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Framing effects in public goods: Prospect Theory and experimental evidence

Iñigo Iturbe-Ormaetxe [a], Giovanni Ponti [a,b,*], Josefa Tomás [a], Luis Ubeda [a]

[a] *Universidad de Alicante, Spain*
[b] *LUISS Guido Carli, Roma, Italy*

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ABSTRACT

This paper studies, both theoretically and experimentally, framing effects in the context of a public good game in which players have to make a costly contribution either (i) to achieve or (ii) not to lose a non-excludable monetary prize. Our protocol leads to public good provision (not deterioration) only if a certain contribution level is achieved. Since both frames differ with respect to the reference point, we apply Prospect Theory to derive testable predictions. In particular, Prospect Theory predicts—and our experimental evidence confirms—greater contribution in the "loss" ("gain") frame when the contribution threshold is high (low). We also estimate the parameters which better suit our experimental evidence and partly confirm previous results in the literature.

1. Introduction

According to standard economic theory, voluntary contribution to a public good yields inefficient underprovision due to opportunistic free-riding. This negative conclusion is partly mitigated by the extensive experimental evidence on the classic Voluntary Contribution Mechanism (VCM), where we find that, under a wide variety of experimental conditions, subjects initially set a contribution that is halfway between the efficient and the (Nash equilibrium) free-riding level. If the contribution game is repeated, average contribution declines, but always stays above the Nash equilibrium level (Ledyard, 1995). More efficient results are obtained in experiments where the VCM is modified by introducing a *threshold* to the total contribution, below which the public good is not provided, and above which the public good is provided, but any contribution above the threshold is wasted. These experimental protocols—usually known as Voluntary Contribution Threshold Games (VCTG)—have multiple equilibria, some of which are efficient (precisely, all strategy profiles where the sum of contributions meets the threshold exactly). In VCTGs these efficient equilibria are often asymmetric, in the sense that optimal free-riding relies on the sacrifice of others.

Consider now a slightly different set-up, where individuals *already enjoy the public good*. However, they realize that at some point in the future the existing public good may deteriorate, or even disappear. They need to contribute to prevent this possibility. We shall refer to this frame as (*prevention of*) *Public Good Deterioration* (PGD), as opposed to the more standard case of *Public Good Provision* (PGP). The crucial difference between PGP and PGD is simply whether or not individuals have the public good initially.

* Corresponding author at: Departamento de Fundamentos del Análisis Económico, Universidad de Alicante, 03071 Alicante, Spain.
E-mail address: giuba@merlin.fae.ua.es (G. Ponti).

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Focusing on VCTGs, the paper seeks to answer, both theoretically and experimentally, this simple question:

Do people contribute more in PGD than in PGP?

Different cognitive biases may induce individuals to contribute more in one setting than in the other. Under the *endowment effect* (Thaler, 1980), individuals value a good they own more than one they do not. This would imply greater contribution in PGD. Under the *omission bias* (Baron, 1988), individuals have the tendency to judge harmful actions more badly than equally harmful omissions. In our set-up, this—again—would imply greater contribution in PGD, since not contributing can be seen as a harmful action (as it can yield the destruction of the public good), while in PGP, not contributing can be seen as a harmful omission. However, strategic considerations may change these conclusions significantly. For example, it could be that some individuals may contribute less in PGD if they believe that the other group members contribute more due to either one of those biases. It seems that a careful analysis is here needed to put forward sensible predictions.

As it turns out, Expected Utility Theory yields the same equilibrium prediction in both frames, which only depends on the contribution threshold, as the unique (symmetric) Bayes Nash equilibrium takes the form of a cutoff rule, by which an individual contributes if and only if the cost of contributing is below a certain threshold value, c^*, which does not depend on the frame (Palfrey and Rosenthal, 1991). However, given that these two frames differ with respect to the initial position, it seems natural to apply Prospect Theory to derive testable predictions. This is because this theory takes explicitly into account that individual preferences depend on the *reference point* used to evaluate costs and benefits of different alternatives. The aim of this paper is precisely to calculate the "Prospect Equilibria" of the two frames and to compare this theoretical benchmark with the experimental evidence of 3-player versions of both PGD and PGP. Although Prospect Theory was originally formulated to deal with individual decision problems, a few papers test some of its elements to strategic environments: Goeree and Offerman (2003) to loss aversion; Armantier and Treich (2009) and Goeree et al. (2002, 2003) to probability weighting in matching pennies games and auctions, etc.

The remainder of this paper is arranged as follows. Section 2 describes the experimental setting, from which Section 3 derives specific PGP and PGD contribution games which are analyzed using Prospect Theory. The theoretical prediction is that when loss aversion is small, as may happen in experiments with small stakes, we should expect greater contribution in PGP when the threshold is low and greater contribution in PGD when the threshold is high. Section 4 contains our experimental results. As Section 4.1 shows, the experimental evidence confirms our conjecture since we find that PGD yields higher contribution when $k = 2$ and $k = 3$, while PGP yields higher contribution when $k = 1$. In this respect, our results contrast greatly with previous experiments on classic VCMs that find greater contribution when the problem is framed as a positive externality (as in our PGP treatment), than when it is framed as a negative externality—as in our PGD (e.g. Andreoni, 1995; Sonnemans et al., 1998; Dufwenberg et al., 2006). In Section 4.2 we explore the issue of efficiency. Efficiency losses can be due either to too little or to too much contribution. We find that the major source of inefficiency is too little contribution. In general, we find that PGD is more efficient, except for the case $k = 1$ where PGP is more efficient. Finally, in Section 4.3 we estimate, by maximum likelihood, the basic parameters of Prospect Theory which better adjust to our experimental evidence, obtaining point estimates which confirm previous studies with similar experimental setups. Section 5 concludes, followed by the supplementary appendix containing additional statistical evidence.

2. Experimental design

2.1. Sessions

Six experimental sessions were run at the Laboratory for Theoretical and Experimental Economics (LaTEx) of the Universidad de Alicante. A total of 144 students (24 per session) were recruited among the undergraduate student population.

All sessions were run in a computer lab. Instructions were provided by a self-paced, interactive computer program that introduced and described the experiment.[1] Subjects were also provided with a written copy of the experiment instructions, identical to the ones they were reading on the screen. Instructions were also read aloud by the session monitor at the beginning of each session.

2.2. Treatments

In each session, subjects played 24 rounds of PGP and 24 rounds of PGD, for a total of 48 rounds. To control for order effects, subjects played either PGP or PGD first in half of the sessions. In each session, subjects were assigned to one *matching group* of 12 and subjects from different matching groups never interacted with each other throughout the session.[2]

Within each round, the 12 subjects belonging to the same matching group were assigned to a group of 3 players, with group composition randomly determined at each round.

[1] The experiment was programmed and conducted using the software *z-Tree* (Fischbacher, 2007).

[2] We shall read our experimental data under the assumption that the history of each of the 12 individual matching groups corresponds to an independent observation of our experimental environment, and build up our statistical procedures accordingly.

Table 1
PGP (reference point $x = c$).

States of the world	$n > k - 1$	$n = k - 1$	$n < k - 1$
Probabilities	p	q	r
C	$g - c$	$g - c$	$-c$
NC	g	0	0

The specific features of the 3-player VCTGs played in the lab, PGP and PGD, can be summarized as follows:

1. PGP: subjects would gain a prize of g if the number of contributors in their group reached the target $k \in \{1, 2, 3\}$, with the individual cost of contributing, c, being subtracted from their initial endowment when contributing.
2. PGD: subjects would lose g from their initial endowment if the numbers of contributors did not reach the target, $k \in \{1, 2, 3\}$, gaining c in case of non-contribution.

Let *time interval* $\tau_i = \{3(i-1) < t \leqslant 3(i)\}$, $i = 1, \ldots, 8$, be the subsequence of the i-th 3 rounds of each treatment, PGP or PGD. Within each time interval τ_i, subjects experienced each and every possible threshold, k, with the order being randomly determined within each τ_i. We did so to keep under control the time distance between two rounds characterized by the same value of k.

After being told the current level of k and c, each subject had to:

1. Choose whether to contribute or not for that round.
2. Elicit her belief on the number of contributors in her own group (excluding herself), receiving a fixed ("small" compared with the contribution game payoffs) prize in case of a correct guess.[3]

After each round, subjects are informed of the contribution decisions and average payoff of the other group members. The same information is also given in the form of a *History table*, so that subjects could easily review the results of all the rounds that have been played so far.

2.3. Financial rewards

All monetary values in the experiment were expressed in Spanish Pesetas (€1 is worth approximately 166 Pesetas).[4] The value of the prize g is fixed to 50 Pesetas, where the cost for contributing is, for all subjects and rounds, an independent draw $c \sim U[0, \bar{c}]$, with $\bar{c} = 55$ Pesetas. At the beginning of each treatment, subjects received 1000 Pesetas as initial endowment. As for the belief elicitation stage, every correct guess would pay off 5 Pesetas. Overall, subjects received, on average, €15 for a 45' experimental session.

3. Theory

We consider two presentations of a public good problem where a public good worth $g = 10/11$ to each of the $N = 3$ players is provided if and only if at least a specified threshold of $k \in \{1, 2, 3\}$ players contribute. Individual contribution costs c are private information and are known to be independently drawn from a uniform distribution on $[0, 1]$. Note that we have normalized $\bar{c}$ and g by dividing by 55.

In the standard presentation of the problem (PGP), the provision of the public good is seen as a gain, while contributing to the public good involves losing c. These gains and losses are computed from a reference point $x = c$. Table 1 describes player i's gains and losses from this reference point for contributing (C) and not contributing (NC), where n is the number of other players that contribute, $p = \Pr(n > k - 1)$, $q = \Pr(n = k - 1)$, and $r = 1 - p - q$.

In an alternative presentation with reference point $x = g$ (PGD), the provision of the public good is not seen as a gain, but instead as preventing a loss, while contributing is seen as not realizing a gain. Player i's gains and losses from this reference point are obtained by subtracting $g - c$ from each cell of Table 1.[5]

Since both presentations are equivalent in terms of final outcomes, Expected Utility Theory and standard equilibrium analysis will predict no framing effect. We then resort to Prospect Theory to try to explain our experimental results.

[3] We borrow this design feature from Nyarko and Schotter (2002). See also Gächter and Renner (2006).

[4] It is standard practice, for all experiments run in Alicante, to use Spanish Pesetas as the 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 2002), 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.

[5] There are two more natural reference points. For PGP $x = 0$ and for PGD $x = g + c$. The interested reader can find a complete analysis in Iturbe-Ormaetxe et al. (2008).

According to Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), the decision maker codes each available option as a prospect or distribution of *gains* and *losses* with respect to some *reference point* x. Dominated prospects are discarded without further evaluation. The value of an undominated prospect is expressed in terms of two functions: a probability weighting function w and a subjective value function v applied to gains and losses. The value of a binary prospect $(y, p; z, 1-p)$, with $p \in [0,1]$, is given by

$$w(p)v(y) + w(1-p)v(z), \tag{1}$$

if $yz \leqslant 0$, which is the case for all undominated prospects in our context.

Capturing *loss aversion*, the value function v is steeper for losses than for gains, $v'(-y) > v'(y) > 0$, for $y > 0$. Reflecting the principle of *diminishing sensitivity* also observed in Psychology, v is concave for gains and convex for losses, $v''(y) \leqslant 0 \leqslant v''(-y)$, for $y > 0$. We normalize $v(0) = 0$ and, as in many other applications where gains and losses are small, we assume $v(\cdot)$ to be piecewise linear with $v(-y) = -\lambda v(y)$, where λ is the coefficient of loss aversion.[6] No loss aversion corresponds to the case $\lambda = 1$.

The probability weighting function w is increasing on $[0,1]$, with $w(0) = 0$ and $w(1) = 1$. Kahneman and Tversky (1979) provide evidence that w overweights small probabilities, $w(p) > p$, and it is *subadditive*, $w(rp) > rw(p)$ for $0 < r < 1$ and small p. They also propose w exhibits *subcertainty*, that is, for all probabilities $0 < p < 1$, $w(p) + w(1-p) < 1$, a property that may explain the Allais Paradox.

As it will become clear in the analysis that follows, both components of Prospect Theory, loss aversion and probability weighting, contribute to the framing effect in a problem of provision of a public good.

Clearly, when a player has cost $c > g$, not contributing dominates contributing, for any reference point x. If $c \leqslant g$, applying (1) to Table 1, the incremental value of contributing vs. not contributing, for reference point $x = c$, is:

$$V_c(c; \lambda, p, q) := w(p+q)(g-c) - \lambda w(r)c - w(p)g. \tag{2}$$

Similarly, for reference point $x = g$, by subtracting $g - c$ from all outcomes, we have

$$V_g(c; \lambda, p, q) := -\lambda w(r)g - \big[w(p)c - \lambda w(q+r)(g-c)\big]. \tag{3}$$

Since, for fixed p, q, and r, V_x is decreasing in $c \in [0,1]$, the best response of a player is a cutoff strategy in c. A symmetric equilibrium for reference point x is then characterized by a contribution threshold, c, that satisfies:

$$F_{xk}(c, \lambda) := V_x\big(c; \lambda, p_k(c), q_k(c)\big) = 0, \tag{4}$$

where $q_k(c) = \binom{N-1}{k-1} c^{k-1}(1-c)^{N-k}$, and $p_k(c) = \sum_{h=k}^{h=N-1} \binom{N-1}{h} c^h (1-c)^{N-1-h}$.

When only one contribution is required ($k = 1$) we have $r = 0$ and F_{x1} is decreasing in c. Then, for each reference point $x \in \{c, g\}$, there is a unique symmetric equilibrium. These equilibria are interior to $(0, g)$. For larger contribution requirements ($k > 1$), for each reference point, there may be multiple equilibria, all with threshold less than g. In particular, $c_x^* = 0$ is an equilibrium.

As a benchmark, with no loss aversion, $\lambda = 1$, and the identity weighting function, $w = I$, we have the standard Bayesian equilibrium using Expected Utility Theory, which is invariant to the reference point x. The equilibrium condition (4) becomes simply $c = q_k(c)g$. For a required threshold contribution of $k = 1$, $q(c) = \Pr(n = 0) = (1-c)^2$, so that the unique symmetric equilibrium threshold cost is $c_{eu}^* = 0.365$. Similarly, for $k = 2$, $q(c) = \Pr(n = 1) = 2c(1-c)$, so that there are two symmetric equilibria, $c_{eu}^* = 0$ and $c_{eu}^* = 0.45$. Finally, for $k = 3$, $q = \Pr(n = 2) = c^2$, thus the only symmetric equilibrium is $c_{eu}^* = 0$.

Theorem 1 below illustrates the role of loss aversion λ on the framing effect. For any k and reference point x, denote by $\bar{c}_{xk}^*(\lambda)$ the maximum symmetric equilibrium contribution threshold. Thus, $F_{xk}(c, \lambda) = 0$ at $c = \bar{c}_{xk}^*(\lambda)$ and $F_{xk}(c, \lambda) < 0$ for all $c \in (\bar{c}_{xk}^*(\lambda), g]$.

Theorem 1. *For any* (*linear or nonlinear*) *probability weighting function w we have*: (a) *For contribution requirement $k \in \{2, 3\}$, $\bar{c}_{ck}^*$ is decreasing in λ if $\bar{c}_{ck}^* > 0$, and non-increasing if $\bar{c}_{ck}^* = 0$.* (b) *For $k \in \{1, 2\}$, $\bar{c}_{gk}^*$ is increasing in λ if $\bar{c}_{gk}^* > 0$, and non-decreasing if $\bar{c}_{gk}^* = 0$.* (c) *$\bar{c}_{c1}^*$ and $\bar{c}_{g3}^*$ are constant in λ.*

Proof. For any $k \in \{2, 3\}$, $\lambda' > \lambda$, and $c \in (\bar{c}_{ck}^*(\lambda), g]$, $r(c) > 0$, so that $F_{ck}(c, \lambda') < F_{ck}(c, \lambda)$, so (a) follows. Similarly, for any $k \in \{1, 2\}$, $\lambda' < \lambda$, and $c \in (\bar{c}_{gk}^*(\lambda), g]$, $p(c) > 0$, so that $F_{gk}(c, \lambda') < F_{gk}(c, \lambda)$, so (b) follows. Finally, for (c) note that both F_{c1} and F_{g3} are constant in λ, since $r = 0$ for $k = 1$ and $p = 0$ for $k = 3$. □

According to Theorem 1, given the weighting function (linear or nonlinear), for any level of required contribution k, the greater loss aversion is, the greater the difference in contribution between frame g and frame c is. We next investigate the role of the weighting function on the framing effect.

[6] See Köbberling and Wakker (2005).

Table 2
Frequency of contribution and provision across treatments and thresholds.

		$k=1$	$k=2$	$k=3$	**Mean**
Frequency of contribution	T_c	0.36	0.39	0.31	**0.35**
	T_g	0.28	0.46	0.57	**0.44**
Mean		**0.32**	**0.43**	**0.44**	**0.40**
Frequency of provision	T_c	0.74	0.35	0.04	**0.37**
	T_g	0.63	0.44	0.21	**0.42**
Mean		**0.69**	**0.40**	**0.13**	**0.40**

Theorem 2. *Suppose the probability weighting function w exhibits subcertainty, i.e., for all $\alpha \in (0,1)$, $w(\alpha) + w(1-\alpha) < 1$. Then, with no loss aversion $\lambda = 1$, (a) $\bar{c}^*_{c1} > \bar{c}^*_{g1}$, (b) $\bar{c}^*_{g3} > \bar{c}^*_{c3}$ if $\bar{c}^*_{g3} > 0$, (c) $\bar{c}^*_{c2} - \bar{c}^*_{g2}$ could be zero, positive or negative.*

Proof. For $k=1$, and any $c \in [\bar{c}^*_{c1}(1), g]$, $r(c) = 0$, and $p(c) = 1 - q(c) \in (0,1)$, so that by subcertainty of w, $F_{g1}(c,1) = w(q)(g-c) - w(1-q)c < (g-c) - w(1-q)g = F_{c1}(c,1) \leqslant 0$, so (a) follows.

Similarly, for $k=3$, and any positive $c \in [\bar{c}^*_{g3}(1), g]$, $p(c) = 0$, and $r(c) = 1 - q(c) \in (0,1)$, so that by subcertainty of w, $F_{c3}(c,1) = w(q)(g-c) - w(1-q)c < (g-c) - w(1-q)g = F_{g3}(c,1) \leqslant 0$, so (b) follows.

To show (c), take a simple weighting function of the form $w(\alpha) = a + b\alpha$, for any probability $\alpha \in (0,1)$. Notice that subcertainty holds if and only if $2a + b < 1$. Then, $F_{c2}(c,1) = F_{g2}(c,1) = b(qg - c) - 2ac$. So that $c^*_{c2} = c^*_{g2} = 1 - ((2a+b)/(2bg))$, since for $N = 3$ and $k = 2$, $q(c) = 2c(1-c)$. Perturbing locally w we can get $c^*_{c2} > c^*_{g2}$ or $c^*_{c2} < c^*_{g2}$, as desired. □

From both of the above theorems, we conclude that, for moderate loss aversion, if the weighting function exhibits subcertainty we can expect greater contribution when framing the problem as a PGP than when framing the problem as a PGD if a single contribution is required ($k=1$), and the opposite relation if all contributions are required ($k=3$). However, if $k=2$, subcertainty does not rule out that contribution is not affected significantly by the framing of the problem. As we see next these results are in agreement with the observed behavior in the experiments.

4. Experimental results

We are now in the position to compare our theoretical conjectures with the experimental evidence. In this respect, remember that c is uniformly distributed in $[0,1]$. Therefore, the equilibrium cost cut-off, c^*, can be directly used as a prediction about the relative frequency of contribution, under the assumption that everybody conforms to the predicted equilibrium strategy.

In what follows, we shall report our experimental findings in detail. Section 4.1 provides some descriptive statistics on the relative frequencies of contributors and public good provision/non-deterioration across frames and thresholds. In Section 4.2, we look at contribution profiles from a welfare perspective (remember that, in our model, inefficiency can arise from both undercontribution and overcontribution). Finally, in Section 4.3, we report a structural estimation of the Prospect Theory parameters that best suit our experimental evidence.

4.1. Contribution profiles

Let us call T_c and T_g the contribution game in which the reference point is equal to c (i.e., PGP) and g (i.e., PGD), respectively. The upper part of Table 2 reports the relative frequency of contributing subjects across treatments and thresholds, while in the lower part we report the relative frequency of cases in which the public good is provided (or its deterioration is prevented).

Table 2 yields the following conclusions[7]:

1. *T_g yields higher levels of both average contribution* (0.44 *vs.* 0.35) *and public good provision/non-deterioration* (0.42 *vs.* 0.37).
2. *The latter evidence does not hold uniformly across threshold levels, k.* In particular, when $k=1$, the above conclusions are reversed.
3. *In T_g, average frequency of contribution increases with k.* By contrast, in T_c, it fluctuates around its average value with no identifiable trend.
4. *Public good provision/non-deterioration declines with k*, with a much stronger effect in T_c, where public good provision is basically zero when $k=3$.

In Figs. A1–A2 (in the supplementary appendix) we refine the evidence of the upper part of Table 2, by disaggregating contribution profiles for cost levels, c (Fig. A1) and over time (Fig. A2). The overall impression we draw from Figs. A1–A2 is

[7] All reported differences are statistically significant at 5% confidence level according to Mann–Whitney non-parametric statistics.

Table 3
Group contribution distributions.

n		0	1	2	3
$k=1$	T_c	0.26	0.45	0.26	0.03
	T_g	0.37	0.45	0.16	0.02
$k=2$	T_c	0.24	0.41	0.27	0.08
	T_g	0.16	0.40	0.35	0.09
$k=3$	T_c	0.33	0.46	0.17	0.04
	T_g	0.09	0.30	0.40	0.21

Table 4
Mean efficiency across treatments and thresholds.

		$k=1$	$k=2$	$k=3$	**Mean**
	T_c	0.80	0.59	0.51	**0.63**
	T_g	0.76	0.66	0.55	**0.66**
Mean		**0.78**	**0.63**	**0.53**	**0.65**

that contribution is highly sensitive to c in both treatments, while it is confirmed that, in T_g, contribution is also sensitive to k (the higher k, the higher average contribution), with only marginal changes over time in both cases. Another striking difference across frames we draw from Fig. A1 refers to the relative frequency of "dominated" contributions, i.e. positive contributions by players for whom $c > g$. In this respect, among the 604 out of 6912 cases in which $c > g$—and, therefore, contributing was a dominated action, independently on k—subjects in T_g contribute 3 times as much as in T_c (with overall relative frequencies equal to 0.25 vs. 0.08, respectively; 0.41 vs. 0.07 when $k=3$).[8] In this sense, subjects are much more willing to "sacrifice" their own material payoff (since public good provision/non-deterioration, even if successful, will never compensate their own effort) in the loss (PGD) frame.

Table 3 complements the information of the lower part of Table 2 by reporting relative frequencies of game outcomes (i.e. the number of group contributors).

First notice that, for $k=1$, higher contribution in T_c mainly yields "inefficient overprovision" (i.e., $n > k$: 0.29 in T_c vs. 0.18 in T_g), since the frequency of outcomes where only one group member contributes (i.e., where group contribution exactly meets the required threshold) is constant across frames (45% of total observations). As for $k=2$, efficient provision is higher in T_g (0.35 vs. 0.27), while for those cases in which group contribution does not reach the target, the relative frequency of 0-contribution groups (i.e. those groups in which contribution is not "wasted" by any group member) is higher in T_c. Finally, it is again the case of $k=3$ in which we find the most striking difference across frames. In this latter case, T_c collects three times as much zero-contribution outcomes (0.33 vs. 0.09), as opposed to T_g, which collects four times as much full contribution outcomes (0.21 vs. 0.04).

4.2. *Efficiency*

Table 3 reports different contribution patterns, conditional on frames and thresholds. This section is concerned with evaluating how these differences affect overall efficiency of the two protocols. To this aim, we build an (ex-post) *efficiency index*, $\eta \in [0,1]$, which measures how close is group cumulative payoff to the maximum attainable for that group and round. Let $\delta_i = 1$ ($\delta_i = 0$) denote i's decision (not) to contribute, with $\delta = (\delta_i, \delta_{-i})$ the group's strategy profile. If $\mu_i(\delta)$ is player i's monetary payoff (given the group strategy profile and cost realization, c_i) and $\mu(\delta) = \sum_i \mu_i(\delta)$ is cumulative group payoff, then:

$$\eta(\delta) = \frac{\mu(\delta) - \min_\delta[\mu(\delta)]}{\max_\delta[\mu(\delta)] - \min_\delta[\mu(\delta)]}, \tag{5}$$

measures the share of the available cumulative payoff that the group is able to attain, given the strategy profile of the group. Maximal efficiency is attained (i.e., $\eta(\delta) = 1$), for example, by $\delta = (0,0,0)$ when $k=3$ and $\sum_i c_i > 3g$, or when $k=1$ and only the player with the lowest cost c contributes. Table 4 reports average efficiency levels, disaggregated by treatments and thresholds.

Table 4 shows that average efficiency is aligned with average contribution, being higher in T_g except when $k=1$. Also notice that the difference in efficiency across thresholds is the highest when $k=2$. By contrast, higher contribution in T_c (T_g) does not yield a significant increase in efficiency for $k \neq 2$, basically due to overprovision (when contributing is dominated in case of $k=3$), as we already noted. Also notice that increasing the threshold, on average, yields a decrease in mean efficiency.

8 Both of these differences are statistically significant at 1% confidence level according to Mann–Whitney non-parametric statistics.

Table 5
Tobit regression.

Dep. var.: η	Coeff.	Std. err.	p-value
ψ_0	0.815	0.014	0.000
ψ_1	0.032	0.014	0.032
ψ_2	−0.171	0.018	0.000
ψ_3	−0.282	0.020	0.000
Left censored		0.1%	
Uncensored		79.3%	
Right censored		20.6%	

Given the above evidence, it seems that *underprovision* (as opposed to overprovision) *is the major source of inefficiency* in our protocols, since greater inefficiency is associated with situations in which subjects contribute too little, rather than too much. To test this preliminary conclusion, we apply a double-censored Tobit model:

$$\eta_t = \psi_0 + \psi_1 I(T_g)_t + \psi_2 I(k=2)_t + \psi_3 I(k=3)_t + v_t, \tag{6}$$

where ψ_0 is a constant term and parameters ψ_1 to ψ_3 measure treatment and threshold effects using dummy variables (i.e., $I(\cdot)=1$ if condition $(\cdot)$ is met). Table 5 reports the partial maximum likelihood estimates of the parameters of (6), where the reported estimated standard errors take into account matching group clustering.

As Table 5 shows, framing and threshold effects are always significant, with more overall efficiency reached in T_g and low thresholds. As for the latter, not only do we detect more efficiency when $k=1$ (omitted dummy) compared when $k=2$ and $k=3$ (see the corresponding p-values of ψ_2 and ψ_3), but we also see that, when $k=3$, overall efficiency is significantly smaller than when $k=2$ ($z=0.111$, std. err. 0.026, $p=0$).

To summarize, we find that our PGD protocol is associated with higher overall efficiency, while higher contribution in T_c when $k=1$ is not enough to reverse this conclusion, as it mainly yields inefficient overprovision.

In Section 7.1.2 (in the supplementary appendix) we look at subjects' elicited beliefs, and find that beliefs are also aligned with contribution profiles, with no significant difference in belief precision across treatments. In other words, *subjects contribute more when they expect the others to contribute more*. In this respect, subjects' behavior does not seem to be driven by "strategic free-riding"—as we were arguing in the introduction—but, rather, by "conditional cooperation" (Fischbacher et al., 2001).

4.3. Estimating Prospect Theory

In this section we use the data from our experiment to estimate the parameters of Prospect Theory. We will briefly outline our empirical strategy in which we use a similar approach to that of Harrison and Rutström (2009) and Harrison (2007).

We use a simple stochastic specification to specify likelihoods conditional on our model. Every time that an individual has to choose between contributing and not contributing, we assume that she uses Prospect Theory to evaluate the two alternatives. Call $V(C)$ and $V(NC)$ the values that she assigns to the two alternatives under Prospect Theory, and call $\Delta V = V(C) - V(NC)$, the difference between these two values. We calculate this difference for each individual decision. Using ΔV we define the cumulative probability of the choice that we observe using the logistic function $\Lambda(\Delta V)$ as:

$$\Lambda(\Delta V) = \frac{\exp(\Delta V)}{1+\exp(\Delta V)}. \tag{7}$$

Now the likelihood, given Prospect Theory, depends on the estimates of the parameters of the model and the observed choices. We will restrict ourselves to the simplest version of Prospect Theory where the value function is linear for gains and losses. The value function is described, therefore, by just one parameter, λ, that captures the degree of loss aversion. Regarding the weighting function, and since only a few probability values enter in the prospects players have to evaluate, we estimate directly the weights of those probabilities, instead of estimating a parametric weighting function, such as the one proposed by Tversky and Kahneman (1992).

Therefore, our conditional log-likelihood is

$$\ln L(\lambda, W; y, X) = \sum_i \big[\big(\ln \Lambda(\Delta V) \bigm| y_i = 1\big) + \big(\ln\big(1-\Lambda(\Delta V)\big) \bigm| y_i = 0\big)\big], \tag{8}$$

where $y_i = 1$ (respectively, $y_i = 0$) means that the agent decides to contribute (not to contribute), X are individual characteristics, and W is the vector of weights of the relevant probabilities.

It remains to describe how we compute the values $V(C)$ and $V(NC)$ for each individual decision. Suppose, for example, that a given subject faces the problem described in Table 1. To compute $V(C)$ and $V(NC)$, we need not only the values assigned to the different payoffs and the reference point from which to compute gains and losses, *but also the probabilities that the subject assigns to how many of the other subjects she believes are contributing.* That is, we treat each decision within the

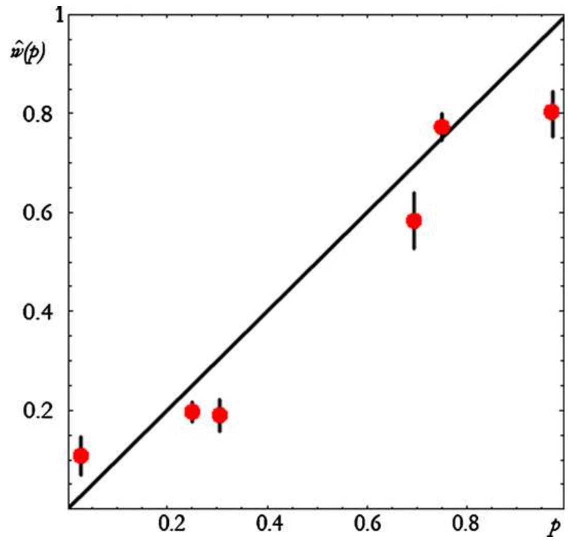

Fig. 1. Estimated prospect theory parameters.

frame of individual choice under uncertainty, where *uncertainty is only strategic*. Using the notation of Table 1, we need to assign values to p and q. Unfortunately, we do not have that information. The only information we have is what we call the "elicited beliefs" on the number of other group members contributing for that round. Here we explain how we derive the values of p and q using these beliefs.

Consider the viewpoint of player i and call π the probability that she assigns to the fact that anyone of the others is contributing. Given that group size is 3 in our experimental setup, the probabilities that i assigns to the events that 0, 1, or 2 subjects are contributing are then $(1-\pi)^2$, $2\pi(1-\pi)$, and π^2, respectively. When we ask about beliefs, subjects can only answer 0, 1, or 2. If a subject reports a belief of 0, this means that $(1-\pi)^2$ is higher than both $2\pi(1-\pi)$ and π^2, which implies that $\pi \in [0, 1/3]$. If her belief is 1, then $2\pi(1-\pi)$ is higher than both $(1-\pi)^2$ and π^2, implying that $\pi \in [1/3, 2/3]$. Finally, if her belief is that 2 subjects will contribute, we have $\pi \in [2/3, 1]$.

Given these restrictions imposed on π for the different beliefs elicited from subjects, we need to go a step further in order to estimate our model. In particular, we need to fix the values of π for the different stated beliefs. Among the various possibilities, we shall assume that π takes values 1/6, 1/2, and 5/6 when the stated beliefs are 0, 1, and 2, respectively. These values tally to the midpoints of the corresponding intervals above. This implies that when a subject declares a belief 0, she believes that the events where 0, 1, or 2 subjects are contributing occur with probabilities 25/36, 10/36, and 1/36, respectively. If her belief is 1, these probabilities are 1/4, 1/2, and 1/4, respectively. When her belief is 2, probabilities are 1/36, 10/36, and 25/36. Fig. 1 plots the estimated values of our 6 probability weights, together with 95% confidence bounds.[9]

We observe that subjects over-estimate very small probabilities (1/36), while they under-estimate all remaining probabilities, except for $27/36 = 3/4$, whose weight is not significantly different from itself. We also find that the estimated weights we get satisfy subcertainty. In particular, $\widehat{w}(1/36) + \widehat{w}(35/36) = 0.91164$, $\widehat{w}(9/36) + \widehat{w}(27/36) = 0.9697$, and $\widehat{w}(11/36) + \widehat{w}(25/36) = 0.7734$. The three sums are lower than 1. Finally, our estimation of λ (1.11, with standard deviation of 0.074) suggests that the degree of loss aversion is quite low, something we already inferred from our descriptive statistics.

For the sake of comparison, Table A4 (in the supplementary appendix) reports the estimated coefficients of our 7-parameter specification, together with the estimated coefficients of a reduced model in which probability weights are estimated using the parametric specification proposed by Tversky and Kahneman (1992), and a further restricted model with loss aversion, but without probability weighting. As Fig. 1 suggests, our evidence does not seem to accept the above restrictions. Standard likelihood ratio tests performed for each pair of specifications always reject the null at any conceivable confidence level.

5. Conclusions

Inspired by the seminal works of Kahneman and Tversky economists have learned that *frames matter* since they affect the way in which people understand problems and plan to solve them. In our paper, we study framing effects in the classic problem of public good provision, a problem which has important policy implications. We therefore applied Prospect Theory to derive different predictions for our two presentations of the problem that differ with respect to the reference

[9] These are the relevant probabilities since, for the different values of k and the different beliefs, the alternatives involve many times the same payoff for different values of n.

point. Theory predicts greater contribution in T_g when $k = 3$ and greater contribution in T_c when $k = 1$. In this respect, our experimental evidence backs up both predictions definitely, since we find a greater contribution in T_g when $k \in \{2, 3\}$. In particular, we find that the largest difference happens when $k = 3$. In this respect, our results contrast with other previous experiments (such as those of Andreoni, 1995 and Sonnemans et al., 1998) that find greater contribution when the problem is framed as a positive externality (T_c) than when it is framed as a negative externality (T_g). By contrast, we obtain this result only when $k = 1$.

One lesson from our experimental evidence is that, if unanimity is needed, it is better to frame the problem as prevention of a bad than as provision of a public good. On the contrary, when the threshold is low and the temptation to free ride is highest, it is better to frame the problem as public good provision.

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Supplementary appendix

The online version of this article contains additional supplementary material.
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