Belief Formation and Evolution in Public Good Games.*

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Abstract

We analyze first-order beliefs in a variation of the Public Good Game. We show that (1) the role that belief elicitation plays in the experiment affects both the contribution behavior and beliefs, and (2) framing influences stated beliefs, as much as contribution behavior. In the second part of the paper, we study the role of heterogeneity in the formation of initial beliefs, and provide an empirical model of the belief up-dating process. Subjects use the past experience, stressing the role of experience that comes from situations similar to the current ones.

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1 Introduction

The aim of this paper is to provide a large experimental analysis of *first-order beliefs*. First-order beliefs can be, informally, defined as expectations of players about how others will play a particular game. The issues, we explore here, concern the importance of beliefs for payoffs, the framing effects, and the role of individual heterogeneity in belief formation and evolution. In our experiment, we use a classic experimental protocol of Public Good Game.

Our study stem from Iturbe-Ormaetxe [10], who study framing effects in a variation of Public Good Game and whose experimental design we borrow. Nevertheless, our study differs with respect to theirs. Since their purpose is to study the contribution behavior, while we completely focus on beliefs, to their two treatments, we add another dimension with respect to the importance beliefs have in the experiment. The second crucial difference is the role of heterogeneity. They only use the individual heterogeneity to control for individual effects in the estimations. Hence, the heterogeneity plays a secondary role in their analysis. This changes in our paper. We use the socio-demographic data and pro-social attitudes of our experimental subjects as a primary aspect to explain belief formation and evolution.

In the first step, we show how belief elicitation affects both the contribution behavior and stated beliefs. To this aim, we perform 4 "degrees" of belief elicitation, concerning the importance of beliefs in experimental payoffs. In one treatment, beliefs are not elicited; in another one, we elicit subjects' first-order beliefs, but we do not use pecuniary incentives for their precision; as next degree, we elicit beliefs and incentivize them, in case they are correct; we call the last degree *belief play*, where subjects only state their beliefs, whereas the decision whether to contribute or not is calculated as a best response to the stated belief, assuming that subjects are self-interested and risk neutral. Note that from the first to the last design, we gradually increase the importance of beliefs in the experimental design. For example, in the first case, beliefs do not play any role, whereas in the last one, all the game is played via beliefs.

In a closely related research, Gachter and Renner [9] report that, in standard lineal Public Good Game, incentivizing beliefs increases their accuracy, whereas the average level of beliefs is not affected. Moreover, the elicitation of beliefs increases contribution.[1]

Second issue we explore is the framing effect on beliefs. There has been a vast amount of literature studying framing effects in the play,[2] while only little has been done concerning beliefs. An exception is Dufwenberg *et al.* [6] who explore the effects of reference points on beliefs in a one-shot Public Good Game. They observe that people expect their opponent to contribute more in the standard Public Good Game framing. As well as Dufwenberg et al., we run treatments with low reference point that correspond to standard Public

[1] In contrast, Nyarko and Schotter [13] reports that, in their experiment, belief elicitation have no effect on observed behavior in a constant-sum game.

[2] See, for instance, Andreoni [1], Brandts and Schwieren [3], Iturbe-Ormaetxe et al. [10] and Sonnemans et al. [14] who all discuss effects of the reference point in public good provision.

Good Game framing, and treatments with high reference point, which, in our experiment, differ in that the public good exists in the beginning and subjects have to contribute in order to preserve it.

Third, the experimental design of Iturbe-Ormaetxe et al. [10] allows to check whether experimental subjects use irrelevant information while creating belief about opponents play. More precisely, the costs of contribution are randomly generated and independent across rounds and agents. While the effect of contribution costs on contribution decision is straightforward, there is no information in the subject's own cost about the possible behavior of her opponents though.[3]

In the second part of the paper, we react to the fear of Nyarko and Schotter [13] that beliefs "*are not available outside of laboratory and hence out-of-sample predictions would be difficult to make.*" In this respect, we propose two econometric models. The first model attempt to use the questionnaire data to model the initial, pre-play beliefs of experimental subjects. We argue that the data elicited via questionnaire are more likely to be observable in real-life situations than beliefs. This would allow for a larger applicability of belief-based models even in one-shot situations.

The second model analyzes the belief updating process. Attanassi and Nagel [2], for instance, report that, in a coordination-like game, if a player believes that another player cooperates with a certain probability and she, actually, does, the first player's predicted probability of cooperation of the next opponent increases. This illustrates a possible influence of past play on current beliefs. Alternatively, Nyarko and Schotter [13] observes that, in a 2×2 constant-sum game, predicted high probability of an action in an experimental round induces a low predicted probability of the same action in next round. Thus, belief might also play an important role in belief up-dating. We analyze these hypothesis on our data.

There are two crucial differences of our paper from the literature analyzing beliefs in public good provision. First, we play a variation of the Public Good Game. In this game, a certain number of contributing individuals has to be reached to provide the public good. This implies that if an agent is pivotal, self-interested individuals prefer to contribute, leading to a multiplicity of equilibria. This design creates a more complex strategic environment, which makes the role of first-order beliefs more relevant for the play.[4] This contrasts with standard lineal Public Good Game, where the beliefs are not as relevant as in the threshold version.[5] It has been observed that such variation increases the frequency of contributions (Ledyard [11]) and this is also confirmed in our case (see Iturbe-Ormaetxe et al. [10] for a more detailed discussion on contribution behavior).

Second, we base the interpretation of our experimental results on the heterogeneity of agents. Traditionally, the experimental literature treats subjects

[3] The phenomenon of using irrelevant information in decision processes has already been observed and is known as *anchoring effect* (Tversky and Kahneman [15]).

[4] This is very well illustrated by Iturbe-Ormaetxe et al. [10], who show that, in the same experimental protocol, the belief of being pivotal is one of the main driving forces for contributing.

[5] On the other hand, this deviation from the standard Public Good Game protocol is small enough to still allow for direct comparisons with the original game.

as homogeneous. In our models, we use the questionnaire data when we explain the observed first-order beliefs, and show that the same types of individuals might state different beliefs, depending on the prevailing experimental design.

In what follows, we briefly reviews the main findings.

We reproduce most of the findings of Gachter and Renner [9]: belief elicitation increases contributions and the incentivizing of the accuracy of beliefs increases lead to slightly better predictions. In contrast to Gachter and Renner, incentivizing affects the distribution of beliefs in our experiment.

Concerning the effect of reference point, we report that this framing affects both the initial, pre-play beliefs and the belief up-dating process. Our evidence goes against the findings of Dufwenberg et al. [6]. The high reference point induces higher beliefs, including the belief experimental subjects hold in the first round.[6] As for the anchoring of stated beliefs on irrelevant information the own contribution cost provides about the possible play of opponents, we report a persistent negative relation between the costs and stated beliefs. This relation is present in all treatments.

Our findings concerning framing and anchoring effects support the argument of Dufwenberg et al. [6]. They suggest that beliefs, rather than directly preferences, can be the way framing can enter into the decision process, and we show that the same might matter for the anchoring of decisions on irrelevant information.

In Section 3.3.1, we show that, contrary to the fear of Nyarko and Schotter [13], we can explain a large fraction on the variation of initial stated beliefs on basis of variables that are more likely to be observable in real life situations.[7] Hence, the explicative variables account for a large fraction of the variability of stated beliefs. The analysis of the belief up-dating process confirms that past play of opponents and past beliefs matter.

The remainder of the paper is organized as follows. Next section describes the experimental design. Section 3 is divided into 2 parts. In the first part, we present the experimental findings, using simple descriptive statistics. Afterwards, we proceed to a more complex statistical analysis in Subsection 3.3. The last section concludes and provides suggestions for further research.

2 Experimental design

In what follows, we describe the features of the experiment in detail.

2.1 Subjects

The experiment was conducted twice, one in December 2005 and another one in February 2007. In total, we run 4 sessions in 2005 and 8 sessions in 2007. A total of 288 students from various fields (24 per session) were recruited among

[6] The only exception are the non-incentivized belief treatment. See below for more details.

[7] The McKelvey and Zavoina's R^2, the most suitable measure of fit for ordered categorical dependent variables (Long [12]), reaches 0.96.

the undergraduate student population of the University de Alicante with no (or very little) prior exposure to game theory.

The experiment was computerized, using the experimental software *z-Tree* (Fischbacher [7]). Instructions were provided by a self-paced, interactive computer program that introduced and described the experiment. Subjects were also provided with a written copy of the experimental instructions, identical to what they were reading on the screen.[8] A particular care was devoted in explaining the two different treatments (i.e. the two frames), and, in the belief treatment (see below), the algorithm the computer uses to calculate the best response.

2.2 Game Form

The game played in each round of the experiment is a threshold version of the Public Good Game. In this game, agents are distributed to groups of 3 and, once assigned to a group, they have to decide whether they want to contribute or not. The contribution is costly. Anytime, an agent decides to contribute she has to pay a cost c. After all the members of the group decide their contribution behavior, the computer counts the number of contributing agents. If this number falls short of the number required, k, that appears on the screen of each subject's computer before she makes her decision, the public good is not provided. Otherwise, the public good, worth 50, is provided to all members of the group, independently of whether they contributed or not. The cost of contributing, c, was, for all subjects and rounds, an independent draw $c \sim U[0, \overline{c}]$, with $\overline{c} = 55$ pesetas.

Let *time interval* $\tau_i = \{3(i-1) < t \leq 3(i)\}$, $i = 1, ..., 8$, be the subsequence of the $i - th$ 3 rounds of each treatment. Within each time interval τ_i, subjects experienced each and every possible $k \in \{1, 2, 3\}$, with the order being randomly determined within each τ_i. The reason for varying k in this manner is two fold. First, different k's create different motivations for contributing and, thus, might affect agents' expectations considerably. Moreover, we can keep under control the time distance between two rounds characterized by the same value of k. As mentioned, each subject was able to see the current values of k, together with c, on the screen, before she made her contribution decision.

In some treatment conditions (see below), each round consists of 2 stages. The first stage coincides with the game described in the previous paragraph. The additional stage serves for the elicitation of subjects' first order beliefs. Each subject have to answer the following question: "How many of the other members of your group (excluding yourself) do you think have contributed in this round?" To preserve simplicity of the experimental protocol, we restricted the possible answers to integer numbers, such that the stated belief had to be either 0, 1, or 2 if the subject believed that noone, 1 or 2 other member from her group have contributed in the corresponding round.[9]

[8] The complete set of instructions, translated into English, is available upon request.

[9] Observe that what we actually observe, using this design, is the mode of the belief distribution of subjects. Since the first-order belief is a distribution over opponents' strategies, we

2.3 Factorial Design

We performed $4 \times 2 = 8$ factorial design. As mentioned in the introduction, we tested 4 degrees of belief elicitation and 2 frames with respect to the reference point.

The 4 degrees of belief elicitation are the following:

- *No elicitation.* In 2 sessions, each round has a unique step, where subjects have to decide whether to contribute or not. Beliefs are not elicited in these sessions.
- *Non-incentivized belief elicitation.* In another 2 sessions, each experimental round consists of 2 stages. In the first stage, subjects have to decide whether to contribute or not. In second, they have to state the number of members of their group, which they believe will contribute in this round. The belief elicitation stage have no monetary consequences.
- *Incentivized belief elicitation.* In 6 session of the experiment, each experimental round is the same as in previous degree, with the difference that the belief elicitation stage is now incentivized. Subject are paid 5 ptas. anytime their guess is correct.[10]
- *Belief play.* In 2 sessions, each experimental round consists of 1 stage. Contrary to other designs, subjects do not have to make the contribution decision. Rather, they only state their beliefs about the play of other members of their group and the computer decides for the them whether to contribute or not, taking into account the stated belief, and assuming that they are risk neutral and self-interested. Since, in this treatment, the whole monetary consequences are determined by the belief, we allow the stated belief to lie in the entire interval between 0 and 2, including non-integer numbers. The possibility of non-integer beliefs is explained to the experimental subjects as the possibility of doubt between possible number of contributing opponents. For example, 1.5 is interpreted as a belief that 1 member of the group cooperate with probability one half and 2 of them with the same probability.[11]

In each session, subjects played a total of 48 rounds. The 48 rounds were divided into 2 phases, 24 rounds each. In each phase, subjects faced a frame with a particular reference point; that is, each subject played both reference points, each in one phase. A frame is uniquely defined by a reference point. Denote x_0 the reference point agent faces in a particular round. Then, there are 2 possible reference points in our experiment, $x_0 = c$ and $x_0 = 50$. Let us call the first (latter) case low (high) reference point[12] and denote it $T_1(T_2)$. The

elicit a proxy variable of this distribution.

[10] There are no monetary consequences for incorrect beliefs.

[11] We are aware that each number is not uniquely determined. For instance, 1.5 can also be the result of believing that noone contributes with probablity 0.25 and 2 member with 0.75.

[12] As explained above, it is not always the case that this reference point is the low one. We, nevertheless, use this terminology in order to simplify the discussion of results.

first case corresponds to the traditional Public Good Game frame. If an agent contributes, she has to pay (loses) c, but if k or more individuals contribute she can earn 50. Thus, the starting, reference point she faces is the cost, which she can hold for herself if she does not contribute. In the case of $x_0 = 50$, each agent starts having the public good, and she decides whether to contribute. If she does not contribute, she earns the contribution cost, but in case that less than the required number of contributors contributes they all lose 50. Thus, the staring point here is 50.

Let us call D_1 (D_2) be the design in which treatment T_1 (T_2) is played the first 24 rounds (see Table 8). To control for the possible order effects of the framing, we conducted each treatment twice (6 times in cases of incentivized belief elicitation), switching the order of framing.

	D_1	D_2
Rounds	$S_1 - S_6$	$S_7 - S_{12}$
1-24	T_c	T_g
25-48	T_g	T_c

Table 1. Experimental Sessions

In each session, the 24 subjects were divided into 2 *cohorts* of 12, with subjects from different cohorts never interacting with each other throughout the session. We shall therefore read our experimental data under the assumption that the history of each individual cohort corresponds to an independent observation of our experimental environment. Thus, we have $12 \times 2 = 24$ independent observations. Within each round $t = 1, ..., 48$, in each cohort, 4 groups of 3 subjects were randomly determined, to preserve anonymity.

After each round each agent was informed of the contribution decision of the other group members (i.e. the outcome for that round), together with her payoff (on both dimensions: belief and contribution game) and the average payoff of her group members (only as for the contribution decision was concerned). The same information was also given in the form of a *History table*, so that subjects could easily review the results of all the rounds that had been played so far.

2.4 Payoffs

At the beginning of each treatment, subjects received 1.000 pesetas (1 euro is approximately 166 pesetas) as an initial endowment.[13] As for T_1, subjects would gain 50 pesetas if the number of contributors in their group would reach the

[13] It is standard practice, for all experiments run in Alicante, to use Spanish ptas. as experimental currency. The reason for this design choice is twofold. First, it mitigates integer problems, compared with other currencies (USD or Euros, for example). On the other hand, although Spanish pesetas are no longer in use (substituted by the Euro in the year 2001), Spanish people still use Pesetas to express monetary values in their everyday life. In this respect, by using a "real" (as a opposed to an artificial) currency, we avoid the problem of framing the incentive structure of the experiment using a scale (e.g. "Experimental Currency") with no cognitive content.

target k (with c being subtracted from their initial endowment); in T_2 subjects would loose 50 from their initial endowment if the numbers of contributors would not reach target, gaining c in case of non contribution. Subjects received, on average, 16 euros for a 90' session.

At the end of the sessions, subjects were asked to answer a detailed questionnaire on their socio-demographic characteristics, together with standard questions to estimate their pro-social behavior.

3 Experimental Results

In this section, we report the results of our experiment. We begin by presenting some descriptive statistics, which summarize the effect of the factorial design in our experiment and other observed regularities. We then estimate 2 econometric models that allow us to study 2 research questions. First, we try to understand how individuals form their decision in new situations on their personal characteristics. In the second model, we depict the belief up-dating process of subject throughout the experiment.

3.1 Descriptive Statistics

We shall divide this section according to the currently discussed effect.[14]

3.1.1 The Effect of Belief Elicitation Method

Question 1. How does the belief-elicitation mechanism affect the contribution behavior?

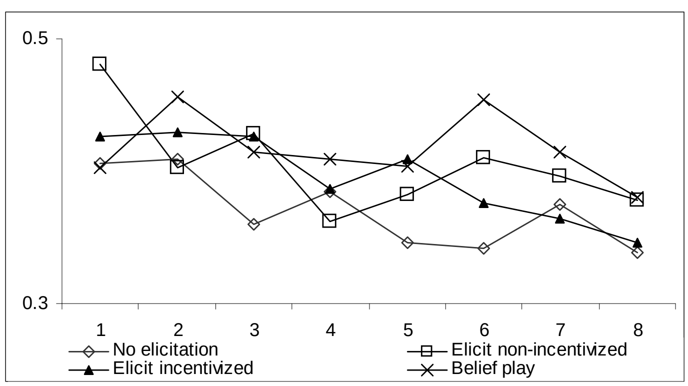


Figure 1. Contribution behavior.

[14] Most of the results presented in this section is presented for time intervals, rather than experimental rounds. With this structure, we like to get rid of the effect of k. The effect of k is studied in more detail in the second part of Section 3.

Figure 1 disaggregates the average contribution behavior by the belief-elicitation method. On x-axis, we plot time intervals; the y-axis reports the percentages of contributing individuals. The frequency of contribution decreases over time in all but the belief play treatment, where it seems not to evolve over time. In all cases, we observe an end-game effect. The salient features of each treatment are:

- *No elicitation.* The frequency of contribution is the lowest in comparison with other treatments, with this more pronounced in the last repetitions of the game.
- *Non-incentivized belief elicitation.* The initial belief is much higher than in any other treatment. Then, we observe a sharp decrease in the first repetition of the game and a roughly constant frequency from $\tau_i = 4$ on.
- *Incentivized belief elicitation.* Very smooth decreasing trend of contribution behavior.
- *Belief play.* Recall that, in this experimental design, people do not decide their contribution behavior on their own. Rather, the computer decides for them, given their stated belief. As a result, we observe no general decreasing trend and high volatility, the former causing that the average frequency is the highest in this treatment in the second half of the experiment. The end-game effect is very strong, but it may also be due to the high volatility in the contribution behavior of this treatment.

The pairwise comparison of the contribution behavior uncovers that there is no real difference between the incentivized and non-incentivized belief elicitation, even though the financial incentives seem to lead to a larger end-game effect, i.e. the contributions are lower in this treatment in the last repetitions of the game. On the other hand, both treatments, together with the belief play, lead to a slightly higher contribution levels, compared to the no elicitation treatment. The belief play contributions are very similar to both belief eliciting treatments.

On average, 37%, 39.5%, 40.5% and 41.7% of individuals contribute in no elicitation, incentivized belief, non-incentivized belief, and belief play treatments, respectively. This leads to the following conjecture:

Result 1 Belief elicitation *does* affects the play in our experiment, driving the contributions upwards, closer to the level of stated beliefs. Contribution behavior does not differ much across treatment, as long as beliefs are elicited.

Question 2. What is the effect of belief elicitation method on stated beliefs?

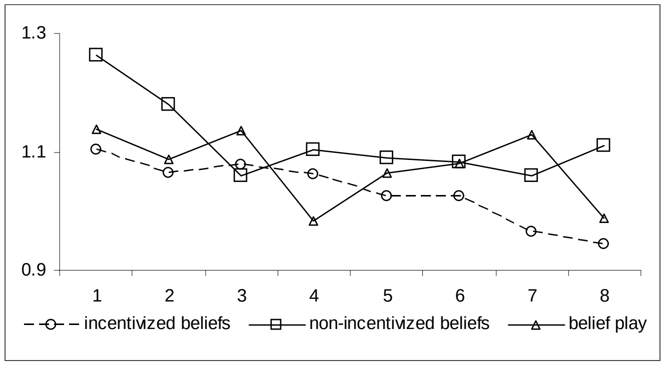


Figure 2. Beliefs.

Figure 2 traces the average beliefs, the x-axis again plotting the time intervals. In all treatments, we observe a decreasing trend of beliefs over time. The initial beliefs of non-incentivized belief elicitation are above the other 2 cases. Hence, when beliefs are not incentivized, subjects initially expect higher contributions. Average beliefs decreases constantly and smoothly in the incentivized belief treatment. In contrast, the non-incentivizing leads to a sharp decreases in the first repetitions, which compensate for the high beliefs in initial rounds, but from $\tau_i = 3$ on, they stay constant. The belief play produces very volatile beliefs with a lower decreasing trend with respect to the other treatments. In the last repetitions, there seems to be a radical decrease of beliefs in this treatment. Nevertheless, we cannot say whether this is due to the end-game effect or the mentioned volatility.

Result 2. Incentivizing of first-observed beliefs decreases their level (toward the actual level of contributions).

Question 3. Do subject predict the play accurately?

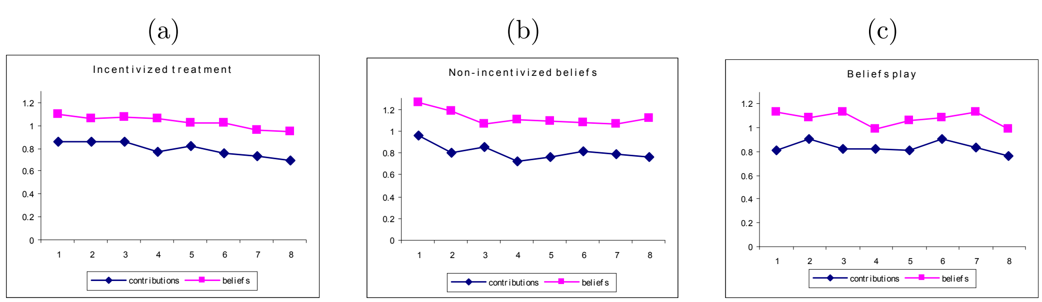


Figure 3. Beliefs and contributions.

Figure 3 illustrates the capacity of experimental subjects to predict the behavior of opponents and its evolution over time. The lower graph traces the average number of contributing opponents of each subject; the upper grey graph traces the average beliefs. The left panel represents this figure for incentivized beliefs; the intermediate corresponds to the non-incentivized elicited beliefs; the right panel reports the averages for the belief play.

The most salient observation from Figure 3 is that stated beliefs and contributions are parallel, i.e. the evolution of both variables is on average very similar. What differs is the level. In all cases, the average level of belief is larger. In other words, people considerably overestimate the number of contributing individuals. Moreover, the difference between beliefs and contributions seems to stay roughly constant over time.

The observed beliefs are correct in 36.7%, 38.5% and 27.3% of cases in non-incentivized beliefs, incentivized beliefs, and belief play treatments, respectively.To illustrate the differences across treatments, Figure 4, which plot the average number of correct predictions on the y-axes, disaggregated by belief elicitation method, summarizes the evolution of averages of correct beliefs. The graph only confirms some of the above observations. Subjects, indeed, do not learn enough to predict the opponents' behavior better in the incentivized belief treatment. However, in the remaining 2 cases, the average frequency of correct beliefs actually decreases over time, being this decline much more pronounced for the belief play.

Pairwisely, incentivizing of correct beliefs slightly rises the accuracy of beliefs in comparison with when they are not incentivized. This is, on average, more salient, as subjects get experienced. The belief play lead to a clear lower capacity to predict the opponents' behavior.

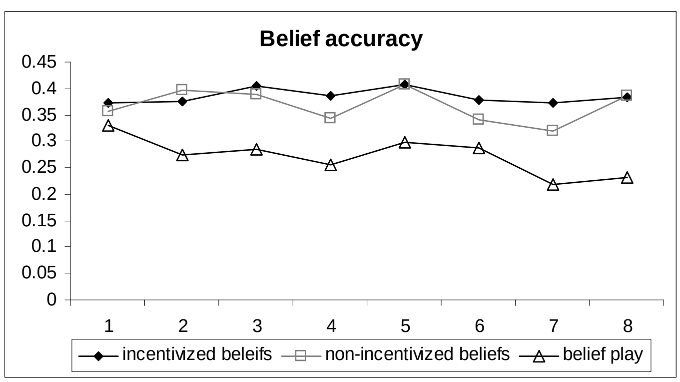


Figure 4. Percentages of correct predictions.

Result 3. Some belief-learning process takes place (beliefs decreases over time intervals), but the learning is not large enough to lead to better predictions of opponents behavior. Incentivizing beliefs' accuracy lead to slightly better predictions.

3.1.2 The Effect of Framing

In this subsection, we analyze the impact of the reference point on beliefs. Recall that we run two frames concerning the reference point, T_1, which represents the standard Public Good Game, and T_2, where the public good initially exists and a sufficient number of individuals has to contribute to maintain it (i.e. if they do not contribute they have a loss).

Figure 5 illustrates graphically the impact the reference point has on average level of beliefs. Again, x-axis traces the time intervals. Figure 5(a) plots the average stated belief, while Figures 5(b-d) disaggregates the data by the belief elicitation mechanism. In each subgraph of Figure 5, the upper plot represents the high reference point treatment T_2, whereas the lower line stands for T_1. Two main conclusions can be driven from Figure 5.

First, there is almost no difference in initial first-order beliefs. Hence, the framing seems to have no effect in the first rounds of the game. This contrast with the findings of Dufwenberg *et al.* [6] who observe that, in the one-shot Public Good Game, the first-order beliefs are significantly higher in the treatment, corresponding to our T_1. A closer look at Figure 5 leads to an even starker contrast of our findings with theirs. In the figure, there actually are tiny differences in the first round beliefs. Nevertheless, the graph of the overall data, as well as 2 out 3 treatments, reverses the rank observed by Dufwenberg *et al.* We observe that, on average, the initial first-order beliefs are higher in the higher reference point frame, T_2.

The second regularity we observe is the contrast in the evolution across the 2 framings. Since the very beginning, stated beliefs are lower in T_1, in harmony with the contribution levels, which have the same order (see Iturbe-Ormaetxe et al.[10] for more evidence on framing effects in the same experimental protocol). Moreover, the later the experimental round, the more pronounced is the difference between the two treatments. People learn both to contribute less in the standard Public Good Game treatment and to expect less contribution from the others. This suggests that, not surprisingly, the past play shapes the beliefs.

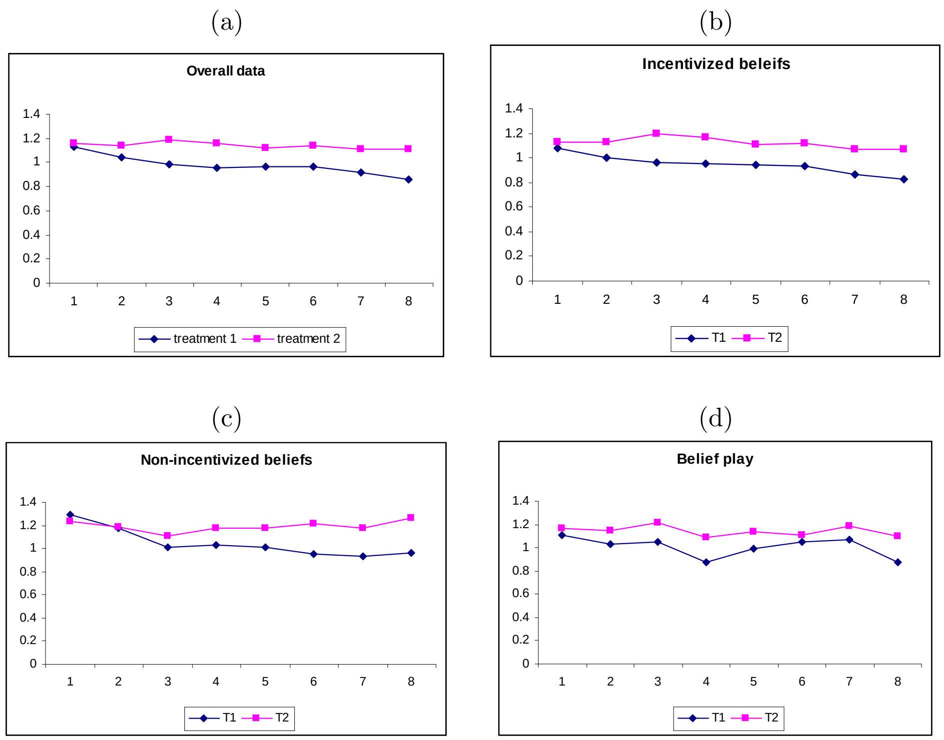
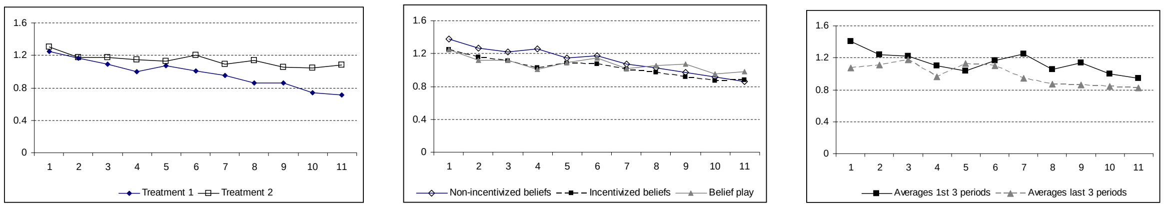


Figure 5. The framing effect on beliefs

Result 4. Framing does not seems to matter initially, but as subjects gain experience, they expect lower contribution levels in the standard Public Good Game framing.

3.2 Anchoring effect

As we already explained in Section 2, the cost of contributing, c, is randomly generated in each round and independent across players. Therefore, knowing own cost in a particular round provides *no* information whatsoever about the possible play of other members of the group. Actually, the observed correlation coefficient between the cost of contribution of an individual and the play of her opponents in the same round is not significantly different from 0 ($\rho = 0.01$, $p = 0.44$). Consequently, experimental subjects should not take their own cost into account when evaluating their prediction of play of others. However, we observe that people use this information.



(a) (b) (c)

Figure 6. The relation of beliefs on cost of contribution

Figure 6 traces the dependence of average beliefs, y-axis, on the individual costs of contribution, x-axis.[15] We observe a negative relation in most of the graphs of Figure 6.

Figure 6(a) stresses the different relation between the two variables across treatments with respect to the reference point. In both cases, there is a negative relation between beliefs and c. The average beliefs are considerably more affected by the cost in the standard Public Good Game framing, T_1. The negative dependence is less pronounced in T_2, but still evident.

The contrast among the belief elicitation degree, illustrated by Figure 6(b), shows that the negative relation between is present in all cases. There is almost no observable difference between the non-incentivized and incentivized belief elicitation, as long as c is large enough. For low c, non-incentivized beliefs are more sensitive on cost than incentivized beliefs. The belief play lead to the least negative relation between beliefs and c. In this case, beliefs are below the average values of the remaining two treatment conditions, whereas for large values, the lower sensitivity causes that the average beliefs turn out to lie above the averages of the other two treatments.

Generally, we can state two following results:

Result 5. The degree of anchoring beliefs on irrelevant information is more influenced by the change in the reference point, rather than in the belief-elicitation method. In the latter case, it seems that the higher payoff consequences of beliefs, the lower is the degree of sensitivity of beliefs on the contribution cost.

To analyze whether people learn not to use their c in their beliefs, Figure 6(c) contrasts the average first-order beliefs in the first and last tine interval. The black line corresponds to the first interval relation; the grey line represents the last interval. We observe a decreasing trend in both cases. In spite of some differences, the lower graphs looks as parallel to the upper line. Thus, there seems to be no real difference in the relation between the 2 variables.[16] Thus, subject does not learn not to use the irrelevant information contained in their own costs, even though there is a zero correlation.

[15] For illustration purposes, we divided all the relevant interval of c into 11 disjoint subintervals.

[16] The shift, clearly, is due to the general lower level of beliefs, as time proceeds.

3.3 Formation and Evolution of beliefs

In the introduction, we argue that beliefs are very relevant for game-theoretical analysis, and, in the previous subsection, we show that beliefs, as well as choices, are influenced by the way they are elicited, by framing etc. Consequently, in this section, we attempt to - at least partially - endogenize first-order beliefs, and provide an empirical model of belief up-dating process. Recall the treatment designs with respect to the belief elicitation are no-elicitation, elicited non-incentivized beliefs, elicited incentivized, and belief play. In the first case, beliefs are not elicited, and, in the belief play treatment, beliefs are allowed to be non-integer. Therefore, only elicited incentivized and non-incentivized beliefs can be analyzed using the same econometric model. Consequently, in this subsection, we only consider a 2×2 factorial design, using treatment, which provides beliefs as an ordered discrete variable. This leads to 4 treatment conditions, which we treat separately in the estimations. To this aim, we define 4 dummy variables f_{it}^{j} with $j = 1, 2, 3, 4$, such that $j = 1$ if subject i in round t participates in the non-incentivized beliefs treatment with T_1; $j = 2$ for the non-incentivized beliefs treatment and T_2; $j = 3$ for the incentivized beliefs treatment with T_1; $j = 4$ for incentivized beliefs with T_2.[17] The dummy variable $f_{it}^{j} = 1$ if agent i in round t participates in treatment condition j.

3.3.1 Belief formation

The main objective of this section is to check whether the unobservability of beliefs, as the main argument against their wider applicability, could be side-tracked by the employment of alternatives. In our case, the questionnaire data extract from our subjects their socio-demographic characteristics and pro-social attitudes, which we relate to the first-round stated beliefs, as a proxy for the initial pre-play beliefs of subjects, that are still not influenced by the play. The goal is to provide a simple, empirically-relevant model which may facilitate the applicability of theories containing beliefs in one-shot situations.

To this aim, we run an ordered logit regression of individuals' beliefs in the first rounds of our experimental sessions. There are two types of explanatory variables. First, we control for the possible effect of the experimental design on the initial beliefs, and, second, we regress beliefs over the questionnaire data. The model also contains interactions of both types of variables. In the following, we list the variables, which we have found to have a significant impact on the dependent variable:[18]

- treatment dummies f^j with $j = 1, 2, 3, 4$;
- the contribution costs, c, in the initial period;
- gender dummy, sex;

[17] Clearly, f_{it}^{j} serves for the panel data analysis in Section 3.4. In the following Section 3.3.1, we only deal with data in round 1. The time subsrcipt is, thus, omitted and, for treatment dummies, we use f_i^j with $j = 1, 2, 3, 4$.

[18] The variable k was fixed for all sessions in the first round and equal to 3.

- the size of the family subjects live in, $familysize$;
- *active* is a dummy variable that takes a value of 1 if the bread-winner in i ‘s family is unemployed and does not actively search a new job;
- *lastweekwork* is a dummy such that $lastweekwork_i = 0$ if i had not worked the week before the experiment, and 1 if she had;
- $lottery_i \in \{0, 1, ..., 7\}$ measures the frequency, with which i engages in lotteries or bets, being $lottery1$ higher, the higher the frequency;
- $riskaversion_i = 1$ if subject i prefers 30, rather than playing a lottery where she earns 45 with probability 80% or 0 with 20% probability, and $riskaversion_i = 0$ if she accepts the lottery, i.e. i is risk averse if $riskaversion_i = 1$;
- $pers2extreme_i = 1(0)$ if i (does not) find herself either extremely quick or extremely slow in reasoning;
- $cognitive \in \{1, 2, ..., 7\}$, measuring individual's subjective opinion about his cognitive skills, being $cognitive_i$ increasing the more skilled finds i herself;
- $pers3extreme_i = 1(0)$ if i (does not) find herself either very easy or very hard to get offended;
- $satisfaction_i = 0$ if i evaluates herself either very satisfied or very unsatisfied with her life, and $satisfaction_i = 1$ in the other case;
- $extremepolitics_i = 1$ for subjects who find politic issues extremely important and extremely unimportant and 0 for less extreme opinions about the importance of politics;
- $religionlow_i = 1$ in case of subjects who find religion unimportant and 0 otherwise;
- $inequality \in \{0, 1\}$ elicits subjects' inclination toward the deservings of higher earnings, when one works more, being $inequality_i = 0$ for individuals who prefer equality of earnings, independently of work performance, and 1 for those who find the performance more relevant in financial evaluation;[19]
- $state1inter \in \{0, 1\}$ is related to *inequality*, such that $state1inter = 1$ if i has a moderate opinion in this respect, i.e. she neither believes that only inequality matters nor that only the individual effort does, and it is 0 for those who tend to stress either the role of equality or the role of effort-related incentives;

[19] The variable is an answer to the following question: *"Consider the following situation: Two secretaries with the same age do exactly the same work. However, one of them earns 20€ per week more than the other. The one that is paid more is more efficient and faster, while working. Do you believe it is fair that one earns more than the other?."* The variable $inequality_i = 0$ if the answer is "No" and 1 otherwise.

- $statement2 \in \{1, 2, ..., 7\}$ measures subjects' opinion on a scale between two extreme statements: "Firms should be private" and "Firms should be state-owned". The closer is i's opinion to the first statement, the lower is $statement2$;

- $statement5 \in \{1, 2, ..., 7\}$ reports the position of i's opinion between two extreme statements, "The competition is positive. It stimulates people to work harder and develop new ideas" and "The competition is negative. It reveals the bad side of humans";

- $statement7 \in \{1, 2, ..., 7\}$ again measures the position between two statements: "Independently of the qualities and deficiencies of parents, they should always be loved and respected" and "Parents who have not earned the love by their attitudes and behavior should not be loved"; the closer the opinion to the first statement the lower $statement7$.

Table 2 reports the estimation results (together with the standard errors, p-values, significancy statistics and odds ratios).

Put Table 2 around here.

Given the aim of this section, we mainly focus on the overall characteristics of the model. In this respect, we run a model specification test, we test the general joint signification of the variables of the model, and discuss briefly its fit.

To test whether our model is correctly specified, we run a model specification test. We cannot reject the correct specification of the model ($p = 0.2$). This is also confirmed by the Likelihood Ratio test. The variables of the model are jointly significant on any reasonable significance level ($LR = 169.893, p = 0$). To check the measure of fit of our model, McFadden's R^2 is 0.478 and McKelvey and Zavoina's R^2 reaches even 0.959.[20] Since we do not reject any of the performed tests and the fit of the model is high, we conclude that it is possible to at least approximate unobserved beliefs, using variables that one observes in the relevant sample.

It is also worth to discuss the effects of design variables on the initial beliefs. In this respect, let us start with the effect of treatment dummies in the model. The average levels of beliefs in the first round of the experiment are 1.21, 1.54, 0.99 and 1.26 for f^1, f^2,$f^3$and f^4, respectively. There seem to be some differences. Beliefs seems to be lower when the reference point is as in the standard Public Good Game, and, within both the low and high reference point framings, beliefs are higher in the non-incentivized belief elicitation treatment, as already observed in Section 3.1.

The most straightforward test is to contrast pairwisely whether the effect of treatment dummies does not differ across the 4 treatments. Therefore, we

[20] We also run an alternative model, where only significant variables are included. In this model, the model specification test's p-values reaches 0.98, McFadden's R^2 is 0.3664 and McKelvey and Zavoina's R^2 is 0.88.

test the joint hypothesis that the estimated coefficients associated to treatment dummies f^2,$f^3$and f^4 are all simultaneously equal to 0, to test the differences between non-incentivized beliefs and low reference and the remaining 3 treatments.[21] To test the differences between treatments 2,3 and 4, we run other 3 joint tests with the null hypothesis that the estimated coefficients, associated to the same variables, do not differ across the 3 treatments.[22] From the estimation results, we can see that this is not the case and the tests, indeed, confirm this ($p = 0$ in all cases). Thus, since, in each treatment, different variables influence the initial beliefs, we conclude that the distribution of initial beliefs in the first rounds of the experiment are generated by different processes. At this point, it is worth stressing that the performed tests only lead to the conclusion that the process of belief generation is different, influenced by diverse factors that depend on treatment conditions.

These results notwithstanding, the average level of beliefs can still be very similar across treatments. This is actually suggested by the average values of beliefs. For example, the average beliefs in f^1 and f^4 are 1.21 and 1.26, respectively. These values are that close that it is hard to belief we would reject their equality in a statistical test, performed on level of beliefs, rather than the roles of individual variables in the model.

Traditionally, this is tested using marginal effects of relevant variables. Marginal effects are calculated on basis of the movement of the concerned variable, holding all other variables constant. This is an unrealistic approach in our data, since a change of a treatment dummy, necessarily, entails a change in another one. Hence, rather than studying marginal effects, we use the estimated probabilities of the dependent variables across the 4 treatment conditions tested in our model, and calculate the average beliefs. Their pairwise comparisons permit us to test whether, in spite of the different processes that generate them, the average estimated levels of beliefs are the same.

The main points, resulting from the tests, are:

1. non-incentivized belief elicitation and high reference point generates the highest pre-play beliefs ($p = 0.09, 0, 0.11$ for f^1, f^3, f^4, respectively), even though the difference is not significant on traditional 5% significance level in two cases, and

2. incentivized elicitation in low reference points treatment leads to significantly lower initial level of beliefs than f^2, as mentioned above, and f^4 ($p = 0$), but not f^1 ($p = 0.24$).

[21] Formally, the 3 hypotheses are that all the estimated coefficients $\widehat{\beta}_{fj}$, $\widehat{\beta}_{fj*c}$, $\widehat{\beta}_{fj*sex}$, $\widehat{\beta}_{fj*famsize}$, $\widehat{\beta}_{fj*lottery}$, $\widehat{\beta}_{fj*riskaversion}$, $\widehat{\beta}_{fj*pers2}$, $\widehat{\beta}_{fj*inequality}$, $\widehat{\beta}_{fj*statement2}$, $\widehat{\beta}_{fj*statement5}$ and $\widehat{\beta}_{fj*statement7}$ for $j = 2, 3, 4$ are all equal to 0.

[22] Formally, the joint hypothesis of this 3 pairwise tests is that, simultaneously, $\widehat{\beta}_{fj} = \widehat{\beta}_{fk}$, $\widehat{\beta}_{fj*c} = \widehat{\beta}_{fk*c}$, $\widehat{\beta}_{fj*sex} = \widehat{\beta}_{fk*sex}$, $\widehat{\beta}_{fj*famsize} = \widehat{\beta}_{fk*famsize}$, $\widehat{\beta}_{fj*lottery} = \widehat{\beta}_{fk*lottery}$, $\widehat{\beta}_{fj*riskaversion} = \widehat{\beta}_{fk*riskaversion}$, $\widehat{\beta}_{fj*pers2} = \widehat{\beta}_{fk*pers2}$, $\widehat{\beta}_{fj*inequality} = \widehat{\beta}_{fk*inequality}$, $\widehat{\beta}_{fj*statement2} = \widehat{\beta}_{fk*statement2}$, $\widehat{\beta}_{fj*statement5} = \widehat{\beta}_{fk*statement5}$ and $\widehat{\beta}_{fj*statement7} = \widehat{\beta}_{fk*statement7}$ for $j = 2, 3, 4$, $k = 3, 4$ and $k > j$.

The relation between f^1 and f^4 from the above example is, indeed, non-significant ($p = 0.33$).

The next step is the role of contribution cost in the belief formation. From Table 2, we see that c is significant for f^1 and the same holds for f^3 and f^4 (p-values of $\widehat{\beta}_c + \widehat{\beta}_{f3*c}$ and $\widehat{\beta}_c + \widehat{\beta}_{f4*c}$ are 0 and 0.03, respectively), while the effect is not significant for f^2 ($p = 0.26$). The interesting pattern is that the effect of c is negative for f^1 and f^3, i.e. for the treatment with the low reference point, and positive otherwise. To interpret this, we test whether the effect is jointly significant for low and high reference point treatments. We cannot accept the significance in the latter case ($p = 0.6$), whereas we accept it in the former ($p = 0$). We conclude that there is the anchoring effect in the standard Public Good Game framing and c negatively effect subjects' beliefs, whereas in the high reference point treatment, people do not take their own cost into account that much.

Finally, we discuss the role of questionnaire data in the belief formation process. At this level, we only briefly summarize the effect of individual variables in the model:

- In most cases, men expect higher contributions.
- We observe a negative effect of the size of family on stated beliefs.
- Subjects, in whose families the bread-winner is economically inactive tend to state higher beliefs.
- Risk aversion, mainly, has a positive effect on stated beliefs.
- There is a big difference in stated beliefs between individuals with extreme opinions and attitudes, and subjects, whose opinions and attitudes are moderate. The effect differs across variables.

3.4 Belief evolution

In this subsection, we exploit the panel structure of our data to analyze the belief-updating process of experimental subjects. To this aim, we run an ordered logit regression of individual beliefs in each round on variables that might play a role in the belief-updating process, and individual characteristics, controlling for possible dependencies of data within cohorts.[23]

We classify the variables of the model into 3 groups. The first group is formed of variables related to the experimental design:

- the number of individuals required for the public good to be provided, k. In order not to impose a linear relation between beliefs and k, we introduce k in the model in form of dummies k_{it}^j with $j = 1, 2, 3$;

[23] Recall that we observe the individual heteregeneity of our subject in the questionnaire data. Hence, we do not have to control for individual effects in the estimation. This simplifies dramatically the statistical analysis of this section.

- the cost of contribution, c_{it};
- the treatment effects, which are, in analogy with the previous section, represented by four dummies f_{it}^{j} with $j = 1, 2, 3, 4$;
- *period*, to control for a possible trend in the data, which is not explained by the variables of model;
- *sequence*, to control for a possible differences between the first and second phases of each session.

The second group contains variables from previous rounds. We further divide these variables into 2 subgroups. The first subgroup consists of variables from previous rounds, independently of the conditions of the corresponding round; in the second subgroup, we include variables from previous rounds with the same k. To clarify the discussion of the estimation results, we below call the first type *lagged* variables, while referring to the the second type, we will use the term *k-lagged* variables. This classification is motivated by Iturbe-Ormaetxe et al. (2007) who finds enormous differences in both contributions and beliefs, as k changes. Our findings also show that this distinction matters.

In the model, we include lags and k-lags of the following variables:

- $belief_{it} \in \{0, 1, 2\}$ is the stated belief.
- $contribute_{it} = 0$ if i does not contribute in period t, and 1 otherwise.
- $hereffort_{it} \in \{0, 1, 2\}$ is the number of other members of i's group contributing.
- $outcome_{it} = 0$ if the public good is not provided, and 1 otherwise.
- $correctbelief_{it} = 0$ if the stated belief is not correct, and 1 otherwise.

The last group includes the variables used and described in the previous section. We do not discuss their individual estimates in the text.

Table 3 summarizes the estimation results. The benchmark case is $f^1 = 1$ and $k^1 = 1$.

Put Table 3 around here.

To check the validity of the model, we first test for the specification of the model. The test statistics is far from the critical value and we can conclude that our model is correctly specified ($p = 0.36$). The Log-Likelihood test leads to the same results. Jointly, the variables of the model are significant on any reasonable level ($p = 0$). As measures of the fit of the model, the McFadden's R^2 is 0.19 and McKelvey and Zavoina's R^2 reaches 0.38.

We start the discussion with discussing the effects of treatments. We cannot separate effects that are due to change in two treatment conditions. Thus, while discussing the effect of reference point and belief incentivizing (treatment dummies) and k's, we focus on comparisons, holding either the treatment dummy or k fixed. In this respect, Table 4 lists the p-values of all concerned pairwise comparisons of average beliefs. In each cell, the null hypothesis is that beliefs are, on average, the same under both design features.

Put Table 4 around here.

Within the same treatment conditions, k has no effect for non-incentivized beliefs and low reference point. For the remaining treatments, there always are significantly different beliefs between $k = 1$ and $k = 2$, the latter inducing higher stated beliefs in all cases. Moreover, there is a significant difference between $k = 1$ and $k = 3$ when beliefs are incentivized and the reference point is high. People expect more contribution for $k = 3$. This is also true in cases of other treatments, even though the effects are not significant. In the remaining cases, the effect of k is not significant.

If we, on the other hand, hold constant k and study between-treatment differences, we can observe, under which condition either the reference point or belief incentivizing have a significant impact on beliefs.

For all values of k, all but two pairwise comparisons lead to the rejection of the equality of average beliefs. The effects are in harmony with the findings of Section 3.1. On general, both high reference point and non-incentivized beliefs induce higher stated beliefs.

Table 3 also confirms the conjecture from Section 3.1 that beliefs depend on c. The effect is statistical significant in all treatments ($p = 0$ for f^1, f^2 and f^3 and $p = 0.02$ for f^4). The sensitive of beliefs on c is the largest in non-incentivized belief treatment with low reference point. The sensitivity is lower in the remaining cases and is not significantly different across them. Since, at this level, we work with the entire data set, we confirm that people do not learn not to use c for the evaluation of the number of contributing opponents.

The last two variables concerning the experimental design, are *period* and *sequence*. Since the first variable, *period,* is not significant, we conclude that the evolution of individual beliefs is captured by other variables of the model.[24] Neither the latter variable is significant, but we observe the expected sign. For people somehow learn to expect less contribution over time, we expect them to use to some extent their past experience in the second phase of the experiment. This is confirmed by the negative sign of this variable.

The main findings of the model are expressed by the lagged and k-lagged variables. From Table 3, we observe that subjects indeed use past information to form beliefs. In the following, we analyze which variables and to what extent.

One of the first observations is that the impact of k-lagged variables clearly exceeds the effect of lagged ones. Therefore, subject use the past play, but they select the experiences that are similar to the actual conditions. This is well illustrated by p-values of the lagged variables. In most cases, they are not significant in the model, whereas the most recent k-lags of our variables are significant.

[24] Obviously, in this model, we impose a linear relation between beliefs and experimental periods. We also ran regressions using different functional forms and the estimation results have not change.

The only lagged variable that has an impact is $hereffort$. The p-values suggest that the behavior of opponents in last 3 periods somehow matters, even though only the first lag is significant on traditional 5% (the p-values are 0, 0.08 and 0.19 for the 1^{st}, 2^{nd} and 3^{rd} lag, respectively). All the 3 lags are positive, suggesting that, not surprisingly, the more the other members of the group contributed in the past, the more likely is an individual to state a higher belief.

In contrast, people do not seem to consider their last belief, whether their last belief was correct, whether the public good was actually provided, what they believed in last round, or whether they contributed. The main driving force among the lagged variables for them was the behavior of others.

Among the k-lagged variables, the most important are k-lagged beliefs. All 6 lags of this variable are significant on 5%.[25] The p-values are 0 in the more recent k-lages and they start to increase with more distant lags. Hence, people use their last beliefs a lot to form their actual beliefs. All the estimated coefficients are positive and all the odd ratios are larger than 1. Thus, the higher any of the past k-lags the higher is the actual belief.

It might be surprising that even such a distant k-lags matter in the actual beliefs. It suggests that the belief up-dating is very rigid and people only slowly adjust their beliefs to the actual play. This is confirmed by the accuracy of beliefs, discussed in Section 3.1, and by the fact that whether subjects' beliefs where correct in last round or not has almost no effect on the belief up-dating. Moreover, concerning past beliefs people carefully select which past expectations they use to up-date current ones.

Again, the behavior of others is very important for the belief adjustment process. The last two k-lags are significant in the model, suggesting that while predicting the behavior of others, contrary to the role of past beliefs, people combine the most recent experience with the experience from situations similar to the actual ones.

In contrast to lagged variables, past contribution behavior, whether the public good was actually provided, and whether the past belief was correct have significant impact on beliefs in case of k-lagged variables.

Concerning, past contribution behavior, people should not take into account their own past behavior in their expectations about others' behavior, unless they do not expect others to be influenced by them. Then, the estimated coefficient would be expected to be positive. However, we observe the reverse sign. If people contributed in last period with the same k, they are less likely to expect others to contribute. If the public good was provided in last round with the same k, people tend to expect more contribution, and a correct guess in the previous round with the same k induces people to expect less contribution in the current round.

The last important result of the estimations is the role of socio-demographics and pro-social attitudes in the evolution process of beliefs. In the model, we

[25] We also replicated the regression including the 7^{th} k-lag, this being still significant. Nevertheless, recall that each k appears only 8 times in each experiment. Then, including the 7^{th} k-lag reduces drastically the number of observations.

use the same set of variables as in Section 3.3.1. Even though these variables explains a great part of the variability of initial beliefs, they have almost no effect in the current model. Therefore, we conclude that the belief up-dating process is not influenced much by these variables. Rather, the history of the play and experimental design are the main driving forces for the evolution of beliefs throughout the experiment.

4 Conclusions

This research project encompasses a large empirical analysis of first-order beliefs. The results suggest that how beliefs are elicited matters for both the play and beliefs in various instances. Moreover, we show that beliefs of individuals could be predicted and approximated, using their attributes that, in many situation, might be more likely to be observable in real-life situations. Last, we report that the up-dating of beliefs is a sophisticated (even though unconscious) learning process, which depends on the whole range of variables. In this paper, we uncover a set of factors that matter and show another aspects that do not. The salient feature is the role of past beliefs as the most relevant factor in belief learning, suggesting that the belief learning process is very rigid, in the sense that people only slowly adjust their beliefs to the actual play. These consideration notwithstanding, we also observe that a large part of the evolutionary process of beliefs is due to the past play of opponents. In this respect, people combine their most recent experience with more distant experience from similar situations.

This paper is meant to be a partial step in a larger empirical modeling of beliefs on basis of more easily observable variables, with the aim to provide theoreticians with regularities that have to be embedded into the existing belief learning theories. It is, for instance, clear that we have not exhausted the whole range of possible explicative variables for better understanding of belief formation and evolution. Our questionnaire focuses on socio-demographic characteristics and pro-social attitudes. We, for example, do not elicit basic variables such intelligence, confidence etc. Future research should concentrate on searching the most robust variables that matter in the belief-related process, independently of experimental design.

Another direction for future research is the analysis of differences among experimental games. There is a stark contrast between cooperative-like games, as for instance Public Good Game analyzed in this paper, and constant sum games. Nyarko and Schotter [13] provides an evidence on the evolution of beliefs in the second type of games, which uncovers that there is a completely different behavior process behind the evolution of beliefs in constant-sum games.

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Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
f2	-59.91302	9.059141	-6.61	0	-77.66861	-42.15743
f3	-40.94495	6.572192	-6.23	0	-53.82621	-28.06369
f4	-37.38235	3.984298	-9.38	0	-45.19143	-29.57326
c	-0.445857	0.0763141	-5.84	0	-0.5954298	-0.2962842
c * f2	0.48557	0.0755772	6.42	0	0.3374414	0.6336987
c * f3	0.3462816	0.0717817	4.82	0	0.205592	0.4869713
c * f4	0.5240089	0.0903491	5.8	0	0.3469278	0.7010899
active	33.21555	1.496275	22.2	0	30.2829	36.14819
lastweekwork	0.8877911	0.5755148	1.54	0.123	-0.2401971	2.015779
pers2extreme	-1.9803	1.011384	-1.96	0.05	-3.962576	0.0019769
pers3extreme	-0.825522	0.8485839	-0.97	0.331	-2.488716	0.837672
satisfaction	2.238174	0.7285328	3.07	0.002	0.8102754	3.666072
politicsextreme	2.142533	0.5198342	4.12	0	1.123677	3.16139
religionlow	-1.531298	0.8931241	-1.71	0.086	-3.281789	0.2191931
state1inter	4.444828	1.24657	3.57	0	2.001595	6.888061
sex	-5.994991	0.9233613	-6.49	0	-7.804746	-4.185236
f2 * sex	-1.159996	2.029024	-0.57	0.568	-5.136809	2.816817
f3 * sex	7.91836	1.180031	6.71	0	5.605542	10.23118
f4 * sex	5.280754	1.687535	3.13	0.002	1.973245	8.588262
familysize	-2.671971	0.5179312	-5.16	0	-3.687098	-1.656845
f2 * famsize	3.160437	1.026696	3.08	0.002	1.14815	5.172725
f3 * famsize	2.704613	0.4572202	5.92	0	1.808478	3.600748
f4 * famsize	1.779394	0.6749642	2.64	0.008	0.4564887	3.1023
lottery	-13.31925	1.17044	-11.38	0	-15.61327	-11.02523
f2 * lottery	13.3195	1.297809	10.26	0	10.77584	15.86315
f3 * lottery	13.60503	1.251986	10.87	0	11.15118	16.05888
f4 * lottery	13.30004	1.164846	11.42	0	11.01698	15.58309
riskaversion	12.97805	0.8976255	14.46	0	11.21874	14.73737
f2 * riskaversion	-16.90061	1.479918	-11.42	0	-19.8012	-14.00003
f3 * riskaversion	-12.47134	1.218489	-10.24	0	-14.85954	-10.08315
f4 * riskaversion	-10.79507	0.7486524	-14.42	0	-12.26241	-9.327742
cognitive	2.385189	0.5114382	4.66	0	1.382788	3.387589
f2 * cognitive	0.390737	0.8361821	0.47	0.64	-1.24815	2.029624
f3 * cognitive	-1.853774	0.8553058	-2.17	0.03	-3.530142	-0.177405
f4 * cognitive	-3.004177	0.6584604	-4.56	0	-4.294736	-1.713619
inequality	11.23619	1.082198	10.38	0	9.115117	13.35725
f2 * inequality	-9.9704	1.550765	-6.43	0	-13.00984	-6.930957
f3 * inequality	-9.289218	1.420684	-6.54	0	-12.07371	-6.504728
f4 * inequality	-8.853907	1.503389	-5.89	0	-11.80049	-5.90732
statement2	2.516139	0.2840697	8.86	0	1.959372	3.072905
f2 * statement2	-0.4487177	0.2673244	-1.68	0.093	-0.9726639	0.0752284
f3 * statement2	-3.191947	0.336031	-9.5	0	-3.850555	-2.533338
f4 * statement2	-2.432466	0.5367134	-4.53	0	-3.484405	-1.380527
statement5	-1.355678	0.20319	-6.67	0	-1.753923	-0.9574332
f2 * statement5	1.365262	0.3829256	3.57	0	0.614742	2.115783

f3 * statement5	1.493354	0.2540361	5.88	0	0.9954518	1.991255
f4 * statement5	0.6246558	0.2980358	2.1	0.036	0.0405164	1.208795
statement7	-4.448238	0.4869394	-9.14	0	-5.402622	-3.493854
f2 * statement7	6.950698	0.7279505	9.55	0	5.523941	8.377455
f3 * statement7	4.267034	0.4883618	8.74	0	3.309862	5.224205
f4 * statement7	5.340376	0.6182029	8.64	0	4.12872	6.552031

Cut-off values: cut1 = -40.625 (4.362), cut2 = -37.088 (3.984)
Note: N = 166, chi2 = $1.01*10^{10}$ (p = 0)
Fit: McFadden R2 = .480, Cox-Snell R2 = .638, McKelvey and Zavoina R2 = .964, Count R2 = .790.

Table 2. Belief Formation: Estimation Results.

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
f2	-1.775719	0.6748965	-2.63	0.009	-3.098492	-0.4529463
f3	-2.135791	0.7029311	-3.04	0.002	-3.513511	-0.7580717
f4	-2.317946	1.006071	-2.3	0.021	-4.289808	-0.3460829
k2	-0.684065	0.4335563	-1.58	0.115	-1.53382	0.1656897
k3	-0.9371951	0.2749261	-3.41	0.001	-1.47604	-0.3983498
f2 * k2	0.7707425	0.428828	1.8	0.072	-0.0697449	1.61123
f2 * k3	1.608416	0.417841	3.85	0	0.7894625	2.427369
f3 * k2	0.6370272	0.4571556	1.39	0.163	-0.2589812	1.533036
f3 * k3	0.7653789	0.2555386	3	0.003	0.2645324	1.266225
f4* k2	0.8326258	0.4640547	1.79	0.073	-0.0769047	1.742156
f4 * k3	0.8609656	0.369369	2.33	0.02	0.1370156	1.584916
c	-0.0564082	0.012994	-4.34	0	-0.081876	-0.0309403
c * f2	0.0427845	0.0130093	3.29	0.001	0.0172867	0.0682822
c * f3	0.0367157	0.0138734	2.65	0.008	0.0095243	0.0639071
c * f4	0.0387602	0.0153805	2.52	0.012	0.008615	0.0689054
period	0.0251593	0.0328696	0.77	0.444	-0.039264	0.0895826
sequence	-0.0422831	0.0788906	-0.54	0.592	-0.1969057	0.1123396
lag1_belief	0.0571451	0.0762198	0.75	0.453	-0.092243	0.2065332
lag2_belief	-0.0049455	0.0546984	-0.09	0.928	-0.1121524	0.1022613
lag3_belief	0.0883978	0.0630702	1.4	0.161	-0.0352174	0.2120131
lag4_belief	-0.051984	0.0985226	-0.53	0.598	-0.2450848	0.1411168
lag5_belief	-0.0109537	0.0859644	-0.13	0.899	-0.1794408	0.1575334
lag1_contribute	-0.0683999	0.1342422	-0.51	0.61	-0.3315097	0.1947099
lag2_contribute	-0.1545462	0.1171965	-1.32	0.187	-0.3842472	0.0751547
lag3_contribute	0.0478741	0.111108	0.43	0.667	-0.1698936	0.2656417
lag4_contribute	0.4159303	0.168591	2.47	0.014	0.0854981	0.7463625
lag5_contribute	-0.1173542	0.1164533	-1.01	0.314	-0.3455984	0.1108899
lag1_hereffort	0.1835875	0.0627694	2.92	0.003	0.0605617	0.3066132
lag2_hereffort	0.1729682	0.0972053	1.78	0.075	-0.0175506	0.363487
lag3_hereffort	0.1044636	0.0797159	1.31	0.19	-0.0517766	0.2607038
lag4_hereffort	-0.1414988	0.1170361	-1.21	0.227	-0.3708853	0.0878877
lag5_hereffort	-0.0178563	0.0963694	-0.19	0.853	-0.2067369	0.1710243
lag1_outcome	0.0734701	0.1486944	0.49	0.621	-0.2179656	0.3649058
lag2_outcome	-0.00662	0.1434709	-0.05	0.963	-0.2878178	0.2745779
lag1_correctbelief	-0.1394478	0.1121919	-1.24	0.214	-0.3593398	0.0804443
lag2_correctbelief	-0.0013101	0.1101352	-0.01	0.991	-0.2171711	0.2145509
lag1_k_belief	0.4894381	0.1275971	3.84	0	0.2393524	0.7395239
lag2_k_belief	0.6177474	0.12505	4.94	0	0.3726538	0.862841
lag3_k_belief	0.3992394	0.0745929	5.35	0	0.25304	0.5454388
lag4_k_belief	0.283327	0.0697977	4.06	0	0.146526	0.420128
lag_5_kbelief	0.181998	0.0678948	2.68	0.007	0.0489266	0.3150695
lag_6_kbelief	0.1647524	0.0752052	2.19	0.028	0.017353	0.3121518
lag_1_kcontribute	-0.280881	0.1544945	-1.82	0.069	-0.5836845	0.0219226
lag2_k_contribute	0.1939147	0.1630044	1.19	0.234	-0.125568	0.5133974
lag1_k_hereffort	0.266405	0.0991953	2.69	0.007	0.0719858	0.4608243
lag2_k_hereffort	0.3723271	0.1122176	3.32	0.001	0.1523847	0.5922695
lag3_k_hereffort	0.0594582	0.1027478	0.58	0.563	-0.1419238	0.2608402
lag4_k_hereffort	0.1325824	0.0908172	1.46	0.144	-0.0454161	0.3105809
lag5_k_hereffort	-0.051273	0.0526316	-0.97	0.33	-0.154429	0.051883
lag1_k_outcome	0.3171835	0.115111	2.76	0.006	0.0915701	0.5427968
lag2_k_outcome	-0.3702924	0.2344428	-1.58	0.114	-0.8297918	0.089207
lag1_k_correctbelief	-0.1384324	0.0809213	-1.71	0.087	-0.2970352	0.0201704
lag2_k_correctbelief	0.0887798	0.1298335	0.68	0.494	-0.1656891	0.3432488

active	-0.0382159	0.2335549	-0.16	0.87	-0.4959751	0.4195433
lastweekwork	0.03813	0.0695005	0.55	0.583	-0.0980885	0.1743485
pers2extreme	0.116937	0.1854155	0.63	0.528	-0.2464707	0.4803447
pers3extreme	-0.0247177	0.1051457	-0.24	0.814	-0.2307995	0.1813641
satisfaction	0.0951164	0.1846367	0.52	0.606	-0.2667649	0.4569978
politicsextreme	0.105328	0.0594406	1.77	0.076	-0.0111734	0.2218294
religionlow	-0.0080779	0.1295819	-0.06	0.95	-0.2620538	0.245898
state1inter	-0.3165468	0.1272724	-2.49	0.013	-0.5659961	-0.0670974
sex	0.2769388	0.2092608	1.32	0.186	-0.1332048	0.6870825
f2 * sex	-0.1710259	0.3703786	-0.46	0.644	-0.8969546	0.5549028
f3 * sex	-0.1037912	0.2596019	-0.4	0.689	-0.6126016	0.4050191
f4 * sex	-0.3269753	0.2352115	-1.39	0.164	-0.7879814	0.1340308
familysize	-0.0888129	0.1332295	-0.67	0.505	-0.3499379	0.1723122
f2 * famsize	0.1597172	0.2916016	0.55	0.584	-0.4118114	0.7312459
f3 * famsize	0.0815818	0.1404871	0.58	0.561	-0.1937679	0.3569315
f4 * famsize	0.0637374	0.1689667	0.38	0.706	-0.2674312	0.394906
lottery	0.0878997	0.0946651	0.93	0.353	-0.0976404	0.2734399
f2 * lottery	0.0006981	0.1296213	0.01	0.996	-0.253355	0.2547511
f3 * lottery	-0.0607023	0.1000839	-0.61	0.544	-0.2568632	0.1354585
f4 * lottery	-0.0590698	0.0993719	-0.59	0.552	-0.2538351	0.1356954
riskaversion	0.108991	0.1796689	0.61	0.544	-0.2431535	0.4611355
f2 * riskaversion	0.0242155	0.24313	0.1	0.921	-0.4523106	0.5007416
f3 * riskaversion	0.3298615	0.2135837	1.54	0.122	-0.0887549	0.7484779
f4 * riskaversion	0.2821822	0.2433968	1.16	0.246	-0.1948667	0.759231
cognitive	-0.0398538	0.1825077	-0.22	0.827	-0.3975623	0.3178547
f2 * cognitive	0.0625958	0.1944096	0.32	0.747	-0.31844	0.4436316
f3 * cognitive	0.0390203	0.1810991	0.22	0.829	-0.3159275	0.3939681
f4 * cognitive	0.0320654	0.1881907	0.17	0.865	-0.3367816	0.4009123
inequality	0.3516115	0.3056063	1.15	0.25	-0.2473659	0.9505889
f2 * inequality	-0.1238701	0.2927759	-0.42	0.672	-0.6977004	0.4499602
f3 * inequality	-0.1199847	0.364656	-0.33	0.742	-0.8346973	0.5947279
f4 * inequality	0.0057669	0.4056232	0.01	0.989	-0.7892399	0.8007738
statement2	-0.0687859	0.0716844	-0.96	0.337	-0.2092848	0.071713
f2 * statement2	-0.1545406	0.1114499	-1.39	0.166	-0.3729784	0.0638973
f3 * statement2	0.074145	0.0966341	0.77	0.443	-0.1152543	0.2635444
f4 * statement2	0.0402586	0.0944877	0.43	0.67	-0.1449339	0.2254511
statement5	0.1075585	0.0427933	2.51	0.012	0.0236852	0.1914319
f2 * statement5	-0.0672796	0.036966	-1.82	0.069	-0.1397317	0.0051724
f3 * statement5	-0.161848	0.0770723	-2.1	0.036	-0.3129069	-0.0107892
f4 * statement5	0.0072845	0.0913236	0.08	0.936	-0.1717065	0.1862756
statement7	-0.0184342	0.0687607	-0.27	0.789	-0.1532026	0.1163343
f2 * statement7	0.0584533	0.133594	0.44	0.662	-0.203386	0.3202927
f3 * statement7	0.0225581	0.0822566	0.27	0.784	-0.138662	0.1837781
f4 * statement7	-0.0231589	0.0775287	-0.3	0.765	-0.1751124	0.1287946

Cut-off values: cut1 = .058 (.633), cut2 = 2.832 (.614)
Note: N = 1963, chi2 = 415.46 (p = 0)
Fit: McFadden R2 = .185, Cox - Snell R2 = .323, McKelvey and Zavoina R2 = .378, Count R2 = .620.

Table 3. Belief evolution: Estimation Results.

f			1			2			3			4	
	k	1	2	3	1	2	3	1	2	3	1	2	3
	1		.77	.31	.02			0			0		
1	2			.21		.42			0			.08	
	3						0			.99			0
	1					.05	.17	.05			0		
2	2						.77		0			0	
	3									0			0
	1								0	.15	.01		
3	2									.30		0	
	3												0
	1											0	0
4	2												.24
	3												

Table 4. Pairwise test of treatment effects: P-values.