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Planning ahead: eliciting intentions and beliefs in a public goods game

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Abstract

In a two-person finitely repeated public goods experiment, we use intentions data to interpret individual behavior. Based on a random-utility model specification, we develop a relationship between a player's beliefs about others' behavior and his contributions' plans, and use this relationship to identify the player's most likely preference "type". Our estimation analysis indicates that players are heterogeneous in their preferences also at the intentional level. Moreover, our data show that deviations from intended actions are positively related to changes in beliefs, thereby suggesting that people are able to plan.

JEL classification: C70; C72; C92; H41

Keywords: Public goods games; Experiments; Latent-class logit; Conditional cooperation

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1. INTRODUCTION

Numerous public goods experiments show that individuals, interacting finitely often, start out by contributing substantial amounts, although contributions decline over time and reach their minimum when the interaction terminates (Ledyard, 1995). Several explanations for this behavior have been put forward. One explanation relies on the inexperience of participants with the game, which makes them choose their initial moves in a state of “confusion” (Andreoni, 1995; Palfrey and Prisbrey, 1996, 1997; Houser and Kurzban, 2002; Binmore, 2005). An alternative explanation asserts that “social preferences” play an important role. Social preferences are mostly discussed in the economic literature under the rubric of altruism (Levine, 1998), inequity aversion (Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000), reciprocity (Dufwenberg and Kirchsteiger, 2004; Falk and Fischbacher, 2006), and conditional cooperation (Fischbacher et al., 2001). Studies on the importance of social preferences have shown that *actual behavior* cannot be explained by confusion alone: even after becoming familiar with the rules of the game, experimental subjects make choices that appear to be inconsistent with monetary payoff maximization.

In spite of the significance of these studies for the hypothesis of social preferences, the exact identification of the latter seems to require a careful exploration not only of the decision maker’s behavior, but also of his *beliefs* about the others’ behavior (Manski, 2004). Moving in this direction, recent studies have investigated how subjective beliefs relate to contribution decisions, noticing that people differ in their ability to learn the rules of the game as well as in the relative weight they attach to their expected monetary payoffs conditional on their beliefs about others’ behavior (González et al., 2005; Fischbacher and Gächter, 2006).

Building upon the above evidence, in this paper we pursue the identification of social preferences further by observing that if other-regarding concerns really matter and are idiosyncratic attitudes, an actor should ‘reveal’ them not only

in the way his immediate actions relate to his beliefs regarding other people's behavior, but also in the way his intentions for future actions are affected by these beliefs. In our view, it is somehow surprising that economists tend to ignore intentions data, leaving the study of, e.g., purchase intentions to marketing research (see, e.g., Morwitz, 1997, and references therein). The usual claim is that people cannot plan ahead,¹ and the empirical divergences between intentions and behavior is typically interpreted as evidence that individuals are poor predictors of their own behavior. However, as pointed out by Manski (1990, p. 934), such conclusion is unwarranted: intended and actual behavior may diverge due to events that occur between the time intentions are measured and the time behavior takes place. This suggests that if we can figure out how new events affect the way individuals perceive a decision problem, both ex-ante and ex-post beliefs can be used to understand the dynamics of cooperative behavior. In particular, it is possible to characterize individuals by their *most likely* social preferences "type" looking at the way in which changes in their beliefs induce deviations from their initial plans of action. This paper represents a first attempt to use the "plans" implemented by an individual to assess his attitudes toward cooperation in a public goods experiment.

We will consider a finitely repeated linear public goods game in which each individual receives feedback about his partner's contribution after each repetition. Being aware of the number of repetitions, it is natural to assume that, at any point of time, each player entertains ex-ante beliefs about what others will do during the rest of the game. Given such beliefs, the assumption that people have complete preferences implies that they are able not merely to choose their immediate contribution, but also to make plans indicating how they intend to act in the future. Common wisdom suggests that, in such a setting, what causes one's own behavior to differ from one's own earlier intentions is a revision of beliefs about others' behavior. In what follows, moreover, we show that dis-

¹On this topic, see, e.g., Bone et al. (2003) or Hey (2005), who study dynamic decision problems under risk involving Nature moves in a probabilistic, rather than strategic, way.

crepancies between what is expected from others and what is actually observed plays a major role in explaining plan revisions.² Taking into account the revision of individual beliefs when comparing plans to actions, we can provide a direct test of whether people’s intended and actual contributions are both consistent with idiosyncratic preferences types. To the best of our knowledge, we are the first to investigate this issue, which we deem to be worthy of consideration because if social preferences really matter and can explain cooperative behavior, then they should show up in the intentions of contributions.

In our experiment, intended contributions are not disclosed to other players. Therefore, a further methodological advantage of using intentions to identify social preferences in our setting is that, unlike current actions data, elicited intentions are uncontaminated by the possibility of strategic decisions aimed at inducing cooperation from future partners via indirect manipulation of beliefs (“social reputation effect” in the terminology of González et al., 2005). Hence, by comparing elicited intentions to actual contributions, we may quantify the extent to which initially high contributions are due to genuine confusion or to forward-looking opportunistic reasoning trying to trigger “optimistic beliefs” from conditional cooperators. The reasoning is that, if a player has opportunistic preferences, then he is more likely to start out contributing positive amounts so as to influence positively the expectations of conditional cooperators. However, this kind of strategic behavior is justified only if it can be observed by others. As participants in our experiment are only informed about the actual contributions made by their partners, and remain unaware of their plans, an opportunistic person has no incentive to conceal his real preferences when formulating his plans.

The rest of the paper is organized as follows. After introducing the basic game, Section 2 sets out the formal structure of the random utility model for the multi-period setting, taking into account actions, beliefs, and intentions.

²We do not consider the possibility that decision makers have “multiple selves”, i.e., we maintain the postulate that preferences are stable across time.

Section 3 describes the experimental design. Section 4 presents the aggregate and estimation results. Section 5 summarizes out central findings and concludes.

2. A REPEATED PUBLIC GOODS GAME

2.1. *Instantaneous Payoffs*

Consider a population with a finite number of individuals, indexed by $i = 1, \dots, N$, who interact in pairs for T periods ($2 \leq T < N$) according to a perfect-stranger matching design (i.e., nobody meets the same person more than once). Every period $t = 1, \dots, T$, each player receives an endowment of 100 monetary units and has to decide how much he wants to contribute to a public good. Denote the contribution decisions of player i and of his partner at time t by $c_{i,t}$ and $c_{i',t}$, respectively.³ Let the instantaneous monetary payoff that player i obtains thereof be given by

$$m_{i,t}(c_{i,t}, c_{i',t}) = 100 + \mu c_{i',t} - (1 - \mu)c_{i,t},$$

with $\mu \in (0.5, 1)$. This leads to the usual public goods situation in which the only dominant strategy in a homogeneous population of monetary-payoff maximizers is to contribute nothing.

Assume, however, that at least some players, besides being interested in their own monetary income, exhibit some altruistic inclinations (i.e., they care about their partners' material well-being) or are, to a certain degree, conditional cooperators (i.e, they dislike contributing different amounts than others). If this is the case, player i 's (ex-post) instantaneous payoff from choosing $c_{i,t}$ in period t can be parameterized as

$$(1) \quad u_{i,t}(c_{i,t}|c_{i',t}) = \alpha_i m_{i,t}(c_{i,t}, c_{i',t}) - \theta_i (c_{i,t} - c_{i',t})^2 + \gamma_i m_{i',t}(c_{i',t}, c_{i,t}),$$

whereby $\alpha, \theta, \gamma \geq 0$ are the idiosyncratic weights that player i gives to the goals of own monetary income maximization, conditional cooperation, and altruism, respectively.

³To simplify notation, we always refer to “the other player” as i' , although this is a different person in each period.

Notice that, since each player has to choose his contribution $c_{i,t}$ being unaware of the current contribution of his partner, $c_{i',t}$, his decision can only be based on his ex-ante expectations. In particular, if $b_{i,s}^{(t)}$ denotes the belief entertained at time t by player i regarding the amount his partner will contribute in period $s \geq t$, then the instantaneous payoff expected by player i in period t can be written as

$$(2) \quad u_{i,t} \left(c_{i,t} | b_{i,t}^{(t)} \right) = \alpha_i m_{i,t} \left(c_{i,t}, b_{i,t}^{(t)} \right) - \theta_i \left(c_{i,t} - b_{i,t}^{(t)} \right)^2 + \gamma_i m_{i',t} \left(b_{i,t}^{(t)}, c_{i,t} \right).$$

The above expression is very general and can accommodate a broad variety of preferences.⁴ For example, if $\alpha_i > \gamma_i = \theta_i = 0$, the behavioral prediction corresponds to the simple case of monetary payoff maximization. Similarly, constellations $\gamma_i > \alpha_i = \theta_i = 0$ and $\theta_i > \alpha_i = \gamma_i = 0$ characterize, respectively, the preferences of pure altruists and perfect conditional cooperators.⁵ In spite of this generality, there is still room for other, not further specified, factors that affect a decision maker's most preferred course of action, but are not captured by α_i , γ_i , and θ_i alone. Assume that, from the point of view of an outside observer, all these additional factors can be modeled as a random process $\varepsilon(c_{i,t})$ affecting the utility function in an additive way. For concreteness, we specify it as an additive i.i.d Extreme Value process with scale parameter $\lambda > 0$. Disregarding for a moment the consequences that a decision in period t may have on future payoffs, this random utility specification translates into a logit behavioral prediction that assigns a positive probability to each feasible

⁴In González et al. (2005), we have shown that assuming a quadratic form for the “conditional cooperation” term in (1) allows the use of point beliefs (instead of arbitrary probability distribution functions with support on the interval $[0,100]$) without loss of generality.

⁵Notice that if player i is just a monetary payoff maximizers or, on the opposite extreme, he is a purely altruistic individual, his optimal contribution choice is independent of his beliefs. Only if $\theta_i > 0$, beliefs will play a role in determining the strategy that maximizes i 's instantaneous payoff.

contribution $c = 0, 1, \dots, 99, 100$, according to

$$(3) \quad \Pr(c_{i,t} = c | b_{i,t}^{(t)}) = \frac{\exp\{\gamma_i^* c - \theta_i^* (c - b_{i,t}^{(t)})^2\}}{\sum_{x=0}^{100} \exp\{\gamma_i^* x - \theta_i^* (x - b_{i,t}^{(t)})^2\}},$$

whereby $\gamma_i^* \equiv [\mu\gamma_i + \alpha_i(\mu - 1)]/\lambda$ and $\theta_i^* \equiv \theta_i/\lambda$ (see González et al., 2005).

2.2. Long-Term Payoffs

If players are forward-looking, they recognize that their behavior may have consequences above and beyond the instantaneous payoff function (2). In particular, player i is aware that a link may exist between his action in period t , $c_{i,t}$, and his future payoffs if observed contributions provide a basis for the revision of beliefs. In a perfect strangers design, where $c_{i,t}$ is not revealed to any player other than i 's partner at time t , $c_{i,t}$ cannot affect the behavior of i 's partner in period $t + 1$. Therefore, $b_{i,t+1}^{(t)}$ is certainly independent of $c_{i,t}$. Nevertheless, due to the possibility of indirect “contagion” (see González et al., 2005), independence between $c_{i,t}$ and beliefs for a more distant future does not necessarily hold: by choosing $c_{i,t}$, player i may influence the beliefs (and thus the optimal choices) that his current partner will make in the future, and although there will be no further interaction with him, this partner may in turn affect the behavior of a third person with whom i has a positive probability of interacting in period $t + 2$ or later.

In addition to anticipating how his own current contribution can affect the contributions of future partners (via indirect belief formation), player i can also anticipate his optimal behavior in future periods given the information currently available to him. In period t , therefore, player i can construct a preliminary plan for future contribution choices, $p_{i,s}^{(t)}$, $s = t + 1, \dots, T$. Notice that the choice of a contribution plan $p_{i,s}^{(t)}$ cannot affect what i 's future partners will do in later periods because plans are never revealed to other players. Thus, the expected

payoff function of a forward-looking player i at time t can be written as

$$\begin{aligned}
 (4) \quad U_{i,t} \left(c_{i,t}, \mathbf{p}_i^{(t)} | \mathbf{b}_i^{(t)} \right) &= u_{i,t} \left(c_{i,t} | b_{i,t}^{(t)} \right) \\
 &+ \beta u_{i,t+1} \left(p_{i,t+1}^{(t)} | b_{i,t+1}^{(t)} \right) \\
 &+ \beta^2 u_{i,t+2} \left(p_{i,t+2}^{(t)} | b_{i,t+2}^{(t)}(c_{i,t}) \right) \\
 &+ \beta^3 u_{i,t+3} \left(p_{i,t+3}^{(t)} | b_{i,t+3}^{(t)}(c_{i,t}) \right) \\
 &+ \dots \\
 &+ \beta^{T-t} u_{i,T} \left(p_{i,T}^{(t)} | b_{i,T}^{(t)}(c_{i,t}) \right),
 \end{aligned}$$

where $\beta \in [0, 1]$ can be thought of as a discount factor (in the sense that players care less about outcomes that are subject to more uncertainty and complexity).

Under the assumption that players have “rational intentions” for periods $t+2$ to T , the above expression can be written as a function of only two decision variables: the current contribution decision, $c_{i,t}$, and the contribution plan for the next period, $p_{i,t+1}^{(t)}$. More specifically, given the information available at time t , choosing the optimal contribution plan for period $s = t+2, \dots, T$, $p_{i,s}^{(t)}$, yields

$$u_{i,s}^* \left(b_{i,s}^{(t)}(c_{i,t}) \right) = \max_p u_{i,s} \left(p | b_{i,s}^{(t)}(c_{i,t}) \right).$$

Thus, one can re-write (4) as

$$\begin{aligned}
 (5) \quad U_{i,t} \left(c_{i,t}, p_{i,t+1}^{(t)} | \mathbf{b}_i^{(t)} \right) &= u_{i,t} \left(c_{i,t} | b_{i,t}^{(t)} \right) + \beta u_{i,t+1} \left(p_{i,t+1}^{(t)} | b_{i,t+1}^{(t)} \right) \\
 &+ \sum_{s=t+2}^T \beta^{s-t} u_{i,s}^* \left(b_{i,s}^{(t)}(c_{i,t}) \right),
 \end{aligned}$$

where the conditioning beliefs in the first two terms of the right-hand side do not depend on $c_{i,t}$.

As in the derivation of (3), one can model other non-specified factors affecting the simultaneous choice of $c_{i,t}$ and $p_{i,t+1}^{(t)}$ by including an additive i.i.d. Extreme Value random process $\varepsilon(c_{i,t}, p_{i,t+1}^{(t)})$ with scale parameter $\lambda > 0$ in the

long-term utility function (5). This yields the bivariate logit-choice probability mass function

$$\begin{aligned}
 (6) \Pr \left((c_{i,t}, p_{i,t+1}^{(t)}) = (c, p) | \mathbf{b}_i^{(t)} \right) &= \frac{\exp \left\{ \gamma_i^* (c + \beta p) - \theta_i^* \left[(c - b_{i,t}^{(t)})^2 + \beta (p - b_{i,t+1}^{(t)})^2 \right] \right\} \cdot R_i(c, t)}{\sum_{x,y=0}^{100} \exp \left\{ \gamma_i^* (x + \beta y) - \theta_i^* \left[(x - b_{i,t}^{(t)})^2 + \beta (y - b_{i,t+1}^{(t)})^2 \right] \right\} \cdot R_i(x, t)} \\
 &= \left[\frac{\exp \left\{ \gamma_i^* c - \theta_i^* (c - b_{i,t}^{(t)})^2 \right\} \cdot R_i(c, t)}{\sum_{x=0}^{100} \exp \left\{ \gamma_i^* x - \theta_i^* (x - b_{i,t}^{(t)})^2 \right\} \cdot R_i(x, t)} \right] \\
 &\quad \times \left[\frac{\exp \left\{ \gamma_i^* \beta p - \theta_i^* \beta (p - b_{i,t+1}^{(t)})^2 \right\}}{\sum_{y=0}^{100} \exp \left\{ \gamma_i^* \beta y - \theta_i^* \beta (y - b_{i,t+1}^{(t)})^2 \right\}} \right] \\
 &= \Pr \left(c_{i,t} = c | b_{i,t}^{(t)}, b_{i,t+2}^{(t)}(\cdot), \dots, b_{i,T}^{(t)}(\cdot) \right) \times \Pr \left(p_{i,t+1}^{(t)} = p | b_{i,t+1}^{(t)} \right)
 \end{aligned}$$

where $R_i(c, t) \equiv \exp \left\{ \sum_{s=t+2}^T \beta^{s-t} u_{i,s}^* \left(b_{i,s}^{(t)}(c_{i,t}) \right) \right\}$ is the “social reputation” factor, capturing the effect that current contributions are expected to have on the behavior of future partners.

The above expression shows that the contribution decision, $c_{i,t}$, and the plan for the next period, $p_{i,t+1}^{(t)}$, are mutually independent, indicating that, for given beliefs, present actions and plans can be considered as separate probabilistic events: they may well differ without entailing inconsistency. Most important, however, is that strategic considerations by forward-looking players (represented by the social reputation factor $R_i(c, t)$) do not appear at all in the marginal probability mass function $\Pr \left(p_{i,t+1}^{(t)} = p | b_{i,t+1}^{(t)} \right)$, confirming that plans are not affected by strategic opportunistic reasoning.

2.3. Learning as Reduction of Noise

So far the probabilistic behavioral prediction regarding the choice of $c_{i,t}$ and $p_{i,t+1}^{(t)}$ has relied on the assumption that the noise parameter λ remains constant over time. However, several studies suggest that learning effects characterize the dynamics typically observed in finitely repeated public goods games (An-

dreoni, 1988, 1995; Palfrey and Prisbrey, 1996, 1997; Houser and Kurzban, 2002). Under this perspective, the stationarity assumption regarding λ seems too restrictive.

For this reason, we introduce learning into our behavioral model in the sense that players become increasingly sensitive to differences in expected payoffs. This allows for situations in which players improve their understanding of the game rules as they gain more experience (eliminating, for instance, such fallacies like the so-called “false consensus hypothesis”). Moreover, it takes into account the fact that the dynamic optimization of (4) becomes simpler with larger t , as there are fewer steps of backward induction. In practice, this is implemented by letting the noise parameter be a decreasing function of time: $\lambda_{i,t} = \lambda/(1 + \rho_i t)$. Doing this, the bivariate logit-choice probability (6) becomes

$$\begin{aligned}
 & \Pr_t \left((c_{i,t}, p_{i,t+1}^{(t)}) = (c, p) | \mathbf{b}_i^{(t)} \right) \\
 &= \frac{\exp \left\{ (1 + \rho_i t) \left[\gamma_i^* (c + \beta p) - \theta_i^* \left((c - b_{i,t}^{(t)})^2 + \beta (p - b_{i,t+1}^{(t)})^2 \right) \right] \right\} \cdot R_i(c, t)}{\sum_{x,y=0}^{100} \exp \left\{ (1 + \rho_i t) \left[\gamma_i^* (x + \beta y) - \theta_i^* \left((x - b_{i,t}^{(t)})^2 + \beta (y - b_{i,t+1}^{(t)})^2 \right) \right] \right\} \cdot R_i(x, t)} \\
 &= \left[\frac{\exp \left\{ (1 + \rho_i t) \left[\gamma_i^* c - \theta_i^* (c - b_{i,t}^{(t)})^2 \right] \right\} \cdot R_i(c, t)}{\sum_{x=0}^{100} \exp \left\{ (1 + \rho_i t) \left[\gamma_i^* x - \theta_i^* (x - b_{i,t}^{(t)})^2 \right] \right\} \cdot R_i(x, t)} \right] \\
 &\quad \times \left[\frac{\exp \left\{ (1 + \rho_i t) \left[\gamma_i^* \beta p - \theta_i^* \beta (p - b_{i,t+1}^{(t)})^2 \right] \right\}}{\sum_{y=0}^{100} \exp \left\{ (1 + \rho_i t) \left[\gamma_i^* \beta y - \theta_i^* \beta (y - b_{i,t+1}^{(t)})^2 \right] \right\}} \right] \\
 &= \Pr_t \left(c_{i,t} = c | b_{i,t}^{(t)}, b_{i,t+2}^{(t)}(\cdot), \dots, b_{i,T}^{(t)}(\cdot) \right) \times \Pr_t \left(p_{i,t+1}^{(t)} = p | b_{i,t+1}^{(t)} \right).
 \end{aligned}$$

The expression above clarifies the advantage of working with intentions data, rather than with actual contributions, in the presence of learning: whereas in the marginal probability distribution of $c_{i,t}$ the dynamic elements represented by $R_i(c, t)$ and $(1 + \rho_i t)$ remain confounded, the parameter ρ_i is unambiguously identifiable in the specification of the marginal probability distribution of $p_{i,t}^{(t)}$. Hence, in what follows, we will concentrate on the estimation of $\Pr_t \left(p_{i,t+1}^{(t)} = p | b_{i,t+1}^{(t)} \right)$.

2.4. *Heterogeneity and Estimation Approach*

If we were ready to assume that the population of participants had homogenous preferences and learning abilities, with the only differences in behavior being due to differences in initial beliefs or random variability, it would be possible to write the likelihood of the reduced-form parameters $\Psi \equiv [\gamma^*\beta, \theta^*\beta, \rho]$ as

$$\mathcal{L}(\Psi) = \prod_{i=1}^N \prod_{t=1}^T \left[\Pr \left(c_{i,t}, p_{i,t+1}^{(t)} | b_{i,t}^{(t)}, b_{i,t+1}^{(t)}; \Psi \right) \right].$$

However, the assumption of homogeneity in preferences seems too unrealistic, and as Wilcox (2006) shows, could lead to significant biases in the estimation results. Thus, we specify a latent-class model in which each subject i has a positive probability of belonging to several “types”.⁶ The standard method to approach this kind of estimation is through the use of the EM algorithm. This algorithm consists of two steps that are iterated K times until the sequence of parameter values $\{[\Psi_1^{(k)}, \dots, \Psi_G^{(k)}]\}_{k=1}^K$ converges numerically, which under regularity conditions is known to yield a root of the “true” likelihood function (see, e.g., McLachlan and Peel, 2000). In our setting, the first step (*Estimation*) uses Bayes rule to calculate, for each individual i , the vector of ex-post probabilities $(\tau_{i,1}^{(k)}, \dots, \tau_{i,G}^{(k)})$ that he belongs to the sub-populations $g = 1, \dots, G$, assuming some initial values of $[\Psi_1^{(k-1)}, \dots, \Psi_G^{(k-1)}]$. The second step (*Maximization*) uses the resulting membership probabilities to obtain a new set of parameters $[\Psi_1^{(k)}, \dots, \Psi_G^{(k)}]$ by maximizing the so-called “complete log-likelihood” function

$$(7) \quad \mathcal{Q}(\Psi^{(k)}) = \sum_{g=1}^G \left[\pi_g^{(k)} + \ln \sum_{i=1}^N \sum_{t=1}^T \tau_{i,g}^{(k)} \Pr \left(c_{i,t}, p_{i,t+1}^{(t)} | b_{i,t}^{(t)}, b_{i,t+1}^{(t)}; \Psi_g^{(k)} \right) \right]$$

where $\pi_g^{(k)}$ is the estimated share of individuals of type $g = 1, \dots, G$ in the population. In this paper, we estimate the probability distribution of one-period-ahead plans using (7) for exactly three subpopulations ($G = 3$).

⁶See Wilcox (2006) for a discussion of the appropriateness of the latent class approach when the population consists of a finite mixture of player types.

3. EXPERIMENTAL DESIGN

Recall that our main issues are (i) to measure people’s cooperative preferences on the basis of their elicited intentions, (ii) to assess whether accounting for beliefs’ revision renders this measure consistent with other measures based on actual behavior, and (iii) to disentangle forward-looking opportunistic reasoning from genuine confusion when explaining initially high contributions. To address these issues, we employ finite populations of $N = 32$ individuals who are randomly paired to play the public goods game described in Section 2.1. The game is repeated 21 periods (i.e, $T = 21$), in which, based on González et al. (2005), we set $\mu = 0.7$. In each period $t \in \{1, \dots, 21\}$, subjects have to state their own contribution in the current period, their beliefs about their partner’s contribution, and their intentions of contributions.

We implement two experimental treatments, which differ only in the number of periods that subjects are required to plan ahead. In one experimental treatment (henceforth, one-plan treatment), we elicit plans (and beliefs) for the next period only. In the other experimental treatment (henceforth, two-plan treatment), we elicit plans (and beliefs) for the next two periods. Specifically, in every period, besides providing their current contribution decision and their beliefs about the contribution of the partner in the current period, participants in the one-plan treatment are asked to state how much they intend to contribute next period, and how much they believe their partner in the next period will contribute. Similarly, participants in the two-plan treatment are asked to state how much they intend to contribute next period and in two-period time, and how much they believe their partner in the next period and their partner in two-period time will contribute.⁷

To check whether the mere act of eliciting plans changes behavior and/or beliefs, we run a control treatment in which the basic decision situation is repeated 21 times without asking for plans, but only for beliefs about the partner’s

⁷For more details see the instructions reported in the Appendix.

contribution in the current period.

The problem with trying to design an experiment involving plans is that we need an incentive-compatible way of eliciting plans so that subjects are motivated to state their intentions honestly. To this aim, we calculate the size of the public good in each period t depending on either the current contribution decision in t or the plan(s) formulated beforehand, with all possibilities being equally likely. In particular, in the one-plan treatment, the size of the public good in each period $t \in \{2, \dots, 21\}$ is determined either by the sum of the contribution decisions in t or by the sum of the plans made one period before (i.e., in period $t - 1$ for period t); in the two-plan treatment, in any period $t \in \{3, \dots, 21\}$, this size can also be determined by the plans made two periods in advance (i.e., in period $t - 2$ for period t).

In addition to their earnings from the public goods experiment, we give subjects financial incentives for correct predictions. The incentives take the form of a bonus to the participant with the most accurate predictions in each session. In the control treatment, the selection of the participant who receives the bonus is based only on the accuracy of current-period beliefs. In the experimental treatments, the selection is based on current-period, one-period, or two-period-ahead expectations (i.e., beliefs about the behavior of the partner in the next (two) period(s)), where all possibilities are equally likely. The participant with the most accurate predictions for the current period or for the randomly selected planning horizon ($t + 1$ or $t + 2$) receives a bonus of €15. The general form of the rule used to calculate subject i 's prediction accuracy is

$$\text{Score}_i = - \sum_{t=1}^{21} (\hat{b}_{i,t+\tau}^{(t)} - c_{i',t+\tau})^2,$$

where $\hat{b}_{i,t+\tau}^{(t)}$ denotes the beliefs stated by i in period t regarding period $t + \tau$, and τ equals 0 in the control treatment, 0 or 1 in the one-plan treatment, and 0, 1, or 2 in the two-plan treatment. Although participants were not informed

about the exact content of this rule, it was explained to them that the closer their predictions were to the partner's actual contributions, the higher their chances of receiving the bonus.

All experimental sessions were run computerized with the help of z-Tree (Fischbacher, 2007) at the laboratory of the Max Planck Institute of Economics in Jena (Germany). Participants were undergraduate students from different disciplines at the University of Jena. After being seated at a computer terminal, participants received written instructions (see the Appendix for an English translation). A control questionnaire was used in order to assure understanding of the rules before the experiment started.

Overall, we ran 6 sessions (two for each of our three treatments) with a total of 192 subjects (32 subjects per session). Sessions took about 75 minutes with most of the time being used up for reading the instructions carefully and answering the control questions. The units of experimental money were tokens, with 100 tokens = €0.75. The average earning per subject was about €19 (including a show-up fee of €2.50).

Subjects interacted in a perfect strangers design. As non-parametric tests for aggregate results require observations to be independent, we rematched subjects within matching groups of 8 players in the first seven periods. This means that for the first seven periods we can rely on 4 independent observations per session (i.e., 8 independent observations per treatment).

At the end of each period, participants received feedback about the actual contribution decision of their current fellow member. No information about intended contributions was disclosed. This implies that opportunistic players have no reason to play strategically when formulating their plans, thereby allowing for a direct test of the relevance of confusion, as compared to strategic play, to initial high cooperation level.

4. EXPERIMENTAL RESULTS

Figure 1 displays the time paths of average current-period contributions and beliefs as well as of average one-period-ahead plan and beliefs, separately for the two experimental treatments (one-plan and two-plan treatments). All the considered variables show a steady decline over time.

Insert Figure 1 about here

Our first issue of interest is to check whether eliciting plans and beliefs for the future (either one or two periods ahead) has a significant effect on subjects' responses regarding their current-period contributions and beliefs. Looking at the data from different periods separately, we find no evidence suggesting that behavioral patterns in the experimental treatments differ from those in the control treatment where subjects had only to provide current-period contributions and beliefs. For instance, if we consider only period 1 (where all individual responses are independent), the Kolmogorov-Smirnov test does not reject the null hypotheses that the distributions of current-period contributions and beliefs in the one-plan and the two-plan treatments are the same as in the control treatment ($p > 0.10$ always). The same conclusion holds if we apply the test to the within-matching-group means across periods 4 to 7 (recall that, between periods $t = 1$ and $t = 7$, there are 8 matching groups in each treatment).

Figure 1 reveals that the trajectories of average current and planned contributions follow their respective belief trajectories. Moreover, the Pearson correlation coefficient between deviations from original plans, $d_{i,t} = c_{i,t} - p_{i,t}^{(t-1)}$, and changes in elicited beliefs, $\Delta b_{i,t} = b_{i,t}^{(t)} - b_{i,t}^{(t-1)}$, has a positive value of $\text{Corr}(d_{i,t}, \Delta b_{i,t}) = 0.329$, with the corresponding Kendall's measure of association being $\tau(d_{i,t}, \Delta b_{i,t}) = 0.354$ (both are significantly different from zero). At the aggregate level, this suggests that people are able to plan, since deviations from originally intended actions are not arbitrary, but can, to a large extent, be explained by changes in the underlying beliefs. However, as Figure 2 shows,

the analysis of aggregate behavior is not sufficient given the great heterogeneity present among the individual behavioral patterns.

Insert Figure 2 about here

Before looking in more detail to the relationship between beliefs, on the one hand, and current and intended contributions, on the other, it is interesting to check whether a change in an individual's belief, $\Delta b_{i,t}$, can be associated with the observed realization of events that were previously uncertain. For this purpose, denote by $e_{i,t} = c_{i',t} - b_{i,t}^{(t-1)}$ the ex-post prediction error in player i 's one-period-ahead beliefs. The experimental data shows that $\text{Corr}(\Delta b_{i,t}, e_{i,t}) = 0.297$ and $\tau(\Delta b_{i,t}, e_{i,t}) = 0.349$, again with levels of significance below 0.01%. From this we can conclude that, at the aggregate level, beliefs about the future tend to adapt to the acquisition of new information in the form of experiences.

Let us now proceed to the estimation results from the logit latent-class model developed in Section 2.4. The estimated parameter values for each of the three subpopulations are presented in Table 1. The numbers in parentheses represent the p -values for the individual coefficients, calculated using the likelihood-ratio test while holding the composition of all subpopulations constant. To interpret the estimation results of the model, it is useful to take a look at the shape of the predicted logit-choice probability mass functions of each subpopulation. Figure 3 plots these predicted behavioral patterns regarding one-period-ahead contribution plans for each of the three subpopulations, both for $t = 1$ and $t = 10$, conditional on beliefs fixed at 50.

Insert Table 1 and Figure 3 about here

Members of Subpopulation 1, whose estimated share in the population is 27.3%, can be classified as “opportunistic players”: the negative value of the coefficient $\gamma^*\beta$ indicates a significant preference for own monetary income maximization, and the conditional cooperation parameter $\theta^*\beta$ is the least significant

among all estimated coefficients. Subpopulation 1, moreover, has the fastest learning rate, as represented by the variance-reduction parameter, ρ .

The estimation analysis reveals that 29.7% of the population of experimental subjects belongs to Subpopulation 2, which – in contrast to the other two subpopulations – appears to have a positive coefficient $\gamma^*\beta$, suggesting that altruistic inclinations are stronger than own monetary income maximization concerns. The estimates for the $\gamma^*\beta$ and $\theta^*\beta$ parameters among the members of Subpopulation 2 exhibit, however, higher p -values than most other coefficient estimates. Moreover, the estimate of ρ has a negative value. This indicates that Subpopulation 2 is closer to purely random behavior than the other two subpopulations, and that the variability in behavior of its members increases over time. In other words, the apparent altruism among Subpopulation 2 is probably associated with difficulties in learning the incentives of the game.

Finally, members of Subpopulation 3 seem to be somewhere between the population of “opportunists” and “altruists”: conditional cooperation does play a significant role for them, even though opportunistic inclinations are also non-negligible. According to our estimation results, about 43% of the population of subjects belong to this group, which we label “conditional cooperators”. For this group, learning (in the form of reduction of variance) is also significant.

After having classified players as “opportunistic”, “altruistic”, and “conditional cooperators”, we now take a closer look at whether each of these types behaves consistently with respect to ex-ante intentions. Figure 4 shows how changes in current-period beliefs relate to deviations from one’s own previous contribution plan.

Insert Figure 4 about here

Subpopulation 1 appears to be the most consistent in this sense because, whatever the changes in beliefs, deviations from original intentions are mostly concentrated around zero. This is exactly what would be expected from fast

learning opportunistic players who only care about own income maximization. The scatter plot for Subpopulation 2, on the other hand, exhibits the largest dispersion in the relationship between deviations from initial plans and changes in beliefs. Nevertheless, the correlation coefficient and the Kendall's measure of association for this subpopulation of "altruists" are both significant, with $\text{Corr}(d_{i,t}, \Delta b_{i,t}) = 0.315$ and $\tau(d_{i,t}, \Delta b_{i,t}) = 0.198$. This gives additional support to our earlier observation that altruists are also characterized by some conditionally cooperative inclinations and confusion (absence of learning) during the game. Finally, the group of "conditional cooperators" shows, as expected, the largest positive correlation between changes in beliefs and deviations from plans, with $\text{Corr}(d_{i,t}, \Delta b_{i,t}) = 0.326$ and $\tau(d_{i,t}, \Delta b_{i,t}) = 0.328$ ($p < 0.01\%$ in both cases). For this subpopulation, actions tend to deviate from earlier plans following adjustments in earlier beliefs.

To conclude this section, it is worth to take a new look at the relationship between individual prediction errors and adjustments in beliefs in the subpopulation level.

Insert Figure 5 about here

It is interesting to verify that the classification we obtain through the latent class model by considering only one-period-ahead plans and beliefs also captures heterogeneity with respect to "learning abilities": all players tend to change their beliefs in the same direction as their experienced prediction errors but, while the opportunistic players seem to do it more systematically, the altruistic-confused players exhibit more variability (see Figure 5). At the subpopulation level, the correlation coefficients are all significantly different from zero: for the opportunistic type, $\text{Corr}(\Delta b_{i,t}, e_{i,t}) = 0.440$ and $\tau(\Delta b_{i,t}, e_{i,t}) = 0.443$; for the altruistic type, $\text{Corr}(\Delta b_{i,t}, e_{i,t}) = 0.275$ and $\tau(\Delta b_{i,t}, e_{i,t}) = 0.297$; and for the conditional-cooperator type, $\text{Corr}(\Delta b_{i,t}, e_{i,t}) = 0.373$ and $\tau(\Delta b_{i,t}, e_{i,t}) = 0.3493$.

5. CONCLUSIONS

Building on previous evidence of learning and social preferences in public goods experiments, we have developed a random-utility model specification that keeps the two concepts separate, taking into account contribution decisions, current and future beliefs about others' behavior, and intentions of future contributions. We have shown that estimates based on intentions data, rather than on actual contribution choices, can avoid the confounding effect of "strategic" cooperation that results when forward-looking players try to induce higher cooperation from future partners in a finitely repeated game. Our latent-class econometric model has also allowed us to classify players according to their most likely "type", whereby we characterize the population as consisting of three distinct subgroups: opportunistic players, conditional cooperators and altruistic-confused players.

Three main conclusions can be drawn from our analysis. First, people have heterogeneous preferences even at the intentional level, with most of them (43%) exhibiting some inclination toward conditional cooperation, even though the estimated proportions of altruistic-confused subjects and almost purely opportunistic subjects are not negligible (27.3%). Second, learning plays a significant role in explaining convergence of behavior toward the benchmark solution. Third, apparent inconsistencies in behavior with respect to original intentions can be explained, to a significant extent, by changes in beliefs, which in turn capture the effect of new information acquired in the interim period between elicitation of intentions and actual choice.

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Jena Economic Research Papers 2007-104

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APPENDIX. EXPERIMENTAL INSTRUCTIONS

In this appendix we report the instructions (originally in German) that we used for the two-plan treatment. The instructions for the one-plan treatment and the control treatment were adapted accordingly. They are available upon request.

Welcome and thanks for participating in this experiment. You receive €2.50 for having shown up on time. If you read these instructions carefully, you can make profitable decisions and earn more money. The €2.50 and any additional amount of money you will earn during the experiment will be paid out to you in cash at the end of the experiment. During the experiment, we shall not speak of euros but rather of tokens. Tokens are converted to euros at the following exchange rate: 100 tokens = €0.75.

It is strictly forbidden to speak to the other participants during the experiment. If you have any questions, please ask us. We will answer your questions individually.

DETAILED INFORMATION ON THE EXPERIMENT

The experiment is divided in 21 periods. In every period, participants will be matched in groups of two persons (pairs). *The composition of the pairs will change after each period*, so that you will be matched with a different person every period. You have *no* chance of interacting with the same participant more than once. The identity of the participants you are matched with will not be revealed to you at any time.

What you have to do

At the beginning of each period, each participant receives 100 tokens. In the following, we shall refer to this amount as *your endowment*. In each period, you as well as the other member of your pair have two tasks.

Task 1

Your first task is to decide how much of your endowment you want to contribute to a joint project in the current period *and* how much you plan to contribute to the joint project in the following two periods. In particular, every period you will have to answer the following three questions:

- (1) How much of the 100 tokens you have received this period do you want to contribute to the joint project in the current period?
- (2) How much of the 100 tokens you will receive next period do you plan to contribute

to the joint project one period ahead?

(3) How much of the 100 tokens you will receive in two periods do you plan to contribute to the joint project two periods ahead?

In other words, in each period $t = 1, \dots, 19$, you will have to provide one contribution decision for the current period t as well as two contribution plans: one for period $t + 1$ and the other for period $t + 2$. Of course, in the second-to-last period (i.e., in $t = 20$) you can only provide a plan for the next period, and in the last period (i.e., in $t = 21$) you cannot provide any plan. In the following, we shall refer to the current contribution decision as “contribution decision t ”, to the one-period-ahead plan as “contribution plan $t + 1$ ”, and to the two-period-ahead plan as “contribution plan $t + 2$ ”.

Your earnings in each period depend on the “*size of the joint project*” in that specific period. This size is determined as follows:

- In the first period, the size of the joint project is simply the sum of the current contribution decisions t made by you and the other member of your pair in period 1.
- In the second period, the size of the joint project can be either
 - (a) either the sum of the current contribution decisions t made by you and the other member of your pair in the current period 2
 - (b) or the sum of the contribution plans $t + 1$ made by you and the other member of your current pair one period ago (i.e., the plans $t + 1$ you both made in previous period 1 regarding current period 2).

These two possibilities are equally likely: with 50% probability the size of the joint project is based on your and your current partner’s actual “contribution decision t ” and with 50% probability the size of the joint project is based on your and your current partner’s “contribution plan $t + 1$ ”.

- In periods 3 to 21, the size of the joint project can be
 - (a) or the sum of the current contribution decisions t made by you and the other member of your pair in the current period,
 - (b) or the sum of the contribution plans $t + 1$ made by you and the other member of your current pair one period ago (i.e., the plans $t + 1$ you both made one period ago regarding the current period)
 - (c) or the sum of the contribution plans $t + 2$ made by you and the other member of your current pair two periods ago (i.e., the plans $t + 2$ you both made two

Jena Economic Research Papers 2007-104

periods ago regarding the current period).

These three possibilities are equally likely: with $1/3$ probability the size of the joint project is based on your and your current partner's actual "contribution decision t ", with $1/3$ probability the size of the joint project is based on your and your current partner's "contribution plan $t + 1$ ", and with $1/3$ probability the size of the joint project is based on your and your current partner's "contribution plan $t + 2$ ".

The income you receive from the joint project in each period is obtained by multiplying the size of the project in that specific period by 0.7. That is:

Period-income from the joint project = $0.7 \times$ Size of the project in that period.

The period-income from the joint project is determined in the same way for the two group members; this means that both receive the same income from the project.

EXAMPLE: Suppose that it is randomly decided that the size of the joint project in period 3 is given by the "contribution plans $t + 2$ " made in the first period, i.e., by the amount of tokens that two periods ago you and your current partner had planned to contribute in the current period (which means in period 1 regarding period 3). If, in $t = 1$, your "contribution plan $t + 2$ " was 60 tokens and your current partner's "contribution plan $t + 2$ " was 40 tokens, then the size of the joint project in period 3 is $60 + 40 = 100$, and *both* you and your current partner receive an income from the project of $(0.7 \times 100) = 70$ tokens.

You keep for yourself the tokens that do enter into the size of the joint project (either because you have not contributed them in the current period, or because you have planned not to contribute them one or two periods ahead).

Your period-earnings therefore consist of two parts:

1. tokens kept in that period, and
2. period-income from the joint project.

Your period-earnings = Tokens kept in that period + Period-income from the joint project

Task 2

In every period, besides deciding about your contribution in the current period and planning your contribution for the next two periods, you have to provide your *best predictions* about the contribution decisions of the participants whom you are matched

Jena Economic Research Papers 2007-104

with in the current period as well as in the following two periods. In particular, in each period, you will have to answer these additional three questions:

- (1) How much do you expect the participant whom you are currently matched with will contribute to the joint project in this period?
- (2) How much do you expect the participant whom you will be matched with next period will contribute to the joint project in the next period?
- (3) How much do you expect the participant whom you will be matched with in two periods will contribute to the joint project in two periods?

At the end of the experiment, we will select one of these three questions at random. The participant with the most accurate predictions in the randomly selected question will receive an additional bonus of €15. The closer your predictions are to the true contribution of the participants you interact with, the higher are your chances of receiving the bonus.

The information you receive at the end of each period

After completing tasks 1 and 2, and before proceeding to the next period, you will be informed about the actual contribution decision of the participant whom you are currently matched with. Similarly, your current group member will be informed about your own contribution decision in that period.

You will not be informed about the contribution plans that your current group member made in the current period or in previous periods.

Your final earnings

Your final earnings will be calculated by adding up your period-earnings in each period of the experiment. The resulting sum will be converted to euros and paid out to you in cash, together with the show-up fee of €2.50.

Before the experiment starts, you will have to answer some control questions to ensure your understanding of the experiment.

Please remain quiet until the experiment starts and switch off your mobile phone. If you have any questions, please raise your hand now.

Table 1: Latent-class model estimates

Coefficient	Subpopulation 1	Subpopulation 2	Subpopulation 3
π	27.3%	29.7%	43.0%
$\gamma^*\beta$	-0.02151 ($< 1 \times 10^{-10}$)	0.01889 (1.42×10^{-9})	-0.00599 ($< 1 \times 10^{-10}$)
$\theta^*\beta$	0.00008 (7.25×10^{-6})	0.00037 (2.18×10^{-8})	0.00010 ($< 1 \times 10^{-10}$)
ρ	9.85696 ($< 1 \times 10^{-10}$)	-0.04055 ($< 1 \times 10^{-10}$)	1.08322 ($< 1 \times 10^{-10}$)

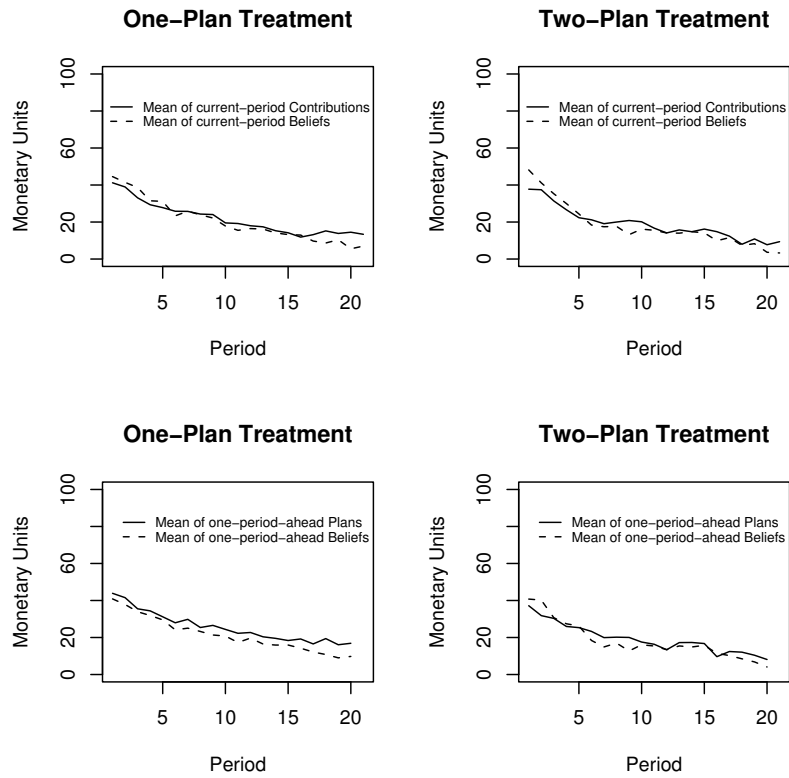


Figure 1: Evolution of mean current-period contributions and beliefs (upper panels), and of mean one-period-ahead plans and beliefs (lower panels), separately for the two experimental treatments

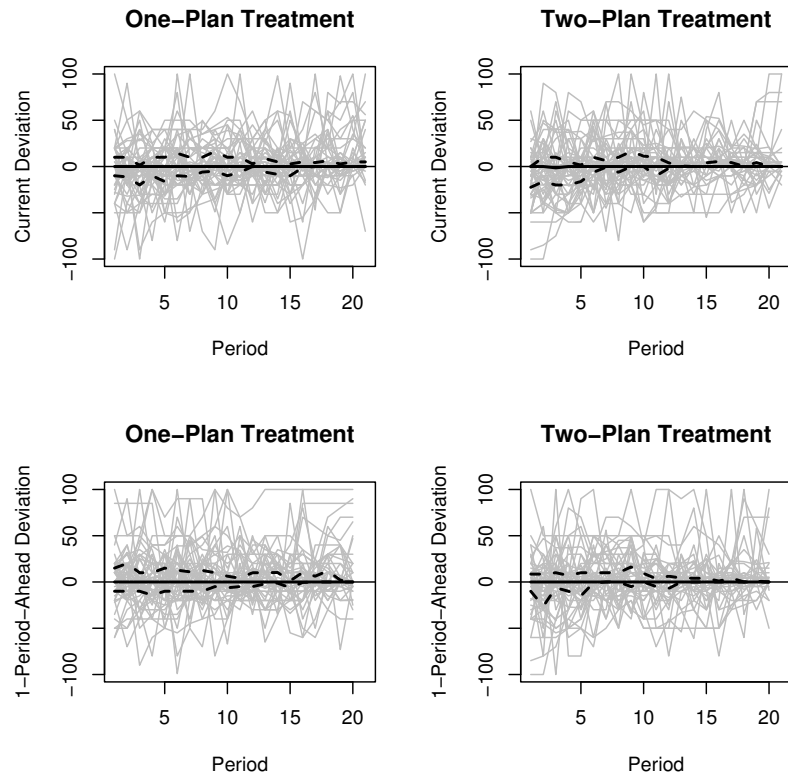


Figure 2: Individual differences between current-period contributions and beliefs (upper panels), and between one-period-ahead intentions and beliefs (lower panels), separately for the two experimental treatments

Note: The dark lines indicate the first quartile, the median, and the second quartile in each period.

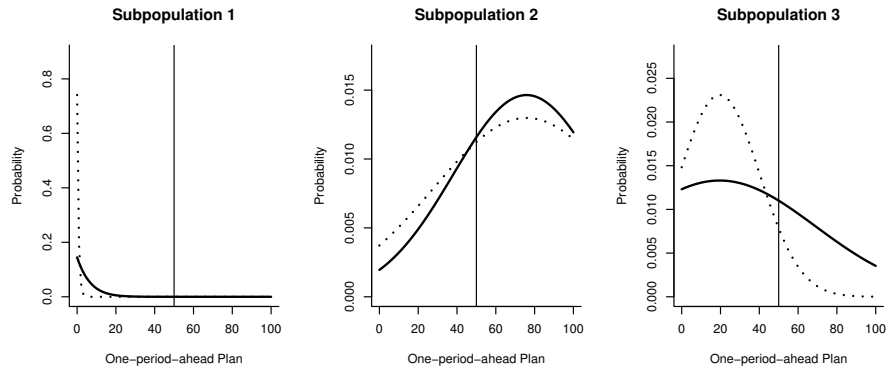


Figure 3: Estimated logit-choice probabilities for $p_{i,2}^{(1)}$ (continuous curves) and $p_{i,11}^{(10)}$ (dotted curves), conditional on $b_{i,2}^{(1)} = b_{i,11}^{(10)} = 50$ (vertical lines).

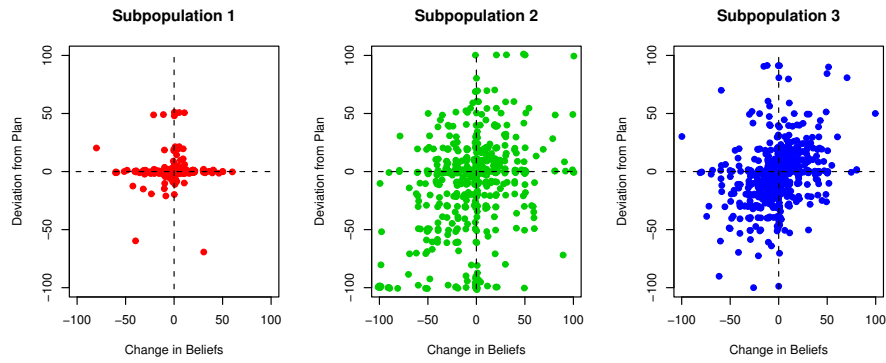


Figure 4: Association between changes in current-period beliefs and deviation from own previously planned contributions

Note: Random noise was added to the data in order to show overlapping points.

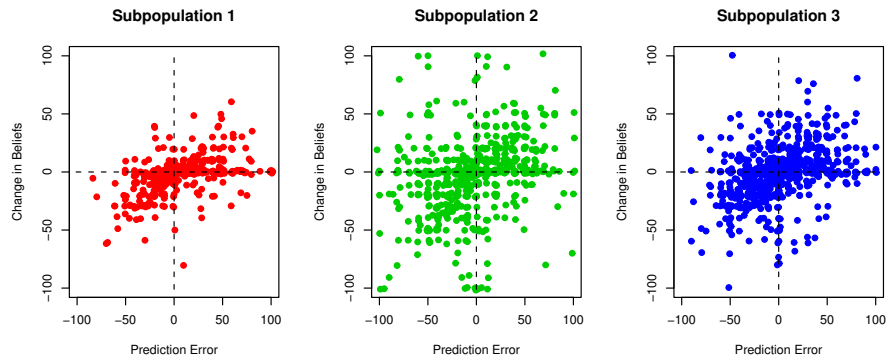


Figure 5: Association between prediction error regarding previous partner's contribution and correction of beliefs regarding current partner's contribution

Note: Random noise was added to the data in order to show overlapping points.