little attempt to explain motivations for leadership and differences among leaders. The only exception that we are aware of is Arbak and Villeval (2008), nevertheless the setting used is rather different as we explain in the introduction.

[13]All players know that in each treatment they will be randomly assigned to a group. Unexperienced subjects are unaware of other players' behaviour, but experienced subjects know their first group behaviour in previous game. Nonetheless, behaviour of leaders and followers is not qualitatively different when experienced or unexperienced.

[14]A potential critique is that endogenous leader behaviour can be affected by the amount paid in the auction. Clearly the two variables display some positive correlation. However, a robustness check shows that the amount paid is unrelated to many of our results. This confirms that neither leaders update their beliefs with the new information conveyed by the second highest bid, nor the price actually paid produces unexpected income effects.

his leadership group would reach lower levels of contribution, then it is plausible that he would pay for the right to move first. Since the auction is a second price auction, he would contribute at most the amount of tokens that he believes he would gain by guiding the group. If he bids more than that value (and someone would bid the same amount), he might win and pay an amount that is higher than the potential gain. If he bids an amount lower than his potential gain and he loses the auction, his payoff might be lower than the possible one. Whatever the distribution of bids, subjects should bid their true valuation[15].

If, as suggested by Cartwright and Patel (2010), a strategist expects other players to be imitators (reciprocators or conditional cooperators), he would be himself a cooperator, since he expects his good example to influence followers' contributions. Such a higher expected return from leadership should entails higher bids. Thus, we expect higher contributions to be associated with higher bids.

The Bid as a Proxy for Cooperativeness

Result 2. *The higher the Bid, the higher the first contribution to public good.*

To begin to explore the positive relationship between contributions and bids, we run a Tobit regression[16] on the first contribution of all players in the $N-Treatment$ against the amount bid in the auction stage. We use first contribution because, in repeated interaction games, behaviour of each players is affected by his team-mates in all periods but the first one. Nevertheless, followers might be influenced by the observed amount played by their leader, hence, to control for this we used a model with leader's contribution.

We find (Table 2.1) that the bid is a good predictor of the first period contribution, in the overall model (1) and both for leaders, model (2), and followers, model (3) (when controlling for leader's first contribution). We further notice that experienced dummy is not significant for leaders, suggesting experience be unrelated to leadership

[15] For example, let's observe that in a group of free riders, each player would gain 300 tokens plus initial income of 120 tokens. Suppose a leader that bids (and pays) all the initial income of 120 tokens, but believes that she could guide the group out of free riding behaviour to Pareto optimum, she would gain 600 tokens instead of 420.

[16] For Tobit regressions, we always report marginal effects.

Model	(1)	(2)	(3)
	1^{st} Contribution All Subjects	1^{st} Contribution Leaders	1^{st} Contribution Followers
Bid	0.1725***	0.1722**	0.1918**
Experienced (dummy)	1.6077	−3.2559	4.8812*
Contribution Leader			0.5332***
Intercept	10.7893***	11.7252**	−0.0747
Obs	96	24	72
Wald-statistic	15.22 on 2 Df	6.11 on 2 Df	19.69 on 3 Df

- *** Significant at 1% level.

- ** Significant at 5% level.

- * Significant at 10% level.

Table 2.1: First contribution as function of the bid ($N - TREATMENT$)

behaviour. On the contrary, followers' experience produces a positive change in the level of contribution.

This result confirms that the bid is indicating a preference for cooperativeness: subjects who bid more in the auction are also likely to contribute more in the public good game. In that sense, we claim that the auction mechanism selects a good leader, i.e. the person in the group who is setting the good example. A more crucial point is that not only bids explain leaders' contributions, but also followers'. This behaviour might be due to the fact that *eliminated leaders* are strategists too. Thus, they are also willing to cooperate more to maintain high level of public good provision and to, possibly, influence other followers in the group.

The Bid and Leader's Personal Traits

The questionnaire run at the end of the experiment allows us to measure several characteristics of our subjects. We would like to assess whether some relationship exists between positive attributes (fairness, honesty, trust) and the probability to become leader.

However, this analysis can not be based on the characteristic of *endogenous leaders* because a selection bias would arise. Therefore, the core aspect of this methodology is to characterize a *potential* leader, i.e. any candidate for the role of leader in the game. As we have previously discussed, in our game, the bid does not only define the potential leader, but gives also an increasing measure of the willingness to lead. Hence, it seems natural to define a continuous measure of potential leadership using the bid.

We run the analysis on the willingness to lead in two different ways: on the bid ex post, after the refinement stage; on the bid ex ante, computed as the time at which the auction is dropped. In the first random experiment, we compute bootstrap probability of becoming leader and we run a Tobit regression of this probability on player's traits. This bootstrap probability is somehow more informative than the crude value of each bid for several reasons. First of all, since groups are assigned randomly in the game, a player who bids all income does not necessarily have probability one of being leader, as a different random matching could have paired him with other 120 tokens bidders[17]. Second, probability measures relative, rather than absolute, effort. For instance, a player who bids 60 does not become a leader because his bid is high, but because it is higher conditionally on other's behaviour. The new dependent variable would therefore account for all these caveats.

The second approach is based on the *ex ante* observation of the time when the auction was dropped. This *dropping time* is defined in the same interval as the bid but it is a more precise measure as it is recorded every second. If we suppose to start at time 0 with the entire sample, we can check at every second how many subjects are *surviving* the auction stage. We can therefore employ a Cox proportional hazard model (Cox, 1972) on the *dropping time* using player's attributes as covariates. Nevertheless, since the results of the two models are equivalent, we report here a detailed explanation of the former methodology only. Interested readers are referred to the Appendix for a discussion and results using the latter approach.

It is worth stressing that the two approaches are not equivalent *stricto sensu*. The endogenous variable in the Tobit model is computed on the final value of the bid, i.e. after players have been asked to refine it; while the endogenous variable in the duration

[17] A similar reasoning can be applied to other bids.

model is related to the behaviour during the auction. The robustness of results can be considered as an indirect test of the consistency of the auction and the refinement stage in our experimental setting.

Description of the Bootstrap Methodology

The bootstrap probability is simply computed from the observed value of the bid and a random rematching. We create a unique sample of 96 players, including both unexperienced and experienced subjects[18] and run 10000 iterations. At each iteration, we draw a sample of four players, compare their bids, and assign to each a probability of winning. The highest bidder is assigned a probability equal to 1. All others receive a probability of 0. In case of a draw, we attribute an equal chance to those players with the highest bid, e.g. if two players out of four are selected, they are assigned a value of 0.5 each. The bootstrap probability of being leader is therefore obtained for each player as the total sum of his own values over the total number of iterations in which he was drawn.

Result 3. *(Bootstrap) Probability of becoming leader is marginally increasing with respect to trust on others.*

Our regression analysis in Table 2.2 summarizes the result of our model specification. We decide to use a Tobit regression as the probability is bounded in the interval $[0, 1]$.

Four specifications out of five are rejected ($p-$value greater than 0.1). However, the only significant model (column 2) captures the salient features of our analysis: the score in the *GSStrust* question has a marginal positive effect; and the emotional stability affects negatively the probability of becoming leader[19].

The result which links the probability to lead to the trust on others is new to the economic literature, to the best of our knowledge. Gächter et al. (2004) find that trust does not affect contributions in a simultaneous public good game. While helpfulness and fairness have a significant positive effect on players contribution. Our

[18] This is possible because the distribution of bids is not significantly different in the two stages. We also run a robustness check doing a separate bootstrap for the two samples but results do not change.

[19] As the latter result is not supported by the duration model specification, we do not discuss this point further.

Probability to become leader					
GSSindex	0.220*				
GSStrust		0.193**			
GSShelp			0.020		
GSSfair				0.088	
Honesty Index					0.202
Generosity	0.026	0.026	0.032	0.026	0.035
Extraversion	0.003	0.020	0.016	0.005	0.016
Agreeableness	0.027	0.032	0.038	0.038	0.035
Consciousness	−0.021	−0.024	−0.017	−0.017	−0.023
Stability	−0.059*	−0.061**	−0.031	−0.037	−0.031
Openness	−0.002	−0.025	−0.023	−0.010	−0.023
Gender	−0.029	−0.044	−0.024	−0.016	−0.017
Volunteering	−0.019	−0.009	−0.009	−0.002	−0.008
Arts & Literature	0.127	0.167**	0.122	0.097	0.097
Economics	0.080	0.116	0.055	0.044	0.062
Marketing & Management	−0.143	−0.096	−0.160	−0.173	−0.133
Nash	0.032	−0.015	0.010	0.039	0.006
Experimental Experience	0.080	0.099	0.088	0.080	0.068
Intercept	0.096	0.102	0.193**	0.139	0.077
$Prob > chi2$	0.162	0.099	0.155	0.469	0.137

- *** Significant at 1% level.
- ** Significant at 5% level.
- * Significant at 10% level.

Table 2.2: Determinants of the willingness to lead (Tobit model).

result is somehow specular to theirs: we find that in a sequential public good game, the probability of being a leader is positively affected by trust on others, but not by their helpfulness and fairness.

However, there is no general consensus on how to interpret the answer to the GSS trust question. Glaeser et al. (2000) find this question to be a measure of trustworthiness rather than trust. By using a large sample of German households, Fehr et al. (2003) find the opposite result: GSS question measures player's trust, but not their trustworthiness.

Sapienza et al. (2007) propose a solution to this puzzle. They distinguish two main components in the concept of trust: *belief-based* trust and *preference-based* trust. *Belief-based* trust measures the expectation about other people's behaviour, given the individual preferences. *Preference-based* trust, instead, measures the preferences of the individual, given the expectation about other's behaviour. Using the strategy method, they find that the GSS trust question measures more the former than the latter.

Furthermore, following Glaeser et al. (2000), we can consider the honesty index as a predictor of individual trustworthiness[20]. The honesty index is positively, but not significantly correlated with the GSS trust answer (correlation coefficient of 0.1244, p-value 0.24). We can therefore conclude that the answer to the GSS question elicits trust rather than trustworthiness.

We thus claim that beliefs about others being trustworthy affect positively a subject's willingness to lead[21]. The auction stage seems to select leaders on the basis of their social trust. This is perfectly consistent with our argument suggesting that potential leaders might be strategist. If higher social trust means an expected positive reaction of team-mates to higher contributions in the public good, potential leaders consider worthwhile to burn a share of their initial endowment in order to increase their expected payoff and overall public good provision.

2.3.2 Unexperienced Subjects

A preliminary idea about the behavioural dynamics of unexperienced subjects, in both the $X-$ and the $N-Treatment$, is given in Figure 2.2. We report, in order, mean total contribution of groups (top left panel); mean contribution of leaders (top right panel); mean contribution of followers[22] (bottom left panel); and mean deviation of followers from leader's contribution, i.e. the mean difference between the contribution of a follower at time t, $c_{f,t}$, and the contribution of his leader at time t, $c_{l,t}$.

As we can observe from the top left panel (Figure 2.2(a)), total contributions are on average higher in $X-Treatment$ with respect to $N-Treatment$ for all periods, except the first one[23]. Although there is high variability in the behaviour from one period to

[20]In our questionnaire, there is not an explicit question about individual trustworthiness. However, Glaeser et al. (2000) conclude that asking about past behaviour is more successful than asking about opinions, as they find that the honesty index predicts realized trustworthiness better than self-reported trustworthiness.

[21]The answer to the question does not seem to be affected by the earnings in the public good game. Simple rank coefficients between standardized total profits and score in the GSS trust question indicate the absence of correlation between the two.

[22]Where not otherwise stated, followers are broadly defined as second movers in the public good game.

[23]For means and statistical tests see the Appendix Table 2.8.

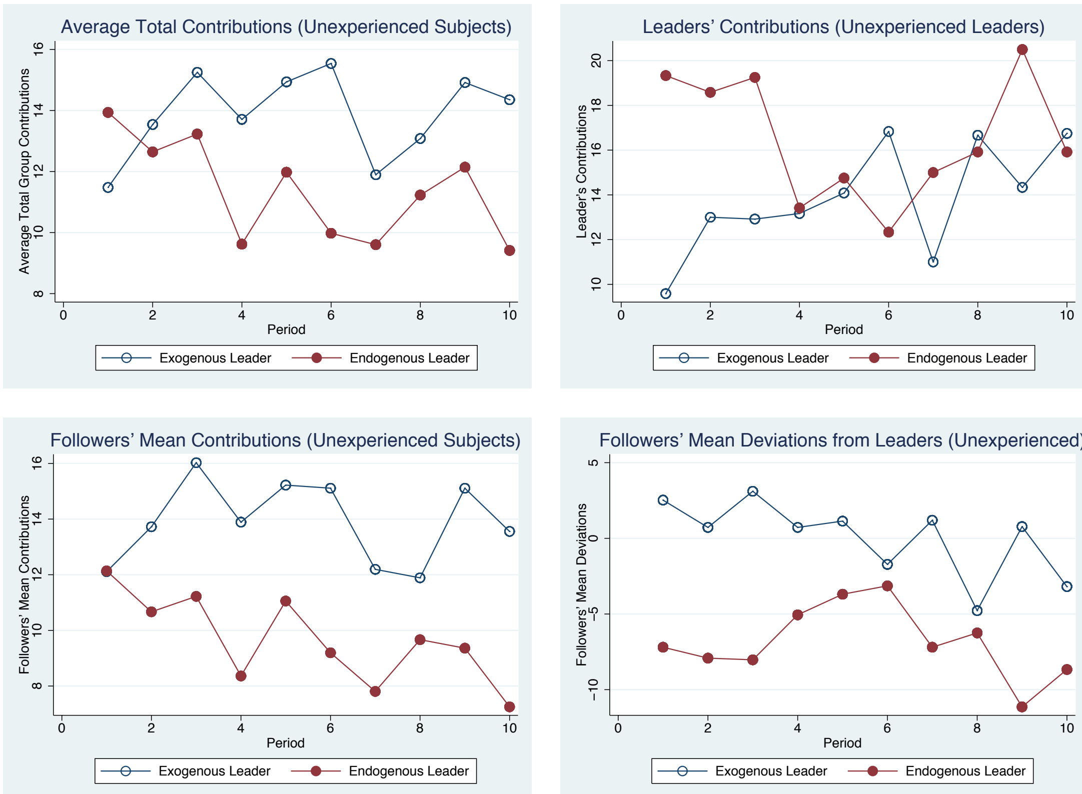

Figure 2.2: Unexperienced Subjects: Average Total Contribution 2.2(a); Leaders' 2.2(b) and Followers' 2.2(c) Mean Contribution; Followers' Mean Deviation From Leader's Contribution 2.2(d)

the other, we can observe the well known decay in time in the $N - Treatment$. Surprisingly, in the $X - Treatment$ there is no evidence of decreasing of total contribution over time. If we split behaviour between leaders and followers, we can observe that followers' mean contribution in the $X - treatment$ are not decreasing over time and leader's mean contribution, which starts at a very low value in the first period (mean 9.58), increases over time (last period mean is 16.75). Randomly chosen leaders start by contributing a really low amount, with respect to endogenous leaders (difference 9.75, p-value 0.004), as they might be exploiting first mover advantage and contribute free riding amounts, as suggested by Varian (1994). This behaviour of random leaders crowds-in followers who contribute, on average, above first movers (2.2(d)) for seven periods over ten. Random leaders increase their contributions in second period to level their contributions with followers. This particular interaction among players could be the explanation for the absence of decay in contributions towards the end of the game in the $X - Treatment$. In contrast, the usual decay in contribution over time is found in $N - Treatment$. As expected, endogenous leaders contribute in mean significantly higher values than randomly chosen ones, especially in the first five periods. However endogenous followers adjust downward (Figure 2.2(d)). Total contributions are lower due to followers not responding to leader's. As a result, leaders reduce their contributions over time.

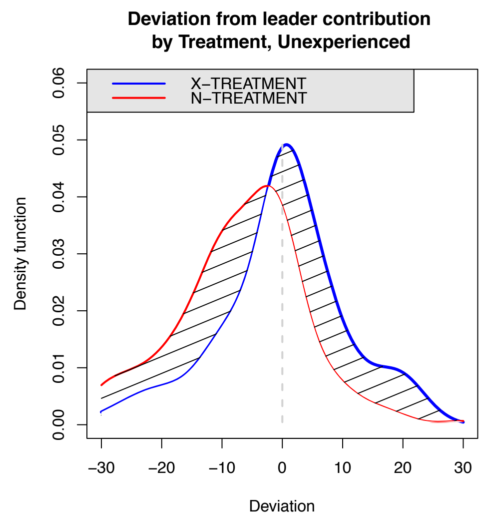

Figure 2.3: Unexperienced Followers' Deviation from Leader's Contribution

To stress the difference between endogenous and exogenous followers, we plot in Figure 2.3 non-parametric densities[24] of deviations of followers from leader's contribution. Kernel densities are computed individually for all periods. We can observe that endogenous followers free ride more on leader's contribution than exogenous ones. Difference in means is statistically significant: endogenous followers mean is -6.83 tokens and exogenous followers one is 0.05 (p-value 0.001). As long as in the $X - treatment$ roles are assigned randomly, participants who wished to be leader may turn out to be followers. As these subjects are generally more cooperative, this effect is likely to shrink the difference between leader's and follower's contribution. By the same argument, self-selection of leaders in the $N - treatment$ likely leads to a larger spread between leaders and followers.

[24] We use a Gaussian Kernel. Bandwidths are computed using Silverman optimal rule, i.e. $h = 1.059\sigma n^{-1/5}$, where σ is the standard deviation and n is the sample size.

Leaders

We present our result using two different model specifications (see Table 2.3). In both specifications, we employ censored Tobit regressions. We express contribution of each leader at time t ($c_{l,t}$) to be explained by individual lagged contribution ($c_{l,t-1}$), by the bid in the endogenous treatment interacted with the endogenous treatment dummy (Bid) and by the period of the game (Period). Moreover, to understand how a leader reacts to other group members, we used the mean lagged contribution of followers ($\bar{c}_{f,t-1}$, in model 1) or the absolute positive/negative deviation of followers from her previous contribution ($|c_{l,t-1} - \bar{c}_{f,t-1}|$, in model 2).

Leader's Contribution ($c_{l,t}$)		
$c_{l,t-1}$	0.4436***	0.7452***
Deviation from group($-$) $\lvert c_{l,t-1} - \bar{c}_{f,t-1}\rvert$ if $c_{l,t-1} < \bar{c}_{f,t-1}$, 0 otherwise		0.0979
Deviation from group($+$) $\lvert c_{l,t-1} - \bar{c}_{f,t-1}\rvert$ if $c_{l,t-1} > \bar{c}_{f,t-1}$, 0 otherwise		-0.3887**
$\bar{c}_{f,t-1}$	0.2792**	
Bid	0.0481*	0.0471*
Period	0.2477	0.2610
Intercept	3.1149	3.6550
Wald statistics	63.3***	64.5***
Observations 216	Left Censored 27	Right Censored 51

- *** Significant at 1% level.

- ** Significant at 5% level.

- * Significant at 10% level.

Table 2.3: Determinants of public good contributions (Unexperienced Leaders).

Result 4. Unexperienced leaders. *Endogenous leaders contribute more than exogenous leaders. Moreover, the higher the bid in the auction stage, the higher the* *contribution of endogenous leaders.*

Both models in Table 2.3 confirm this result. The marginal effect of the variable Bid is positive and significant, meaning that the higher is the amount bid, the higher is the contribution to the public good. Since all leaders in the endogenous treatment have bid positive values to compete for leadership, Bid captures not only an individual fixed effect, but also the endogenous treatment effect[25].

We have already seen the explanatory power of the bid for first period contribution (see Table 2.1). One might expect this positive effect not to be significant in the long run, as it may be overwhelmed by group dynamics. However, in models (1) and (2), positive explanatory power of Bid is evident and does hold for the entire game.

Result 5. UNEXPERIENCED LEADERS. *Leaders respond asymmetrically to followers' contributions. If followers contribute on average below her, she adjusts downward her contribution in the following period. If they contribute above, the adjustment is positive, but not significantly different from zero.*

If we observe only model (1), we might conclude that first mover adjusts her contribution in the same direction of followers. A first problem which arises is that leader's contribution at time t influences followers' contributions in the same period, thus the marginal effects are not clear. Furthermore, subjects may respond asymmetrically to other group members' deviations from their early contributions, as already proved in the literature on simultaneous public good games (e.g. Ashley et al., 2010 and Eckel et al., 2010).

As a matter of fact, regardless their previous contributions to the public good, first movers update their decisions according to other group members differently if they contributed above or below them[26]. When followers contribute on average below the leader ($c_{l,t-1} < c_{f,t-1}$), she levels to second movers, adapting downward her next contribution. This is consistent with a strategic behaviour with updated beliefs: the

[25]We do not use both variables to avoid multicollinearity. Models with only dummy for endogenous treatment instead of the bid give similar but less informative results, thus, we decide to omit them.

[26]This behaviour is consistent for both endogenous and exogenous leaders. We controlled for the interaction between the mean deviation and the dummy treatment: the asymmetry and significance of coefficients for $|c_{l,t-1} - \bar{c}_{f,t-1}|$ is maintained.

leader realises that setting the example is costly and reduces cooperation in the next period. Contrary, when followers contribute above her ($c_{l,t-1} > c_{f,t-1}$), she does not change her contribution on average. Again, this is a coherent behaviour. Strategists are payoff maximizers, hence, if they are gaining more than expected from the public good, they would not adjust upward (that is what we might have expected from a reciprocator or a conditional cooperator).

Finally, notice that, unlike the majority of the public good literature, we do not find evidence of decreasing contribution over time: the variable Period is not significant, suggesting that any possible variation with respect to previous contribution in period is given by asymmetric response to followers behaviour and personal characteristics (e.g. bid, previous contributions)[27].

Followers

We now turn to the analysis of unexperienced follower behaviour. Recall that among followers we can distinguish those who were randomly chosen in the $X - Treatment$, those that *self-select* themselves to be followers in the $N - Treatment$ and *eliminated leaders*, who bid positively but not enough to win leadership. In Table 2.4, we used Tobit models clustered by group. We model the followers' choice at time t ($c_{i,t}$) to depend on straight off leader's contribution ($c_{l,t}$), individual lagged contribution ($c_{i,t-1}$), mean lagged contribution of other two followers ($\bar{c}_{-i,t-1}$) and the period of the game (Period). Moreover, in the endogenous treatment not all followers bid positively so, differently from leader analysis, we used both the dummy variable (Dummy auction) and the bid (Bid). Furthermore, in model (2), we would like to observe how previous response to leader affects contribution of follower at time t. In other words, we are interested to find out if there is any tendency of followers to react asymmetrically to lagged contributions of the leader. Hence, similarly to the analysis of leaders' behaviour, we use absolute positive and negative deviations of followers from their leader $|c_{i,t-1} - c_{l,t-1}|$.

Result 6. UNEXPERIENCED FOLLOWERS. *If the follower has bid a positive amount in the auction stage, he contributes more to the public good. The contribution is also increasing with the bid.*

[27] This is consistent also when we add an interaction term between period and dummy treatment.

Follower's Contribution ($c_{i,t}$)		
`Model`	`(1)`	`(2)`
$c_{l,t}$	0.3345***	0.4158***
Deviation from leader ($-$) $\lvert c_{i,t-1} - c_{l,t-1} \rvert$ if $c_{i,t-1} < c_{l,t-1}$, 0 otherwise		-0.2153**
Deviation from leader ($+$) $\lvert c_{i,t-1} - c_{l,t-1} \rvert$ if $c_{i,t-1} > c_{l,t-1}$, 0 otherwise		0.3557***
$c_{i,t-1}$	0.3960***	0.1738**
$\bar{c}_{-i,t-1}$	0.0996	0.1989***
Dummy auction	-6.8146***	-5.5158***
Bid	0.2008***	0.1983***
Period	-0.3043*	-0.2709
Intercept	3.7674**	3.5095**
Cluster by Group	0.0228	0.0213
Wald statistics	215.8***	237.7***
Observations 648	Left Censored 120	Right Censored 66

- *** Significant at 1% level.

- ** Significant at 5% level.

- * Significant at 10% level.

Table 2.4: Determinants of public good contributions (Unexperienced Followers).

Ceteris paribus, Bid grasps heterogeneity among eliminated leaders. Therefore, not only a follower is more cooperative when he bids a positive amount in the auction, but his contribution to the public good is constantly higher, the higher his bid. The bid has therefore a positive explanatory power in predicting subject contributions for unexperienced followers in the $N - Treatment$ too.

Although *eliminated leaders* contribute more than *self-selected followers* (as the variable Bid has a marginal positive effect), the total contribution of followers in the endogenous treatment is lower than in the exogenous one.

Result 7. UNEXPERIENCED FOLLOWERS. *When subjects are unexperienced, follower contribution is on average higher in the exogenous treatment.*

Followers are sensitive to treatment variables. As we have already argued for Figure 2.2(d) and 2.3, followers contribute in mean less in the $N - Treatment$ with respect to the $X - Treatment$. This is mirrored in the regression Table by the Dummy auction being negative in model (1), as well as in model (2).

It is crucial to assess the dynamics of followers behaviour. In both models, we can see that individual lagged contribution, $c_{i,t-1}$, significantly and positively affects present contribution, $c_{i,t}$.

It is also interesting to discuss how information alters follower decisions. The last information that a follower receives, before making his own choice, is the contribution of the leader, $c_{l,t}$. The leader provides her example, and the follower responds in the same direction: the higher is the leader's contribution, the more followers contribute.

However, it is reasonable to expect followers to respond as well to other members in the group[28]. Model (1) suggests followers being unresponsive to the average contribution of other second movers, $\bar{c}_{-i,t-1}$. Yet, this result is not entirely satisfactory.

As long as leader's and other followers' lagged contributions are positively correlated, the standard omitted variable argument applies to the coefficient of $\bar{c}_{-i,t-1}$, which is therefore not significant[29]. As soon as we introduce asymmetries with respect to the leader lagged contribution, the coefficient related to $\bar{c}_{-i,t-1}$ becomes positive as expected (model 2).

Finally, we consider asymmetries in follower's responses to the leader lagged contribution.

Result 8. UNEXPERIENCED FOLLOWERS. *Followers have stable preferences for the public good, i.e. if they contribute more (less) than the leader today, this has, ceteris paribus, a marginal positive (negative) effect on their contribution tomorrow.*

A popular result in the literature is that second movers follow the leader but with a tendency to behave selfishly (see, e.g. Gächter et al., 2010b), i.e. they always contribute

[28] In fact, other two followers' contributions can potentially count up to half of the total provision per period.

[29] In a regression model, this refers to the omission of an important causal factor. This produces biased and inconsistent estimates if omitted and included covariates are correlated.

slightly less than the leader.

However, when controlling for asymmetries in follower's response, we can dig deeply into the matter. Although followers contribute on average less than the leader also in our experiment, they have a stable behaviour throughout the game. Contributing above (below) the leader today entails, everything being equal, a positive (negative) impact on follower's provision tomorrow. This finally implies followers to have stable preferences for public good provision.

A final aspect to be noticed is that, although the contribution of followers is steadily decreasing over time as in other sequential and simultaneous public good games, the time variable is significant only in model (1), when we do not control for asymmetries in follower's responses.

2.3.3 Experienced Subjects

Experienced subjects have already played a ten-period sequential public good, thus, they have familiarity with the game and their contributions are less volatile. A detailed picture of the dynamic behaviour of experienced subjects, in both the $X-$ and the $N - Treatment$, is plotted in Figure 2.4. We again report separately the total contribution (top left panel); the mean contribution of leaders (top right panel); the mean contribution of followers (bottom left panel); and the followers' deviation from the leader (bottom right panel).

As we can observe from the top left panel (Figure 2.4(a)), contrary to unexperienced players, total contributions are higher in the $N - treatment$ for all periods. In the last five periods, there is a difference in contribution of roughly 5 tokens between the two treatments (p-value 0.1, see the Appendix, Table 2.9). Finally, in the last period only, there is a noticeable end-game effect in the $N - treatment$, which makes the total average contribution almost identical between treatments.

Although leaders start from a similar mean contribution, endogenous leader contributions are steady and higher over time, as compared to exogenous leader contributions. Followers behaviour does not change dramatically in the two treatments: they simply adjust their actions to the leader. The slight decrease over time is due to the decay of leader's contributions, as it is confirmed by the analysis of deviations (Figure 2.5).

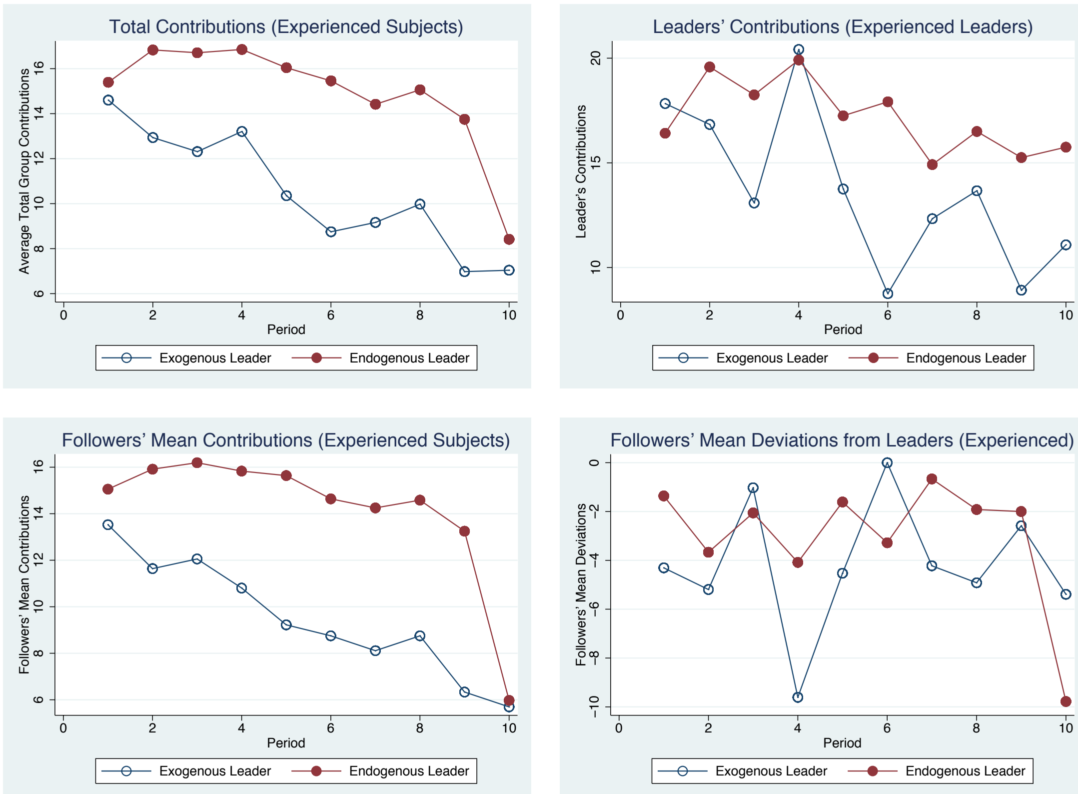

Figure 2.4: Experienced Subjects: Average Total Contribution 2.4(a); Leaders' 2.4(b) and Followers' 2.4(c) Mean Contribution; Followers' Mean Deviation From Leader's Contribution 2.4(d)

The distributions of deviations in the $X-$ and $N-Treatment$ are in fact statistically equivalent (average are respectively -4.17 and -3.04, p-value 0.23).

We argue that quality of leadership for experienced subject drives the difference between exogenous and endogenous treatment. As a matter of fact, endogenous leaders are more effective in maintaining higher cooperation, with the exception of the last period. Conversely, exogenous leaders do not have a real grip on their followers: for example, in period 4, they try to pull contributions up ineffectively.

A comparison with Figure 2.2 leads to similar conclusions. A more stable leadership has the effect of controlling followers behaviour in the endogenous treatment. For the exogenous treatment, it appears that a change in leadership entails an adjustment in followers. While unexperienced exogenous leaders start from very low contributions and then increase over time, experienced ones have exactly the opposite behaviour. Thus, while followers take over leadership in the unexperienced case, they go after the leader in the experienced one.

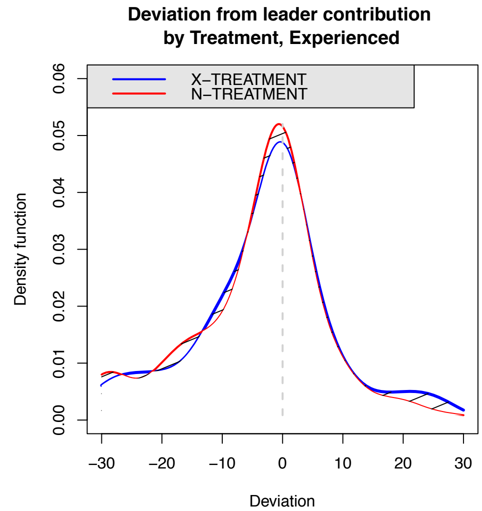

Figure 2.5: Experienced Followers' Deviation from Leader's Contribution

Leaders

Our main results are robust to experienced subjects.

Result 9. EXPERIENCED LEADERS. *Experienced leaders behave similarly to unexperienced ones. Endogenous leaders contribute more than exogenous leaders. Moreover, the higher is the bid in the auction stage, the higher the contribution of endogenous leaders.*

We compare results for experienced leaders, Table 2.5, with unexperienced ones, Table 2.3. We notice that there are not substantial differences between the two. The bid has once more a positive effect on contributions. Nevertheless, the marginal effect of the bid more than doubles with respect to unexperienced subjects (coefficient for experienced leaders 0.13 versus unexperienced 0.05). This suggests that when subjects are willing to become leader in the second part of the experiment, for the same bid, their cooperation to the public good is higher.

The other determinants of leader's behaviour are similar in the experienced game. Leaders respond positively to an increase in followers' contribution, in model (1), and to their previous contributions, in both model.

Leader's Contribution ($c_{l,t}$)		
`Model`	`(1)`	`(2)`
$c_{l,t-1}$	0.4596***	0.7881***
Deviation from group($-$) $\lvert c_{l,t-1} - \bar{c}_{f,t-1} \rvert$ if $c_{l,t-1} < \bar{c}_{f,t-1}$, 0 otherwise		-0.1693
Deviation from group($+$) $\lvert c_{l,t-1} - \bar{c}_{f,t-1} \rvert$ if $c_{l,t-1} > \bar{c}_{f,t-1}$, 0 otherwise		-0.5448***
$\bar{c}_{f,t-1}$	0.2984*	
Bid	0.1308***	0.1264***
Period	-0.5166	-0.5437
Intercept	5.1599	7.1633**
Wald statistics	88.1***	91.3***
Observations 216	Left Censored 9	Right Censored 32

- *** Significant at 1% level.

- ** Significant at 5% level.

- * Significant at 10% level.

Table 2.5: Determinants of public good contributions (Experienced Leaders).

Result 10. Experienced leaders. *Leaders respond asymmetrically to followers' contributions. If followers contribute on average below her, she adjusts downward her contribution in the following period. If they contribute above, the adjustment is still negative, but not significantly different from zero.*

As a matter of fact, when we disentangle the variables affecting leader's response to followers, we find same sign and significance of the coefficient for negative deviations of followers. Experienced leaders are very prompt in reducing their contribution when followers are below them and they have a more negatively sloped reaction curve (coefficient for experienced leaders -0.5448 versus unexperienced -0.3887). The main difference is that now leaders respond on average by adjusting downwards to cooperative followers. However, the coefficient is not significant.

Finally, although with experience there is a tendency to decrease contributions over time, this trend is not significant as for unexperienced leaders. This effect is captured by the response of leaders to followers who contribute below them.

Followers

Last of all, we discuss here results for experienced followers. We use all variables presented in previous analysis. In addition, we replace the Bid, which is not a good predictor of followers behaviour any more, by the dummy variable Eliminated Leaders that takes value 1 if the endogenous follower has bid a positive amount during the auction stage and 0 otherwise. In Table 2.6, we present results of censored Tobit regressions clustered by group.

Result 11. EXPERIENCED FOLLOWERS. *Experienced followers behave differently than unexperienced followers. Eliminated leaders contribute more to the public good, nevertheless the bid does not explain heterogeneity among them.*

Although the sign of the bid is still positive (models (1) and (3)), it is not significantly different than zero. The bid is not able any more to capture differences among those players who bid positively. Nevertheless, when we plug the dummy variable for eliminated leaders in the $N-Treatment$ (models (2) and (4)), we find that eliminated leaders contribute more to public good compared to other followers.

Result 12. EXPERIENCED FOLLOWERS. *When subjects are experienced, there is no difference in the behaviour of exogenous and endogenous followers, except for eliminated leaders that contribute more to the public good.*

In models (1) and (3), when Bid has no explanatory power, the Dummy Auction captures all the difference among treatments. Its positive sign might suggest that a treatment effect is at work, with endogenous followers contributing more. However, by replacing Bid with a dummy for *eliminated leaders*, the Dummy Auction loses all its predictive power. This rather points out towards no distinctions between treatments: the difference is more likely to come from followers who bid positively. Eliminated

Follower's Contribution ($c_{f,t}$)				
`Model`	`(1)`	`(2)`	`(3)`	`(4)`
$c_{l,t}$	0.3337***	0.3508***	0.4123***	0.4203***
Deviation from leader (−) $\lvert c_{i,t-1} - c_{l,t-1}\rvert$ if $c_{i,t-1} < c_{l,t-1}$, 0 otherwise			−0.2863**	−0.2696***
Deviation from leader (+) $\lvert c_{i,t-1} - c_{l,t-1}\rvert$ if $c_{i,t-1} > c_{l,t-1}$, 0 otherwise			0.2454**	0.2226**
$c_{i,t-1}$	0.6449***	0.6381***	0.4276**	0.4399**
$\bar{c}_{-i,t-1}$	0.1065	0.0839	0.2146***	0.1905***
Dummy auction	2.5432**	0.7092	2.1938**	1.0837
Bid	0.0061		0.0154	
Eliminated Leader		3.5505**		2.4478*
Period	−0.5075***	−0.5139***	−0.5444***	−0.5446***
Intercept	−3.3449	−2.7611	−1.5083	−1.2587
Cluster by Group	0.0588	0.0373	0.0455	0.0324
Wald statistics	407.7***	415.90***	443.9***	447.6***
Observations 648	Left Censored 138		Right Censored 91	

- *** Significant at 1% level.

- ** Significant at 5% level.

- * Significant at 10% level.

Table 2.6: Determinants of public good contributions (Experienced Followers).

leaders contribute, in fact, more than both endogenous *self selected followers* and randomly selected followers in the $X - treatment$.

Result 13. Experienced followers. *As unexperienced subjects, followers have stable preferences for the public good.*

As with unexperienced subjects, when we introduce response of follower to previous leader's contribution, we are able to observe a steady behaviour of followers (models

(3) and (4)). Those who contribute above (below) the leader have a tendency to have a higher (lower) contribution in the following period. Moreover, while in model (3), lagged mean contribution of other followers do not affect contribution at time t, when we take into account their behaviour with respect to the leader this coefficient becomes significant.

Followers seem to maintain the same behaviour with respect to leader's contribution at time t and their own lagged contribution. However, while the former and other group member's coefficients are similar to unexperienced case, the latter's coefficients are much higher in all models. This suggests experienced followers having a more stable preferences for the public good.

Finally, time decay is evident from the negative marginal effect of the period variable. Coefficients for this variable are significant in all models and higher than in the unexperienced case. However, if we introduce in all models a dummy for the last period, this time effect disappears, suggesting this result being entirely due to the sharp decrease in contribution in the very last period (see Figure 2.4).

2.4 Conclusions

Voluntary leadership is generally studied as a costless, deliberate act of subjects. Nevertheless, in real situations, actions directed to achieve the role of first mover could be individually costly, in particular if there is competition among agents. This paper carries on the important need of a deeper understanding of mechanisms and motives underneath self-selection of leaders; and of a better analysis of their behaviour in a social dilemma game.

Using a modified second price auction, we show that a substantial amount of subjects bid to achieve the role of leader. We propose two formal explanations for people to bid: either they are free riders *à la* Varian and they try to exploit first mover advantage; or they wish to become leader to foster cooperation in the group. No matter if we believe the former or the latter to be the most reasonable explanation, we can simply test how much the amount bid in the auction affects contributions in the public good game (or at least the contribution in the first period).

On the one hand, we find that voluntary leaders are more prone to cooperate to the public good than randomly chosen leaders. On the other hand, not only subjects exercise higher effort by bidding positive amounts, but this effort has a positive marginal effect on contributions. This holds for the first period of the public good game and, more generally, as a fixed effect for contributions throughout the game. This sheds lights on the positive link between costly effort to obtain leadership and cooperative behaviour in a public good framework.

As it might seem counterintuitive to pay for achieving a role which can be exploited by free riders, personal characteristics and beliefs of bidders could explain this choice. We, therefore, relate the amount bid in the auction stage with the information gathered in the questionnaire. We show that more social trust induces a higher probability of becoming leader. To the best of our knowledge, trust has never been associated to behaviour in sequential public good game and it leaves open questions for further research in this field.

We argue that more trust implies higher willingness to lead which, in turns, implies higher contributions. If an individual believes others to be trustworthy, it is likely also to believe others to cooperate in the public good game. Thus, we reasonably believe people bid as they expect their leadership to compensate the loss incurred in the auction stage. In this sense, we sustain that our players are strategist, i.e. they maximize their expected payoff given their beliefs on others' trustworthiness.

However, outcomes regarding the total contribution are unforeseeable. On the one hand, we find an increase of contributions in the endogenous treatment driven by the higher leader's contributions. On the other hand, followers may not cooperate with endogenous leaders, thus the total effect on the provision of public good is unpredictable and depends on followers reaction function. In fact, in sequential public good games, first mover contributions may either crowd-out and crowd-in effects on second movers'.

Hence, a question which is left to understand is how to improve total cooperativeness. Cooperation is of key importance to reach Pareto superior outcomes and the leading example is effective only if followers reciprocate. Through our former findings, we suggest that a good way to select cooperative leaders might be to create competition among them. Moreover, with the same competition process, we can select those subjects more willing to cooperate (recall that potential leader were always contributing more than others). Thus, by clustering groups, we might reduce free riding and reach higher levels of public good provision.

2.5 Appendix A: Instructions and Questionnaire

2.5.1 Lab Instructions

Welcome Screen

Good morning! You are taking part in an economic experiment about decisional processes. Following the instructions on the screen, you will be asked to make some decisions: please read everything very carefully.

At the end of the experiment, you will be paid cash (up to 22 euros) according to your results. These results depend both upon your decisions and upon the decisions of your group.

During the experiment you will use *tokens*: every token will be converted to 2.5 euro cents.

Your responses will be anonymous relative to other subjects and to the experimenter.

The experiment consists of two separate phases. You will be paid for results of only one of these two phases (at the end of the experimental session, a toss of a coin will randomly determine which one of the two phases will be paid).

If you have any question, please raise your hand. The experiment will come to clarify your doubts.

IT IS FORBIDDEN TO COMMUNICATE WITH OTHER PLAYERS DURING THE EXPERIMENT. EVERY MISBEHAVIOUR WILL BE PUNISHED WITH EXCLUSION FROM THE EXPERIMENT.

Phase I: Exogenous Treatment

If this phase will be selected, you will receive 120 tokens independently of your choices. Tokens that you will obtain via your choices will be added to the 120 tokens (each token that you obtain will be converted in euros at the end of the experiment).

This first phase consists of 10 periods (from 1 to 10). At the beginning of the phase, you will be randomly assigned to a group of 4 participants selected among the people in this lab. The group stays the same until the end of the first phase.

In each of the periods from 1 to 10, an endowment of 30 tokens will be given to each participant.

You can choose how much to contribute to a common project, from 0 to 30 tokens. Each token invested in the common project, by all members of your group, will be multiplied by 2 and redistributed equally among all four group members (namely, it will have a value of 0.5 tokens for each of member in the group).

Each token that you will keep in your private account (the difference between your endowment and how much you contribute to the common project) will be valued for you 1 token.

Computation of payoffs for each period. In each of these ten periods, your earnings come from two sources:

- The part of the endowment that you kept on you private account (for example, $30 -$ your contribution to the project) will be valued one token for each token that you have in your account;

- The payoff you get from the common project: you will earn 0.5 tokens for each token that the group have contributed to the project.

The earning from each of these periods will be as follows:

- *Example 1*: if the group total contribution is 70 tokens, each subject in that group will earn for the common project: 70/2=35 tokens. If the group total contribution is 10 tokens, each subject in that group will earn 10/2=5 token from the common project.

- *Example 2*: Anna has an endowment of 30 tokens. If Anna contributes 15 tokens to the common project and the total contribution of her group is 60, Anna's payoff for that period is:

$$\boxed{\text{(30-15) + (60:2)=15+30=45}}$$

- *Example 3*: Mario has an endowment of 30 tokens. If Mario contributes 30 tokens to the common project and the total contribution of his group is 60, Mario's payoff for that period is:

$$\boxed{(30\text{-}30)+\ (60{:}2)=0+30=30}$$

- *Example 4*: Carlo has an endowment of 30 tokens. If Carlo contributes 0 tokens to the common project and the total contribution of his group is 60, Carlo's payoff for that period is:

$$\boxed{(30\text{-}0)+(60{:}2)=30+30=60}$$

Structure of each period. Every period is divided into two parts:

- In the first part, a participant randomly drawn in each group (called **player one**) chooses how much to contribute to the common project, from 0 to 30 tokens

- In the second part, the other three participants (called **players two**) will simultaneously choose their contribution to the common project, from 0 to 30 tokens, upon observation of the contribution of **player one**.

After everyone has chosen his contribution, a screen appears, and each participant will be informed about his group total contribution to the common project, and about his payoff for the current period.

Computation of the final payoffs for phase I. The total payoff for the first phase is computed as the sum of the initial endowment of 120 tokens plus the sum of all tokens earned in the 10 periods of the game, as previously described.

Payoffs are computed the same way for all participants.

Phase I: Quiz

To verify your understanding of the game, please answer to this questionnaire:

1. How many periods are played?

2. Each group is composed by 4 subjects. TRUE or FALSE

3. What is your initial endowment at each period? a) 10, b) 20, c) 30, d) 40

4. *Subject one* observes the choices of other subjects in his group and, only after that, he makes his own. TRUE or FALSE

5. *Subject two* observes the choice of *subject one* in his group and, only after that, he makes his own. TRUE or FALSE
6. If you have chosen to contribute 24 tokens to the common project, how many tokens would you keep?
7. If you have chosen to contribute 5 tokens to the common project and the group total contribution is 90 tokens, how much will be your payoff for that period?
8. If you have chosen to contribute 5 tokens to the common project andand the group total contribution is 40 tokens, how much will be your payoff for that period?

[**After the first phase was played, new instructions for the second phase were given.**]

Phase II: Endogenous Treatment

If this phase will be selected, you will receive 120 tokens independently of your choices. You can use this initial endowment at period 0 as it will be described in the following.

This second phase consists, as the first one, of 10 periods plus a preliminary part, which we refer to as *period 0*.

At the beginning of phase two, you will be randomly **reassigned** to a group of 4 people. The group stays the same until the end of this second phase.

Periods from 1 to 10 are exactly as explained before: every player has an endowment of 30 tokens for each period and he will have to decide how much to contribute to a common project. In part one, *player one* contributes to the common project; in part two, *players two* observe *player one*'s contribution and make their own choices.

The only difference is in period 0. You can now choose to use a part of your initial endowment of 120 tokens to become *player one*.

Period 0: choice of *player one*. You can use part of your 120 tokens to become *subject one* within your group in this second phase. At period 0, a screen will appear indicating an amount to be chosen to become *player one* and a countdown clock: every 10 seconds, the amount will increase by 10 tokens. That is: from second 120 to 111, the amount will be 0; from 110 to 101, it will be 10; from 100 to 91, it will be 20 and so on until 0 (and beyond) when the amount will be equal to 120. When the amount you wish to chose to become *player one* appears on the screen, click on the button DROP and stop the countdown.

In this part, you can choose to use any amount between 0 and 120 tokens.

How is player one chosen? Among the 4 members in your group, *player one* will be the one who has chosen the highest value between 0 and 120 tokens in period 0. If two or more participants, within the same group, have chosen the same amount, *player one* will be drawn at random among them. Only the person who finally becomes *player one* will be asked to give away a part of his participation tokens. All other group members will keep their 120 tokens, no matter the amount they have chosen.

Computations of results at period 0. All players obtain an initial endowment of 120 tokens.

$$\boxed{\text{120 participation tokens - 0 tokens}}$$

Player one will have to give away an amount equal to the difference between his 120 tokens minus the *second highest bid* in the group.

$$\boxed{\text{120 participation tokens - second highest bid in the group}}$$

At the end of period 0, a screen will inform you about your role in the game, i.e. if you are either a *player one* or a *player two*, and you payoff after period 0.

Example: Suppose that, at period 0, Andrea, Beatrice, Carlo and Dario belong to the same group and they have chosen the following amounts: Andrea=50, Beatrice=30, Carlo=60, Dario=40:

- Carlo, who has chosen 60, will be *player one* in the group. Anna, Beatrice and Dario will be *players two*;
- Carlo has to pay 50 tokens, that is the second highest amount chosen in his group;
- payoffs for period 0 will be: Andrea, 120 tokens; Beatrice, 120 tokens; Carlo, 120-50=70 tokens; Dario, 120 tokens.

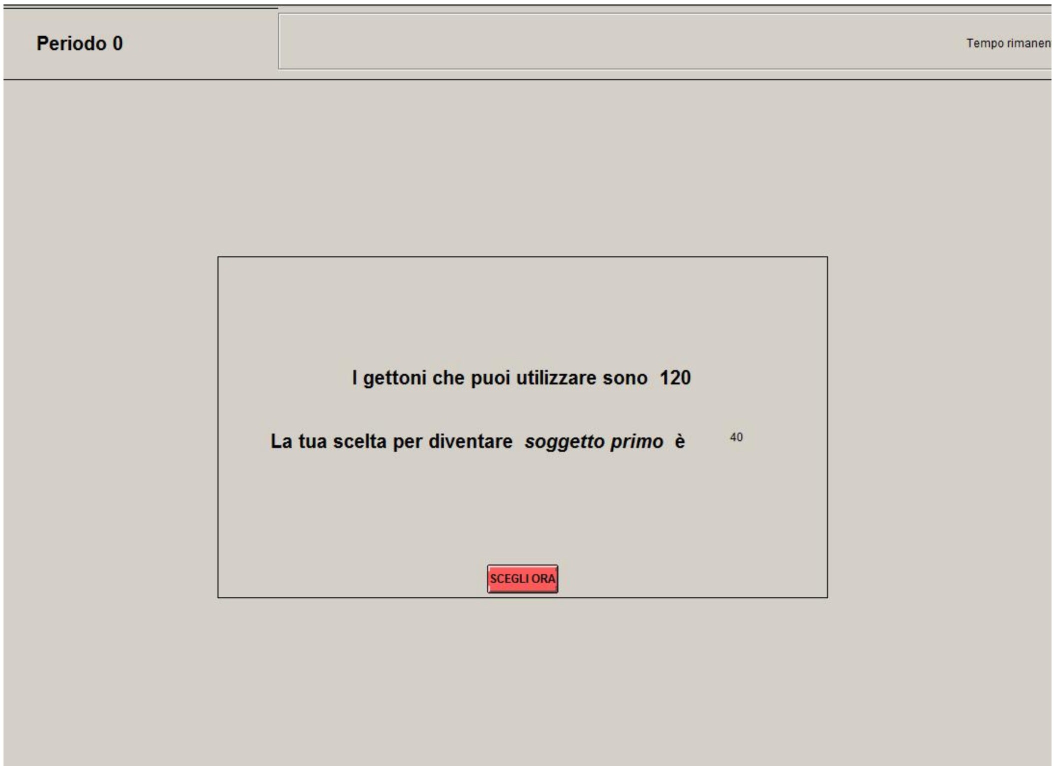

Figure 2.6: Example of screen in Period 0.

Computation of results for Phase II. The final payoff of Phase II is the sum of the payoff obtained in period 0 plus the sum of all tokens earned in periods from 1 to 10, as previously described.

2.5.2 The Questionnaire

Description

For our questionnaire, we first used a measure of the *Big-five factors* personality test, so-called *Ten-Item Personality Inventory* (TIPI). The *Big-five factors* test is composed of 60 questions which investigate five broad domains used to describe the human personality: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. However, we chose to use a brief measure of these five factors which is less accurate, but it reaches adequate levels in terms of convergence between self and observed ratings (see Gosling et al., 2003). Players have to agree on a statement related about their personality on a scale of 1 (disagree strongly) to 7 (agree strongly). The score for each factor is given by the mean score obtained for the corresponding questions.

We further wish to measure players' own degree of honesty, trust and altruism. A measure of the former was acquired using a self-reported honesty index, which is given by the average of a five-question rating frequency of lying to parents, roommates, acquaintances, close friends and partners on a scale of 1 (very often) to 5 (never). As discussed in Glaeser et al. (2000), this honesty index can be used as a proxy for trustworthiness and it is often more reliable than asking a direct question about personal trustworthiness. Trust has been determined using the *General Social Survey* questions about others' fairness, helpfulness and trust. These questions can be used to evaluate whether a subject is more inclined either to trust or not to trust others. The latter characteristics (altruism) has been assessed via questions about having ever been volunteers and the average amount of money given to charity every year, which are very close in spirit to those used in Glaeser et al. (2000).

Content

(i) Control Questions: gender; age; nationality; parent's nationality; marital status; experimented before; work; major (if student); average monthly income; knowledge of the concept of Nash equilibrium.

(ii) Ten Item Personality Inventory (TIPI)[30]: Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other. To answer this question, use the same scale from 1 (strongly disagree) to 7 (strongly agree). I see myself as:

1. Extraverted, enthusiastic.

[30] Italian Translation of the TIPI was provided by dr. Erica Carlisle (ECarlisle@rmsg.com) of Rosetta Marketing Strategies Group, Princeton, NJ. Translations were done by a very large and reputable global market research company and double checked by a second set of native speakers.

2. Critical, quarrelsome.
3. Dependable, self-disciplined.
4. Anxious, easily upset.
5. Open to new experiences, complex.
6. Reserved, quiet.
7. Sympathetic, warm.
8. Disorganized, careless.
9. Calm, emotionally stable.
10. Conventional, uncreative.

(iii) GSS Fair: Do you think most people would try to take advantage of you if they got the chance or would they try to be fair?

1. Would take advantage of you.
2. Would try to be fair.
3. It depends.
4. I do not know.

(iv) GSS Help: Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves.

1. Try to be helpful.
2. Just look out for themselves.
3. It depends.
4. I do not know.

(v) GSS Trust: Generally speaking, would you say, that most people can be trusted or that you cannot be too careful in dealing with people?

1. Most people can be trusted.
2. Cant be too careful.
3. It depends.

4. I do not know.

(vi) Charity and Volunteering: Have you ever actively been a volunteer (for association, NGO, chuches,etc.)? How much money you donate to charity every year (on average in euros)?

(vii) Honesty Index: How often do you lie to (please answer on a scale from 1, very often, to 5, never):

1. Parents.
2. Roomates.
3. Acquaintances
4. Close friends.
5. Partners.

Data Manipulation

All variables in the questionnaire have been demeaned and normalized by the standard deviation. For the General Social Survey questions, we have been following the procedure in Gächter et al. (2004), so that higher value of the variables correspond to higher level of trust[31]. A *GSS index* has been obtained as the sum of the three questions, normalized into the interval $[0, 1]$. The same procedure has been applied to obtain a *honesty index*, which corresponds to the mean score on the five questions on lying, properly normalized in the interval $[0, 1]$.

We also control for a set of variables, such as gender, past participation to economics experiments, knowledge of the concept of Nash equilibrium and the major of studies (Arts and Literature, Economics or Marketing and Management).

[31] Subjects dispose of four options to answer GSS questions: "Do not trust"; "Trust"; "Depends" and "Don't know". The option "Depends" in the GSS questionnaire has been taken to have intermediate value between "Do not trust" and "Trust". The option "Don't know" has been eliminated from the sample.

2.6 Appendix B: Some Further Analysis and Descriptive Statistics

2.6.1 Duration Models and the Characterization of the Leader

As we have discussed in section 2.3.1, it is possible to give a different characterisation to the model we have used to explain leader's traits.

In particular, we can retrieve information about the time when players drop the auction. This variable can be used to construct a model in which time represents the dependent event.

Duration (or survival) models serve as a tool to frame the time elapsed before some events occur (for a review, see den Berg, 2001). A standard example is given by unemployment spells: when we observe a panel of individuals over time, we can compute how many weeks they have been staying jobless. In our particular application, we use a so-called Cox proportional hazard model (Cox, 1972), which relates the underlying event with some exogenous covariates.

In our experiment we observe players entering the game at time 0 and at each second we can assess how many of them are *surviving* the auction stage, i.e. we observe the duration of staying in the auction for each player.

The event "dropping the auction" is the one we want to relate with the characteristics we observe in the questionnaire. We suppose that the intensity of the Poisson distribution which determines the occurrence of this event is constant over time.

Table 2.7 reports the result of such a regression. Coefficients need to be read with the opposite sign, i.e. a negative coefficient means a positive marginal relation with being a potential leader. As it can be easily inferred, these results are not substantially different from what we have shown in section 2.3.1. The only difference is that now the model including the GSS index is also significant. The main message still holds true: a higher level of trust decreases the probability of dropping the auction and therefore it increases the probability of being leader.

Time at which the auction to become leader is dropped					
GSSindex	-0.777^{**}				
GSStrust		-0.715^{***}			
GSShelp			-0.211		
GSSfair				-0.269	
Honesty Index					-0.852
Generosity	-0.111	-0.135	-0.140	-0.114	-0.165
Extraversion	0.004	-0.077	-0.003	0.018	0.026
Agreeableness	-0.047	-0.014	-0.077	-0.079	-0.080
Consciousness	0.180	0.207	0.171	0.175	0.168
Stability	0.233	0.234	0.184	0.138	0.201
Openness	-0.024	0.065	-0.023	-0.033	-0.019
Gender	0.254	0.227	0.156	0.112	0.099
Volunteering	-0.202	-0.198	-0.148	-0.170	-0.113
Arts & Literature	-0.282	-0.479	-0.116	-0.090	0.015
Economics	-0.619	-0.827^{*}	-0.461	-0.412	-0.481
Mark & Man	0.301	0.029	0.457	0.463	0.254
Nash	0.159	0.348	0.212	0.120	0.286
Experiment	-0.301	-0.404	-0.287	-0.326	-0.202
$Prob > chi2$	0.037	0.034	0.167	0.113	0.167

- *** Significant at 1% level.

- ** Significant at 5% level.

- * Significant at 10% level.

Table 2.7: Determinants of the willingness to lead (Proportional hazard model).

2.6.2 Additional Tables

		1	1 to 5	5 to 10	10
Average Mean contribution	X-TREATMENT	11.48	13.78	13.96	14.35
	N-TREATMENT	13.94	12.28	10.47	9.42
	Difference	-2.46	1.50	3.49	4.93
	$p - value$	(0.225)	(0.356)	(0.094)	(0.088)
Leaders' Mean Contribution	X-TREATMENT	9.58	12.55	15.12	16.75
	N-TREATMENT	19.33	17.07	15.933	15.92
	Difference	-9.75	-4.52	-0.82	0.83
	$p - value$	(0.004)	(0.056)	(0.583)	(0.884)
Followers' Mean Contribution	X-TREATMENT	12.11	14.19	13.57	13.55
	N-TREATMENT	12.14	10.69	8.65	7.25
	Difference	-0.03	3.50	4.92	6.30
	$p - value$	(0.977)	(0.053)	(0.050)	(0.043)
Average Profit Leader	X-TREATMENT	43.37	45.02	42.80	41.96
	N-TREATMENT	38.54	37.5	35.02	32.92
	Difference	4.83	7.52	7.78	9.04
	$p - value$	(0.056)	(0.001)	(0.026)	(0.032)
Average Profit Follower	X-TREATMENT	40.85	43.37	44.34	45.15
	N-TREATMENT	45.74	43.88	42.29	41.58
	Difference	-4.89	-0.50	2.05	3.57
	$p - value$	(0.083)	(0.729)	(0.564)	(0.355)

Table 2.8: Unexperienced Subjects: Tests on difference between treatments for period 1 (column 1), period 10 (column 4) and the average per individual(group) from period 1 to 5 (column 2) and 6 to 10 (column 3). All test are Mann-Whitney non-parametric tests.

		1	1 to 5	5 to 10	10
Average Mean Contribution	X-TREATMENT	14.60	12.68	8.83	7.04
	N-TREATMENT	15.39	16.37	13.42	8.42
	Difference	−0.79	−3.69	−4.59	−1.38
	$p - value$	(0.665)	(0.204)	(0.094)	(0.602)
Leaders' Mean Contribution	X-TREATMENT	17.83	16.38	10.95	11.08
	N-TREATMENT	16.42	18.28	16.07	15.75
	Difference	1.42	−1.9	−5.12	−4.67
	$p - value$	(0.747)	(0.603)	(0.248)	(0.211)
Followers' Mean Contribution	X-TREATMENT	13.53	11.45	7.53	5.69
	N-TREATMENT	15.06	15.73	12.54	5.97
	Difference	−1.53	−4.28	−5.01	−0.28
	$p - value$	(0.954)	(0.149)	(0.165)	(1.000)
Average Profit Leader	X-TREATMENT	41.37	38.98	35.82	33
	N-TREATMENT	44.37	44.45	40.77	31.08
	Difference	−3	−5.47	−4.96	1.92
	$p - value$	(0.506)	(0.126)	(0.248)	(0.325)
Average Profit Follower	X-TREATMENT	45.68	43.92	39.24	38.39
	N-TREATMENT	45.74	47.01	44.30	40.86
	Difference	−0.05	−3.09	−5.06	−2.47
	$p - value$	(0.665)	(0.419)	(0.119)	(0.452)

Table 2.9: Experienced Subjects: Tests on difference between treatments for period 1 (column 1). period 10 (column 4) and the average per individual(group) from period 1 to 5 (column 2) and 6 to 10 (column 3). All test are Mann-Whitney non-parametric tests.

Chapter 3

A Semi-parametric Reanalysis of Public Good Experiments with Type Classification

Abstract In this paper, we want to address two issues for a better understanding of experiments on repeated public good games by considering old experiments[1]. First, we intend to replace a fully parametric analysis, which is usually proposed to study these particular games, with non-parametric tools in the preliminary description of data and semi-parametric regressions to describe the overall behaviour of subjects in the game. The second aim of the paper is to use previous findings of the literature to categorize subjects according to their types and to benefit from this information to improve the fitting of experimental data.

JEL Codes: C1, C9, H4.

Keywords: Public good experiment, Semi-parametric, Type, Session-effects, Cooperation.

[1]We are grateful to Jim Andreoni, Urs Fischbacher and Simon Gächter for giving us access to their data.

3.1 Introduction

In recent years, there has been a growing literature on how to use econometrics in the analysis of experiments[2]. In general, despite the fact that econometrics and statistics have provided many tools to describe and study data in different contexts, the devices used in experimental economics is usually limited. In this paper, we want to show that it is possible to address new, relevant research questions using non-parametric econometrics to study the subjects behaviour in public good experiments. Instead of proposing a new experiment, we re-analyse well-known, linear repeated public good games focusing the attention on the most simple design. Moreover, in the spirit of giving a better analysis of experimental results, we suggest a simple way of clustering similar subjects by using previous findings on types selection. Aggregating different behaviours may produce bias estimations and misleading results.

Public good experiments usually consist in a group game where subjects have to divide an initial endowment between a private account and an account in common with other group members. To contribute to the common pool is individually costly so that a rational agent should always free ride on other players. If not stated elsewhere, we restrict our attention to *repeated linear public good games*, in which the equilibrium is to contribute zero and the Pareto optimum is to fully contribute. A well known result of experimental literature is that subjects differ in their levels of cooperation and they can be divided into well defined types.

Many *ad hoc* experiments have been conducted to recognize types[3] and aggregate their behaviour to understand observed deviations from equilibrium outcomes. Al-

[2] Ashley et al. (2010); Bardsley and Moffatt (2000, 2007); Cox and Oaxaca (2008); Galbiati et al. (2009); Harrison (2007); Hey (2011, 2005)

[3] The most adopted method to detect types follows Fischbacher et al. (2001). They use a strategy method to elicit conditional cooperation in a one shot public good game. Subjects are asked to respond to each possible mean contribution of other group members in order to disclose their reaction functions. Despite being an appealing mechanism, it has some drawbacks. On the one hand, Fischbacher et al. strategy method is an additional task given to experimental players: it is time consuming (i.e. to give instructions and play the game) and it increases experimental costs (i.e. subjects have to be incentivized). On the other hand, it is a static game. If used to predict a type's behaviour in dynamic repeated public good games, it may fail to reach the goal (see for example, Burlando and Guala (2005) for different methods to detect types and Volk et al. (2011); Schliffke (2011) for, respectively, persistence of types in time and in games).

though there is no clear definition on the precise way to define these categories, it is commonly recognized that three main types of subjects are present in a large proportion in public good experiments.

A first type is the *free rider*. The free rider is typically the rational agent who maximizes his profit assuming everyone else free rides too. Many authors define a free rider as the player who is contributing zero whatever the contribution of other players and/or each period (e.g. Fischbacher and Gächter (2010),Volk et al. (2011)). Usually, he does not contribute to the public good even if others do. In other papers, to characterize free riders, a less strict definition than equilibrium prediction is used. Subjects are allowed to make some mistakes: free riders may sometimes contribute little amounts to the public good (e.g. Burlando and Guala (2005)); or they can deviate for some periods from the subgame perfect equilibrium, when the game is repeated. Other definitions require free riders to be contributing below a given threshold in the overall game (e.g. Burlando and Guala (2005), Houser and Kurzban (2003)) or in the first period (e.g. Gunnthorsdottir et al. (2007)).

Specular to the free rider, we have the *cooperator*. This type of agent always contributes to the public good with a large, positive amount. As for the free rider, classification strictly depends on the paper we are referring to (see previously cited literature), so a cooperator can be a subject who always contributes all his endowment, or a part which is higher than the average contribution or above a given threshold.

An important thing to notice is that these two types are easy to detect: on the one hand, they are unconditional subjects, in other words, their behaviour should not change with variations in others contributions; on the other hand, their contributions are polarized at the extremes of the endowment and/or of the overall distribution.

The third and larger class of subjects present in public good games is the class of *conditional cooperators*. Their contributions depend positively on the behaviour of other subjects, when sequentiality gives information about others' actions or when the subject is asked to reply to hypothetical contributions of others (e.g. by means of strategy method). However, when others' choices are not known or suggested by the experimentalist, conditional cooperators contribute according to their beliefs about others' contributions. If the public good game is simultaneous and repeated, it has been shown (Fischbacher and Gächter, 2010) that beliefs are automatically updated every period with information gathered early in the game. Thus, if beliefs are not elicited in the game, the previous average contribution is used as a proxy for "informal beliefs". In general, conditional cooperators have a monotonically increasing reaction function with respect to others' contributions: the higher (lower) the others contribute, the higher (lower) this type of agent is willing to contribute. Kurzban and Houser (2005) classify subjects with a regression line of their contributions on mean contribution of other group members to extrapolate the reaction function in a sequential repeated game. If the slope and the intercept of a subject are positive, he is classified as a conditional cooperator (the slope can be thought of as the "condition" part and the intercept as the "cooperative" one). Another definition considers subjects always contributing slightly above or below the perfect conditional contribution line Houser and Kurzban (2003) or roughly half of their endowment Burlando and Guala (2005). However, despite the fact that conditional cooperators exhibit a similar behaviour, the "confusion" in the way they are classified makes it difficult to detect them. In addition, many theoretical explanations for their behaviour (e.g. altruism, warm glow (Andreoni, 1989), reciprocity, inequity aversion (Fehr and Schmidt, 1999)) do not clearly allow one to distinguish differences among them: it is a pool of agents who have some similar behaviour, but it could be for different reasons.

We can find some other recognizable types, nevertheless their percentage in the games is low and their strategies might be difficult to identify. It is worth mentioning that there can be maximizing agents that incorporate heterogeneity of types in their reaction function among those subjects. These subjects are sometimes named *strategists*. Bardsley and Moffatt (2007) find experimental evidence of the presence of strategists in sequential public good games. Cartwright and Patel (2010) have theoretically proved that, if a strategist believes that his contribution can influence reciprocators and/or conditional cooperators, he contributes to the public good, otherwise, he free rides.

In general, in a subject pool, we expect to find around 15-25% of free riders, 5-15% of cooperators and 40-60% of conditional cooperators and some unclassifiable types. Given their multiplicity of strategies, it is necessary to separate at least those subjects with well identifiable behaviour to reduce the bias that may rise in analysing the overall sample.

We suggest a simple way of categorizing types on the basis of their contributions to the public good. Moreover, instead of a strict definition of types, we allow them to make mistakes, in the sense that they can deviate from their type at most once. We define a *free rider* a subject who contributes below the first quartile of the overall contributions to the public good in *almost all* periods; and a *cooperator* a subject who contributes *almost always* more than the third quartile of the overall distribution of contributions in the experiment. Since it is difficult to detect conditional cooperators, as we have previously mentioned, we do not intend to suggest any arbitrary definition for them. Nevertheless, by previous findings of the literature, we expect the remaining part of the subjects to be a mixture of conditional cooperators and unclassifiable subjects. Moreover, we presume they are mostly composed of conditional cooperators, which is the largest class of types in public good experiments.

An important approach in analysing conditional cooperation is given by Ashley et al. (2010). Their paper is the closest in spirit to our work, considering that they take "two classic studies in search of [new] evidence...in light of theoretical and econometric advances in the field". They try to test possible motives for the conditional contribution in public goods considering subjects' asymmetric responses to previous group contributions. They find that, overall, subjects reduce their contribution when they had previously earned less than others. However, if their payoffs were higher than those of other group members, they do not react with an increase in contribution. They suggest this behaviour to be consistent with inequality aversion and they give little support for reciprocity, altruism and warm glow concerns.

So far, these kinds of results are usually obtained by pulling together all subjects, independently of their type. Differently in this paper, by separating unconditional subjects from others, we can better investigate asymmetric behaviour of a class that is mainly composed of conditional cooperators.

Clearly, one of the most interesting aspects is to study the role of the types in augmenting the total provision of public good. Therefore, we might be interested in understanding not only what the relevant variables that different types are concerned about, but also what devices can be used to increase their contributions. However, as far as we know, the analysis of repeated public good games does not usually address this particular question. A common approach is, for example, to estimate contributions of subjects using a linear regression. Explanatory variables are usually divided into two subsets: continuous variables, as the individual lagged contribution; and dummy (or categorical) variables, as those that capture differences among treatments. Categorical variables in a linear regression have the only effect of shifting the intercept[4]. In this sense, if we add a dummy variable for types and another for treatments in a parametric linear regression, we are implicitly assuming that: (1) all types react in the same way to the remaining variables; (2) different treatments do not affect the way subjects respond to other variables, but only affect their mean contribution. Note that in many cases, given the low capacity of labs, a particular treatment is performed in more than one session. Thus, we might be interested in knowing if there are some session-effects, in the sense that subjects in one session might behave differently from subjects in another. Once more, if we try to catch this effect with a dummy variable, the underlying assumption requires that (3) the session effect is intercept shifting.

Implications of session effects has recently been discussed in a paper by Fréchette (forthcoming). He makes a first attempt to define session-effects and to list possible problems in data analysis. Fréchette observes that standard solutions can be inadequate to control for session effects. Although he tries to debunk some widespread "myths", he does not propose a method to detect them. In this paper, we consider an approach that can determine, given certain conditions, whether the session might, or might not, be a relevant variable to explain results in public good games.

Instead of assuming the above mentioned hypotheses on types, sessions and treatments, we test them by means of recent findings in semi-parametric varying coefficient models. At the same time, we want to show that using different econometric tools can expand the number of research questions that one can address. Moreover, these models sometimes have statistical properties that are more appropriate for the analysis and description of experimental data.

[4]Suppose that two treatments are represented by a dummy variable in a regression. Roughly speaking, the estimated coefficient for this dummy variable would only determine if in one treatment contributions are on average higher than in the other. We will return to this definition later in the paper.

The use of semi-parametric methods overcomes some difficulties regarding fully parametric and fully non-parametric models by combining them together. Non-parametric regressions allow for more flexibility: they capture the shape of data without any predetermined specification of a functional form for the data generating process (as it is assumed in parametric analysis). However, they might incur in the "curse-of-dimensionality" which occurs when the space of continuous variables increases and the subsets on which estimations should be done contain sparse data. In these cases, the rate of convergence of the non-parametric estimators toward its true values slows down. In experimental economics, the scarcity of data and the number of explanatory variables usually used requires some assumptions to be made to pursue the analysis. However, the use of fully parametric models does not capture important features as, for example, when "the functional form with respect to a subset of regressors (...) is not known" or when "we might also envision situations in which some regressors may appear as a linear function (i.e., linear in variables), the functional form of the parameters with respect to the other variables is not known"(Racine, 2008). In these cases, parametric estimators would be misspecified and lead to a biased estimation. Halfway, lie the semi-parametric methods. We believe that the analysis of repeated public good games can achieve great improvement through the use of semi-parametric models: first, the curse-of-dimensionality does not allow for the application of non-parametric regressions; second, fully parametric regressions are too strict in their assumptions.

Hence in this paper, we are going to revise the analysis of well-known repeated public good games (Andreoni, 1995; Fischbacher and Gächter, 2010) in a semi-parametric fashion, following Li et al. (2011). We further propose to use non-parametric statistics as a descriptive tool for the choice of appropriate regressors and to account for types while interpreting data. We show that this kind of analysis leads to a considerable improvement in the goodness of fit and helps to disentangle treatment or type effects in the reaction of players to some other variables.

In section (3.2), we briefly introduce non- and semi-parametric models that we will use in the analysis, focusing on the features that can be relevant for repeated public good experiments. In section (3.3), we introduce the datasets with simple statistics and determine which are the variables that we use to estimate the contribution of subjects to the public good. Then, we compare results between simple linear regressions and semi-parametric regressions. First, we analyse the issue of session and treatment effects, then, the categorization of types and the goodness of fit of the models.

3.2 On Non-parametric and Semi-parametric Econometrics

In this section, we examine two econometric tools that we will use later on: kernel regressions and semi-parametric varying coefficient models. The aim is to give some hints on the advantages and disadvantages of these models and possible applications to experimental analysis.

3.2.1 Non-parametric Regression: Kernel Estimators

Suppose you observe a pair of variables $Y, X \in \mathbb{R}^2$ and that the true functional relationship between them can be written as:

$$Y = f(X) + \varepsilon \tag{3.1}$$

where ε is an i.i.d. error term with mean zero and variance σ_ε^2 such that $E(\varepsilon|X) = 0$ and $f(.)$ is a smooth function. When using a liner regression model, we implicitly state that

$$f(X) = \beta_0 + \beta_1 X \tag{3.2}$$

Since the true model is non-linear, a linear specification can lead to serious inference errors.

Non-parametric estimators are used exactly for this reason: they are able to capture the functional relation between Y and X without imposing any constraint on its form.

Suppose, now, to observe a sample realisation of the variables Y and X, denoted as $X_1, ..., X_n$ and $Y_1, ..., Y_n$. The most commonly used non-parametric estimator is the Nadayara-Watson kernel regression estimator (Nadaraya (1964),Watson (1964)):

$$\hat{f}(x) = \frac{\sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right) Y_i}{\sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right)} \tag{3.3}$$

where $K(.)$ is a strictly positive and bounded function[5], such that:

$$\int K(u)du = 1, \qquad \int uK(u)du = 0, \qquad \int K(u)^2 du < \infty.$$

and h is a bandwidth parameter which can be chosen using different methods (for an overview of these methods, see, e.g. Racine, 2008). In a nutshell, the kernel estimator computes the local weighted average of the variable Y where the weights are functions of the conditioning variable X. In this sense, for each x, the kernel estimator is making an estimation for the function $f(x)$ by weighting with $K(.)$ the realizations of Y within a given interval h from x.

The Nadayara-Watson kernel regression estimator requires continuous variables. If we consider discrete/categorical variables, we encounter limits to the application of this particular kernel. Li et al. (2011) propose a variant of the Aitchison and Aitken (1976) kernel function for unordered categorical variables.

Suppose, now, that we observe a pair of variables Y, Z such that Y is a continuous variable and Z is a unordered categorical variable that takes $c \geq 2$ different values $\{0, 1, ..., c-1\}$, such that:

$$Y = f(Z) + \varepsilon$$

where ε is an i.i.d. error term with mean zero and variance σ_ε^2 such that $E(\varepsilon|Z) = 0$.

A kernel density estimator for unordered categorical variables can be defined as:

$$l(Z_i, Z, \lambda) = \begin{cases} 1, & \text{when } Z_i = Z, \\ \lambda, & \text{otherwise} \end{cases} \tag{3.4}$$

where λ is, now, the smoothing parameter which can take values in $[0, 1]$. It is worth noticing that, if $\lambda = 0$, the kernel reduces to a simple indicator function. When $\lambda = 1$, the kernel is a simple uniform weight function[6]. In the intermediate cases, where $\lambda \in (0, 1)$, the kernel permits to "borrow" information from other categories other than the one in which Z_i belongs. Thus, the lower is λ, the less important is the weight put on the other categories; the higher is the smoothing parameter, the higher is the weight that other categories have in the kernel estimation.

[5]For specification of different kernel functions $K(.)$ see, for example, Cameron and Trivedi (2005).

[6]As for the bandwidth for continuous kernel, interested readers are referred to Li et al. (2011) the discussion for the estimation of the smoothing parameter λ.

So far, we have discussed a simple non-parametric regression that we will use later in the analysis. Nevertheless, we would like to focus on some of the weaknesses of such approaches. First of all, the curse of dimensionality. The higher the number of independent continuous variables, the higher the space where estimations should be made and the higher the probability of finding subsets with scarce data. Interpretability is another problem with estimates from non-parametric kernel regressions: the relation between the dependent variable and its regressors is not described with parameters, thus sometimes not easy to interpret. A graphical analysis is usually needed to visualize this relationship. Another of the drawbacks of non-parametric kernel regression methods is that their rate of convergence to the true function is usually slower than parametric ones[7]. However, if the parametric model is not correctly specified, the estimators are biased. As we understand, there is a trade-off in using one method or the other.

To benefit from both methods, we proceed as follows. First, we use a non-parametric analysis to obtain an approximate idea of the functional form of data in order to indirectly test which is the relationship between dependent and independent variable. Second, we would like to keep the flexibility of non-parametric regressions for some variables and the nice convergence and easier interpretation of parametric models to evaluate players' responses in public good games. This is the reason why we propose using semi-parametric models as a good trade-off between the two specifications.

3.2.2 Semi-parametric Regression: Categorical Varying-Coefficient Models

A large number of semi-parametric models has been conceived to combine appealing characteristics of parametric and non-parametric analyses. In this paper, we focus on varying coefficient models.

We introduce the simplest varying-coefficient model to explain basic features. Sup-

[7]Rate of convergence for parametric models is $\frac{1}{n^{1/2}}$, where n is the sample size. For non-parametric kernels models, it is always lower, since we are not imposing any assumption on the data generating process. Moreover, the rate of convergence of non-parametric models increases with the dimension, namely the number of explanatory variables used.

pose we observe a triple of variables $Y, X, Z \in \mathbb{R}^2 \times \mathrm{c}$, where X, Y are continuous and Z is an unordered categorical variable with $c \geq 2$. Suppose that the true functional relationship between them can be written as:

$$\begin{aligned} Y &= f(Z, X) + \varepsilon \qquad (3.5) \\ &= \beta(Z)X + \varepsilon \qquad (3.6) \end{aligned}$$

where ε is an i.i.d. error term with mean zero and variance σ_ε^2 such that $E(\varepsilon|X, Z) = 0$. Note that the Z variable does not directly influence Y, but it has an impact on the way Y responds to X. Henceforth, to distinguish between explanatory variables, we use a different terminology: by *regressors* (X), we mean those variables that directly influence the dependent one (Y); by *covariates* (Z), those explanatory variables that influence coefficients of the regressors.

If we consider a simple linear regression model to estimate the functional form $f(Z, X)$, it would take the form:

$$f(Z, X) = \beta_0 + \beta_X X + \beta_Z Z \qquad (3.7)$$

In this model, the categorical variable Z has the only role of *intercept shifting*, for individuals belonging to different groups. In order to better illustrate this effect, let's take an example.

Suppose Y and X are, respectively, subjects contribution to the public good and mean contribution of other subjects in the same group. Suppose Z is a dummy variable that takes value 1 if subjects are in treatment A and 0 if in treatment B. Let's take two individuals j and k in the two treatments facing the same average contribution of other group members, $X_j = X_k$. The estimated coefficient $\hat{\beta}_Z$ will only capture the difference in the average contribution between the two subjects. This difference in average contribution will be attributed to a treatment effect. Clearly, if we assume subjects respond in the same way to all other regressors, in our example X, model (3.7) is correctly specified. Nevertheless, if subjects in different treatments respond to X in a different manner, a better approach is to assume $f(Z, X) = \beta(Z)X$. If we want to maintain a parametric model, we can proceed in many ways, however, there might be drawbacks. Let's observe some examples.

Consider, once more, the simplest example so that Z is a dummy variable with two possible outcomes. We can produce as many regressions as the numbers of categories of Z. "Separated" linear regressions by treatments would be:

$$f(Z,X) = \begin{cases} \beta_0 + \beta_1 X, & \text{if } Z = 1, \\ \beta_0' + \beta_1' X, & \text{if } Z = 0 \end{cases} \tag{3.8}$$

However, when the categorical covariate has many classes or there is more than one discrete covariate that affects coefficients of the regressors[8], the number of "separated" regressions increases and many degrees of freedom are consumed with a fully parametric approach (or we might have regressions where the number of data in the sub-sample is inadequate).

A common parametric approach is to add to the simple linear regression interaction among variables to capture changes in response in the two treatments. An example of a fully saturated model would be:

$$f(Z,X) = \beta_0 + \beta_1 X + \beta_2 Z + \beta_3 (XZ) \tag{3.9}$$

as before, the degrees of freedom might increase too much with respect to the sample size[9]. Moreover, a high degree of multicollinearity and the more complicated way to interpret results make this kind of model less attractive[10]. Usually the increasing number of parameters to estimate incurs in a loss of their explanatory power of the overall model and of single parameters (this can be easily detected by some well known criteria, e.g. BIC which penalizes models with a large number of parameters).

Therefore, we might be interested in a semi-parametric model that maintains a parametric part for the continuous regressors, but allows "an automatic and flexible approach to the other part" (Li et al., 2011), i.e. how categorical covariates influence coefficients of the parametric part.

[8]Note the simple case of two dimensional dummy variables, $Z_1 \in \{0,1\}$ and $Z_2 \in \{0,1\}$. We need to estimate four linear regressions one for each possible mixed class of $[Z_1, Z_2]$ (namely, $[0,0], [0,1], [1,0], [1,1]$).

[9]In the case of the two dimensional dummy variables defined in previous footnote, Z_1 and Z_2, there would be 6 coefficients to estimate (namely, for the variables X, Z_1, Z_2, XZ_1, XZ_2, Z_1Z_2)

[10]In model (3.9), the marginal effect of X in treatment A is equal to $\beta_1 + \beta_3$. In treatment B, the marginal effect would be only β_1. Moreover, $\beta_0 + \beta_2$ and β_0 are, respectively, the intercept shifting effects for treatment A and B. Note that, as the number of categories of Z increases, the analysis gets even more complicated.

Let's, once more, consider the simple case where the true value of the function is in equation (3.6). A *semi-parametric categorical varying-coefficient model* is given by:

$$Y_i = \beta(Z_i)X_i + u_i, \qquad\qquad i = 1, ..., n \tag{3.10}$$

where $E(u_i|X_i, Z_i) = 0$. The model is semi-parametric because it maintains its parametric linear part for the regressor, but it allows us to make its coefficient to vary across realizations of the covariate in a non-parametric fashion.

Li et al. (2011) proved that a consistent estimation of the β coefficients would be:

$$\hat{\beta}(Z) = \left[\frac{1}{n}\sum_{i=1}^{n} XXl(Z_i, Z, \lambda)\right]^{-1} \left[\frac{1}{n}\sum_{i=1}^{n} XYl(Z_i, Z, \lambda)\right] \tag{3.11}$$

where $l(Z_i, Z, \lambda)$ is the kernel function for categorical covariates presented in previous section. We can note similarities of this estimator of β with the OLS estimator. However, realizations of X and Z are weighted with the kernel density estimator for categorical variables.

Two cases may arise: the Z covariate can be *relevant* or it can be *irrelevant*. A covariate is irrelevant if the $\beta(.)$ coefficient associated with the regressor X does not vary as Z changes. When $\beta(.)$ is not constant for Z taking different values, the covariate is said to be relevant.

Li et al. (2011) have shown that the selection of the optimal λ helps detect if covariates are relevant or irrelevant. The smoothing parameter λ goes to 0 when the Z covariate is a relevant variable. When Z is irrelevant, there is a positive probability α that it reaches the value $\hat{\lambda} = 1$. They find that, although "it is difficult to determine the exact value of α for the general case...our simulation shows there is usually about a $50 - 60\%$ chance that $\hat{\lambda}$ takes the upper extreme value 1".

This result can be a powerful tool for experimental analysis as it can help select important variables and/or automatically exclude those that are not pertinent to the analysis.

3.3 Results

3.3.1 Experimental Data

In this section, we re-analyse, by means of the tools previously described, two experiments: Andreoni (1995) and Fischbacher and Gächter (2010) (respectively A1995 and FG2010, hereafter).

Both experiments consist of a 10-period repeated linear public good game with random rematching. A1995 consists in a "simple" experiment, in the sense that the subjects are asked to play the repeated game and the only information for each period is the group total contribution to the public good. FG2010 is more complex because subjects are not only playing the repeated game, but also they are asked to elicit their beliefs about others' contributions in each period. In addition, Fischbacher and Gächter make subjects play a strategy method (i.e. Fischbacher et al. (2001)) to elicit subjects' conditional cooperation[11]. In one treatment, subjects are first asked to play the strategy method and then the ten-period repeated game. In the other, the sequence of the play reversed: first, the repeated game, then the strategy method. We will therefore refer to *sequence one* as the former treatment and *sequence two* as the latter.

In Andreoni (1995), two treatments are present. They only differ in the framing of the game, not in incentives to subjects nor in equilibria outcomes. He refers to the *positive* treatment as the standard case where an endowment is given to each subject and it is asked to use part of it to contribute to the public good. In the *negative* treatment, subjects are asked if they want to use part of their endowment for the

[11] Note that we ignore this information because we are interested in analysing only simple settings. Clearly, if we use additional information, the fits might be better. However, this would need more time and a more complicated design. The aim, here, is to use statistical tools to reduce the (costly) set of information that we need to get the maximum advantage.

private account. In each period, a general linear pay-off scheme is given by:

$$\Pi_i = a(w_i - y_i) + b(y_i + \sum_{j=1}^{N-1} y_j) \qquad \text{positive treatment} \tag{3.12}$$

$$\Pi_i = ax_i + b((w_i - x_i) + \sum_{j=1}^{N-1} y_j) \qquad \text{negative treatment} \tag{3.13}$$

where w_i is the initial endowment of each subject that can be used to individually contribute to the public good, y_i, or to the private good x_i. Since $w_i = x_i + y_i$, the two problems are quantitatively the same. b is the per capita marginal return to the public good: each subject receives b times the amount contributed by all group members. a is the marginal return to the private good, namely what is devoted to the private account. In both experiments, $0 < b < a < Nb$. Thus, the incentive is to free ride because the marginal return to the private good is higher than the public good one. Nevertheless, the Pareto optimum is achieved when all subjects contribute all their endowments. All subjects in FG2010 play a 10-period *positive* treatment. Subject pool for A1995 is 80 subjects, for FG2010 consists of 140 subjects. Other differences between Andreoni's setting and Fischbacher and Gächter's are: initial endowment, respectively, $w_{A1995} = 60$ and $w_{FG2010} = 20$; per capita marginal return to public good, b, is $b_{A1995} = 0.5$ and $b_{FG2010} = 0.4$; and group numerosity, $N_{A1995} = 5$ and $N_{FG2010} = 4$. The marginal return to private good, a, is the same in both experiments, namely $a_{A1995} = a_{FG2010} = 1$.

Let's begin with a brief description of the data. In FG2010, the mean contribution is 4.83 tokens, namely 24.15% of the endowment. The mean contribution for the positive treatment in A1995 is 20.15 tokens and 9.72 for the negative one (respectively, 33.58% and 16.20% of the endowment). Note that, although the A1995 positive frame and the FG2010 experiment have similar behaviours, the percentage of endowment contributed is different. Cooperation in public good games depends on the per capita marginal returns to public good and endowment chosen in the experimental setting, even if the equilibria outcomes are the same.

Andreoni (1995) uses a Mann-Whitney rank-sum test to find that the "positive frame significantly increases the amount of the endowment contributed to the public good". He also notes that the percentage of free riding contributions is higher in the negative treatment (the free riding equilibrium is played 63.5% times when the frame is negative and 34.5% when positive).

Fischbacher and Gächter assess the importance of belief formation and type elicitation. They find that, overall, subjects decline their contributions for two main reasons. First of all, because conditional cooperation is imperfect, namely conditional cooperators do not contribute one-to-one but less. Second, because a high fraction of free riders facilitates the fast decay by reducing the mean contribution. In addition, the experimental setting elicits the subjects' conditional contribution in a simultaneous game *via* strategy method. Fischbacher and Gächter benefit from this information to calculate expected contributions in each repeated period of the public good game. The best simulated model benefits from both these two pieces of information. They claim that the contribution formation is a weighted average of beliefs and predicted contributions: where beliefs are calculated by updating previous period beliefs with observed contribution of other group members; and where predicted contributions are obtained by plugging beliefs into the individual strategy method table to calculate the expected conditional contribution. We can consider certain results when analysing simpler settings: beliefs are updated with observed contributions; and type-detection plays an important role in predicting individual contributions.

3.3.2 On the Determinants of Individual Contribution

Before moving to the description of types, we, first, have a preliminary analysis of which variables may influence the individual contribution of subjects in both experiments. The aim is to use only the simple setting of repeated pubic good.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
A1995	0.00	0.00	2.00	14.93	30.00	60.00
FG2010	0.00	0.00	2.00	4.83	8.00	20.00

Table 3.1: Distributions of Contributions

Each period t, subject i has to choose a contribution $y_{i,t}$. The information that he holds is: his previous contribution $y_{i,t-1}$, the period he is facing t and the mean contribution of previous group members $\bar{y}_{-i,t-1}$. We expect: time t to capture the decay in contribution usually found in repeated public good experiments; individual lagged contribution to be positively related to his next contribution; and the mean contribution of others to have an important role in explaining the change in behaviour with respect to the previous period. Since we are interested in capturing differences that appear in separate settings, an important variable to account for is the dummy treatment Z. In the case of A1995 data, it takes value 1, if it is in the positive treatment, and 0, if in the negative; in FG2010, it takes value 1, if it is in sequence one treatment, and 0, if in sequence two. When assigned to different treatments, subjects are randomly divided into sessions, S. In A1995, there are two sessions for the positive frame and two for the negative; in FG2010 there are three sessions per treatment.

Moreover, when taking into account what other group members have chosen in the previous period, we can follow Ashley et al. (2010). They have shown that there is an asymmetric response to lagged deviation with respect to others' contributions, $\bar{y}_{-i,t-1}$. Since we consider simultaneous games, we might expect that a player replies differently when he is informed about his behaviour relative to others. For example, a reciprocator would reduce his contribution if he finds out that others free ride on him. Or, he would increase his cooperation if others contribute above him. We, thus, construct two variables for the lagged deviation from mean contribution: positive lagged deviation, when $y_{i,t-1} - \bar{y}_{-i,t-1} > 0$ and negative lagged deviation, when $y_{i,t-1} - \bar{y}_{-i,t-1} < 0$.

Note that, since the three variables $y_{i,t-1}$, $\bar{y}_{-i,t-1}$ and $(y_{i,t-1} - \bar{y}_{-i,t-1})$ are linearly dependent, we can not include all of them in a linear regression without incurring in perfect multicollinearity.

If we consider a linear regression, we are assuming that the independent variables just described have a linear impact on the contribution of subjects. Thus, if we want to use $y_{i,t-1}$ to capture consistency in individual contributions, the linear parametric model is:

$$y_{i,t} = \alpha + \beta_1 y_{i,t-1} + \beta_2 \bar{y}_{-i,t-1} + \beta_3 t + \beta_4 Z_i + \beta_5 S_i + \epsilon_i \tag{A}$$

If we allow for asymmetric responses, the model is:

$$\begin{aligned} y_{i,t} =& \alpha + \beta_1 y_{i,t-1} + \beta_2 \max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0] + \\ &+ \beta_3 \max[\bar{y}_{-i,t-1} - y_{i,t-1}, 0] + \beta_4 t + \beta_5 Z_i + \beta_6 S_i + \epsilon_i \end{aligned} \tag{B}$$

where i indicates the subject and t the period, ϵ_{ij} are $N[0, \sigma_\epsilon^2]$ and $E(\epsilon_i|X_i) = 0$ (where X_i indicates all explanatory variables). Clearly, we are assuming that all explanatory variables "linearly" influence contributions of subjects.

Models:	Full model	No Session	No Type
A1995 - (A)	5977	5965	6071
A1995 - (B)	5960	5948	6057
A1995 - (A)	7115	7088	7278
A1995 - (B)	7109	7081	7271

Table 3.2: BIC values

A common approach to choose among models is by comparing some measure of the goodness of fit. To select among the two proposed models, we use the Bayesian Information Criterion (BIC) that penalizes models with a lot of parameters. In Table (3.2), we report BICs values for the two linear parametric models. In all different specifications, the models with lagged deviations from mean contributions gives a lower BIC. Although the addition of one parameter, all models are preferable with respect to the same one but with the variable lagged others' contribution.

Nevertheless, the BIC criterion is only an overall measure of goodness of fit and does not give any hint on the functional forms that exist among variables. We propose a "rule-of-thumb" to determine which variables might be included or not in the regression.

3.3.3 Choice of Variables: Non-parametric Kernel Regressions

When considering linear models, we are assuming that the relationship between the independent and the dependent variable is linear. The violation of this assumption leads to a serious bias in the estimation of parameters. However, nonlinear relationships might be difficult to address. We might want to graphically suggest if the behaviour of the explanatory variables has some linearity with respect to the endogenous variable. As explained in the previous section, some hints can be given by non-parametric regressions.

We stress, once more, that the functional form in non-parametric regressions is not restricted to the linear model. The estimated functional form is left free to adapt to data as we have previously discussed. However, the absence of estimated parameters which explains the outcomes, as the β coefficients in previous models, makes results not always easy to interpret. On the other hand, we can infer some behaviour from a graphical analysis and discuss the shape of the relationship among variables.

Another drawback of a non-parametric analysis is that we can not analyse many variables at the same time without incurring in the curse of the dimensionality (given the, relative, scarcity of experimental data). Besides, with few independent variables (i.e. one or two regressors), we can graphically grab some features of data that might suggest a different approach for the choice of variables.

In Figures (3.1) and (3.2), we plot the estimated functions for the following kernel regressions[12], respectively for A1995 and FG2010:

$$y_{i,t} = f(y_{i,t-1}, t) \tag{3.14}$$

$$y_{i,t} = f(\bar{y}_{-i,t-1}, t) \tag{3.15}$$

$$y_{i,t} = f((y_{i,t-1} - \bar{y}_{-i,t-1}), t) \tag{3.16}$$

In Figures (3.1, top-right) and (3.2, top-right) the lagged contribution of other group members, *lothery*, is far from having a linear relationship with the dependent variable. For each period t, we can observe that *lothery* (namely, $\bar{y}_{-i,t-1}$) seems to explain the dependent variable with a concave relation. In fact, it is graphically clear for A1995 that as $\bar{y}_{-i,t-1}$ increases, the subject's response to previous contributions, y_i, increases up to a peak in the centre, then his contribution decreases. If we model this

[12] All kernel regressions are Nadaraya-Watson regressions with generalized cross-validation bandwidth selection method. Results were generated using R Development Core Team (2011) and the `np` package Hayfield and Racine (2008).

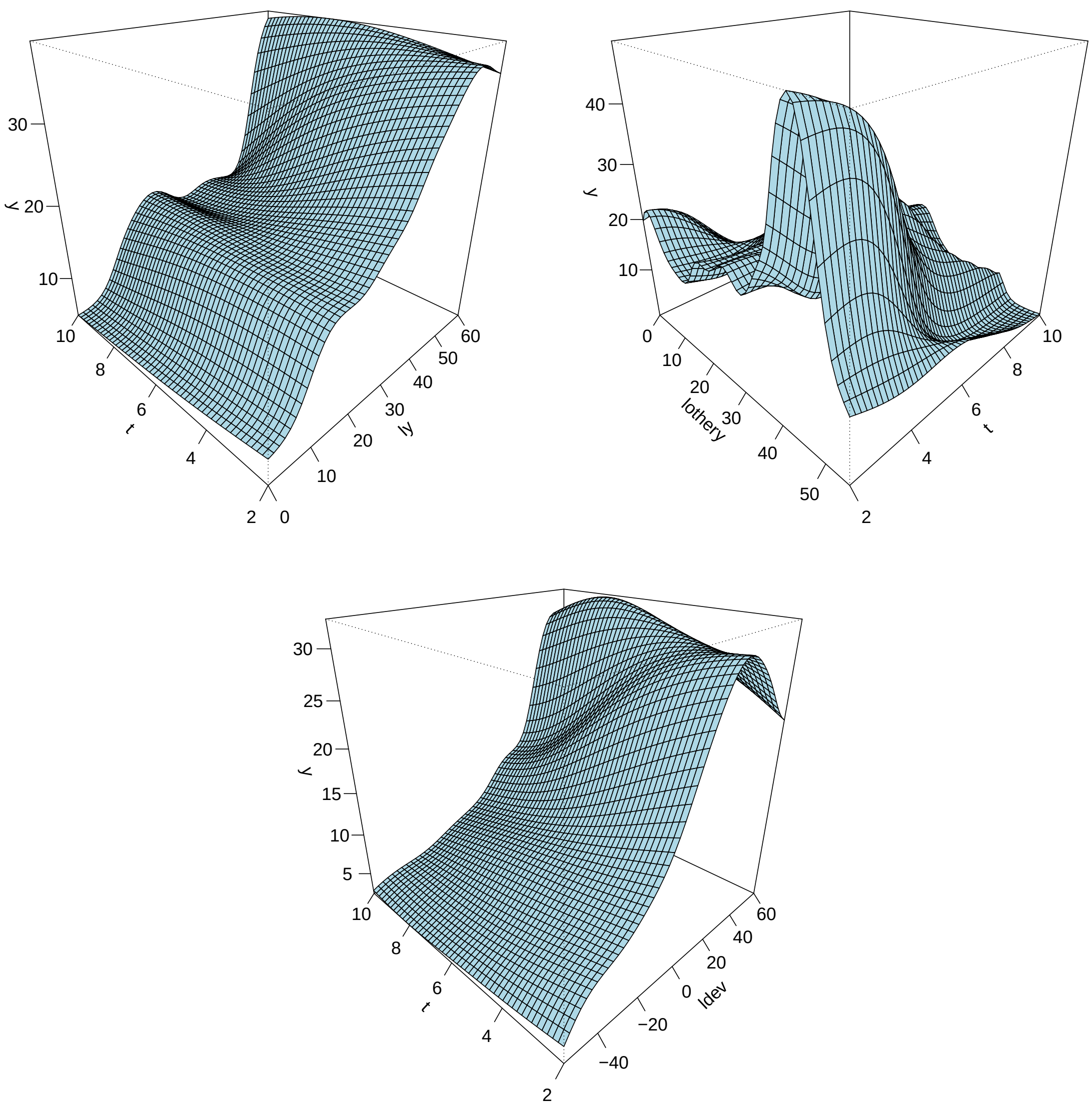

Figure 3.1: A1995 fitted values for kernel regression (3.14) for contribution respect to lagged contribution (top-left), regression (3.15) average lagged others contributions (top-right) and regression (3.16) lagged deviation from others' contributions (bottom).

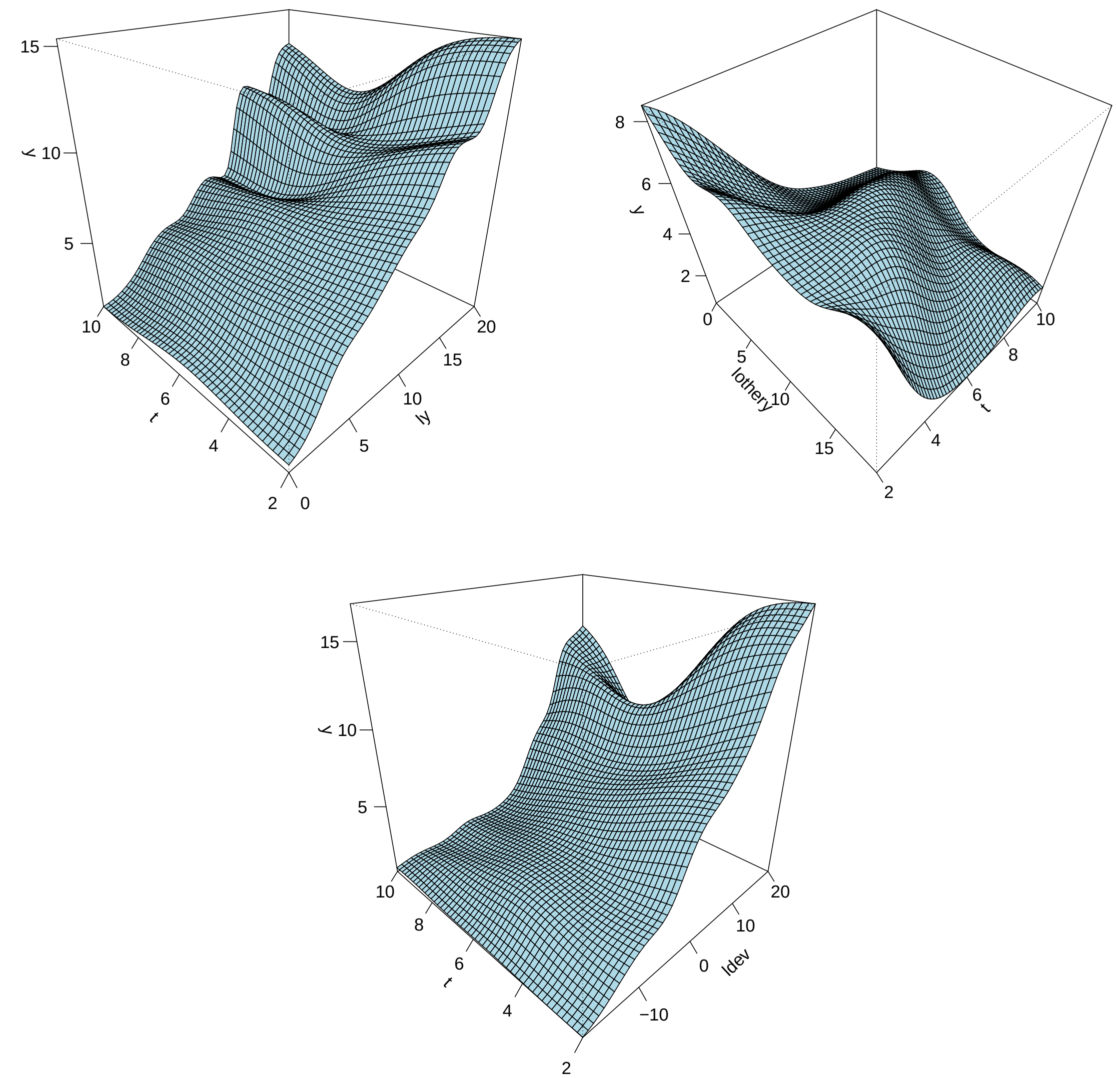

Figure 3.2: FG2010 fitted values for kernel regression (3.14) for contribution respect to lagged contribution (top-left), regression (3.15) average lagged others contributions (top-right) and regression (3.16) lagged deviation from others' contributions (bottom).

relationship in a linear manner (e.g. $f(\bar{y}_{-i,t-1}, t) = \gamma_0 + \gamma_1 \bar{y}_{-i,t-1} + \gamma_3 t$), the estimated coefficient associated with $\bar{y}_{-i,t-1}$ would be completely incorrect and it would give misleading results[13].

Differently, for the other variables, ly lagged contribution ($y_{i,t-1}$), $ldev$ lagged deviation ($y_{i,t-1} - \bar{y}_{-i,t-1}$), and time ($t$), even with some bumps, the behaviour seems at least monotonic. Bumps might appear because of scarcity of data for high levels of contribution. However, we are not drawing any conclusions from these non-parametric regressions: the preliminary approach serves uniquely to give a correct choice of variable to include in a linear regression.

We carry on with the analysis by estimating the linear models with ($y_{i,t-1} - \bar{y}_{-i,t-1}$). That is because, first, it fits the overall data better, conclusion driven from the comparison with BIC, and, second, because of the linearity behaviour with respect to the dependent variable, observable from the preliminary non-parametric graphical analysis.

Parametric Linear Regressions

In Table (3.3), we observe estimated coefficients for parametric regressions for A1995, column (1), and for FG2010, column (4)[14]. Let's first observe the relevance of two variables: treatment and session. The latter variable should not be of any relevance in determining the contribution of a subject and, in fact, it is what we find in both datasets. Having all estimated coefficients no significance, the session does not determine any shift in the intercept. On the contrary, the treatment variable captures a relatively higher average contribution in the positive frame in A1995, in models (1) and (2). When subjects are assigned to the negative frame, they contribute less than the same subjects assigned to the positive one. However, we can not infer why and how this result appears. In FG2010, models (4) and (5), the two treatments do not have a different characterization (recall that they differ only for when the strategy method is proposed to a subject, before or after the repeated public good game). So, as expected, this does not turn out to be important in determining intercept shifts in

[13]Note that, introducing a quadratic term could help dealing with the *lothery* variable for A1995, but it might not for FG2010.

[14]Note that, henceforth, we use in tables this notation: $\hat{\beta}_{lposdev} = \hat{\beta}_{\max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0]}$ and $\hat{\beta}_{lnegdev} = \hat{\beta}_{\max[\bar{y}_{-i,t-1} - y_{i,t-1}, 0]}$.

individual contributions.

Signs of estimated coefficients are consistent with results already found in other experiments. Individual contribution depends positively on the value of his own lagged contribution, it is decreasing in time and there is asymmetry in the way a subject responds to previous deviation from group mean contribution. We might conclude that subjects decrease their contribution when they realize that they have been exploited by other group members, but do not change their contribution when they were contributing below others. Ashley et al. (2010) suggest that this "behaviour is consistent with inequity aversion (Fehr and Schmidt, 1999), which asserts that people care about inequality, but that they care more when their income is below than when it is above others' income". However, this asymmetry might be reflecting a simple satisfying behaviour: subjects who have contributed less than others have already reached a satisfying payoff, while those contributing more might prefer to decrease their contribution to the public good with the aim of increasing their payoffs.

As has been said, the approach presented till now is inadequate: it does not account for heterogeneous behaviour, so results are biased. For example, unconditional subjects are not affected by other contributions. To have an idea of the difference in fits, we plot in Appendix Figures (3.5) and (3.6) the fitted values, respectively, for model (1) and model (4) against our semi-parametric model (that we will present later in the paper) and the mean contribution for type. It is evident that pulling together all types has to be corrected in some way. We can conclude that heterogeneity creates distortion in estimation, we, thus, suggest a simple way of dealing with this kind of problem.

3.3.4 On the Construction of Types and Improvements in Fit

In this section, we describe the way we define types. As discussed in the introduction, there are two main difficulties in the selection of types: first, experimental literature presents many definitions and uses *ad hoc* experiments to test their hypothesis; second, several theories have been suggested to explain the behaviour of the large class of "conditional cooperators". This leads to a great confusion and little implementation of results on type classification in simple experiments (with the exception of adding Fischbacher et al.'s strategy method).

OLS Reg	A1995	A1995	A1995	FG2010	FG2010	FG2010
Models	(1)	(2)	(3)	(4)	(5)	(6)
$y_{i,t}$	OLS-notype	OLS-session	OLS-type	OLS-notype	OLS-session	OLS-type
$\hat{\alpha}$	8.7577	8.8467	5.4963	1.6666	1.9074	1.4802
	(0.0000)	(0.0002)	(0.0120)	(0.0018)	(0.0019)	(0.0067)
$\hat{\beta}_{y_{i,t-1}}$	0.7330	0.7320	0.6166	0.8248	0.8181	0.6168
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{\beta}_{lposdev}$	-0.4351	-0.4344	-0.4939	-0.3086	-0.3037	-0.2857
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{\beta}_{lnegdev}$	-0.0344	-0.0353	0.0165	0.0672	0.0620	0.0552
	(0.6437)	(0.6403)	(0.8134)	(0.1225)	(0.1609)	(0.1861)
$\hat{\beta}_t$	-0.6838	-0.6855	-0.8701	-0.1251	-0.1296	-0.2606
	(0.0067)	(0.0070)	(0.0002)	(0.0218)	(0.0184)	(0.0000)
$\hat{\beta}_{Z_i=1}$	3.3904	3.3711	1.0920	-0.0486	-0.2433	-0.1760
	(0.0142)	(0.0782)	(0.4010)	(0.8393)	(0.5520)	(0.4324)
$\hat{\beta}_{S_i=2}$	–	-0.0742	–	–	-0.2433	–
	–	(0.9654)	–	–	(0.5313)	–
$\hat{\beta}_{S_i=4}$	–	-0.1334	–	–	-0.2570	–
	–	(0.9358)	–	–	(0.4969)	–
$\hat{\beta}_{S_i=5}$	–	–	–	–	-0.2909	–
	–	–	–	–	(0.8001)	–
$\hat{\beta}_{S_i=6}$	–	–	–	–	0.1028	–
	–	–	–	–	(0.8772)	–
$\hat{\beta}_{Residuals}$	–	–	9.1007	–	–	2.1282
	–	–	(0.0000)	–	–	(0.0000)
$\hat{\beta}_{Cooperators}$	–	–	42.7651	–	–	8.8446
	–	–	(0.0000)	–	–	(0.0000)
Unadj-R^2	0.3431	0.3431	0.4354	0.4506	0.4510	0.5219
BIC	6043	6056	5947	7243	7271	7082

Table 3.3: Parametric analysis (p-values in parenthesis).

	Free Riders	Residuals	Cooperators
A1995	27%	70%	3%
positive treatment	18%	77%	5%
negative treatment	37%	63%	0%
FG2010	19%	75%	6%
sequence one	19%	75%	6%
sequence two	19.5%	75%	5.5%

Table 3.4: Percentage of Types

To overcome these problems, we define only unconditional players and leave the unclassifiable types in a residual class. We concentrate on the unconditional subjects because their behaviour should not be affected by other's choices and so it is easier to detect. Previous literature has pointed out that although types are persistent during the game, subjects can make mistakes (see, for example, Bardsley and Moffatt, 2007; Burlando and Guala, 2005). We, thus, admit mistakes in two directions: time consistence, a subject can deviate from his type at most 10% of time; and amount contributed, we allow subjects to "free ride", thus contributing little amounts to the public good, and to "cooperate", thus contributing high amounts, relatively to the overall pool of subjects.

We define a *free rider* as a subject that contributes less than the first quartile of the overall distribution of contributions[15] and at least 90% of the time. And a *cooperator* as a subject that at least 90% of times contribute more than the third quartile. We call the rest of the subjects, who do not enter into these two categories, *residuals*.

In Table (3.4), we report percentages of types[16] relative to the overall dataset, and separated by treatments. The first thing to notice is that in spite of differences in

[15] In both experiments considered in this paper, the first quartile of the distribution of subjects contribution corresponds to zero, see Table (3.1). However, we uphold this definition for the simple reason that cooperation in public good experiments highly depends on the parameters chosen for the pay-off function (e.g. per capital marginal return to private and public good, endowment, etc.).

[16] The codes describing the algorithm to determine types are in Appendix (3.5). All codes are written in R (R Development Core Team, 2011).

the average percentage of endowment contributed in A1995 positive treatment and in FG2010[17], we can observe that the percentage of free riders, cooperators and residuals are similar. Moreover, the proportion of categorized subjects is similar to those found in other experiments. Thus, we can infer that the residual class should be mostly composed of conditional cooperators. Since the latter are estimated to be at least 50% of the overall subjects, we can suppose that at least 71% of the residual class should consist of conditional cooperators.

To compare the two treatments, Andreoni (1995) counts the number of zero outcomes and observes that in the negative frame subjects are more willing to play the equilibrium prediction. This is reflected in our study of types: the number of free riders doubles in the negative frame and there is no presence of cooperators.

Parametric Linear Regressions with Types

Let's now observe the results in Table (3.3) when we add types, models (3) and (6). The presence of types have actually increased the goodness of fit of both models. Not only the unadjusted$-R^2$ has increased (10% more in A1995 and 8% in FG2010), but also we find that adding types increases the predictive power of the models from the BIC criterion, which accounts for the higher number of parameters introduced.

Estimation for type variables suggests that cooperators are those contributing the most and free riding the less. This is not surprising, since that was exactly the way types have been constructed with our algorithm. Signs of the first four variables are not so different. In spite of this, the introduction of types in the regression model cancels the predictive power of the treatment variable in A1995: except for the different percentage of types, positive and negative frames have no differences. From model (1) we might conclude that all variations in the mean contribution is explained by types.

Notwithstanding, the type variable is "intercept shifting" in the sense that it captures differences in mean contributions as we have previously discussed. However, estimates are biased because types do react differently to variables such as time and others' contributions. This is clear with an example. Note that the intercept is positive and significantly different than zero. This model would predict that a free rider would

[17] As we have seen in the descriptive analysis.

contribute positive values (and decrease their contributions in time), because the estimation is affected by the large group of residuals. To see this, observe fitted values in Figures (3.3) and (3.4). In the lower part of both graphs, we can find the predictions of, respectively, models (3) and (6) for free riders in red. Note that they predict values too high in first periods and too low in the later, with respect to the mean values per type in black.

Even though, type classification has improved the understanding of how different framing affects the subjects. Andreoni finds that subjects free ride more in the negative treatments. At this point of the analysis, we can add that the negative frame has the effect of increasing the number of free riders who actually drive the overall mean contribution to lower amounts.

Clearly, type classification can not enter as intercept shifting in OLS models. We might be interested in letting the regressors to interact with the type variable, however, for the arguments given in section (3.2.2), we will address these problems by means of a semi-parametric varying-coefficient model.

3.3.5 Semi-parametric Regressions

Up to now, we have seen the inadequacy of the OLS linear regression to answer important questions on subject behaviour. Let's summarize those that have not yet found an answer. We need to obtain a more clear understanding of the effects of sessions and treatments in the dynamics of the game. Do particular treatments and/or sessions change the way subjects respond to the information that they obtain in the repeated public good game? If so, in which manner? Is our classification of unconditional subjects helping us understand how the residual class behaves? Can we infer which types are mostly present in this class? How do these subjects respond to treatments?

We proceed by commenting on the results for both experiments, A1995 and FG2010. First, by analysing sessions and treatments effects, then types classification, by means of semi-parametric models presented in the previous section. Supported by the categorical semi-parametric varying-coefficient model, we try to answer these questions in a relatively simple way. Recall that the categorical varying-coefficient model might automatically detect if a discrete variable has no effect on other relevant variables.

First, we propose an approach to determine whether the session might, or might not, be a relevant variable to explain the results. In this context, we define *session-effects* if the variable session is not independent of all other variables (namely, all explanatory variables and the dependent one). In the absence of these effects, the session variable should not influence the estimation of the linear part of the model: it is common among researchers to assume that the same treatment performed in different sessions gives the same results.

We are testing these hypotheses, with the following model for both datasets:

$$\begin{aligned} y_{i,t} =& \alpha + \beta_1(Z_i, S_i)y_{i,t-1} + \beta_2(Z_i, S_i)\max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0] + \\ &+ \beta_3(Z_i, S_i)\max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0] + \beta_4(Z_i, S_i)t + \epsilon_i \end{aligned}$$

where Z_i is the treatment, S_i the session and $E(\epsilon_i|X_i, Z_i, S_i) = 0$.

If the model selects a high bandwidth for the session variable, then, we can exclude the presence of session-effects, as we have defined them. We will analyse both datasets.

SEMIPAR REGRESSION					
Treatment A1995	$\hat{\alpha}$	$\hat{\beta}_{y_{i,t-1}}$	$\hat{\beta}_{lposdev}$	$\hat{\beta}_{lnegdev}$	$\hat{\beta}_t$
positive frame	10.3622	0.7778	-0.4362	-0.0445	-0.6179
	(0.0004)	(0.0000)	(0.0000)	(0.2453)	(0.0337)
negative frame	7.3442	0.8181	-0.5399	0.0942	-0.5534
	(0.0006)	(0.0000)	(0.0000)	(0.0884)	(0.0202)
Bandwidths: Positive	0.2291	Session	1	R^2:	0.3469

Table 3.5: A1995 semi-parametric categorical varying-coefficients estimations with session and treatment dummies (p-values in parenthesis)

In A1995 dataset, we have two treatments and four sessions (two for each treatment). In Table 3.5, we find results for the semi-parametric categorical varying coefficients model. The first thing to notice is that the model selects a bandwidth equal to 1 for the session covariate. We, thus, find evidence of no session effects: the session variable is irrelevant in the sense that it is independent from both the dependent variable y_i and the regressors (namely, $E(X_iS_i) = E(Y_iS_i) = 0$).

By contrast, the bandwidth selected for the covariate treatment is low and equal to 0.23. This suggests that coefficients of the explanatory variables are different in the two treatments. However, we can note that this bandwidth does not go to zero, as would be preferable thus posing a question of importance in the results of the treatment effect. A treatment effect exists, but it might not be so strong.

SEMIPAR REGRESSION					
Treatment FG2010	$\hat{\alpha}$	$\hat{\beta}_{y_{i,t-1}}$	$\hat{\beta}_{lposdev}$	$\hat{\beta}_{lnegdev}$	$\hat{\beta}_t$
sequence one - session one	1.4781	0.8359	-0.3055	0.0987	-0.1235
	(0.0066)	(0.0000)	(0.0000)	(0.0155)	(0.0211)
sequence one - session five	1.3053	0.8183	-0.2638	0.1053	-0.0979
	(0.0095)	(0.0000)	(0.0003)	(0.0082)	(0.0432)
sequence one - session six	1.6253	0.8308	-0.3416	0.0780	-0.1209
	(0.0042)	(0.0000)	(0.0000)	(0.0622)	(0.0220)
sequence two - session two	1.7581	0.8112	-0.3172	0.0548	-0.1251
	(0.0015)	(0.0000)	(0.0000)	(0.1089)	(0.0248)
sequence two - session three	1.7202	0.8486	-0.3333	0.0411	-0.1383
	(0.0006)	(0.0000)	(0.0000)	(0.1364)	(0.0066)
sequence two - session four	1.9518	0.8070	-0.2951	0.0269	-0.1434
	(0.0002)	(0.0000)	(0.0000)	(0.2498)	(0.0057)
Bandwidths: Sequence	0.8457	Session	0.4855	R^2:	0.4559

Table 3.6: FG2010 semi-parametric categorical varying-coefficients estimations with session and treatment dummies (p-values in parenthesis).

In FG2010 dataset, we have two treatments and six sessions (three for treatment). We report results in Table 3.6. First, let's observe the bandwidth estimations: covariates, session and treatment, have high bandwidth values far from zero. The treatment in FG2010 depends on whether subjects play a strategy method before or after the repeated public good game. This seems to have very little effect on the overall behaviour of subjects. Although, we usually expect to have lower session effects than treatment effects, the impact of the session on the dependent variable seems higher than the treatment effect. When we observe coefficient estimations, we understand that there is not much difference among treatments and sessions. The real divergence can be found in the lagged negative deviation from mean contributions. However, we can conclude that, although in FG2010 we can not completely exclude independence between sessions, treatments and other variables, the estimation suggests a feeble relationship.

We have seen how estimates of smoothing coefficients have an important role in determining irrelevant and relevant variables. We now move our attention to the differences that can emerge among types. Since, in the definition of types, we have separated unconditional subjects from other subjects, we expect the type covariate to be relevant and to capture type characteristics in both datasets.

Let's start with Andreoni's experiment. We have already excluded session effects, nevertheless, the treatment bandwidth selected was low enough to expect some differences. However, we have no guess on how different frames might modify the analysis. If, after accounting for types, the associated bandwidth reveals an irrelevant covariate, the treatment will not be important in the determinants of the subjects behaviour and all differences would be captured by heterogeneous types.

Whenever treatment is relevant, we propose two hypotheses to be tested. On the one hand, if linear models are correctly specified, we should find that the treatment covariate affects only the intercept: in this case, estimated coefficients in the linear regressions, other than the intercept, should be similar in different treatments. Moreover, estimations should be similar with respect to the linear regression in Table (3.3). On the other hand, if the estimated coefficients differ between positive and negative frames, we can conclude that subjects react differently to variables in the two treatments.

We are testing our hypotheses, with the following model:

$$\begin{aligned} y_{i,t} =& \alpha + \beta_1(Z_i, T_i) y_{i,t-1} + \beta_2(Z_i, T_i) \max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0] + \\ &+ \beta_3(Z_i, T_i) \max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0] + \beta_4(Z_i, T_i) t + \epsilon_i \end{aligned}$$

where Z_i is the treatment covariate, T_i the type variable and $E(\epsilon_i | X_i, Z_i, T_i) = 0$

SEMIPAR REGRESSION					
Treatment A1995	$\hat{\alpha}$	$\hat{\beta}_{y_{i,t-1}}$	$\hat{\beta}_{lposdev}$	$\hat{\beta}_{lnegdev}$	$\hat{\beta}_t$
free rider - positive	1.5000	-0.0861	0.0761	-0.0198	-0.1035
	(0.0546)	(0.1316)	(0.1701)	(0.0908)	(0.1658)
free rider - negative	2.2341	-0.0969	0.0791	0.0510	-0.1613
	(0.1849)	(0.2048)	(0.2469)	(0.2229)	(0.3160)
residual - positive	21.3864	0.6078	-0.6257	-0.1017	-1.4262
	(0.0000)	(0.0000)	(0.0000)	(0.1382)	(0.0003)
residual - negative	12.7823	0.6408	-0.3695	0.2779	-1.1205
	(0.0001)	(0.0000)	(0.0031)	(0.0091)	(0.0025)
cooperator - positive	0.8820	0.9853	0.0001	0.1771	-0.0001
	(0.2494)	(0.0000)	(0.3781)	(0.0031)	(0.3997)
cooperator - negative	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA
Bandwidths: Positive	0.1568	Type	0.0000	R^2:	0.4631

Table 3.7: A1995 semi-parametric categorical varying-coefficients estimations with types and treatment dummies (p-values in parenthesis).

We have found in the previous section that the percentage of types is different in the two treatments: a higher amount of free riders in the negative frame might be the explanation for lower contributions. So, we would like to study the impact of the treatment covariate on the regressors after having controlled for type differences. Thus, we can compare which differences between the positive and negative frames appear in the reaction of types to regressors. Note that we will not discuss behaviour of the cooperator group because they represent only 2.5% of the population (two subjects) and because this class does not appear in the negative frame. However, we do not need to arbitrary exclude them from the analysis as we might do with outliers in other contexts. The varying-coefficient model, by estimating a smoothing parameter close to zero for types, treats them as a category itself which does not affect other categories. In a linear regression, these "outliers" would bias other classes' estimates; in a varying coefficient model, they are treated separately precisely because their behaviour has been determined to be different (via bandwidth selection).

Firstly, we describe results on free riders' behaviour. Taking into account the way free riders are selected, note that any significance of estimated coefficients would capture what we call *time inconsistency*, namely the one period deviation from the zero contribution. In the negative frame, free riders are not overall time inconsistent. However, in the positive treatment, the intercept α and the negative deviation $\beta_{lnegdev}$ for free riders are slightly significant (at 10% level), suggesting that they deviate with a positive amount from the equilibrium. We can conclude that not only a lower amount of free riders is found in the positive treatment, but also when they contribute to the public good, they do it in a positive significant way.

We now consider the larger class of residual subjects. Recall that among these subjects, there is a large amount of conditional cooperators. Lagged individual contribution and time have similar coefficients in the two treatments, suggesting that the differences among subjects in the residual class lies in responses to others' contributions. The intercept is higher in the positive treatment, suggesting more cooperation when subjects are asked to contribute to a public good than when they can move part of their endowment from the common pool to the private account. This might be due to greater free riding that has the effect of reducing conditional cooperators contributions. In fact, we can observe the difference in the way the subjects respond to previous deviations. In both treatments, the representative subject of this class reduces his contribution to the public good if others have previously contributed less than him. However, when other group members have contributed above him, he responds upward in the negative frame, but does not change his contribution in the positive one. This is in contrast from what we observes in the parametric regression in Table (3.3) column (3). The estimated parametric coefficient is not significant, but it refers to all the population (all types in both treatments). In the residual class, we still find proofs of asymmetric inequality aversion behaviour, but with a higher tendency to reciprocate when the frame is negative.

The magnitude of coefficients is noteworthy. Residual subjects in the negative frame increase and decrease contributions equally. By contrast, when residual types adjust their contribution downward if they were exploited in the previous period, in the positive frame they do it more than in the negative one. In other words, despite the lower number of free riders in the positive treatment, residual subjects give up cooperation faster than in the negative one. Still we have pooled together many types of subjects in the residual class and distinctions among conditional cooperators remains unclear. We believe that a more accurate analysis of types could better explain in which direction subjects react to others' contributions, what is the magnitude and why.

Let's now try to compare goodness of fit of the different models considered. To compare OLS results and semi-parametric models, we will use the results for the unadjusted-R^2 in Table (3.10)[18]. The goodness of fit indicated by R^2 is always higher for the semi-parametric models and reaches its highest value for the categorical semi-parametric varying-coefficient model with types.

Finally, we plot the estimated mean values of the two complete models with respect to the observed average by types. It is clear that the varying-coefficient model better captures the distinction among types, while the intercept shifting effect makes the parametric model not a good fit for free riders. Moreover, we observe that the semi-parametric model grabs the end period effect and on average does not exceed boundaries, contrary to the parametric one: the former is more able to capture the "extreme" behaviour of cooperators and free riders; the latter is biased by mean values of the large residual class that affects all estimation.

To conclude, for Andreoni's dataset, we are able to extend previous findings. On the one hand, the basic analysis of Andreoni (1995) was only able to detect a decrease in the mean contribution in the negative frame due to an increase in the number of zero contributions. In addition, we can say why this happens. Framing the public good in a negative way has not only the effect of increasing the number of free riders, but also the second effect of slowing down cooperation of the residual class, mostly composed of conditional cooperators. On the other hand, Ashley et al. (2010) suggestion of studying asymmetric lagged deviation from a mean contribution has to be contextualised. By

[18] We are aware that the R^2 is an overall measure and does not account for the number of parameters, nevertheless, as far as we know, it is the only measure we can use to compare semi-parametric and parametric models. For the consistency and the comparability of R^2 between parametric and semi-parametric models see, for example, Racine (2008)

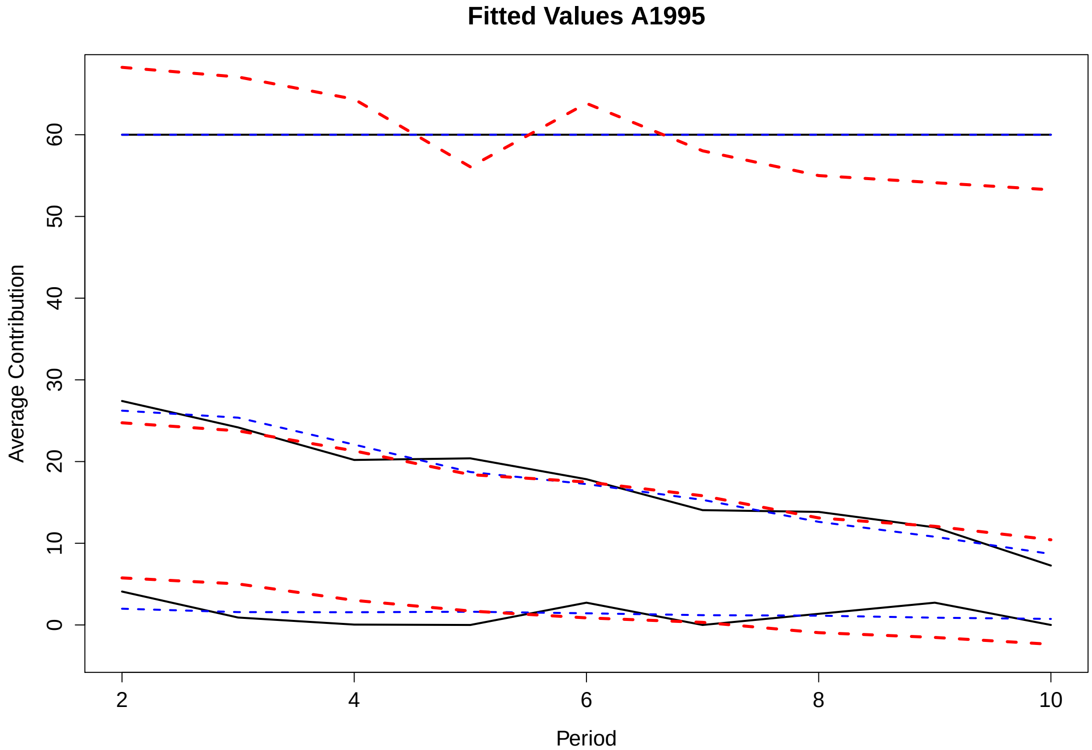

Figure 3.3: A1995 fitted values for OLS model Table (3.3) column (3) (red long dashes), varying coefficient model Table (3.7) (blue short dashes) and mean contribution (black line) by type.

aggregating all types in the same pool, estimations are in fact biased: free riders influence all variable estimations also those related to others' contributions (recall that by definition they are unconditional subjects). Asymmetric behaviour is present in both treatments, however, there is more reciprocity in the negative frame and inequality aversion in the positive one.

Last of all, we replicate the same analysis made so far, for Fischbacher and Gächter experiment. Since treatment and session effects are not particularly strong, we will exclude them and only concentrate on type distinction. We use the following model:

$$\begin{aligned} y_{i,t} =& \alpha + \beta_1(T_i)y_{i,t-1} + \beta_2(T_i)\max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0] + \\ & + \beta_3(T_i)\max[y_{i,t-1} - \bar{y}_{-i,t-1}, 0] + \beta_4(, T_i)t + \epsilon_i \end{aligned}$$

where T_i is the type variable and $E(\epsilon_i|X_i, T_i) = 0$. In Table (3.8), we report results.

Treatment FG2010	Type	$\hat{\alpha}$	$\hat{\beta}_{y_{i,t-1}}$	$\hat{\beta}_{lposdev}$	$\hat{\beta}_{lnegdev}$	$\hat{\beta}_t$
FG2010	factor.fit	Intercept	ly	lposdev	lnegdev	t
1	free rider	0.4254	-0.0427	0.0223	-0.0357	0.0087
		(0.2574)	(0.3724)	(0.4538)	(0.1988)	(0.4510)
2	residual	3.8251	0.6534	-0.3309	0.0958	-0.3397
		(0.0000)	(0.0000)	(0.0000)	(0.0451)	(0.0000)
3	cooperator	3.1468	0.8261	-0.0643	3.0122	-0.1039
		(0.1257)	(0.0000)	(0.3287)	(0.0043)	(0.2737)

Table 3.8: FG2010 semi-parametric categorical varying-coefficients estimations with type dummy (p-values in parenthesis).

Free rider behaviour is in line with zero contribution equilibrium, time inconsistency is not significant as it was for A1995 positive frame. Cooperators are again very few.

In the residual class, subjects respond significantly to both higher and lower contributions with respect to other group members in previous period. However, this effect is larger when they have been exploited than when they are the lower contributors. This slight tendency to free ride on others supports, once more, the need to distinguish subjects that are defined as conditional cooperators. Asymmetric behaviour might lead to the conclusion that subjects are mostly inequity averse in positive frames, namely when they are asked to contribute to the public good. However, comparison with A1995 results on the negative frame could suggest a different interpretation. If we assume that the residual class is made of inequality averse subjects and reciprocators in some proportion, a negative frame might influence only the former subjects. This could explain why there is a higher percentage of players classifiable as free riders and why when the residual class is matched with higher contributors it increases the following period donation.

To conclude the analysis on FG2010, we compare fits of the above mentioned models. Once more, goodness of fit captured by the unadjusted-R^2 in Table (3.10) selects the semiparametric model as being more suitable with respect to the parametric models. In fact, in Figure (3.4), again we observe a better fit of the semi-parametric model for all classes of subjects with respect to the linear regression models.

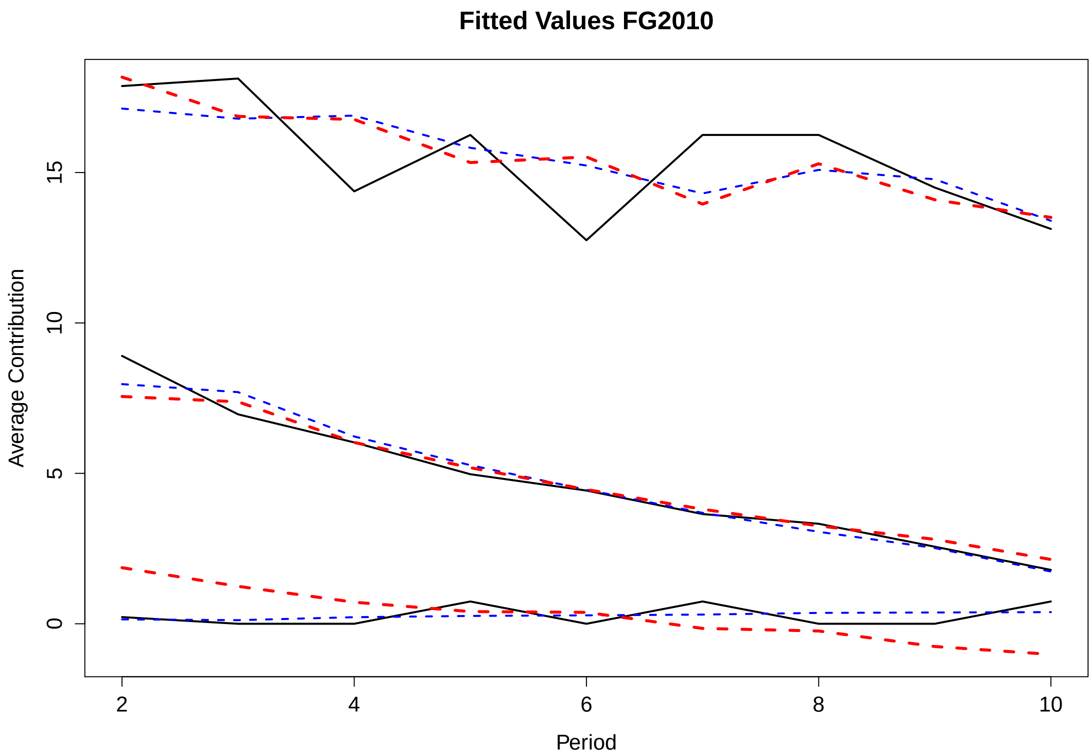

Figure 3.4: FG2010 fitted values for OLS model Table (3.3) column (6) (red long dashes), varying coefficient model Table (3.8) (blue short dashes) and mean contribution (black line) by type.

3.4 Conclusions

We re-examine two well-known public good experiments by means of statistical tools which are not often used in experimental economics. We show that this can lead to an improvement in the interpretation of results.

We suggest using semi-parametric categorical varying-coefficient models to capture different subjects' reactions to experimental treatments. These models are useful for two main reasons that go beyond their statistical properties. On the one hand, they can solve different research questions at the same time; on the other, they can automatically detect if some variables are irrelevant. This can help data analysis in two directions: focus attention on the relevant variables and better explain differences in data. Lastly, with a good categorization of data, the varying coefficient model allows us not to arbitrarily eliminate outliers that can affect overall estimations. On the contrary, it can treat categories separately only if they are selected as relevant (this can be seen as a double check on the way categories are defined).

Moreover, we have shown that categorizing subjects into similar types may reverse previous findings, that do not consider heterogeneity, and gives a more consistent understanding of different behaviours. However, since there is no clear way of defining types, we are only able to disentangle unconditional subjects from the other players, that do not show a clear path of contribution. This simple classification still leads to great improvement in the goodness of fit of models. We believe that a similar but more accurate method to classify types has to be presented. However, as far as we know, types are usually defined with *ad hoc* procedures, such as strategy method or experimentally driven sequential public good games. Nevertheless, an effort in incorporating a simple detection of types within the repeated public good game should be made.

Having shown that a more appropriate analysis is possible, it is fundamental to use these (or other) methods not only to re-analyse old experiments, but also to rethink experimental designs. The two procedures presented in this paper highlight some facts which were not yet observable. Varying-coefficient models set the basis for the proposal of new research questions and determine relevance (or irrelevance) of some variables (for example, on the effectiveness of punishment and reward in augmenting contributions to public goods). Adding to these models a simple categorization of types disentangles the effects on different individuals (e.g. for which type the punishment is more effective and how large the effect is).

A caveat of this approach is that we are not able to enlarge the class of varying-coefficient models to censored regressions. In fact, since the contribution to the public good is bounded within some intervals, censored models seem to be the most appropriate tools. This leave room to further research on this point in the future.

3.5 Appendix

3.5.1 Additional Tables

Bandwidth Covariates	Type	Treatment	Session
A1995	-	0.2290793	0.9999999
A1995	1.284147e-05	0.1567985	-
FG2010	-	0.8457352	0.4855067
FG2010	4.67066e-05	-	-

Table 3.9: Bandwidths estimations.

R^2	Semi-par	OLS-type	OLS-session	OLS-notype
A1995	0.4631	0.4354	0.3431	0.3431
FG2010	0.5457	0.5219	0.4510	0.4506

Table 3.10: Unadjusted-R^2.

3.5.2 Additional Figures

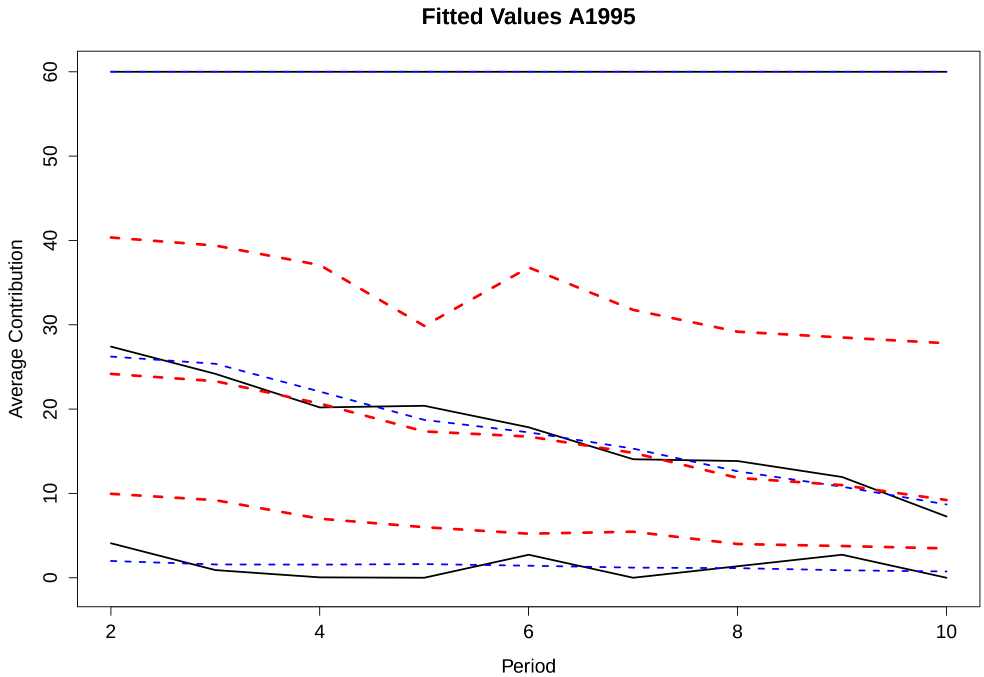

Figure 3.5: A1995 fitted values for OLS model Table (3.3) column (1) (red long dashes), varying coefficient model Table (3.7) (blue short dashes) and mean contribution (black line) by type.

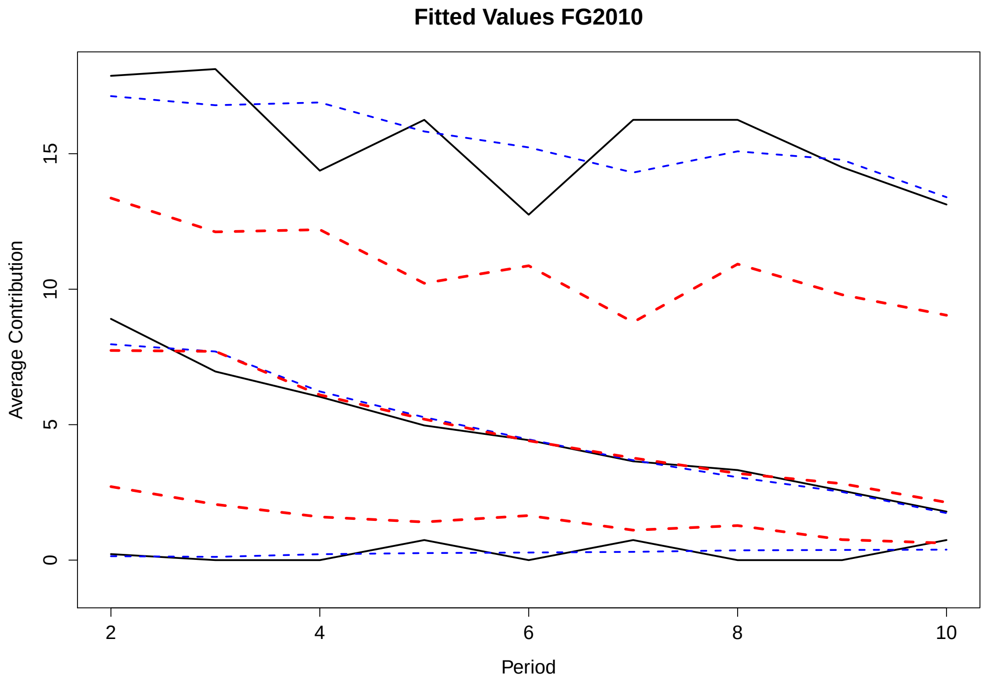

Figure 3.6: FG2010 fitted values for OLS model Table (3.3) column (4) (red long dashes), varying coefficient model Table (3.8) (blue short dashes) and mean contribution (black line) by type.

3.5.3 Codes

Type

Example of algorithms for detection of types using A1995 dataset.

```
#####################################################
#######     IDENTIFICATION OF TYPES        ########
#####################################################
#original dataset
dataexp <- read.table("C:.../Dati/A1995/A1995_data.txt", header=TRUE )
#################
## FREE RIDERS ##
#################
#the first quartile of distribution of contribution
first.quart.y <- fivenum(dataexp$y)[2]
#errors at 10\% of periods
epsilon <- max(dataexp$t)*0.9
#count number of zero contributions
n <-length(dataexp$y)/10
zeros.vector  <- integer(n)
first.quart.vector  <- integer(n)
```

```
#count number of zero contributions per subjects
#count number of less or equal than the first quartile contributions per subjects
j <- 0
for (i in min(dataexp$idsubj):max(dataexp$idsubj)) {
  subdataid <- subset(dataexp,dataexp$idsubj==i)
  if (nrow(subdataid) > 0){
      j <- j+1
      zero <-sum(subdataid$y==0)
          first.quart <-sum(subdataid$y<=first.quart.y)}
 zeros.vector[j] <- zero
 first.quart.vector[j] <- first.quart}
#definition of strong free riders: those that contribute at least epsilon times zero
matzeros <- matrix(zeros.vector,ncol=length(1:10),nrow=length(zeros.vector))
matzeros <- t(matzeros)
zeros <- as.vector(matzeros)
strong.fr <- ifelse(zeros>=epsilon,1,0)
sum(strong.fr==1)/10
#definition of free rider: those that contribute at least epsilon times less or equal
    than the first quartile
matlowvalues <- matrix(first.quart.vector,ncol=length(1:10),nrow=length(first.quart.
    vector))
matlowvalues <- t(matlowvalues)
lower.first.quart <- as.vector(matlowvalues)
fr <- ifelse(lower.first.quart>=epsilon,1,0)
sum(fr==1)/10
#in A1995 strong free riders and free riders are equally defined since first.quartile
    =0
sum(strong.fr==1)/10-sum(fr==1)/10
#merge variables into the dataset
dataexp <- data.frame(dataexp,zeros,strong.fr,fr)
#remove variables from the workspace
rm(zeros,strong.fr,fr,fr.percentage)
#################
## COOPERATORS ##
#################
#take the third quartile of distribution of contribution
third.quart.y <- fivenum(dataexp$y)[4]
# errors at 10\% of periods
epsilon <- max(dataexp$t)*0.9
#count number of full contributions
n<-length(dataexp$y)/10
full.vector  <- integer(n)
third.quart.vector  <- integer(n)
#count number of full contributions per subjects
#count number of more or equal than the third quartile contributions per subjects
```

```
j <- 0
for (i in min(dataexp$idsubj):max(dataexp$idsubj))
{ subdataid <- subset(dataexp,dataexp$idsubj==i)
  if (nrow(subdataid) > 0){
      j <- j+1
      full <-sum(subdataid$y==20)
          third.quart <-sum(subdataid$y>=third.quart.y)}
 full.vector[j] <- full
 third.quart.vector[j] <- third.quart}
#definition of strong cooperators: those that contribute at least epsilon times full
    contribution
matfull <- matrix(full.vector,ncol=length(1:10),nrow=length(full.vector))
matfull <- t(matfull)
full <- as.vector(matfull)
strong.coop <- ifelse(full>epsilon,1,0)
sum(strong.coop==1)/10
#definition of cooperators: those that contribute at least epsilon times more or equal
     than the third quartile
mathighvalues <- matrix(third.quart.vector,ncol=length(1:10),nrow=length(third.quart.
    vector))
mathighvalues <- t(mathighvalues)
higher.third.quart <- as.vector(mathighvalues)
coop <- ifelse(higher.third.quart>epsilon,1,0)
sum(coop==1)/10
#in A1995 strong cooperators are less than cooperators
sum(strong.coop==1)/10-sum(coop==1)/10
#merge variables into the dataset
dataexp <- data.frame(dataexp,full,strong.coop,coop)
#remove variables from the workspace
rm(full,strong.coop,coop)
#creation of types: 1) free rider, 3) cooperator, 2) not free rider nor cooperator
type.1 <- ifelse(dataexp$fr==1,1,2)
type <- ifelse(dataexp$coop==1,3,type.1)
#merge type variable into the dataset
dataexp <- data.frame(dataexp,type=as.factor(type))
```

Non-parametric Regressions

Example of non-parametric regressions using A1995 dataset.

```
##############################################
#######     KERNEL REGRESSION        ########
##############################################
#computing non parametric regressions
fit.lothery.t <- npregbw(y ~ lothery + t,GCV=T,data=dataexp)
```

```
fit.ly.t <- npregbw(y ~ ly + t,GCV=T,data=dataexp)
fit.ldev.t <- npregbw(y ~ ldev + t,GCV=T,data=dataexp)
#figure (1)
plot(npreg(fit.ly.t),theta=-45,phi=25,view="fixed",main="")
plot(npreg(fit.lothery.t),theta=45,phi=25,view="fixed",main="")
plot(npreg(fit.ldev.t),theta=-45,phi=25,view="fixed",main="")
```

Semi-parametric Regressions

Example of semi-parametric regressions[19] and plotted values using A1995 dataset.

```
#####################################################
#######     SEMIPARAMETRIC REGRESSION        ########
#####################################################
#dataset for period greater than 1
datamod <- subset(dataexp,dataexp$t > 1)
################
## ESTIMATION ##
################
#compute the bandwidth for the model in table (7)
bw <- npscoefbw(y ~ ly + lposdev + lnegdev + t|
                type + positive.dum + session.dum,
                data=datamod,
                ukertype="liracine",
                okertype="liracine",
                nmulti=100)
#fit the model
model <- npscoef(bws=bw,betas=TRUE)
#in the summary the dummy session is smoothed out
summary(model)
summary(bw)
#create table with estimated coefficients
factor.fit <- c("free␣rider␣-␣positive","residual␣-␣positive","cooperator␣-␣positive",
    "free␣rider␣-␣negative","residual␣-␣negative","cooperator␣-␣negative")
model.coef <- rbind(coef(model)[which(datamod$type == 1 & datamod$positive.dum==1)
    ,][1,],
coef(model)[which(datamod$type == 2 & datamod$positive.dum==1),][1,],
coef(model)[which(datamod$type == 3 & datamod$positive.dum==1),][1,],
coef(model)[which(datamod$type == 1 & datamod$positive.dum==0),][1,],
coef(model)[which(datamod$type == 2 & datamod$positive.dum==0),][1,],
coef(model)[which(datamod$type == 2 & datamod$positive.dum==0),][1,])
xtable(cbind(factor.fit,formatC(model.coef,digits=4,format="f")))
#compute bootstrap standard errors as in Li-Ouyang-Racine (2011)
#create variables
```

[19] Part of this R code is borrowed from Li et al. (2011).

```r
set.seed(42)
num.boot <- 500
model <- npscoef(bws=bw,betas=TRUE)
k <- length(coef(model)[1,])
#note that we compute the bootstrap standard errors for each subset
coef.mat.type.row.1 <- matrix(NA,num.boot,k)
coef.mat.type.row.2 <- matrix(NA,num.boot,k)
coef.mat.type.row.3 <- matrix(NA,num.boot,k)
coef.mat.type.row.4 <- matrix(NA,num.boot,k)
coef.mat.type.row.5 <- matrix(NA,num.boot,k)
coef.mat.type.row.6 <- matrix(NA,num.boot,k)
datamod.orig <- datamod
for(j in 1:num.boot) {
  print(j)
  datamod <- datamod.orig[sample(1:nrow(datamod.orig),replace=T),]
  model.bs <- npscoef(bws=bw,betas=TRUE)
  model.coef.bs <- rbind(coef(model.bs)[which(datamod$type==1 & datamod$positive.dum
      ==1),,drop=FALSE][1,,drop=FALSE],
                      coef(model.bs)[which(datamod$type==2  & datamod$positive.dum==1)
                          ,,drop=FALSE][1,,drop=FALSE],
                      coef(model.bs)[which(datamod$type==3  & datamod$positive.dum==1)
                          ,,drop=FALSE][1,,drop=FALSE],
                      coef(model.bs)[which(datamod$type==1 & datamod$positive.dum==0)
                          ,,drop=FALSE][1,,drop=FALSE],
                      coef(model.bs)[which(datamod$type==2  & datamod$positive.dum==0)
                          ,,drop=FALSE][1,,drop=FALSE],
                      coef(model.bs)[which(datamod$type==2  & datamod$positive.dum==0)
                          ,,drop=FALSE][1,,drop=FALSE])
  coef.mat.type.row.1[j,] <- model.coef.bs[1,]
  coef.mat.type.row.2[j,] <- model.coef.bs[2,]
  coef.mat.type.row.3[j,] <- model.coef.bs[3,]
  coef.mat.type.row.4[j,] <- model.coef.bs[4,]
  coef.mat.type.row.5[j,] <- model.coef.bs[5,]
  coef.mat.type.row.6[j,] <- model.coef.bs[6,]}
#compute the standard deviations for each subset
colsd <- function(data) {
  colsd <- numeric(ncol(data))
  for(i in 1:ncol(data)) {
    colsd[i] <- sd(data[,i])}
  return(colsd)}
colsd.dat <- rbind(colsd(coef.mat.type.row.1),
                   colsd(coef.mat.type.row.2),
                   colsd(coef.mat.type.row.3),
                   colsd(coef.mat.type.row.4),
                   colsd(coef.mat.type.row.5),
```

```r
                   colsd(coef.mat.type.row.6))
#create the table for the standard deviations
xtable(cbind(factor.fit,formatC(colsd.dat,digits=4,format="f")))
#compute the p-values for each subset with four degree of freedom
deg.free <- 4
colpvalue <- 1 -pt(abs(model.coef/colsd.dat),length(datamod$y)-deg.free)
#create the table for the p-values
xtable(cbind(factor.fit,formatC(model.coef,digits=4,format="f")))
#compute unadjusted-R^2 for the model as in Li-Ouyang-Racine (2011)
fit.model <- fitted(model)
num <- sum((datamod$y - mean(datamod$y))*(fit.model - mean(datamod$y)))^2
den <- sum((datamod$y - mean(datamod$y))^2)*sum((fit.model - mean(datamod$y))^2)
r.sqr.model <- num/den
#############
## FIGURES ##
#############
#visual comparison: OLS vs semi-parametric estimates for types
#estimation and fit of data for the linear model
model.lm <- lm(y ~ ly + lposdev + lnegdev  + t + type + positive.dum, data=datamod.
    orig)
fit.model.lm <- fitted(model.lm)
summary(model.lm)
#model without type
model.lm.notype <- lm(y ~ ly + lposdev + lnegdev  + t + positive.dum, data=datamod.
    orig)
fit.model.lm.notype <- fitted(model.lm.notype)
summary(model.lm.notype)
#dataset with fitted values for each model (OLS with types, semiparametric, OLS
    without types)
datamod.graph <- data.frame(datamod.orig,fit.model.lm,fit.model,fit.model.lm.notype)
#subset for each type
datamod.graph.fr <- subset(datamod.graph, type==1)
datamod.graph.no <- subset(datamod.graph, type==2)
datamod.graph.co <- subset(datamod.graph, type==3)
#mean value for each type and period
aggregate.mean.y.fr <- aggregate(datamod.graph.fr$y, list(datamod.graph.fr$t), "mean")
aggregate.mean.y.no <- aggregate(datamod.graph.no$y, list(datamod.graph.no$t), "mean")
aggregate.mean.y.co <- aggregate(datamod.graph.co$y, list(datamod.graph.co$t), "mean")
#mean of estimated values for type in the three models
aggregate.mean.fit.model.fr <- aggregate(datamod.graph.fr$fit.model, list(datamod.
    graph.fr$t), "mean")
aggregate.mean.fit.model.no <- aggregate(datamod.graph.no$fit.model, list(datamod.
    graph.no$t), "mean")
aggregate.mean.fit.model.co <- aggregate(datamod.graph.co$fit.model, list(datamod.
    graph.co$t), "mean")
```

```
aggregate.mean.fit.model.lm.fr <- aggregate(datamod.graph.fr$fit.model.lm, list(
    datamod.graph.fr$t), "mean")
aggregate.mean.fit.model.lm.no <- aggregate(datamod.graph.no$fit.model.lm, list(
    datamod.graph.no$t), "mean")
aggregate.mean.fit.model.lm.co <- aggregate(datamod.graph.co$fit.model.lm, list(
    datamod.graph.co$t), "mean")
aggregate.mean.fit.model.lm.notype.fr <- aggregate(datamod.graph.fr$fit.model.lm.
    notype, list(datamod.graph.fr$t), "mean")
aggregate.mean.fit.model.lm.notype.no <- aggregate(datamod.graph.no$fit.model.lm.
    notype, list(datamod.graph.no$t), "mean")
aggregate.mean.fit.model.lm.notype.co <- aggregate(datamod.graph.co$fit.model.lm.
    notype, list(datamod.graph.co$t), "mean")
#figure (3)
plot(aggregate.mean.y.fr, lwd=2, type="l",xlab="Period",ylab="Average␣Contribution",
    main="Fitted␣Values␣A1995",ylim = c(-3,67))
lines(aggregate.mean.fit.model.fr, lwd=2,lty=2, col="blue")
lines(aggregate.mean.fit.model.lm.fr, lwd=3,lty=2, col="red")
lines(aggregate.mean.y.no, lwd=2)
lines(aggregate.mean.fit.model.no, lwd=2,lty=2, col="blue")
lines(aggregate.mean.fit.model.lm.no, lwd=3,lty=2,col="red")
lines(aggregate.mean.y.co, lwd=2)
lines(aggregate.mean.fit.model.co, lwd=2,lty=2, col="blue")
lines(aggregate.mean.fit.model.lm.co, lwd=3,lty=2,col="red")
#figure (5)
plot(aggregate.mean.y.fr, lwd=2, type="l",xlab="Period",ylab="Average␣Contribution",
    main="Fitted␣Values␣A1995",ylim = c(-1,60))
lines(aggregate.mean.fit.model.fr, lwd=2,lty=2, col="blue")
lines(aggregate.mean.fit.model.lm.notype.fr, lwd=3,lty=2, col="red")
lines(aggregate.mean.y.no, lwd=2)
lines(aggregate.mean.fit.model.no, lwd=2,lty=2, col="blue")
lines(aggregate.mean.fit.model.lm.notype.no, lwd=3,lty=2,col="red")
lines(aggregate.mean.y.co, lwd=2)
lines(aggregate.mean.fit.model.co, lwd=2,lty=2, col="blue")
lines(aggregate.mean.fit.model.lm.notype.co, lwd=3,lty=2,col="red")
```

Bibliography

J. Aitchison and C. G. G. Aitken. Multivariate binary discrimination by the kernel method. *Biometrika*, 63(3):413–420, 1976.

J. Andreoni. Giving with impure altruism: Applications to charity and ricardian equivalence. *The Journal of Political Economy*, 97(6):1447–1458, December 1989.

J. Andreoni. Impure altruism and donations to public goods: A theory of warm-glow giving? *Economic Journal*, 100(401):464–77, June 1990.

J. Andreoni. Warm-glow versus cold-prickle: The effects of positive and negative framing on cooperation in experiments. *The Quarterly Journal of Economics*, 110 (1):1–21, 1995.

J. Andreoni, P. Brown, and L. Vesterlund. What makes an allocation fair? some experimental evidence. *Games and Economic Behavior*, (40):124, 2002.

E. Arbak and M.C. Villeval. Endogenous leadership selection and influence. Working Papers 0707, March 2008.

R. Ashley, S. Ball, and C. Eckel. Motives for giving: A reanalysis of two classic public goods experiments. *Southern Economic Journal*, 77(1):15–26, 2010.

N. Bardsley and P. Moffatt. The experimetrics of public goods: Inferring motivations from contributions. *Theory and Decision*, 62:161–193, 2007.

N. Bardsley and P. G. Moffatt. An econometric analysis of voluntary contributions. Technical report, 2000.

T. Bergstrom, L. Blume, and H. Varian. On the private provision of public goods. *Journal of Public Economics*, 29(1):25–49, February 1986.

M. Bernasconi. Free-riding and the psychology of choice or where does "warm-glow" come from? *Public Finance = Finances publiques*, 51(4):490–506, 1996.

R. Burlando and F. Guala. Heterogeneous agents in public goods experiments. *Experimental Economics*, 8(1):35–54, 2005.

A. C. Cameron and P. K. Trivedi. *Microeconometrics: Methods and Applications*. Cambridge University Press, 2005.

E. Cartwright and A. Patel. Imitation and the incentive to contribute early in a sequential public good game. *Journal of Public Economic Theory*, 12(4):691–708, 2010.

D. R. Cox. Regression Models and Life-Tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2):187–220, 1972.

J. C. Cox and R. L. Oaxaca. *Experimetrics: The Use of Market Experiments to Evaluate the Performance of Econometric Estimators*. Elsevier, 2008.

G. J. Van den Berg. Duration models: specification, identification and multiple durations. volume 5 of *Handbook of Econometrics*, pages 3381 – 3460. Elsevier, 2001.

C. Eckel, E. Fatas, and R. Wilson. Cooperation and status in organizations. *Journal of Public Economic Theory*, 12(4):737–762, 2010.

E. Fehr and K. M. Schmidt. A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics*, 114(3):817–868, August 1999.

E. Fehr and K. M. Schmidt. Theories of fairness and reciprocity - evidence and economic applications. Technical report, 2000.

E. Fehr, U. Fischbacher, Jürgen Schupp, Bernhard von Rosenbladt, and Gert Georg Wagner. A Nationwide Laboratory Examining Trust and Trustworthiness by Integrating Behavioural Experiments into Representative Surveys. *CEPR Discussion Papers*, April 2003.

U. Fischbacher. z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10(2):171–178, June 2007.

U. Fischbacher and S. Gächter. Social preferences, beliefs, and the dynamics of free riding in public goods experiments. *American Economic Review*, 100(1):541–56, 2010.

U. Fischbacher, S. Gächter, and E. Fehr. Are people conditionally cooperative? evidence from a public goods experiment. *Economics Letters*, 71(3):397–404, June 2001.

G. Fréchette. Session-effects in the laboratory. *Experimental Economics*, pages 1–14, forthcoming.

S. Gächter, B. Herrmann, and C. Thöni. Trust, voluntary cooperation, and socio-economic background: survey and experimental evidence. *Journal of Economic Behavior and Organization*, 55(4):505 – 531, 2004.

S. Gächter, D. Nosenzo, E. Renner, and M. Sefton. Sequential vs. simultaneous contributions to public goods: Experimental evidence. *Journal of Public Economics*, 94 (7-8):515 – 522, 2010a.

S. Gächter, D. Nosenzo, E. Renner, and M. Sefton. Who Makes a Good Leader? Social Preferences and Leading-by-Example. *Economic Inquiry*, 2010b. ISSN 1465-7295.

R. Galbiati, K. Schlag, and J. van der Weele. Can sanctions induce pessimism? an experiment. Technical report, 2009.

E. L. Glaeser, D. I. Laibson, J. A. Scheinkman, and C. L. Soutter. Measuring trust. *The Quarterly Journal of Economics*, 115(3):811 – 846, August 2000.

S. D. Gosling, P. J. Rentfrow, and W. B. Swann. A very brief measure of the big-five personality domains. *Journal of Research in Personality*, 37:504–528, 2003.

A. Gunnthorsdottir, D. Houser, and K. McCabe. Disposition, history and contributions in public goods experiments. *Journal of Economic Behavior & Organization*, 62(2): 304–315, 2007.

G. Harrison. House money effects in public good experiments: Comment. *Experimental Economics*, 10(4):429–437, 2007.

T. Hayfield and J. S. Racine. Nonparametric econometrics: The np package. *Journal of Statistical Software*, 27(5), 2008. URL `http://www.jstatsoft.org/v27/i05/`.

B. E. Hermalin. Toward an economic theory of leadership: Leading by example. *The American Economic Review*, 88(5):1188–1206, December 1998.

J. Hey. Why we should not be silent about noise. *Experimental Economics*, 8:325–345, 2005.

J. Hey. An experimental sandwich with econometrics as the bread [abstract]. In *2011 ESA European Conference Luxembourg*, page 21. Economic Science Association, September 2011.

D. Houser and R. Kurzban. Conditional cooperation and group dynamics: Experimental evidence from a sequential public goods game. 2003.

D. Kagel, J. H Levin. Independent private value auctions: Bidder behaviour in first-, second- and third-price auctions with varying numbers of bidders. *Economic Journal*, 103:868–879, 1993.

C. Keser. Cooperation in public goods experiments. Technical report, CIRANO, Montral, 2000.

C. Kumru and L. Vesterlund. The effect of status on charitable giving. *Journal of Public Economic Theory*, 12(4):709–735, 08 2010.

R. Kurzban and D. Houser. An experimental investigation of cooperative types in human groups: A complement to evolutionary theory and simulations. *Proceedings of the National Academy of Sciences*, 102(5):671–690, 2005.

M. V. Levati and T. Neugebauer. An Application of the English Clock Market Mechanism to Public Goods Games. *Experimental Economics*, 7:153–169, 2004.

Q. Li, D. Ouyang, and J. S. Racine. Categorical semiparametric varying-coefficient models. *Journal of Applied Econometrics*, pages 1099–1255, 2011.

C. Meidinger and M. C. Villeval. Leadership in teams: Signaling or reciprocating ? 2002.

E. A. Nadaraya. On estimating regression. *Theory of probability and its applications*, 9:141–142, 1964.

J. Potters, M. Sefton, and L. Vesterlund. Why announce leadership contributions? : An experimental study of the signaling and reciprocity hypotheses. Discussion Paper 100, Tilburg University, Center for Economic Research, 2001.

J. Potters, M. Sefton, and L. Vesterlund. After you–endogenous sequencing in voluntary contribution games. *Journal of Public Economics*, 89(8):1399–1419, August 2005.

J. Potters, M. Sefton, and L. Vesterlund. Leading-by-example and signaling in voluntary contribution games: an experimental study. *Economic Theory*, (33):169182, 2007.

R Development Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2011. URL `http://www.R-project.org/`.

M. Rabin. Incorporating fairness into game theory and economics. *American Economic Review*, 83(5):1281–1302, December 1993.

J. S. Racine. Nonparametric econometrics: A primer. *Foundations and Trends in Econometrics*, 3(1):1–88, 2008.

M. F. Rivas and M. Sutter. The dos and don'ts of leadership in sequential public goods experiments. Working Papers 2008-25, Faculty of Economics and Statistics, University of Innsbruck, December 2008.

R. Romano and H. Yildirim. Why charities announce donations: a positive perspective. *Journal of Public Economics*, 81:423–447, 2001.

P. Sapienza, A. Toldra, and L. Zingales. Understanding trust. Working Paper 13387, National Bureau of Economic Research, September 2007.

P. Schliffke. Inconsistent people? an experiment on the impact of social preferences across games. Working paper (available at ssrn: http://ssrn.com/abstract=1924864), 2011.

A. Tversky and D. Kahneman. Loss aversion in riskless choice: a reference-dependent model. *The Quarterly Journal of Economics*, page 10391061, November 1991.

H. Varian. Sequential contributions to public goods. *Journal of Public Economics*, 53 (2):165–186, February 1994.

S. Volk, C. Thoeni, and W. Ruigrok. Temporal stability and psychological foundations of cooperation preferences. 2011.

G. S. Watson. Smooth regression analysis. *Sankhya: The Indian Journal of Statistics (Series A)*, 26:359–372, 1964.

Conclusions to the Dissertation

This dissertation investigates public good games from three different, but related, perspectives. In the entire work, we place emphasis on cooperation and on leadership, both theoretically and experimentally. Our final goal is to provide a set of new frameworks and tools which can be used to understand motivations for contributing (or not) to the public good. Moreover, we want to put relevance on the interaction between heterogeneous subjects. On the one hand, we theoretically show that reference dependent agents motivated by others can increase the provision of public good. Observing contribution of other group members can produce imitation and larger cooperation also with heterogeneous interactions. On the other hand, we investigate public goods from an experimental point of view. The concept of leadership competition developed in the second work is an example of a device which can be used to select, among heterogeneous participants, those who are more cooperative. In addition, the aim of the latter chapter is to improve understanding of motives for giving by means of econometric tools new in the experimental analyses of public goods. It is clear that each essay has a completely different approach to the subject, however, the focus of the entire work goes in the same direction.

Chapter one has examined implications of reference dependent agents' contributions to public goods. We find that having as reference point others' contributions, let subjects free ride less than expected. In some cases, reference dependent agents can imitate others' actions. This result can be included in the growing literature in economics investigating motives for the conditional cooperative behaviour. Moreover, we investigate on heterogeneity of types. Although, in simultaneous games, a standard agent always takes advantage of a reference dependent agent, in sequential games, the former can in certain cases adopt a pro-social behaviour. In fact, when a standard leader is asked to give the example to a conditional cooperator, instead of free riding, she is cooperating to the public good to increase follower's contribution.

In chapter two, we find that competition for leadership not only selects more cooperative leaders than those randomly chosen, but we also find a positive link between the amount bid to compete and the cooperative behaviour. Moreover, the study highlights that higher willingness to pay for leadership is associated with trustworthiness. These results support the idea that bidding for the right of moving first is a strategic act. A subject who believes he can trust others might also believe that others will follow his leadership. However, the impact of high leader's contributions on followers is not always the desired one. In our experiment, the experience of the sequential repeated public good game on followers is of great importance. If subjects have experienced a lack of leadership in the first repeated game played, they are more prone to follow cooperative voluntary leaders. An implication of these findings is that a competitive mechanism can be used to group together cooperators to achieve better contribution performances.

The last part of the dissertation has emphasized that a better use of previous findings on types categorization and the application of semi-parametric models can be of central importance in the analysis of public good games. This chapter is more methodological, in the sense that it suggests to use econometric techniques unusual in experimental analyses. On the one hand, we proceed with a more accurate choice of variables to include in the parametric part of the model by means of non-parametric regressions. On the other hand, we show that a semi-parametric varying coefficient model can help researches at investigating new questions as the relevance of type, session and treatment effects.

Estratto per riassunto della tesi di dottorato

Studente:	Laura Concina
Matricola:	955404
Dottorato:	Economia
Ciclo:	XXIII

Titolo della tesi: Three Essays on Leadership and Cooperation in Public Good Games

Abstract: The issues explored in this thesis concerns public good games. We tackle the topic from different prospectives focusing on leadership and cooperation. Each chapter considers public good games from different angles. In the first chapter, we analyse reference dependent agents (that use a reference point to determine their choices) and standard agents who interact in simultaneous or in sequential public good situations. The second chapter consists of a sequential repeated public good experiment where subjects participate to a competitive mechanism to become leader in a group. Finally, in the third chapter, we study the implication of non- and semi-parametric methods in the re-analysis of two well-known public good experiments.

Estratto: In questa tesi, le questioni considerate riguardano giochi con beni pubblici. Affrontiamo l'argomento da diversi punti di vista focalizzando l'attenzione sulla leadership e sulla cooperazione. In ogni capitolo consideriamo i giochi di beni pubblici da prospettive diverse. Nel primo capitolo, analizziamo agenti reference dependent (che utilizzano un punto di riferimento per determinare le loro scelte) e agenti standard i quali interagiscono in situazione simultanee o sequenziali concernenti i beni pubblici. Il secondo capitolo consiste in un esperimento di beni pubblici ripetuto e sequenziale dove i soggetti partecipano ad un meccanismo competitivo per diventare leader in un gruppo. Infine, nel terzo capitolo, studiamo l'implicazione dei metodi non- e semi-parametrici nella rianalisi di due esperimenti di beni pubblici ben noti.