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COLLECTIVE ACTION: EXPERIMENTAL EVIDENCE

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Abstract. We conducted a laboratory experiment to test the comparative statics predictions of a new approach to collective action games based on the method of stability sets. We find robust support for the main theoretical predictions. As we increase the payoff of a successful collective action (accruing to all players and only to those that contribute) the share of cooperators increases. The experiment also suggests new avenues to refine the theory. We find that as the payoff of a successful collective action increases, subjects tend to upgrade their prior beliefs on the expected share of cooperators. Although this does not qualitatively affect comparative static predictions, using the reported distribution of beliefs rather than an ad hoc uniform distribution reduces the gap between theoretical predictions and observed outcomes. This finding also allows us to decompose the mechanism that leads to more cooperation in a ‘belief effect’ and a ‘range of cooperation effect’.

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1. Introduction

The rational-choice theory of collective action comprises two main paradigms. Olson's model regards collective action as a prisoners' dilemma with only one equilibrium (Olson, 1965), while Schelling's model conceives it as a tipping game with multiple equilibria (Schelling, 1978). Medina (2007) develops a unifying framework that covers both paradigms and produces novel comparative statics predictions about the effects of the parameters of the game on the probability of a successful collective action. In this paper we use a simple laboratory experiment to test some of these implications.

The unifying framework relies on the notion of stability sets to deal with multiple equilibria. The method of stability sets originally proposed by Harsanyi and Selten (1988) and further developed and applied to collective action problems by Medina (2007) is a very useful theoretical tool to study large games of collective action with multiple equilibria. The crucial advantage of the stability sets method is that it provides an assessment of the likelihood of different equilibria as a function of the payoffs of the game and the distribution of prior beliefs. Thus, the method generates clear predictions on the comparative statics of the probability of a successful collective action with respect to any variable that affects the payoffs of the collective action game. The focus of this paper is to test these comparative statics predictions using a controlled randomized laboratory experiment. In particular, we concentrate on testing a key theoretical prediction of the new framework. The probability of a successful collective action should increase with the benefit accrued to all players involved, including those who do not contribute if the collective action is successful, as well as with the extra benefit obtained by those who contribute.

In order to test these predictions we conducted a laboratory experiment at Universidad de San Andrés and Universidad Nacional de La Plata, in the province of Buenos Aires, Argentina. We recruited undergraduate and graduate students from any field of study and regardless of their knowledge of game theory and economics. We conducted 16 sessions (7 in Universidad de San Andrés and 9 in Universidad Nacional de La Plata) with 20 subjects each, totaling 320 participants. In each round of each session, subjects were randomly allocated into groups of 10 and asked to play a simple game. At the beginning each subject has one point and must decide to invest it or not. The probability that the investment is successful depends on the share of subjects that contribute their

point. If the investment is successful all players obtain B points and those that contributed obtains s extra points. Depending on the values of B and s , the game has one Nash equilibrium in which nobody contribute, or three Nash equilibria, one in which nobody contributes, another in which all contribute and a third one in which each player contributes with positive probability (the same for all players). We consider 4 possible treatments. Treatment 1 is the baseline free rider Olsonian model with one Nash equilibrium in which nobody contributes. In treatments 2 to 4 we gradually increase B and/or s inducing multiple equilibria. Furthermore, the probability of a successful collective action predicted by the stability sets method is 0 in treatment 1 and increases to 0.25, 0.50, and 0.75, in treatments 2, 3, and 4, respectively (assuming initial beliefs on the expected share of cooperators are uniformly distributed).

In general we find robust support for the main theoretical predictions of the stability sets method applied to collective action. As B and/or s are increased the share of cooperators and, hence, the probability of a successful collective action increases. Analogous results are obtained for the payoffs. The effects are statistically significant whether or not we include controls for individual characteristics, level of understanding of the game measure by the performance in a quiz before playing the rounds, fixed effects by session, if subjects are asked to report their prior beliefs on the expected share of cooperators, whether in the previous round the collective action was successful, and the number of players in the same group that decided to invest in the previous round.

We also find that on average there is more cooperation than predicted by the theory when theoretical predictions are obtained under different assumptions on the distribution of expected cooperators. As a benchmark, we first assume that subjects' prior beliefs on the share of cooperators has a uniform distribution on $[0,1]$ for all treatments. This can be considered a Laplacian assumption when no information on prior beliefs is available. Second, in some randomly selected sessions, before subjects start playing, we asked them to report their prior beliefs on the share of cooperators in each treatment. We find that subjects' prior beliefs are not uniformly distributed and vary among treatments. Specifically, as the benefit of cooperation increases, subjects upgrade their assessments on the expected share of cooperators. Using reported prior beliefs to compute the theoretical prediction on the probability of a successful collective

action reduces the gap between the model predictions and observed behavior. Still, in the data there is more cooperation than expected.

Finally, taking into account that prior beliefs vary among treatments, we decompose the total effect on the probability of a successful collective action in two analytically different effects. In particular, as the benefit of cooperation increases, subjects upgrade their assessments on the expected share of cooperators. We illustrate how to compute the change in the probability of a successful collective action attributed to belief upgrading (belief effect) and to an increase in the range of prior beliefs that induce cooperation (range of cooperation effect).

There are two branches of experimental literature connected with this work. First, there exists a vast literature on laboratory and field experiments with voluntary contribution games, public goods games and common pool resource games. Second, many experiments have been conducted employing games with multiple equilibria.

Experiments with Public Good Games. Many laboratory experiments have been conducted with *static public good games with only one Nash equilibrium*.² Most of these studies have found levels of cooperation that are significantly above theoretical prediction. Several mechanisms have been proposed to explain this phenomenon (kindness, altruism, conditional cooperation, reciprocity, repetition, etc.³). Although we also find more cooperation than predicted by the theory in most of our treatments and, in particular, in treatment 1 which only has one Nash equilibrium, the focus of our work is on testing the comparative static predictions of the stability set methods in the context of multiple equilibria. Closer to our work are the experiments with *static threshold public good games*.⁴ In contrast to standard public good games, threshold public good games have many efficient equilibria, resulting in a coordination problem.⁵ The collective action game we consider in this paper can have multiple equilibria, but never multiple efficient equilibria. More importantly, to the best of our knowledge, the predictions

² See among others Marwell and Ames (1981), Isaac, Walker, and Williams (1994), Andreoni (1995), Ostrom, (1998), Cherry et al (2005), Hichri (2005), Sefton, Shupp, and Walker (2007), and Baker, Williams and Walker (2009).

³ See for example Andreoni (1990), Anderson, Goeree and Holt (1998), and Fischbacher, Gächter and Fehr (2001).

⁴ An extensive number of studies using variations of the design of public good experiments have been synthesized in Davis and Holt (1993), Ledyard (1995), Offerman (1997) and Chaudhuri (2011).

⁵ See among others, Cadsby and Maynes (1998), Saunders (2010), and Banerjee et al. (2011).

provided by the stability sets method has never been tested in the context of a threshold public good game.⁶

Multiple equilibria and selection. There is also a large literature on experiments with multiple equilibria games and equilibrium selection.⁷ Most of this literature has been focused on testing different equilibrium selection criteria and learning rules. In some sense we adopt and test a different approach to multiple equilibria. Instead of focusing on identifying different criteria for equilibrium selection we use the stability sets method to obtain theoretical predictions on the probability of occurrence of each of the Nash equilibrium of the collective action game.⁸

The rest of the paper is organized as follows: Section 2 presents the theoretical framework. Section 3 describes the laboratory experiment. Section 4 shows that subjects understood the game they were playing and that the randomization was balanced. Section 5 presents descriptive statistics for the main variables. Section 6 contains the main results of the paper. Section 7 shows a decomposing of a change in the predicted share of cooperators in a ‘belief effect’ that captures the change in prior beliefs and a ‘range of cooperation effect’ that captures the change in the range of prior beliefs that induced cooperation. Finally, Section 8 concludes.

2. Theoretical Framework

In this section we present a collective action model based on Medina (2007). Then, we adapt the model for use in a laboratory experiment. We focus on the comparative static results of the model under two different assumptions on the distribution of prior beliefs

⁶ Not only laboratory, but also field experiments with collective action games have been conducted. See, for example, Schmitt (2000), Cardenas (2003), and Barr et al. (2012). However, none of them have tested the comparative statics predictions derived from the stability set method.

⁷ See among others Van Huyck et al. (1990) for coordination games; Van Huyck et al. (1991) for average opinion games; Battalio et al. (2001) and Golman and Page (2010) for stag-hunt games; Cason et al. (2004), Neugebauer et al. (2008) and Oprea et al. (2011) for hawk-dove games; and Haruvy and Stahl (2000) for symmetric normal-form games with multiple Nash equilibria. There is also a large literature on tests of equilibrium selection theories in multiple equilibrium games with repeated interactions. See, for example, Van Huyck et al. (1990, 1991) and Iwasaki et al. (2003).

⁸ Golman and Page (2010) use a related approach, to compare cultural learning versus belief-based learning. They consider a class of generalized stag-hunt games, in which agents can choose from among multiple potentially cooperative actions or can take a secure, self-interested action. Though the set of stable equilibria is identical under the two learning rules, the basins of attraction for the efficient equilibria are much larger for cultural learning. Moreover, as the stakes grow arbitrarily large, cultural learning always locates an efficient equilibrium while belief-based learning never does.

on the expected share of cooperators. First, we assume that the distribution of prior beliefs is fixed for the whole set of parameters of the collective action game. Second, we relax this assumption and we assume that a change in parameters that increases the set of beliefs that induce cooperation leads to a new distribution of prior beliefs that first order stochastically dominates the old one.

2.1. A Collective Action Model (based on Medina 2007). Consider a set of players $N > 2$. For each player the set of pure strategies is $A_i = \{C_i, D_i\}$, where $C_i = 1$ and $D_i = 0$ mean cooperate and defect, respectively. Let a_i indicates a generic element of A_i . The set of mixed strategies is $\Delta(A_i)$ and α_i indicates a generic element of $\Delta(A_i)$, where $\alpha_i = \Pr(C_i)$ and $(1 - \alpha_i) = \Pr(D_i)$. Let $A = \times_{i=1}^N A_i$ and a indicates a generic element of A . There are two possible outcomes: either the collective action is a success or it is a failure, indicated by S and F respectively. The probability that the collective action is successful is a function G of the proportion of players that cooperate. Formally $\Pr(S) = G(\gamma(a))$, where $\gamma(a) = \frac{1}{N} \#\{i: a_i = C_i\}$. Logically, $\Pr(F) = 1 - \Pr(S)$. G is assumed continuous, monotonically increasing (as the proportion of cooperators increases the probability of success also increases) and $G(0) = 0$. The payoff of each player u_i only depends on her action and the outcome of the collective action. Thus, u_i can be fully described with just four numbers: $u_i(C_i, S)$ (the payoff when i cooperates and the collective action is successful), $u_i(C_i, F)$ (the payoff when i cooperates and the collective action does not prosper), $u_i(D_i, S)$ (the payoff when i defects and the collective actions is successful), and $u_i(D_i, F)$ (the payoff when i defects and the collective action does not prosper). Moreover, we will assume that for all i it is always the case that $\min\{u_i(C_i, S), u_i(D_i, S)\} > u_i(D_i, F) > u_i(C_i, F)$.

Medina (2007) studies this game when $N \rightarrow \infty$, i.e., he focuses on a large game of collective action. We briefly summarize his results when all players have identical payoff functions. Any correlated equilibrium of a large game of collective action can be represented by an aggregate share γ_μ . Define $W = \frac{u_i(D_i, F) - u_i(C_i, F)}{u_i(D_i, F) - u_i(C_i, F) + u_i(C_i, S) - u_i(D_i, S)}$. If $W > 1$, then there exists a unique equilibrium where nobody cooperates ($\gamma_\mu = 0$). However, if $0 < W < 1$, the large game of collective action has three correlated

equilibria. One equilibrium in which all players cooperate ($\gamma_\mu = 1$), another in which nobody cooperates ($\gamma_\mu = 0$) and a third one with an intermediate level of cooperation given by $G(\gamma_\mu) = W$. In order to deal with multiplicity of equilibria, Medina (2007) extends the notion of stability sets originated in Harsanyi and Selten (1988). He uses a methodology known as the tracing procedure to assign to each equilibrium a set of initial belief conditions, which can be represented as a share of expected cooperators γ_η . Then, the stability set of an equilibrium is defined as the set γ_η assigned to it. The key result states that $\gamma_\eta < W$ belongs to the stability set of $\gamma_\mu = 0$, while $\gamma_\eta > W$ belongs to the stability set of $\gamma_\mu = 1$. As Medina (2007) emphasizes, the threshold value of γ_η that separates the stability set of $\gamma_\mu = 0$ from the one of $\gamma_\mu = 1$ is associated with the mixed strategy equilibrium implicitly given by $G(\gamma_\mu) = W$. In order to see this more clearly, assume that $G(\gamma) = \gamma$. Then, the stability set of $\gamma_\mu = 0$ is the set of all share of expected cooperators lower than the mixed strategy equilibrium share of cooperators $\gamma_\mu = W$, while the stability set of $\gamma_\mu = 1$ is the set of all share of expected cooperators higher than the mixed strategy equilibrium share of cooperators $\gamma_\mu = W$.

Finally, Medina (2007) shows how to use stability sets to compute the probability of cooperation. In order to do so, assume that the initial belief conditions γ_η is distributed with the CDF H . Then:

$$\Pr(\gamma_\mu = 1) = \Pr(\gamma_\eta > W) = 1 - \Pr(\gamma_\eta < W) = 1 - H(W)$$

This expression is very useful to deduce comparative static results. In particular note that as W increases the probability of cooperation decreases. To illustrate the results we have just summarized consider the following examples.

Olson's Model (Single Nash Equilibrium for N Large): The standard Olson's public good model of collective action is a special case of the above model when the payoffs are given by:

$$u_i(C_i, S) = B - c, u_i(D_i, S) = B, u_i(C_i, F) = -c, u_i(D_i, F) = 0 \quad (1)$$

where $c > 0$. For this model $W = \infty$. Hence, when $N \rightarrow \infty$, the unique equilibrium is $\gamma_\mu = 0$. More intuitively, in a large group ($N \rightarrow \infty$) there is a free rider problem (it is a

dominant strategy for every player to defeat) that impedes the members of the group to advance their common interests.

Schelling's Model (Multiple Nash Equilibria for N Large): Consider a simple modification of Olson's model.

$$u_i(C_i, S) = B - c + s, u_i(D_i, S) = B, u_i(C_i, F) = -c, u_i(D_i, F) = 0 \quad (2)$$

where $s > c > 0$. For this model $W = \frac{c}{s} < 1$. Hence, when $N \rightarrow \infty$, there are three Nash equilibria $\gamma_\mu = 0$, $\gamma_\mu = 1$, and γ_μ such that $G(\gamma_\mu) = \frac{c}{s}$. The stability set of $\gamma_\mu = 0$ is $\{\gamma_\eta: 0 \leq \gamma_\eta < W\}$, while the stability set of $\gamma_\mu = 1$ is $\{\gamma_\eta: W < \gamma_\eta \leq 1\}$. More intuitively, introducing an extra payoff $s > c$ obtained only by those who cooperate when the collective action is successful, transforms Olson's game into a coordination game with multiple equilibria. If everybody defeat, the best strategy is to defeat, but if everybody cooperates, the best strategy is to cooperate. Moreover, there is a threshold in the share of expected cooperators ($W = \frac{c}{s}$) such that players cooperate if and only if they expect more cooperators than this threshold. Finally, if the expected share of cooperators γ_η is distributed with the cumulative distribution function H we have:

$$\Pr(\gamma_\mu = 1) = 1 - H\left(\frac{c}{s}\right)$$

Hence, as c decreases and/or s increases the probability of cooperation increases. Thus, for Schelling's model the method of stability sets predicts as c decreases and/or s increases, it is more likely that players coordinate in the efficient equilibrium.

2.2. Laboratory Adaptation. In order to test the predictions derived by Medina (2007) using a laboratory experiment we need to make some adjustments to the model in the previous section. The most important change is that we must consider the case when N is finite. This implies that we need to compute a threshold for the number of players such that the game with finite N has the same set of equilibria as the large game. To do so, we focus on simple cases. In particular, we will assume $G(\gamma) = \gamma$ and study the Olson and Schelling models.

We begin by defining a Nash equilibrium of the game of collective action when N is finite. Let $S(k) = \{a: \sum_j a_j = k\}$ and $S(k, i) = \{a_{-1}: \sum_{j \neq i} a_j = k\}$. $S(k)$ is the set of pure strategy profiles in which k players cooperate, while $S(k, i)$ is the set of pure strategy

profiles of all players except i in which k players cooperate. Given a strategy profile $\alpha = (\alpha_i, \alpha_{-i})$, we can compute the probability that k players cooperate given that player i does not cooperate. It is given by $P(k, i) = \sum_{a_{-i} \in S(k, i)} \prod_{j \neq i} \alpha_j^{a_j} (1 - \alpha_j)^{1 - a_j}$.

Therefore, the payoff of player i associated with the strategy profile $\alpha = (\alpha_i, \alpha_{-i})$ is given by:

$$U_i(\alpha_i, \alpha_{-i}) = \alpha_i \sum_{k=0}^{N-1} \left[(u_i(C_i, S) - u_i(C_i, F)) G\left(\frac{k+1}{N}\right) + u_i(C_i, F) \right] P(k, i) \\ + (1 - \alpha_i) \sum_{k=0}^{N-1} \left[(u_i(D_i, S) - u_i(D_i, F)) G\left(\frac{k}{N}\right) + u_i(D_i, F) \right] P(k, i)$$

Definition 1 A Nash equilibrium of the collective action game with N finite is a strategy profile α such that for each i one of the following conditions holds:

$$U_i(1, \alpha_{-i}) \geq U_i(0, \alpha_{-i}) \text{ and } \alpha_i = 1 \\ U_i(1, \alpha_{-i}) \leq U_i(0, \alpha_{-i}) \text{ and } \alpha_i = 0 \\ U_i(1, \alpha_{-i}) = U_i(0, \alpha_{-i}) \text{ and } \alpha_i \in (0, 1)$$

The following proposition characterizes the set of Nash equilibria for the Olson and Schelling collective action games when N is finite and $G(\gamma) = \gamma$.

Proposition 1 Suppose that N is finite and $G(\gamma) = \gamma$. Then:

1. **Olson's Model:** Assume that u_i is given by (1). Then, if $N < \frac{B}{c}$, the unique Nash equilibrium is C_i for all i , while if $N > \frac{B}{c}$, the unique Nash equilibrium is D_i for all i .
2. **Schelling's Model:** Assume that u_i is given by (2). Then, if $N < \frac{B+s}{c}$, then C_i for all i is the unique Nash equilibrium, while if $N > \frac{B+s}{c}$, there are three Nash equilibria: C_i for all i , D_i for all i , and $\alpha_i = \hat{\alpha} = \frac{cN - B - s}{s(N-1)}$ for all i . Moreover, in the third Nash equilibrium the expected share of cooperators is $\mathbf{E}\left[\frac{k}{N}\right] = \hat{\alpha}$.

Proof: See Online Appendix 1. ■

Summing up, when $N > \frac{B}{c}$ the unique Nash equilibrium of Olson's model with N finite is D_i for all i , which coincides with the equilibrium of the Olson's model when $N \rightarrow \infty$. Similarly, when $N > \frac{B+s}{c}$, the set of Nash equilibria of the Schelling's model with N finite is: C_i for all i , D_i for all i , and $\alpha_i = \hat{\alpha} = \frac{cN-B-s}{s(N-1)}$ for all i , which is analogous to the set of Nash equilibria of the Schelling's model when $N \rightarrow \infty$. Note in particular that $\lim_{N \rightarrow \infty} \hat{\alpha} = \frac{c}{s}$, the share of cooperators in the mixed strategy equilibrium in the large game.

Suppose that as in the large game of collective action we use the mixed strategy equilibrium of the Schelling's model with N finite to compute the probability of occurrence of the two pure strategy equilibria. In particular, assume that the share of expected cooperators γ_η is distributed according to the cumulative distribution function H . Then:

$$\Pr (C_i \text{ for all } i) = 1 - H(\hat{\alpha})$$

Changes in $\hat{\alpha}$. The probability of cooperation increases with B and s and decreases with c . Formally:

$$\frac{\partial \Pr (C_i \text{ for all } i)}{\partial B} = -H'(\hat{\alpha}) \frac{\partial \hat{\alpha}}{\partial B} > 0$$

$$\frac{\partial \Pr (C_i \text{ for all } i)}{\partial s} = -H'(\hat{\alpha}) \frac{\partial \hat{\alpha}}{\partial s} > 0$$

$$\frac{\partial \Pr (C_i \text{ for all } i)}{\partial c} = -H'(\hat{\alpha}) \frac{\partial \hat{\alpha}}{\partial c} < 0$$

because $\frac{\partial \hat{\alpha}}{\partial B} < 0$, $\frac{\partial \hat{\alpha}}{\partial s} < 0$, and $\frac{\partial \hat{\alpha}}{\partial c} > 0$. For example if H is the uniform distribution we have $\Pr (C_i \text{ for all } i) = \frac{(s-c)N+B}{s(N-1)}$ and, hence $\frac{\partial \Pr (C_i \text{ for all } i)}{\partial B} = \frac{1}{s(N-1)} > 0$, $\frac{\partial \Pr (C_i \text{ for all } i)}{\partial s} = \frac{(N-1)cN+B}{[s(N-1)]^2} > 0$ and $\frac{\partial \Pr (C_i \text{ for all } i)}{\partial c} = \frac{-N}{s(N-1)} < 0$. Intuitively, as B and/or s increases or c decreases, the threshold in the share of expected cooperators that makes players indifferent between cooperating and defeating decreases. Cooperation becomes more attractive and, hence, players require a lower share of expected cooperators in order to

cooperate. Thus, given the distribution of the share of expected cooperators, the probability of cooperation increases.

Changes in H induced by changes in $\hat{\alpha}$. Suppose that H is not independent of $\hat{\alpha}$. In particular, assume that we have a family of distributions indexed by $\hat{\alpha}$. We write $H(\gamma_\eta, \hat{\alpha})$ to indicate the probability that the expected share of cooperators is less than or equal γ_η when $\alpha_i = \hat{\alpha} = \frac{cN-B-s}{s(N-1)}$ for all i is the mixed strategy Nash equilibrium of the collective action game. Furthermore, assume that $H(\gamma_\eta, \hat{\alpha}') \leq H(\gamma_\eta, \hat{\alpha})$ for all γ_η whenever $\hat{\alpha}' < \hat{\alpha}$, i.e., $H(\cdot, \hat{\alpha}')$ first order stochastically dominates $H(\cdot, \hat{\alpha})$ when $\hat{\alpha}'$ is lower than $\hat{\alpha}$. Then, we have:

$$\begin{aligned}\frac{\partial \Pr(C_i \text{ for all } i)}{\partial B} &= -[H_1(\hat{\alpha}, \hat{\alpha}) + H_2(\hat{\alpha}, \hat{\alpha})] \frac{\partial \hat{\alpha}}{\partial B} > 0 \\ \frac{\partial \Pr(C_i \text{ for all } i)}{\partial s} &= -[H_1(\hat{\alpha}, \hat{\alpha}) + H_2(\hat{\alpha}, \hat{\alpha})] \frac{\partial \hat{\alpha}}{\partial s} > 0 \\ \frac{\partial \Pr(C_i \text{ for all } i)}{\partial c} &= -[H_1(\hat{\alpha}, \hat{\alpha}) + H_2(\hat{\alpha}, \hat{\alpha})] \frac{\partial \hat{\alpha}}{\partial c} < 0\end{aligned}$$

H_1 (H_2) is the partial derivative with respect to the first (second) argument, $H_2 > 0$ because $H(\cdot, \hat{\alpha}')$ first order stochastically dominates $H(\cdot, \hat{\alpha})$ whenever $\hat{\alpha}' < \hat{\alpha}$, $\frac{\partial \hat{\alpha}}{\partial B} < 0$, $\frac{\partial \hat{\alpha}}{\partial s} < 0$, and $\frac{\partial \hat{\alpha}}{\partial c} > 0$. Note that if $H(\cdot, \hat{\alpha}')$ first order stochastically dominates $H(\cdot, \hat{\alpha})$ whenever $\hat{\alpha}' < \hat{\alpha}$, then the dependence of H on $\hat{\alpha}$ magnifies all the comparative statics derivatives, without affecting their signs. Intuitively, as B and/or s increases or c decreases, the probability of cooperation increases for two reasons. First, the threshold in the share of expected cooperators that makes players indifferent between cooperating and defeating decreases. Second, initial beliefs on the expected share of cooperators are updated in the sense that the new distribution gives at least as high a probability of an initial belief at least γ_η as does the old distribution.

3. The Laboratory Experiment

In this section we describe our laboratory experiment. First, we provide a general description of the experiment, including its monetary payoffs, number of sessions and rounds, matching procedure, and the instructions received by the subjects. Second, we

give a detailed description of the game subjects played. Finally, we summarize the treatments and compute the corresponding theoretical predicted outcomes.

3.1. General Description of the Experiment. The experiment was conducted between May and October 2014 at Universidad de San Andrés and Universidad Nacional de La Plata, located in the province of Buenos Aires, Argentina. We recruited undergraduate and graduate students from any field of study and regardless of how familiar they were with game theory and economic theory. We conducted 16 sessions with 20 subjects each, totaling 320 participants. Subjects were allowed to participate in only one session. Every session included four treatments, which avoids any selection problem among treatments. In each treatment, subjects were asked to play a collective action game. The experiment was programmed and conducted using z-Tree software (Fischbacher, 2007). Each session lasted approximately 50 minutes. The experiment proceeded as follows:

1. Allocation to Computer Terminals. Before each session began subjects were randomly assigned to computer terminals.

2. Instructions. After subjects were at their terminals, they received the instructions, which were also explained by the organizers. Subjects then had time to read the instructions on their own and ask questions. Online Appendix 2.1 and 2.2 contain an English translation from Spanish of the script we employed for instructions and the printed version, respectively. This was the last opportunity that subjects had to ask questions.

3. Prior Beliefs. At the beginning of the session, in randomly selected sessions, subjects were asked to report their assessments on how the game would develop.⁹ In particular, for each treatment, we asked each subject how many subjects from a group of 10 would contribute their point. This allowed us to obtain an empirical distribution of individual's prior beliefs on the expected share of cooperators for each treatment. The questions we asked can be found in Online Appendix 2.3.

4. Quiz. In order to check whether participants understood the rules of the game, we asked them to take a five-question quiz. The quiz was administered after we had given the instructions, but before the rounds began. Subjects were paid approximately US\$

⁹ For each session, all participants were asked to report their prior beliefs with probability 1/2. Thus, on average in half of the sessions subjects reported their prior beliefs.

0.25 per correct answer, but we never informed them which ones they had correctly answered. The quiz questions can be found in Online Appendix 2.4.

5. Rounds. After subjects had finished the quiz, they began playing rounds, during which they interacted solely through a computer network using z-Tree software. Subjects played 16 rounds of the collective action game. The first 4 rounds were for practice, and the last 12 rounds were for pay. At the end of each round, subjects received a summary of the decisions taken by both themselves and their partners, including payoffs per round, their own accumulated payoffs for paid rounds, and nature's decision. Online Appendix 2.5 contains a sample of the screens that subjects visualized.

6. Matching. In odd rounds 10 players were randomly matched and play treatment 1 (T_1) and the other 10 players play treatment 3 (T_3). In even rounds 10 players were randomly matched and played treatment 2 (T_2) and the other 10 players played treatment 1 (T_4). See below for a detailed explanation of the treatments.

7. Questionnaire. Finally, just before leaving the laboratory, all the subjects were asked to complete a questionnaire, which was designed to enable us to test the balance across experimental groups and to control for their characteristics in the econometric analysis. Online Appendix 2.6 contains the questionnaire.

8. Payments. All subjects were paid privately, in cash. After the experiment was completed, a password appeared on each subject's screen. The subjects then had to present this password to the person who was running the experiment in order to receive their payoffs. Subjects earned, on average, US\$ 11.80, which included a US\$ 2 show-up fee, US\$ 0.25 per correct answer on the quiz, and US\$ 0.25 for each point they received during the paid rounds of the experiment. All payments were made in Argentine currency; at the time, US\$ 1 was equivalent to AR\$ 8.¹⁰

3.2. Treatments and Predicted Outcomes. Once they finished the quiz, subjects directed their attention to their computers and proceeded to play the first round of the session. In each round subjects were randomly assigned to one of two groups, each consisting of 10 participants. At the beginning of the round they received one point and then they decided whether to keep it for them or invest it in a common fund. The

¹⁰ Since Argentina's rate of inflation was very high, we adjusted the conversion rate in order to maintain the purchasing power of the payments constant. Specifically, from May to July the conversion rate was 2 pesos per point, while from August to October it was 2.4 pesos per point.

probability that the investment in the common fund is successful equals the share of subjects that contribute their point in the group of 10. If the investment was successful all players obtained B points and those that contributed obtained s extra points.

The experiment consisted of four different treatments. The first treatment represents a scenario of no cooperation opportunities ($B = 1.25$ and $s = 0$); in other words, this is the free rider Olsonian model with one Nash equilibrium in which nobody contributes. In treatment 2 to 4 we gradually increase B and/or s inducing multiple equilibria. Specifically, the second treatment represents a scenario of low cooperation opportunities ($B = 1.25$ and $s = 1.25$); the third treatment a scenario of high (but not full) cooperation opportunities ($B = 3$ and $s = 1.25$); and the fourth, a scenario where the incentives to cooperate are the highest ($B = 3$ and $s = 1.75$).

Table 1 summarizes the relevant parameters of each treatment and indicates the predicted share of contributors and the predicted profit if there are 10 players in each group and assuming that prior beliefs are uniformly distributed in the interval $[0, 10]$.

Table 1: Treatments and Predicted Share of Cooperators with a Uniform Prior

Treatment	N	B	C	S	Predicted Share of Cooperators (Priors Uniformly Distributed) $\Pr(C_i \text{ for all } i)$	Predicted Payoff (Priors Uniformly Distributed)
	(1)	(2)	(3)	(4)	(5)	(6)
T_1	10	1.25	1	0.00	0.000	1.000
T_2	10	1.25	1	1.25	0.333	1.500
T_3	10	3.00	1	1.25	0.490	2.625
T_4	10	3.00	1	1.75	0.667	3.500

4. Understanding of the Game and Randomization Balance

In this section we show that subjects understood the game and the randomization was balanced. Table 2 shows that on average subjects understood the rules of the game. Indeed, 81% of them correctly answered question 1, 96% question 2, 80% question 3, and 90% question 4. It seems that subjects found that question 5 was more complicated and only 71% of them correctly answered it.

Table 3 shows the randomization balance across treatments. Note that the same group of 20 subjects were randomly matched to play T_1 and T_3 in odd rounds and T_2 and T_4 in even rounds. Thus, we check whether subjects with some particular

characteristics were more frequently allocated to some treatment. In the comparisons among the four treatments, all characteristics and levels of understanding of the game were perfectly balanced between T_1 and T_2 and between T_3 and T_4 . In some of the other cases, there is a slight imbalance in graduate studies and nationality, mostly at a 5% significance level. Nevertheless, it was only in less than 10% of the tests that we rejected the null hypothesis at the 10% and 5% levels of statistical significance. Moreover, the imbalance in nationality and graduate students is probably due to the fact that there were very few foreigners (96.8% of the subjects were Argentines) and very few graduates in the sample (93.46% of the subjects were undergraduate).

Table 2: Balance across Treatments (I)

	All Subjects			T_1		T_2		T_3		T_4	
	Number of Subjects	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Characteristics of Subjects											
Age	320	21.76	3.34	21.62	3.27	21.78	3.36	21.91	3.41	21.74	3.32
Nationality (Argentine=1)	320	0.95	0.21	0.95	0.22	0.96	0.19	0.96	0.20	0.94	0.23
Studied Game Theory (=1)	320	0.47	0.50	0.45	0.50	0.47	0.50	0.50	0.50	0.48	0.50
Gender (male=1)	320	0.51	0.50	0.51	0.50	0.51	0.50	0.51	0.50	0.51	0.50
Graduate Studies (=1)	320	0.06	0.23	0.05	0.21	0.07	0.25	0.07	0.25	0.04	0.20
Spanish Language (=1)	320	0.97	0.16	0.97	0.16	0.98	0.14	0.98	0.15	0.97	0.17
Understanding of the Experiment											
Answered correctly: question 1	320	0.81	0.39	0.82	0.39	0.82	0.39	0.80	0.40	0.80	0.40
Answered correctly: question 2	320	0.95	0.22	0.95	0.22	0.95	0.22	0.95	0.22	0.95	0.22
Answered correctly: question 3	320	0.78	0.42	0.77	0.42	0.77	0.42	0.78	0.41	0.78	0.41
Answered correctly: question 4	320	0.89	0.31	0.89	0.31	0.88	0.32	0.89	0.31	0.90	0.30
Answered correctly: question 5	320	0.70	0.46	0.71	0.46	0.71	0.46	0.69	0.46	0.70	0.46

Note: Mean is the sample mean and S.d. is the standard deviation for the corresponding variable in each line. Entries in columns (1)-(3) indicate the values for the complete sample, in columns (4)-(5) for the subjects that played treatment 1, in columns (6)-(7) for those that played treatment 2, in columns (8)-(9) for those that played treatment 3, and in columns (10)-(11) for those that played treatment 4.

Table 3: Balance across Treatments (II)

	T_1/T_2	T_1/T_3	T_1/T_4	T_2/T_3	T_2/T_4	T_3/T_4
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristics of Subjects						
Age	-0.164	-0.287*	-0.123	-0.123	0.041	0.164
Nationality (Argentine=1)	-0.017*	-0.012	0.004	0.005	0.021**	0.016*
Studied Game Theory (=1)	-0.021	-0.054**	-0.033	-0.033	-0.012	0.021
Gender (male=1)	0.004	0.003	-0.001	-0.001	-0.005	-0.004
Graduate Studies (=1)	-0.023**	-0.021**	0.002	0.002	0.025**	0.023**
Spanish Language (=1)	-0.007	-0.006	0.001	0.001	0.008	0.007
Understanding of the Experiment						
Answered correctly: question 1	0.001	0.017	0.016	0.016	0.015	-0.001
Answered correctly: question 2	0.002	0.002	0.000	0.000	-0.002	-0.002
Answered correctly: question 3	-0.002	-0.014	-0.012	-0.012	-0.010	0.002
Answered correctly: question 4	0.008	0.002	-0.005	-0.006	-0.013	-0.007
Answered correctly: question 5	0.002	0.014	0.012	0.012	0.010	-0.002

Note: Each entry indicates the mean difference between the two treatments in the column for the corresponding variable in each line. * indicates that the difference of means test is significant at 10%; ** significant at 5%; *** significant at 1%.

5. Descriptive Analysis

In this section we first present descriptive statistics of the decisions taken by the subjects (share of cooperators and payoffs by treatment). Then, we study the distribution of the initial beliefs on the share of expected cooperators subjects reported. Finally, we show that the average share of cooperators and average payoffs do not differ in the sessions in which subjects were asked to report their initial beliefs from those in which they were not.

5.1. Cooperation Decision. Table 4 shows descriptive statistics for the share of cooperators for all subjects (first panel), the subset of subjects who were asked to report their prior beliefs (second panel), and the subset of subjects who were not required to report their prior beliefs (third panel). For each treatment Table 4 indicates the total number of observations, sample mean and standard deviation for the share of cooperators, computed as the proportion of players out of the 10 participants who decided to invest their point in each round, treatment and session. In order to facilitate comparisons with theoretical predictions we also report the model prediction for the share of cooperators assuming that expected share of cooperators is uniformly

distributed and the model prediction for the share of cooperators when the empirical distribution for the expected share of cooperators is employed. As predicted by the model, the average share of cooperators increases from T_j to T_{j+1} for $j = 1, 2, 3$. However, for all treatments it exceeds the one predicted by the model either when priors beliefs are assumed uniformly distributed or when the empirical distribution of prior beliefs is employed. Note, however, that in the former the gap between the observed average share of cooperators and theoretical predictions significantly decreases for T_2 , T_3 , and T_4 (by definition the distribution of prior beliefs does not affect theoretical predictions for T_1).

Table 4: Share of Cooperators (Descriptive Statistics)

	Number of Observations	Model Prediction (Prior Beliefs Uniformly Distributed)	Model Prediction (Prior Beliefs Empirically Distributed)	Mean	S.d.
All Subjects					
T_1	96	0.000	0.000	0.072	0.085
T_2	96	0.333	0.340	0.590	0.238
T_3	96	0.490	0.599	0.811	0.181
T_4	96	0.667	0.910	0.927	0.103
Subjects who Reported Priors					
T_1	48	0.000	0.000	0.058	0.084
T_2	48	0.333	0.340	0.604	0.273
T_3	48	0.490	0.599	0.806	0.184
T_4	48	0.667	0.910	0.925	0.101
Subjects who Did Not Report Priors					
T_1	48	0.000	0.000	0.085	0.084
T_2	48	0.333	0.340	0.575	0.197
T_3	48	0.490	0.599	0.817	0.179
T_4	48	0.667	0.910	0.929	0.104

Notes: For each treatment there are 6 observations per session of the share of cooperators. Because we conducted 16 sessions, the total number of observation per treatment is 96.

5.2. Payoffs. Table 5 shows the sample mean and standard deviation of payoffs per treatment. As predicted by the model, the payoff is on average higher in T_{j+1} than in T_j for $j = 1, 2, 3$ (4.327 points in T_4 , 3.294 points in T_3 , 1.710 points in T_2 and 1.019 points in T_1), but in all treatments the average payoff exceeds the one predicted by the model when prior beliefs are assumed to be uniformly distributed. Specifically, in T_1 all

players earned, on average, 1.9% more than what the model predicted, in T_2 14% more, in T_3 25.5% more, and in T_4 23.9% more. The average payoff is very close to theoretical predictions when the empirical distribution of prior beliefs is employed. Specifically, in T_1 all players earned, on average, 1.9% more than what the model predicted, in T_2 13.3% more, in T_3 12% more and in T_4 1.9% less than predicted by the model.

Table 5: Payoffs (Descriptive Statistics)

	Number of Observations	Model Prediction (Prior Beliefs Uniformly Distributed)	Model Prediction (Prior Beliefs Empirically Distributed)	Mean	S.d.
All Subjects					
T_1	960	1.000	1.000	1.019	0.396
T_2	960	1.500	1.509	1.710	0.966
T_3	960	2.625	2.948	3.294	1.663
T_4	960	3.500	4.414	4.327	1.266
Subjects who Reported Priors					
T_1	480	1.000	1.000	1.046	0.401
T_2	480	1.500	1.509	1.888	0.879
T_3	480	2.625	2.948	3.342	1.625
T_4	480	3.500	4.414	4.426	1.095
Subjects who Did Not Report Priors					
T_1	480	1.000	1.000	0.993	0.390
T_2	480	1.500	1.509	1.532	1.017
T_3	480	2.625	2.948	3.246	1.701
T_4	480	3.500	4.414	4.228	1.410

Notes: For the payoffs in each treatment there are 60 observations per session. Because we conducted 16 sessions, the total number of observation per treatment is 960.

5.3. Prior Beliefs. For each treatment Table 6 show descriptive statistics for the prior beliefs on the expected share of cooperators reported by the subjects.¹¹ Note that prior beliefs differ across treatments.¹² In particular, the expected share of cooperators is higher in T_{j+1} than in T_j for $j = 1, 2, 3$.

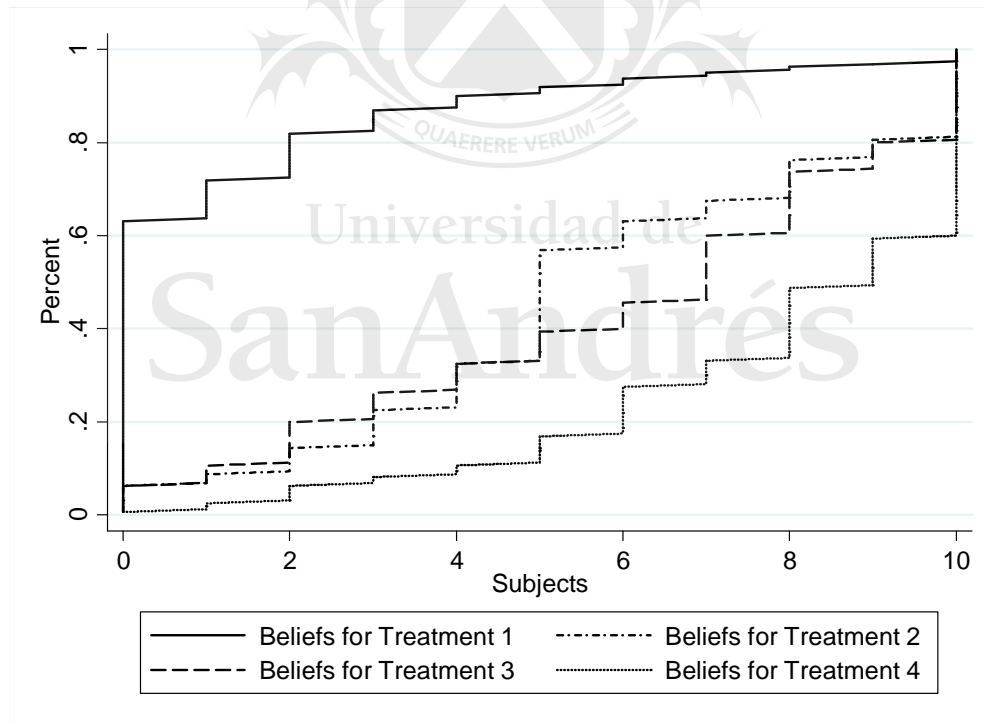
¹¹ Recall that in randomly selected sessions and, before they start playing, subjects were asked to report their assessments on the expected number of cooperators.

¹² In line with this finding, Palfrey and Rosenthal (1991) show that subjects' prior beliefs of the probability that a subject contributes is biased up with respect to an unbiased Bayes-Nash equilibrium. In the same vein, Orbell and Dawes (1991) argue that cooperators expect significantly more cooperation

Table 6: Prior Belief (Descriptive Statistics)

	Mean	Median	S.d.	Min	Max
Prior Beliefs for T_1	1.325	0	2.423	0	10
Prior Beliefs for T_2	5.713	5	2.993	0	10
Prior Beliefs for T_3	6.056	7	3.191	0	10
Prior Beliefs for T_4	7.863	9	2.509	0	10

Figure 1 shows the cumulative distribution function of prior beliefs on the expected share of cooperators across treatments. The horizontal axis measures the number of participants in a group of 10 that subjects believe will contribute their point in the each treatment. Let H^j denote the cumulative distribution function of prior beliefs for treatment $j = 1, 2, 3, 4$. Note that H^4 first order stochastically dominates H^3 and H^2 and H^3 and H^2 first order stochastically dominates H^1 .

Figure 1: Cumulative Distribution Function of Prior Beliefs

In order to formally compare the distribution functions of prior beliefs we conduct the nonparametric Wilcoxon matched-pair sing-rank test. The null hypothesis of this test is that the distribution of the prior belief for T_j (denoted as H^j) is equal to the

than do defectors.

distribution of the prior belief for T_k (denoted as H^k) and the alternative hypothesis is that H^j is shifted to the left of H^k . Table 7 shows the results of this test. Note that in all cases, except T_2 vs T_3 , the null hypothesis of equal distributions can be rejected at 0.17% of significance.¹³ Therefore, there is evidence that distribution of prior beliefs for T_1 is shifted to the left of T_2 , T_3 , T_4 , while the distribution of prior beliefs for T_2 is shifted to the left of T_4 as well as the distribution of prior beliefs for T_3 is shifted to the left of T_4 .

Table 7: Comparison of Distribution of Priors Beliefs

	Statistic	$p - value$
$H_0: H^1 = H^2$	385.0	0.000
$H_0: H^1 = H^3$	239.5	0.000
$H_0: H^1 = H^4$	173.5	0.000
$H_0: H^2 = H^3$	3247.0	0.098
$H_0: H^2 = H^4$	1447.5	0.000
$H_0: H^3 = H^4$	648.0	0.000

5.4. Reporting Prior Beliefs. The first panel (second panel) in Table 8 shows the results of the difference in means test of the share of cooperators (payoffs) between the sample composed by participants who reported their prior beliefs and those who did not report them. Standard errors are clustered by session. Note that it is not possible to reject the null hypothesis of equal means in the share of cooperators (payoff) in all treatments.

Table 8: Difference in Means Test (Share of Cooperators and Payoffs)

	$t - value$	$Pr(T > t)$
<i>Share of Cooperators</i>		
All Subjects	-0.06	0.950
T_1	-1.08	0.299
T_2	0.29	0.778
T_3	-0.13	0.896
T_4	-0.1	0.921
<i>Payoff</i>		
All Subjects	0.80	0.436
T_1	1.19	0.251
T_2	1.48	0.159

¹³ We use the Bonferroni correction to counteract the problem of d multiple simultaneously comparisons. The Bonferroni correction tests each individual hypothesis at a significance level of α/d . Therefore, if we test six hypotheses with a desired $\alpha = 0.01$, then the Bonferroni correction would test each individual hypothesis at $\alpha = 0.05/6 = 0.0017$.

T_3	0.20	0.848
T_4	0.53	0.604

Summing up, the descriptive analysis shows that: (i) The average share of cooperators increases from T_j to T_{j+1} for $j = 1, 2, 3$. (ii) The average share of cooperators in all treatments exceeds the one predicted by the model, but the gap is smaller once we compute theoretical predictions using reported prior beliefs rather than the uniform distribution. (iii) Payoffs are on average higher in T_{j+1} than in T_j for $j = 1, 2, 3$. (iv) Average payoffs exceed model predictions when prior beliefs are assumed to be uniformly distributed, but they are closer to theoretical predictions when the empirical distribution of prior beliefs is employed. (v) Prior beliefs differ across treatments. The average expected share of cooperators is higher in T_{j+1} than in T_j for $j = 1, 2, 3$. H^4 first order stochastically dominates H^3 and H^2 and H^3 and H^2 first order stochastically dominate H^1 . (vi) The average share of cooperators and the average payoffs are not statistically different in the sessions in which subjects were asked to report their prior beliefs and in sessions in which they were not.

6. Results

In this section we formally test the main comparative static results using regression analysis. Note that in the context of perfect experimental data, where no controls are needed for identification of the causal effects of interest, the analysis is completely non-parametric as it only entails to compare the mean outcome differences across treatment groups and inference also could be made non-parametric. In all cases robust and clustered standard errors are computed by session.

6.1. Cooperation Decision. In order to formally test the hypothesis that the probability of a successful collective action increases with B and S we use the following regression model:

$$Coop_{ips} = \alpha + \beta_1 DT + \beta_2 X_{ips} + \sum_{s=1}^{16} \beta_3 D\theta_s + \varepsilon_{ips}$$

where i indexes subjects, $p = 1, 2, 3, \dots, 12$ indexes experimental rounds, and $s = 1, 2, 3, \dots, 16$ indexes experimental sessions. $Coop_{ips}$ is the dependent variable. It indicates whether player i decided to invest his/her point in each session, round and treatment ($Coop_{ips} = 1$ if he contributes and $Coop_{ips} = 0$ if he does not). The explanatory variable of interest is DT , a dummy variable indicating treatment status (T_j for $j = 2, 3, 4$). In some specifications we also include control variables. We control for individual characteristics X_{ips} (gender, age, nationality, university, whether the subject has ever taken a course in game theory, whether the subject is a graduate student and the subjects' level of understanding of the game as measured by the his/her answers to the quiz questions) and for fixed effects by session ($D\theta_s$). According to our theoretical predictions, we should expect $\hat{\beta}_1$ to be positive when comparing T_{j+1} with T_j for $j = 1, 2, 3$.

Columns (1), (3) and (5) in Table 9 summarize the results of regressing $Coop_{ipr}$ in each of the treatments separately without controls for all the subjects in the sample, those subjects who reported their beliefs and those who did not report them, respectively. Robust standard errors are reported in regular brackets and standard errors clustered by session are shown in square brackets. In keeping with the model's prediction, the probability of cooperators in each treatment is significantly different (at a confidence level of 99% in most cases) and the coefficient associated with treatment is positive in all cases. Indeed, note that when we compare the probability of cooperation in T_4 vs. T_1 the coefficient associated is the highest.¹⁴ Thus, as predicted by the model, a higher value of B and/or s leads to a higher share of cooperators and, hence, to a higher probability of cooperation. Column (2), (4) and (6) in Table 9 report the results once the entire set of controls is included. As the table shows, the results do not change in any meaningful way.

¹⁴ Recall that T_1 represents a scenario of no cooperation opportunities ($B = 1.25$ and $s = 0$); in other words, this is the free rider Olsonian model with one Nash equilibrium in which nobody contributes, while T_4 represents a scenario where the incentives to cooperate are the highest ($B = 3$ and $s = 1.75$).

Table 9: Cooperation Decision (Regression Analysis)

	All Sample		Subjects Who Reported Prior Beliefs		Subjects Who Did Not Report Prior Beliefs	
	(1)	(2)	(3)	(4)	(5)	(6)
$T_1 = 0$ vs $T_2 = 1$						
$\hat{\beta}_1$	0.518*** (0.018) [0.044]	0.518*** (0.018) [0.044]	0.546*** (0.025) [0.080]	0.548*** (0.024) [0.079]	0.490*** (0.026) [0.040]	0.489*** (0.026) [0.042]
R-squared	0.303	0.315	0.336	0.362	0.271	0.288
$T_1 = 0$ vs $T_3 = 1$						
$\hat{\beta}_1$	0.740*** (0.015) [0.039]	0.742*** (0.015) [0.039]	0.748*** (0.021) [0.053]	0.743*** (0.021) [0.052]	0.731*** (0.022) [0.061]	0.736*** (0.021) [0.063]
R-squared	0.555	0.562	0.570	0.596	0.540	0.557
$T_1 = 0$ vs $T_4 = 1$						
$\hat{\beta}_1$	0.855*** (0.012) [0.025]	0.855*** (0.012) [0.025]	0.867*** (0.016) [0.037]	0.864*** (0.016) [0.037]	0.844*** (0.017) [0.037]	0.847*** (0.017) [0.037]
R-squared	0.731	0.734	0.751	0.762	0.712	0.715
$T_2 = 0$ vs $T_3 = 1$						
$\hat{\beta}_1$	0.222*** (0.020) [0.045]	0.222*** (0.020) [0.046]	0.202** (0.029) [0.065]	0.197** (0.028) [0.064]	0.242*** (0.029) [0.066]	0.244*** (0.028) [0.066]
R-squared	0.059	0.077	0.049	0.115	0.069	0.100
$T_2 = 0$ vs $T_4 = 1$						
$\hat{\beta}_1$	0.338*** (0.018) [0.050]	0.336*** (0.018) [0.050]	0.321*** (0.025) [0.087]	0.321*** (0.025) [0.084]	0.354*** (0.025) [0.054]	0.352*** (0.025) [0.053]
R-squared	0.155	0.169	0.143	0.193	0.168	0.183
$T_3 = 0$ vs $T_4 = 1$						
$\hat{\beta}_1$	0.116*** (0.015) [0.025]	0.115*** (0.015) [0.025]	0.119** (0.022) [0.034]	0.124** (0.021) [0.037]	0.113** (0.021) [0.037]	0.111** (0.021) [0.036]
R-squared	0.029	0.043	0.030	0.108	0.029	0.093
Controls	No	Yes	No	Yes	No	Yes
Number of Observations	1920	1920	960	960	960	960

Note: * significant at 10%; ** significant at 5%; *** significant at 1% (using standard errors clustered by session). Robust standard errors in regular bracket and standard errors clustered by sessions in square brackets. Controls: (i) Individual characteristics X_{ipr} : gender, age, nationality, university, whether s/he has ever taken a course in game theory, whether s/he is a graduate or not; (ii) Level of understanding of the game measured by the subject's correct answers to the quiz questions; and (iii) Fixed effects by session $D\theta_r$.

6.2. Payoffs. In order to formally test the hypothesis that the average payoff of a player increases with B and/or s we use the following regression model:

$$Payoff_{ips} = \gamma + \delta_1 DT + \delta_2 X_{ips} + \sum_{s=1}^{11} \delta_3 D\theta_s + \varepsilon_{ips}$$

The dependent variable $Payoff_{ips}$ is payoff denominated in points obtained by subject i in round p and session s . The regressors are the same as in the model for the share of cooperators. The explanatory variable of interest is DT , a dummy variable indicating treatment status (T_j for $j = 2, 3, 4$). According to our theoretical predictions, we should expect $\hat{\delta}_1$ to be positive when comparing T_{j+1} with T_j for $j = 1, 2, 3$.

Table 10: Payoffs (Regression Analysis)

	All Sample		Subjects Who Reported Prior Beliefs		Subjects Who Did Not Report Prior Beliefs	
	(1)	(2)	(3)	(4)	(5)	(6)
$T_1 = 0$ vs $T_2 = 1$						
$\hat{\delta}_1$	0.691*** (0.034) [0.120]	0.691*** (0.033) [0.120]	0.842*** (0.044) [0.155]	0.847*** (0.044) [0.153]	0.539** (0.050) [0.177]	0.539** (0.049) [0.175]
R-squared	0.180	0.206	0.276	0.297	0.109	0.164
$T_1 = 0$ vs $T_3 = 1$						
$\hat{\delta}_1$	2.275*** (0.055) [0.251]	2.268*** (0.055) [0.255]	2.296*** (0.076) [0.419]	2.282*** (0.074) [0.422]	2.253*** (0.080) [0.306]	2.245*** (0.080) [0.315]
R-squared	0.470	0.482	0.485	0.534	0.455	0.475
$T_1 = 0$ vs $T_4 = 1$						
$\hat{\delta}_1$	3.308*** (0.043) [0.187]	3.309*** (0.042) [0.186]	3.380*** (0.053) [0.303]	3.379*** (0.051) [0.304]	3.235*** (0.067) [0.237]	3.242*** (0.065) [0.236]
R-squared	0.757	0.771	0.808	0.826	0.710	0.726
$T_2 = 0$ vs $T_3 = 1$						
$\hat{\delta}_1$	1.584*** (0.062) [0.240]	1.583*** (0.061) [0.241]	1.454*** (0.084) [0.345]	1.445*** (0.080) [0.348]	1.714*** (0.090) [0.352]	1.713*** (0.091) [0.351]
R-squared	0.253	0.284	0.237	0.333	0.273	0.286
$T_2 = 0$ vs $T_4 = 1$						
$\hat{\delta}_1$	2.617*** (0.051) [0.204]	2.619*** (0.050) [0.203]	2.538*** (0.064) [0.271]	2.542*** (0.060) [0.264]	2.696*** (0.079) [0.322]	2.706*** (0.080) [0.322]
R-squared	0.575	0.606	0.621	0.674	0.546	0.558
$T_3 = 0$ vs $T_4 = 1$						
$\hat{\delta}_1$	1.033*** (0.067) [0.203]	1.036*** (0.066) [0.207]	1.084*** (0.089) [0.257]	1.099*** (0.081) [0.257]	0.982** (0.101) [0.331]	0.979** (0.099) [0.331]
R-squared	0.109	0.174	0.133	0.307	0.090	0.147
Controls	No	Yes	No	Yes	No	Yes
Number of Observations	1920	1920	960	960	960	960

Note: * significant at 10%; ** significant at 5%; *** significant at 1% (using standard errors clustered by session). Robust standard errors in regular brackets and standard errors clustered by sessions in square brackets. Controls: see note in Table 9.

Table 10 summarizes the results. The corresponding clustered standard errors are shown in square brackets. As predicted by our model, the payoff in each treatment is significantly different and the coefficient associated with each treatment is positive. Hence, operating under the parameters in T_{j+1} rather than in T_j for $j = 1, 2, 3$ induces a positive and statistically significant effect on the payoff.

As a robustness check, we repeated the estimations in Tables 9 and 10 introducing two new explanatory variables, namely DR and I . DR is a dummy variable that indicates whether in the previous round the collective action was successful or not, and I is the number of players in the same group that decided to invest in the previous round. These variables capture the possibility that subjects decide to cooperate in a treatment just because either in the previous round the collective action was successful or the number of investors was relatively high. The results do not change in any meaningful way. The coefficients associated with each treatment are still significantly different and positive

6.3. Prior Beliefs. In order to test if asking subjects to reveal their prior beliefs biased their decisions during the game, we performed a test of equality of the regression coefficients. Table 11 panel 1 summarizes the results of a test whose null hypothesis is that the effects of each treatment on the share of cooperators are the same for the subjects who reported their prior beliefs (β_1) and those who did not report them (β_1^*). Standard errors are clustered by sessions. In all cases the null hypothesis of equal coefficients cannot be rejected. Analogously, Table 11 panel 2 summarizes the results of a test whose null hypothesis is that effects of each treatment on the payoffs are identical for subjects who reported their prior beliefs (δ_1) and subjects who did not report them (δ_1^*). Standard errors are clustered by sessions. In all cases the null hypothesis of equal coefficients cannot be rejected¹⁵. Thus, it is possible to confirm that asking subjects to reveal their prior beliefs before the game started did not introduce any bias in their decisions during the game.

¹⁵ The results of the tests hold when we add controls in the regression of the share of cooperators (and payoffs) in each of the treatments. We do not report the corresponding F statistics for sake of simplicity.

Table 11: Reporting versus Not Reporting Prior Beliefs
(Difference in Average Treatment Effects)

	$F(1,7)$	$Pr > F$
<i>Share of Cooperators ($H_0: \beta_1 = \beta_1^*$)</i>		
$T_1 = 0$ vs $T_2 = 1$	1.99	0.201
$T_1 = 0$ vs $T_3 = 1$	0.08	0.791
$T_1 = 0$ vs $T_4 = 1$	0.39	0.551
$T_2 = 0$ vs $T_3 = 1$	0.36	0.568
$T_2 = 0$ vs $T_4 = 1$	0.38	0.558
$T_3 = 0$ vs $T_4 = 1$	0.03	0.871
<i>Profit ($H_0: \delta_1 = \delta_1^*$)</i>		
$T_1 = 0$ vs $T_2 = 1$	2.92	0.131
$T_1 = 0$ vs $T_3 = 1$	0.02	0.892
$T_1 = 0$ vs $T_4 = 1$	0.37	0.56
$T_2 = 0$ vs $T_3 = 1$	0.55	0.484
$T_2 = 0$ vs $T_4 = 1$	0.24	0.639
$T_3 = 0$ vs $T_4 = 1$	0.09	0.767

Note: $F(1,7)$ indicates the F statistic with 1 degree of freedom in the numerator and 7 degrees of freedom in the denominator. $Pr > F$ indicates the significance level of each test.

Summing up, the regression analysis produces robust support for the main comparative statics theoretical predictions. Increases in B and/or s have a significant positive effect on the share of cooperators and, hence, on the probability of a successful collective action, as well as on the payoffs of the players.¹⁶ The effects are statistically significant whether or not we include controls for individual characteristics, level of understanding of the game and fixed effects by session. Asking subjects to report their prior beliefs before the game started did not introduce any significant effect on their decisions. Introducing into the control variables whether in the previous round the collective action was successful or not and the number of players in the same group that decided to invest in the previous round does not change the results in any meaningful way.

7. Exploring a Decomposition of Changes in $\hat{\alpha}$

In this section we decompose a change in $\hat{\alpha}$ in a 'belief effect' and a 'range of cooperation effect'. The idea is to learn about the mechanism that induce more cooperation when $\hat{\alpha}$ decreases.

¹⁶ More cooperative prior beliefs with the same B and/or s (i.e., within a treatment), however, do not induce more cooperation.

Table 12 shows the average share of cooperators as well as the predicted share of cooperators for each treatment, both using a uniform distribution for all treatments, and the empirical distribution of prior beliefs for each treatment.

Table 12: Model Prediction of the Share of Cooperators

	Empirical Probability of Cooperation	Model Prediction (Prior Beliefs Uniformly Distributed)	Model Prediction (Prior Beliefs (Empirically Distributed for T1)	Model Prediction (Prior Beliefs (Empirically Distributed for T2)	Model Prediction (Prior Beliefs (Empirically Distributed for T3)	Model Prediction (Prior Beliefs (Empirically Distributed for T4)
T_1	0.072	0.000	0.000	0.000	0.000	0.000
T_2	0.590	0.333	0.054	0.340	0.448	0.687
T_3	0.811	0.490	0.079	0.424	0.599	0.819
T_4	0.927	0.667	0.121	0.742	0.717	0.910

As we showed in section 5.3., the distribution of prior beliefs is not the same in every treatment. As the benefit of cooperation augments, subjects tend to increase their assessments on the share of cooperators. The effect of these changes in theoretical predictions can be observed in Table 12. Except for T_1 , for which theoretical predictions do not change with the distribution of prior beliefs, for the rest of the treatments, the predicted share of cooperators increases as we employ the prior beliefs associated with a treatment with a lower $\hat{\alpha}$.¹⁷ For example, for T_2 if we use the priors of T_1 the predicted share of cooperators is 0.054, it is 0.340 with the priors of T_2 , 0.448 with the priors of T_3 and 0.687 with the priors of T_4 . This suggests that we can decompose a change in the predicted share of cooperators in two analytically different effects. A ‘belief effect’ that captures the change in prior beliefs and a ‘range of cooperation effect’ that captures the change in the range of prior beliefs that induced cooperation.

More technically, the distribution of the expected share of cooperators H is not independent of $\hat{\alpha}$. Although this does not affect the sign of the comparative statics of the model, it is interesting to explore what fraction of the change in predicted share of cooperators can be attributed to a change in prior beliefs, and what fraction to a change in the range of prior beliefs that induce cooperation. Thus, we are now interested in

¹⁷ Recall from section 2.2 that a lower $\hat{\alpha}$ is associated with higher B and/or s ; in other words $\frac{\partial \hat{\alpha}}{\partial B} < 0$, $\frac{\partial \hat{\alpha}}{\partial s} < 0$.

distinguishing the mechanism through which a decrease in $\hat{\alpha}$ leads to a higher probability of a successful collective action.

Let H^j denote the cumulative distribution function of the expected share of cooperators for treatment T_j and Pr^j the probability of a successful collective action in treatment T_j . Then

$$Pr(T_j) - Pr(T_k) = H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_j) = [H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_k)] + [H^j(\hat{\alpha}_k) - H^j(\hat{\alpha}_j)]$$

Define $\Delta^I(T_k \rightarrow T_j) = \frac{H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_k)}{H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_j)}$. $\Delta^I(T_k \rightarrow T_j)$ is the proportion of the change attributed to a change in the distribution of expected cooperators. Naturally, $1 - \Delta^I(T_k \rightarrow T_j)$ is the proportion of the change in the probability of a successful collective action due to a change in the range prior beliefs that induce cooperation. Table 13 shows the decomposition of a change in the predicted share of cooperators into the belief and range of cooperation effects.

Table 13: Decomposition of Changes in $\hat{\alpha}$: I

	$H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_j)$	$\Delta^I(T_k \rightarrow T_j)$	$1 - \Delta^I(T_k \rightarrow T_j)$
$T_1 \rightarrow T_2$	0.340	0.00	1.00
$T_1 \rightarrow T_3$	0.599	0.00	1.00
$T_1 \rightarrow T_4$	0.910	0.00	1.00
$T_2 \rightarrow T_3$	0.259	0.42	0.58
$T_2 \rightarrow T_4$	0.570	0.61	0.49
$T_3 \rightarrow T_4$	0.311	0.71	0.29

To some extent, this decomposition is arbitrary, in the sense that we can vary first H and then $\hat{\alpha}$ or the other way round. Formally, we can also decompose $Pr(T_j) - Pr(T_k)$ as follows:

$$Pr(T_j) - Pr(T_k) = H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_j) = [H^k(\hat{\alpha}_k) - H^k(\hat{\alpha}_j)] + [H^k(\hat{\alpha}_j) - H^j(\hat{\alpha}_j)]$$

and define the proportion of the change attributed to a change in the distribution of expected cooperators by $\Delta^{II}(T_k \rightarrow T_j) = \frac{H^k(\hat{\alpha}_j) - H^j(\hat{\alpha}_j)}{H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_j)}$. Table 13 shows this decomposition.

Table 14: Decomposition of Changes in $\hat{\alpha}$: II

	$H^k(\hat{\alpha}_k) - H^j(\hat{\alpha}_j)$	$\Delta^H(T_k \rightarrow T_j)$	$1 - \Delta^H(T_k \rightarrow T_j)$
$T_1 \rightarrow T_2$	0.340	0.159	0.841
$T_1 \rightarrow T_3$	0.599	0.132	0.868
$T_1 \rightarrow T_4$	0.910	0.133	0.867
$T_2 \rightarrow T_3$	0.259	0.324	0.676
$T_2 \rightarrow T_4$	0.570	0.705	0.295
$T_3 \rightarrow T_4$	0.311	0.379	0.621

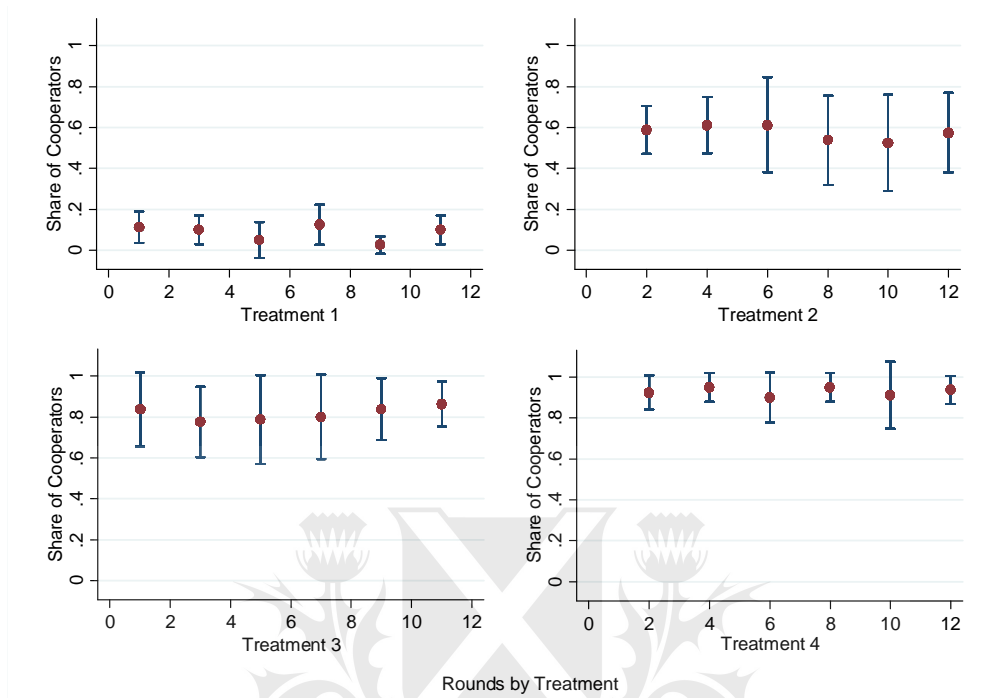
Except when we move from T_3 to T_4 both decompositions assign similar proportions to both effects. When the starting point is T_1 both decompositions assign a very high proportion of the change to the range of cooperation effect (at least 84%). When the starting point is T_2 and we move to T_3 (T_4), the first and second decomposition attribute 42% and 32.4% (61% and 70%) of the change to a switch in beliefs, respectively.

A potential concern about these decompositions is that they rely on the empirical distribution of prior beliefs reported by the subjects before the rounds began. It is possible that these prior beliefs evolve as the experiment proceeds and subjects learn from previous rounds. However, we do not observe any temporal pattern in the data. For example, Figure 2 shows the mean share of cooperators per round across treatments for all the subjects in the sample (first panel), the subjects who reported their beliefs (second panel), and subjects who were not required to report their beliefs (third panel). The mean share of cooperators fluctuates without any clear pattern.

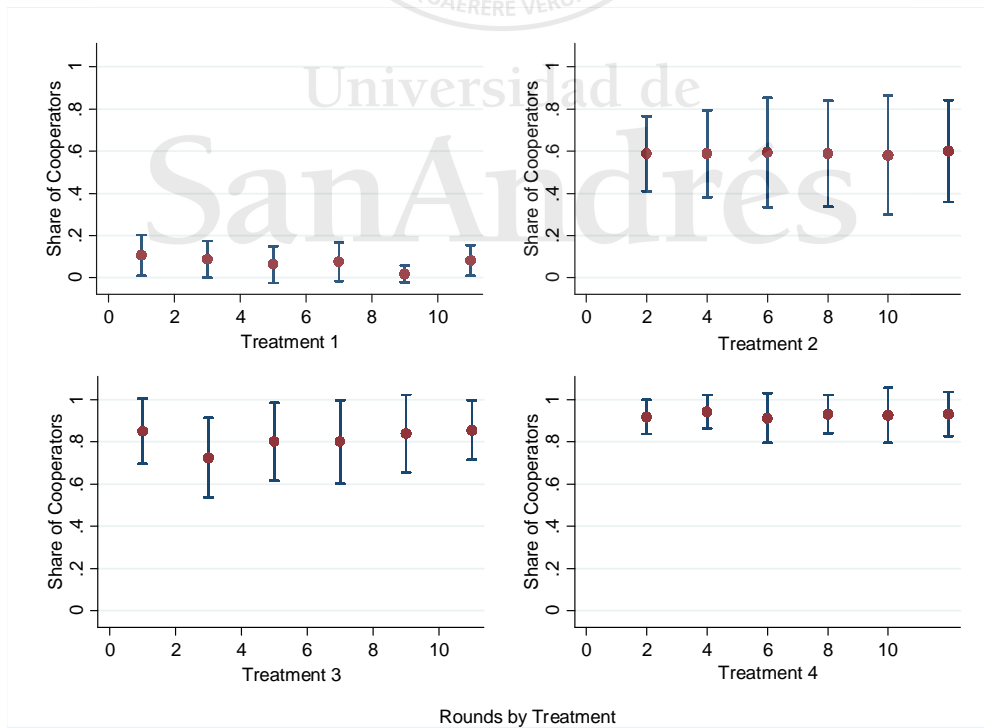
Summing up, there are two mechanisms operating simultaneously that induce a higher predicted share of cooperators. First, as $\hat{\alpha}$ decreases subjects increase their assessments on the expected share of cooperators (the belief effect). Second, given any distribution of the assessments, a lower $\hat{\alpha}$ increases the assessments that induce subjects to contribute (the range of cooperation effect). Except when we move from T_3 to T_4 both decompositions lead to similar results.

Figure 2: Share of Cooperators

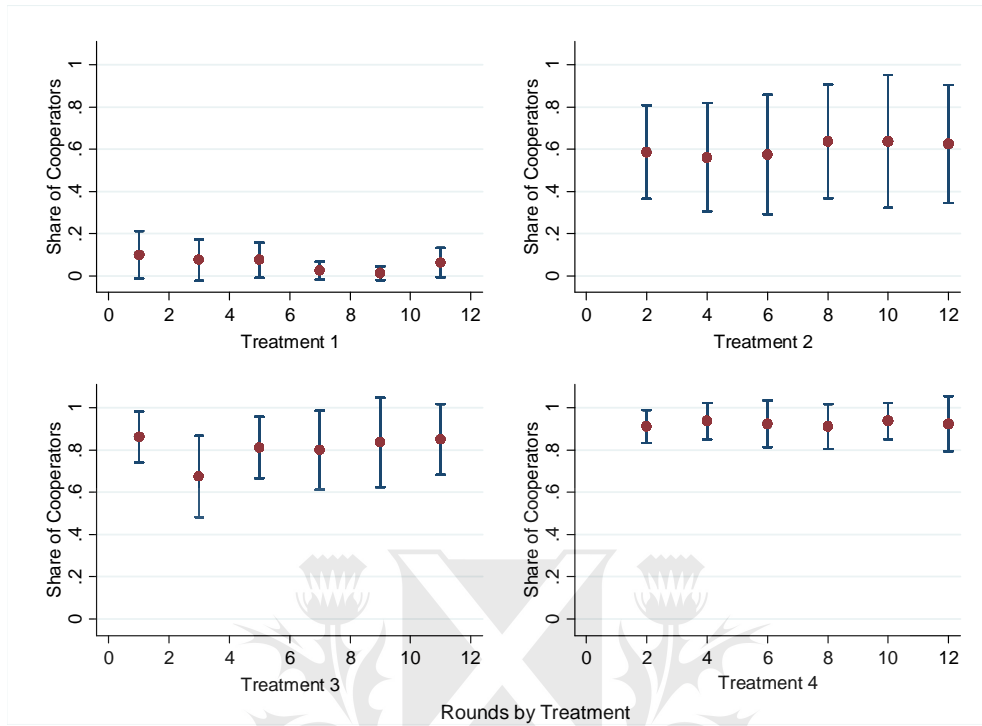
All Subjects



Subjects Who Reported Prior Beliefs



Subjects Who Did Not Report Prior Beliefs



Note: Red diamonds denote average value of the variable per treatment/round within treatment. Blue bars indicate one standard deviation from the mean, calculated in standard form.

8. Conclusions

We have conducted a laboratory experiment in order to test the main implications of the stability sets methods applied to collective action games. We have found strong support for the key comparative static predictions of the theory. As we increase the payoff of a successful collective action accruing to all players (B) and only to those that contribute (s) the share of cooperators and payoffs increase. As in many other laboratory experiments we found that subjects have a more cooperative behavior than predicted by the theory. But we have also shown that the gap between theoretical predictions and observed behavior significantly decrease when we refine the theory allowing for a distribution of prior beliefs that varies with the parameters of the model. Overall, the experiment indicates that the stability sets method could be a very useful tool to study games with multiple equilibria.

The experiment also suggests a refinement of the theory. We found that as the range of cooperation increases subjects upgrade their prior beliefs on the expected share of cooperators. We have shown that if the new distribution of prior beliefs first order stochastically dominates the old one, the signs of the comparative static derivatives are not affected, but all effects are magnified. For practical purposes, this refinement improves the power of the theory to predict the observed behavior. Analytically, it allows us to decompose the mechanism that produces cooperation in a 'belief effect' and a 'range of cooperation effect'. Using our experiment, we have computed these decompositions and found evidence of the presence of both effects. This might have interesting implications for political economy. For example, a policy change that affects the payoffs of a collect action game can produce a bigger change in the likelihood of cooperation than the one we would expect if we do not take into account that agents update the distribution of prior beliefs.

Understanding the logic of collective action is crucial in political economy. Explicit or implicitly, collective action is in the core of many models of political influence, political representation and coalition formation. A new approach to collective action can produce significant impacts on the way we attack those topics. To illustrate this point, consider the following examples. In the standard common agency model of lobbying (Dixit, Grossman and Helpman, 1997 and Grossman and Helpman 2000) groups are assumed either organized (meaning the group have solved the collective action problem and they can lobby to advance their common interest) or unorganized. The stability sets approach can provide an assessment of the likelihood that a group is organized as a function of structural parameters that characterize the collective action problem of group organization. Thus, combining the common agency model of lobbying with the stability sets approach to collective action we can build a more accurate theory of political influence. Another interesting example is Acemoglu and Robinson's model of political regime determination (Acemoglu and Robinson 2006). This is a dynamic model in which in every period with some exogenous probability a group with no de-jure political power can get organized and obtain de-facto political power. Again, combining this model with the stability sets approach to collective action can help us improving the theory of political transitions.

References

- Anderson, S., Goeree, J., and Holt, C. (1998). A theoretical analysis of altruism and decision error in public goods games. *Journal of Public Economics*, vol. 70, pp. 297–323.
- Andreoni, J. (1990). Impure altruism and donations to public goods: a theory of warm-glow giving. *Economic Journal*, vol. 100, pp. 464–477.
- Andreoni, J. (1995). Cooperation in public-goods experiments: kindness or confusion? *The American Economic Review*, vol. 85(4), pp. 891-904
- Baker II, R. J., Walker, J. M., and Williams, A. W. (2009). Matching contributions and the voluntary provision of a pure public good: Experimental evidence. *Journal of Economic Behavior & Organization*, vol. 70(1), pp. 122-134.
- Banerjee, P., Chakravarty, S., and Mohanty, R. (2012). Equilibrium play and learning in a stochastic public goods experiment. *Journal of Quantitative Economics*, vol. 10(2), pp. 60-77.
- Barr, A., Mugisha, F., Serneels, P., and Zeitlin, A. (2012). Information and collective action in the community monitoring of schools: field and lab experimental evidence from Uganda. Unpublished manuscript.
- Battalio, R., Samuelson, L., and Van Huyck, J. (2001). Optimization incentives and coordination failure in laboratory stag hunt games. *Econometrica*, vol. 69(3), pp. 749-764.
- Cadsby, C. B., and Maynes, E. (1999). Voluntary provision of threshold public goods with continuous contributions: experimental evidence. *Journal of Public Economics*, vol. 71(1), pp. 53-73.
- Cardenas, J. C. (2009). Experiments in Environment and Development. Working Paper. Bogota: Universidad de los Andes, Economics Faculty.
- Cason, T. N., Saijo, T., Yamato, T., and Yokotani, K. (2004). Non-excludable public good experiments. *Games and Economic Behavior*, vol. 49(1), pp. 81-102.
- Chaudhuri, A. (2011). Sustaining cooperation in laboratory public goods experiments: a

selective survey of the literature. *Experimental Economics*, vol. 14(1), pp. 47-83.

Cherry, T. L., Kroll, S., and Shogren, J. F. (2005). The impact of endowment heterogeneity and origin on public good contributions: evidence from the lab. *Journal of Economic Behavior & Organization*, vol. 57(3), pp. 357-365.

Davis, D. D., and Holt, C. A. (1993). *Experimental economics*. Princeton, NJ: Princeton University Press.

Dixit, Avinash, Gene Grossman and Elhanan Helpman, 1997, Common Agency and Coordination: General Theory and Application to Government Policy Making, *Journal of Political Economy*, 105, 752-769.

Fischbacher, U. (2007). Z-tree 2.1: Zurich Toolbox for Readymade Economic Experiment, *Experimental Economics*, vol. 10, pp. 171-178.

Fischbacher, U., Gächter, S., and Fehr, E. (2001). Are people conditionally cooperative? Evidence from a public goods experiment. *Economics Letters*, vol. 71(3), pp. 397-404.

Golman, R., and Page, S. E. (2010). Individual and cultural learning in stag hunt games with multiple actions. *Journal of Economic Behavior & Organization*, vol. 73(3), pp. 359-376.

Grossman, Gene, and Elhanan Helpman (2000). *Special Interest Politics*. Cambridge, Mass. And London UK: MIT Press.

Harsanyi, J., and Selten, R. (1988). *A General Theory of Equilibrium Selection in Games*. Cambridge, Mass.: MIT Press.

Haruvy, E., and Stahl, D. (2000). Initial play and equilibrium selection in symmetric normal-form games. *Working Paper*.

Hichri, W. (2005). The individual behaviour in a public goods game. *International Review on Public and Nonprofit Marketing*, vol. 2(1), pp. 59-71.

Isaac, R. M., Walker, J. M., & Williams, A. W. (1994). Group size and the voluntary provision of public goods: experimental evidence utilizing large groups. *Journal of Public Economics*, vol. 54(1), pp. 1-36.

- Iwasaki, A., Imura, S., Oda, S. H., and Ueda, K. (2003). Accidental Initial Outcomes and Learning in Experimental Games with Multiple Equilibria. International ESA meeting, Pittsburgh, PA USA, pp. 19-22.
- Ledyard, J. (1995). Public Goods: A Survey of Experimental Research, in: *Handbook of Experimental Economics*, ed. by John Kagel and Alvin Roth, Princeton, NJ: Princeton University Press.
- Marwell, G. and R. Ames (1981). Economists free ride, does anyone else? Experiments on the provision of public goods, IV. *Journal of Public Economics*, vol. 15, pp. 295–310.
- Medina, L. F. (2007). *A Unified Theory of Collective Action and Social Change*. Ann Arbor: University of Michigan Press.
- Neugebauer, T., Poulsen, A., and Schram, A. (2008). Fairness and reciprocity in the hawk–dove game. *Journal of Economic Behavior & Organization*, vol. 66(2), pp. 243-250.
- Offerman, T. (1997). *Beliefs and Decision Rules in Public Goods Games: Theory and Experiments*. Dordrecht, the Netherlands: Kluwer Academic Publishers.
- Olson, M. (1965). *The Logic of Collective Action: Public Goods and the Theory of Groups*. Cambridge, MA: Harvard University Press.
- Oprea, R., Henwood, K., and Friedman, D. (2011). Separating the Hawks from the Doves: Evidence from continuous time laboratory games. *Journal of Economic Theory*, vol. 146(6), pp. 2206-2225.
- Orbell, J. and R. M. Dawes (1991). A 'cognitive miser' theory of cooperators' advantage. *American Political Science Review*, vol. 85, pp. 515–528.
- Ostrom, E. (1998). A Behavioral Approach to the Rational-Choice Theory of Collective Action. *American Political Science Review*, vol. 92(1), pp. 1-22.
- Palfrey, T. and H. Rosenthal (1991). Testing game-theoretic models of free riding: New evidence on probability bias and learning. In T. Palfrey (Ed.), *Laboratory Research in Political Economy*, pp. 239–268. Ann Arbor, MI: University of Michigan Press.
- Saunders, D. K. (2012). Coordinating Contributions to a Threshold Public Good in a Noisy

Best Response Framework. *Mimeo*.

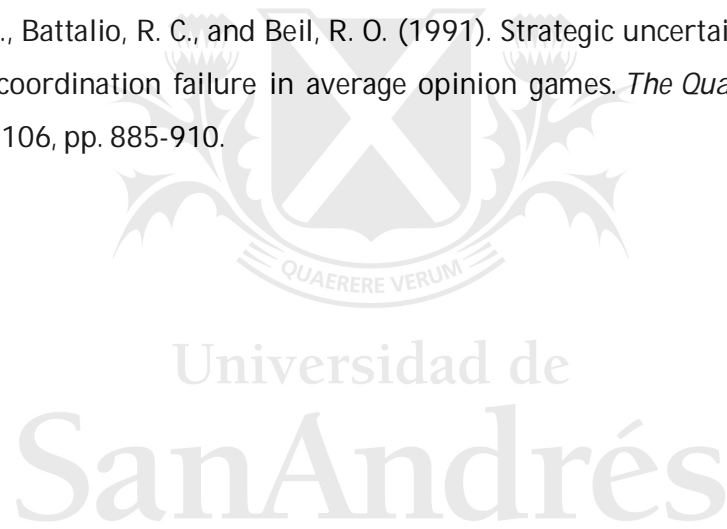
Schelling, T. C. (1978). *Micromotives and Macrobehavior*. New York: W. W. Norton.

Schmitt, P., Swope, K., and Walker, J. (2000). Collective action with incomplete commitment: Experimental evidence. *Southern Economic Journal*, vol. 66, pp. 829-854.

Sefton, M., Shupp, R., & Walker, J. M. (2007). The effect of rewards and sanctions in provision of public goods. *Economic Inquiry*, vol. 45(4), pp. 671-690.

Van Huyck, J. B., Battalio, R. C., and Beil, R. O. (1990). Tacit coordination games, strategic uncertainty, and coordination failure. *The American Economic Review*, vol. 80, pp. 234-248.

Van Huyck, J. B., Battalio, R. C., and Beil, R. O. (1991). Strategic uncertainty, equilibrium selection, and coordination failure in average opinion games. *The Quarterly Journal of Economics*, vol. 106, pp. 885-910.



Online Appendix 1: Proposition 1

In this Appendix we present the proof of proposition 1.

Olson's Model: The expected payoff of player's i is given by:

$$\begin{aligned}
 U_i(\alpha_i, \alpha_{-i}) &= \alpha_i \sum_{k=0}^{N-1} \left[B\left(\frac{k+1}{N}\right) - c \right] P(k, i) + (1 - \alpha_{-i}) \sum_{k=0}^{N-1} B\left(\frac{k}{N}\right) - P(k, i) \\
 &= \sum_{k=0}^{N-1} \left[\alpha_i B\left(\frac{k+1}{N}\right) - \alpha_i c + (1 - \alpha_{-i}) B\left(\frac{k}{N}\right) \right] P(k, i) \\
 &= \alpha_i \left(\frac{B}{N} - c \right) \sum_{k=0}^{N-1} P(k, i) + \sum_{k=0}^{N-1} B\left(\frac{k}{N}\right) P(k, i)
 \end{aligned}$$

The second term does not depend on α_i . When $\frac{B}{N} > c$ ($\frac{B}{N} < c$) the first term adopts a maximum for $\alpha_i = 1$ ($\alpha_i = 0$). Therefore, if $N < \frac{B}{c}$ the unique Nash equilibrium is C_i for all i , while if $N > \frac{B}{c}$ the unique Nash equilibrium is D_i for all i . ■

Schelling's Model: A Nash equilibrium is a profile α such that for all $i = 1, \dots, N$ one of the following conditions must hold:

$$\sum_{k=0}^{N-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) \geq 0 \quad \text{and} \quad \alpha_i = 1 \tag{3}$$

$$\sum_{k=0}^{N-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) \leq 0 \quad \text{and} \quad \alpha_i = 0 \tag{4}$$

$$\sum_{k=0}^{N-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) = 0 \quad \text{and} \quad \alpha_i \in (0, 1) \tag{5}$$

where $P(k, i) = \sum_{a_{-i} \in S(k, i)} \prod_{j \neq i} \alpha_j^{a_j} (1 - \alpha_j)^{1-a_j}$ and $S(k, i) = \{a_{-i} : \sum_{j \neq i} a_j = k\}$.

Lemma 1: If $\alpha_i = 1$ and $\alpha_h = 0$, then $P(k, i) = P(k+1, h)$. **Proof:** Since players' strategies are not correlated, the probability that $k+1$ players cooperate when we exclude h is equal to the probability that k players cooperate when we exclude i and h times the probability that i cooperates plus the probability that $k+1$ players cooperate excluding i and h times the probability that i does not cooperate. Formally,

$$\begin{aligned}
P(k+1, h) &= \Pr\left(\sum_{j \neq h} a_j = k+1\right) \\
&= \Pr\left(\sum_{j \neq i, h} a_j = k\right) \alpha_i + \Pr\left(\sum_{j \neq i, h} a_j = k+1\right) (1 - \alpha_i) \\
&= \Pr\left(\sum_{j \neq i, h} a_j = k\right) \\
&= \Pr\left(\sum_{j \neq i} a_j = k-1\right) \alpha_h + \Pr\left(\sum_{j \neq i} a_j = k\right) (1 - \alpha_h) \\
&= \Pr\left(\sum_{j \neq i} a_j = k\right)
\end{aligned}$$

The third line uses $\alpha_i = 1$. Again, since strategies are not correlated, the probability that k players cooperate when we exclude i and h is equal to the probability that $k-1$ players cooperate when we exclude i times the probability that h cooperates plus the probability that k players cooperate excluding i and h times the probability that h does not cooperate. This justifies the fourth line. Finally, the last line is due to $\alpha_h = 0$. ■

Lemma 2: If $\alpha_i > \alpha_h$ and $k \geq 1$, then $P(k, h) \geq P(k, i)$. Moreover, if there exist $k-1$ players different from i, h for which $\alpha_j > 0$, then $P(k, h) > P(k, i)$. **Proof:** Using the same argument we employed in Lemma 1 we have:

$$\begin{aligned}
P(k, i) &= \Pr\left(\sum_{j \neq i} a_j = k\right) \\
&= \Pr\left(\sum_{j \neq i, h} a_j = k-1\right) \alpha_h + \Pr\left(\sum_{j \neq i, h} a_j = k\right) (1 - \alpha_h)
\end{aligned}$$

Analogously,

$$\begin{aligned}
P(k, h) &= \Pr\left(\sum_{j \neq h} a_j = k\right) \\
&= \Pr\left(\sum_{j \neq i, h} a_j = k-1\right) \alpha_i + \Pr\left(\sum_{j \neq i, h} a_j = k\right) (1 - \alpha_i)
\end{aligned}$$

Therefore,

$$P(k, h) - P(k, i) = (\alpha_i - \alpha_h) \left[\Pr\left(\sum_{j \neq i, h} a_j = k-1\right) - \Pr\left(\sum_{j \neq i, h} a_j = k\right) \right]$$

$$= (\alpha_i - \alpha_h) \Pr \left(\sum_{j \neq i, h} a_j = k - 1 \right) [1 - \alpha_i(1 - \alpha_h) - \alpha_h(1 - \alpha_i)]$$

$$= (\alpha_i - \alpha_h) \Pr \left(\sum_{j \neq i, h} a_j = k - 1 \right) [(1 - \alpha_i)(1 - \alpha_h) + \alpha_i \alpha_h]$$

The second line uses the fact that $\Pr(\sum_{j \neq i, h} a_j = k) = \Pr(\sum_{j \neq i, h} a_j = k - 1)[\alpha_i(1 - \alpha_h) + \alpha_h(1 - \alpha_i)]$. By assumption $(\alpha_i - \alpha_h) > 0$, $\Pr(\sum_{j \neq i, h} a_j = k - 1) \geq 0$, and $1 - (1 - \alpha_i)(1 - \alpha_h) + \alpha_i \alpha_h > 0$. Moreover, if there exist $k - 1$ players different from i, h for which $\alpha_j > 0$, then $\Pr(\sum_{j \neq i, h} a_j = k - 1) > 0$ and, hence, $P(k, h) > P(k, i)$.

■

Case 1 (all cooperate): Suppose that $\alpha_i = 1$ for $i = 1, \dots, N$. Then, $P(k, i) \neq 0$ if and only if $k = N - 1$ and, hence, the Nash conditions become:

$$\left[\frac{B + sN}{N} - c \right] P(N - 1, i) \geq 0$$

Since $s > c$ these conditions always hold. Therefore, $\alpha_i = 1$ for $i = 1, \dots, N$ is always a Nash equilibrium.

Case 2 (nobody cooperate): Suppose that $\alpha_i = 0$ for $i = 1, \dots, N$. Then, $P(k, i) \neq 0$ if and only if $k = 0$ and, hence, the Nash conditions become:

$$\left[\frac{B + s}{N} - c \right] P(0, i) \leq 0$$

These conditions hold if and only if $N \geq \frac{B+s}{c}$. Thus, if $N \geq \frac{B+s}{c}$, $\alpha_i = 0$ for all i is a Nash equilibrium.

Case 3 (some cooperate, some do not cooperate and some play a mixed strategy):

Suppose that there is a Nash equilibrium in which n_1 players are cooperating, n_2 are playing a complete mixed strategy and $N - n_1 - n_2$ are not cooperating. Without loss of generality assume that $\alpha_i = 1$ for $i = 1, \dots, n_1$, $\alpha_i \in (0, 1)$ for $i = n_1 + 1, \dots, n_2$, and $\alpha_i = 0$ for $i = n_2 + 1, \dots, N$. Then, for $i = 1, \dots, n_1$ we have $P(k, i) \neq 0$ if and only if $n_1 - 1 \leq k \leq n_2 - 1$. Thus, the Nash conditions become:

$$\sum_{k=n_1-1}^{n_2-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) \geq 0$$

For $i = n_1 + 1, \dots, n_2$ we have $P(k, i) \neq 0$ if and only if $n_1 \leq k \leq n_2 - 1$. Thus, the Nash conditions become:

$$\sum_{k=n_1}^{n_2-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) = 0$$

Finally, for $i = n_2 + 1, \dots, N$ we have $P(k, i) \neq 0$ if and only if $n_1 \leq k \leq n_2$. Thus, the Nash conditions become:

$$\sum_{k=n_1}^{n_2} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) \leq 0$$

Arbitrarily select $i < n_1$ and $n_1 + 1 \leq h \leq n_2$. Then, $\alpha_i = 1$ and $\alpha_h = 0$, and Lemma 1 implies that $P(k, i) = P(k+1, h)$. Therefore:

$$\begin{aligned} \sum_{k=n_1-1}^{n_2-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) &= \sum_{k=n_1-1}^{n_2-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k+1, h) \\ &= \sum_{k=n_1}^{n_2} \left[\frac{B + sk}{N} - c \right] P(k, h) \end{aligned}$$

But, this leads to a contradiction because the Nash condition for i implies that $\sum_{k=n_1}^{n_2} \left[\frac{B+sk}{N} - c \right] P(k, h) \geq 0$, while the Nash condition for h implies $\sum_{k=n_1}^{n_2} \left[\frac{B+s(k+1)}{N} - c \right] P(k, h) \leq 0$. Note that the argument does not depend on the existence of a group of players that are playing a complete mixed strategy. In other words, if $n_2 = n_1$, the same argument holds. Hence, there cannot be a Nash equilibrium in which some players cooperate with probability 1 and other players do not cooperate at all.

Case 4 (all play a mixed strategy): Suppose that $\alpha_i \in (0, 1)$ for $i = 1, \dots, N$. Then $P(k, i) \neq 0$ for all k . Thus, the Nash conditions become:

$$\sum_{k=0}^{N-1} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) = 0$$

Since $\sum_{k=0}^{N-1} P(k, i) = 1$, these conditions are equivalent to:

$$\sum_{k=0}^{N-1} k P(k, i) = \sum_{k=1}^{N-1} k P(k, i) = \frac{cN - B - s}{s}$$

Arbitrarily select i and h and without loss of generality assume that $\alpha_i > \alpha_h$. Then, from Lemma 2, it must be the case that $P(k, h) > P(k, i)$ for all $k \geq 1$. But this leads to a contradiction because $\sum_{k=1}^{N-1} k P(k, i) = \frac{cN-B-s}{s}$ and $\sum_{k=1}^{N-1} k P(k, h) = \frac{cN-B-s}{s}$ cannot simultaneously hold. Thus, in a Nash equilibrium in which all players are playing a complete mixed strategy, it must be the case that $\alpha_i = \hat{\alpha} \in (0,1)$ for $i = 1, \dots, N$. In this case $P(k, i) = \binom{N-1}{k} \hat{\alpha}^k (1 - \hat{\alpha})^{N-1-k}$, i.e. $k \sim \text{binomial}(N-1, \hat{\alpha})$. Therefore,

$$\sum_{k=0}^{N-1} \left[\frac{B + s(k+1)}{N} \right] \binom{N-1}{k} \hat{\alpha}^k (1 - \hat{\alpha})^{N-1-k} = c$$

$$\sum_{k=0}^{N-1} k \binom{N-1}{k} \hat{\alpha}^k (1 - \hat{\alpha})^{N-1-k} = \frac{cN - B - s}{s}$$

$$\hat{\alpha}(N-1) = \frac{cN - B - s}{s}$$

The last line uses the fact that the expected value of $k \sim \text{binomial}(N-1, \hat{\alpha})$ is $\hat{\alpha}(N-1)$. Therefore $\hat{\alpha} = \frac{cN-B-s}{s(N-1)}$. Note that $s > c$ implies that $\hat{\alpha} < 1$, while $\hat{\alpha} > 0$ if and only if $N > \frac{B+s}{c}$. Thus, $\alpha_i = \hat{\alpha} = \frac{cN-B-s}{s(N-1)}$ for $i = 1, \dots, N$ is a Nash equilibrium if and only if $N > \frac{B+s}{c}$.

Case 5 (some cooperate and some play a mixed strategy): Suppose that there is a Nash equilibrium in which n_1 players are cooperating and $N - n_1$ are playing a complete mixed strategy. Without loss of generality assume that $\alpha_i = 1$ for $i = 1, \dots, n_1$ and $\alpha_i \in (0,1)$ for $i = n_1 + 1, \dots, N$. Then, for $i = 1, \dots, n_1$, the Nash conditions become $\sum_{k=n_1-1}^{N-1} \left[\frac{B+s(k+1)}{N} - c \right] P(k, i) \geq 0$ or, which is equivalent:

$$\sum_{k=n_1-1}^{N-1} k P(k, i) \geq \frac{cN - B - s}{s}$$

For $i = n_1 + 1, \dots, N$, the conditions become $\sum_{k=n_1}^{N-1} \left[\frac{B+s(k+1)}{N} - c \right] P(k, h) = 0$ or, which is equivalent:

$$\sum_{k=n_1}^{N-1} k P(k, h) = \frac{cN - B - s}{s}$$

Using the same argument that we employed to prove that if in a Nash equilibrium all player are playing a mixed strategy, they must play the same strategy, we can prove that in a Nash equilibrium $\alpha_i = \tilde{\alpha}$ for all $i = 1, \dots, n_1$. As a consequence $P(k, i) = \binom{N - n_1 - 1}{k - n_1} \tilde{\alpha}^{k - n_1} (1 - \tilde{\alpha})^{N - 1 - k}$ and, therefore:

$$\sum_{k=n_1}^{N-1} \binom{N - n_1 - 1}{k - n_1} \tilde{\alpha}^{k - n_1} (1 - \tilde{\alpha})^{N - 1 - k} = \frac{cN - B - s}{s}$$

This implies that:

$$\tilde{\alpha} = \frac{cN - B - (1 + n_1)s}{s(N - 1 - n_1)}$$

For $i = n_1 + 1, \dots, N$ we have that $P(k, i) = \binom{N - n_1}{k - n_1 + 1} \tilde{\alpha}^{k - n_1 + 1} (1 - \tilde{\alpha})^{N - k - 1}$.

Therefore:

$$\sum_{k=n_1-1}^{N-1} k \binom{N - n_1}{k - n_1 + 1} \tilde{\alpha}^{k - n_1 + 1} (1 - \tilde{\alpha})^{N - k - 1} \geq \frac{cN - B - s}{s}$$

This implies:

$$\tilde{\alpha} \geq \frac{cN - B - n_1 s}{s(N - n_1)}$$

Since $s > c$, $\tilde{\alpha} = \frac{cN - B - (1 + n_1)s}{s(N - 1 - n_1)}$ and $\tilde{\alpha} \geq \frac{cN - B - n_1 s}{s(N - n_1)}$ never hold simultaneously.

Case 6 (some do not cooperate and some play a mixed strategy): Suppose that there is a Nash equilibrium in which n_2 are playing a complete mixed strategy and $N - n_2$ are not cooperating. Without loss of generality assume $\alpha_i \in (0, 1)$ for $i = 1, \dots, n_2$, and $\alpha_i = 0$ for $i = n_2 + 1, \dots, N$. Then, for $i = 1, \dots, n_2$ we have $P(k, i) \neq 0$ for $0 \leq k \leq n_2 - 1$. Thus, the Nash conditions become:

$$\sum_{k=0}^{n_2-1} \left[\frac{B + s(k + 1)}{N} - c \right] P(k, i) = 0$$

Since $\sum_{k=0}^{N-1} P(k, i) = 1$, these conditions are equivalent to:

$$\sum_{k=0}^{n_2-1} kP(k, i) = \sum_{k=1}^{n_2-1} kP(k, i) = \frac{cN - B - s}{s}$$

For $i = n_2 + 1, \dots, N$ we have $P(k, i) \neq 0$ for $0 \leq k \leq n_2$. Thus, the Nash conditions become:

$$\sum_{k=0}^{n_2} \left[\frac{B + s(k+1)}{N} - c \right] P(k, i) \leq 0$$

Since $\sum_{k=0}^{N-1} P(k, i) = 1$, these conditions are equivalent to:

$$\sum_{k=0}^{n_2} kP(k, i) = \sum_{k=1}^{n_2} kP(k, i) \leq \frac{cN - B - s}{s}$$

Arbitrarily select $i \leq n_2$ and $h > n_2$. Then, from Lemma 2 we have $P(k, h) > P(k, i)$ for all $k \geq 1$, which implies $\sum_{k=1}^{n_2-1} kP(k, h) \geq \frac{cN - B - s}{s}$. But, this leads to a contradiction because $\sum_{k=1}^{n_2-1} kP(k, h) \geq \frac{cN - B - s}{s}$ and $\sum_{k=1}^{n_2} kP(k, h) \leq \frac{cN - B - s}{s}$ cannot hold simultaneously. ■

Only Appendix 2. Description of the Experiment

In this appendix we present the script for the general instructions, the instructions given to the participants, the quiz, and the questionnaire.

Appendix 2.1. Script for General Instructions

We would like to welcome everyone to this experiment. This is an experiment in decision making, and you will be paid for your participation in cash, at the end of the experiment. Different subjects may earn different amounts. What you earn depends partly on your decisions, partly on the decisions of others, and partly on chance.

The entire experiment will be conducted through computer terminals, and all interaction between participants will take place through the computers. It is highly important for you not to talk or to try in any way to communicate with other subjects during the experiment.

In your workstation you will find a pencil, a paper with instructions, and scratch paper. During the experiment you can use the scratch paper to make calculations.

We will now start with a brief instruction period. During the instruction period, you will be given a complete description of the experiment. If you have any questions during the instruction period, please raise your hand and your question will be answered so everyone can hear it. If any difficulties arise after the experiment has begun, raise your hand, and one of the persons conducting the experiment will come and assist you.

You are one of 20 students who have been called to this experiment. In each round you will be randomly assigned to one of two groups, consisting of 10 persons each. Then, you will play the computer game, which will appear on the screen, with the members of the same group. At the beginning of the each round, the parameters of the game will appear on the screen, as the timing. At the end of the round, you will be informed of the result of the game, the points you have earned as well as the points you have accumulated so far. In the next round, all players will again be randomly assigned to one of the two new groups of 10 people each.

The experiment you are participating in is broken down into four unpaid practice rounds and twelve separate paid rounds. At the end of the last round, you will be paid

the total amount you have accumulated during the course of the last twelve rounds. Your profit is denominated in POINTS. Your PESO profit is determined by multiplying your earnings in points by a conversion rate. In this experiment, the conversion rate is 2 pesos to 1 point.¹⁸ Everyone will be paid in private and you are under no obligation to tell others how much you earned.

Please read carefully the instructions that you will find in your desktop. You have 10 minutes. Please, remember that if you have any question, you should ask it aloud.

Appendix 2.2. Instructions

1. In each round you receive ONE point. You can keep it for yourself or invest it in a common fund. You have 90 seconds to make your decision. When you select an option, please press the "Next" button. If after 90 seconds you do not select an option, the computer will randomly do it for you.

2. Once all players have taken a decision, the outcome of the game will appear on the screen: if the investment is successful, each of the ten players will receive B points, and those who have decided to invest their point will receive s additional points. If the investment fails, nobody gets a profit, and those who have decided to invest their point, will lose the point they initially have invested.

Therefore:

- If you have decided to invest your point in the common fund and the investment is successful, you will accumulate $B + s$ points;
- If you have decided to maintain your point and the investment is successful, you will accumulate $B + 1$ points;
- If you have decided to invest your point in the common fund and the investment fails, you will earn 0 points;
- If you have decided to maintain your point and the investment fails, you will earn 1 point.

¹⁸ The conversion rate was adjusted by inflation (20% since August). Hence, from August the rate was adjusted to 2.4 pesos for 1 point. 2 and 2.4 Argentine pesos were equivalent to approximately 0.25 and 0.28 dollars, respectively.

3. The probability of success of the investment depends on the proportion of players in your group who have decided to invest:

$$\text{Successful Investment Probability} = \frac{(\text{Number of players who invested their Point})}{10}$$

Thus, the greater the number of players who have decided to invest their point, the greater is the probability that the investment will be successful.

For example, if six of ten participants choose to invest their point in the common fund, the chances of success are 60%. If the investment is successful, those six participants get $B + s$, and the remaining four obtain $B + 1$. However, if the investment fails, the six participants who decided to invest their point get 0 units, while the remaining four get 1 point.

Suppose another case in which from ten players only two decide to invest their points in the common fund. Therefore, the chances of success are 20%. If the investment is successful, those two participants get $B + s$, and the remaining eight obtain $B + 1$. However, if the investment fails, the two participants who decided to invest their point get 0 units, while the remaining eight get 1 point.

At the end of each round you will be informed how many players have decided to invest their point in the common fund, if the investment was successful or not, the gain in this round, and the total amount of points accumulated from the 5th round. To end this round, please press the "Next" button.

At the beginning of the next round, you will be randomly assigned to a new group. Pay attention because the parameters of the game may have changed. That is, in each round, B and / or s may vary.

After the 16th round you will be asked to answer a few questions about you. Finally, by clicking "Finish", the screen will display a WORD. It is IMPORTANT to remember this word because you have to present this password to the person who was running the experiment in order to receive your payoff.

Appendix 2.3. Belief Questions

The following depiction provides a sample of the questions about the beliefs of the subjects as seen by them in the screen.

Screen: Before you begin to play, we want to ask you some questions about the experiment. These questions are only for information purposes and there is no right or wrong answers. You will not be paid for answering them.

1. Suppose that $B = 1.25$ and $s = 0$, how many players, in group of ten 10 subjects, do you believe that will invest their point in the common fund? [11 options].
2. Suppose that $B = 1.25$ and $s = 1.25$, how many players, in group of ten 10 subjects, do you believe that will invest their point in the common fund? [11 options].
3. Suppose that $B = 3$ and $s = 1.25$, how many players, in group of ten 10 subjects, do you believe that will invest their point in the common fund? [11 options].
4. Suppose that $B = 3$ and $s = 1.75$, how many players, in group of ten 10 subjects, do you believe that will invest their point in the common fund? [11 options].

Appendix 2.4. The Quiz

After a general explanation of the rules of the game, subjects took the following quiz:

1. Suppose the following parameters of the game: $B = 2$ and $s = 0$. If all players, including you, decide NOT to invest their point in the common fund and the investment fails. How many points do you obtain at the end of this round? [5 options]
2. Suppose the following parameters of the game: $B = 2$ and $s = 1$. If all players, including you, decide to invest their point in the common fund and the investment is successful. How many points do you get at the end of this round? [5 options]
3. Consider the following two possible games:
 - First game: $B = 3$ and $s = 1$;
 - Second game: $B = 4$ and $s = 1$;

If you decide NOT to invest your point and the investment fails, in which of the two games do you accumulate more points? [3 options]

4. If there are 10 players and 8 of them decide to invest their point, what is your best option if the parameters of the game are: $B = 0.5$ and $s = 2$? [3 options]
5. If there are 10 players and 4 of them decide to invest their point, what is your best option if the parameters of the game are: $B = 1$ and $s = 1$? [3 options]

Appendix 2.5. Sample Screen

At the end of each round subjects visualized a summary of the decisions taken in the round, whether the investment was successful or not and the payoff obtained in the round as well as their own accumulated payoffs for paid rounds.

- **Screen:**

You have decided (not) to invest your point.

(1, 2, 3, 4, 5, 6, 7, 8, 9 or all) subjects in your group have decided to invest their point.

The investment was (not) successful.

Your earning in this round was ____ points.

You have accumulated ____ points since the start of the game.

Appendix 2.6. The Questionnaire

Thank you for participating in this experiment! Please complete the following questionnaire before leaving.

Question 1: Gender (male/female)

Question 2: Age (in years)

Question 3: Nationality

Question 4: Fluent in English

Question 5: Have you ever taken a course in game theory? (Yes/No)

Question 6: Current Studies (Graduate/Undergraduate)

Question 7: Degree in: a) Economy; b) Business Administration or Accountant; c) Finance; d) Political Science, International Affairs, Humanities, or Law; e) Marketing or Human Resources; f) Other (specify).

Question 8: Number of approved courses over total courses in your degree program.