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AN ECONOMETRIC ANALYSIS OF VOLUNTARY CONTRIBUTIONS: THE RANDOM EFFECTS TWO-LIMIT P-TOBIT MODEL

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ABSTRACT

Contributions to public goods simulated in economists' laboratory experiments have two peculiarities from the perspective of statistical modelling. There is a variety of contributor behaviours (Ledyard, 1995), suggestive perhaps of separate classes of individuals, and contributions are doubly censored. We present an econometric model of contributions in sequential play, which takes into account the censoring, admits variation both within and between individuals, and allows for the existence of a distinct class of free-riders. The model synthesises the 2-limit tobit analysis of Nelson (1976), the extension of tobit to panel techniques by Kim and Maddala (1992) and the "p-tobit" hurdle model of Deaton and Irish (1984). We estimate it for panel data from a public good experiment reported in Bardsley (2000). It reveals pronounced inter- and intra-individual variation, and shows significant effects for subjects' order in a sequential game, others' contributions and the position of the choice task within the experiment. These effects are plausibly attributable to egoism, reciprocity and learning respectively. In addition, the existence of a distinct class of free-riders, who conform to a game theoretic prediction of unconditional non-contribution, is confirmed. The model is estimated for tasks in which "others' behaviour" was controlled by the experimenter (but without using deception). We compare its predictions for actual play (in which others' behaviour is not controlled) with behaviour in a real game task. The predictions are consistent with the data.

1. Introduction

In a typical public good experiment, each subject has to divide an endowment between a public account and a private account. Total contributions are multiplied up by some factor and divided equally between the group of participants. Davis and Holt (1993, ch.5) and Ledyard (1995) provide an overview of the data from such experiments. Common findings include considerable variation in contribution across individuals, with a substantial proportion of subjects free-riding and a downward trend in contributions if the game is repeated.

Data analysis usually takes the form of hypothesis testing within experiments, and occasionally meta-analysis across trials, though most designs employ study-specific manipulations. Econometric modelling within experiments is generally precluded by non-independence of contributions across subjects, since most public good experiments use a design which iterates a stage game, with subjects getting feedback between stages. The upshot is that there is usually only one independent observation per group.[1] In the experiment modelled here, in contrast, each subject repeatedly performed a *one-shot* contribution task. There is reason to believe contributions in each task to be independent across subjects (see below), so a panel data model is appropriate. The model adopted in this paper can distinguish between intra- and inter-individual variation, explores the extent of "reciprocity" and free-riding, and estimates the effect of task repetition independently of any strategic effects of stage game repetition observed in other experiments.

The statistical analysis of voluntary contributions is not straightforward. Since they constitute a doubly censored dependent variable (subjects may contribute a minimum of nothing and a maximum of the endowment to the public account), a 2-limit Tobit model is required to estimate subjects' responsiveness to experimental variables. Also, several authors on voluntary contributions make a distinction between different types of agent; the clearest sub-class would appear to be that of free-riders. (See, for example, Fehr and Gächter (1998), and Offerman, Sonnemans and Schram (1996). See also Sugden (1984) where such a distinction is implicit.) The model adopted in this paper identifies a subject as a free-rider if she displays a tendency to contribute zero which cannot be attributed to the values of the explanatory variables to which she was subjected.

The next section describes the experiment, section three reviews the factors determining contributions, section four presents some basic descriptive statistics and section five describes the model. Section six compares a simulation based on the model, which was estimated from tasks in which "others' behaviour" was a controlled experimental variable, with data from a real game task, and section 7 concludes.

2. Experiment

One aim of the experiment was to probe the inter-relatedness of subjects' contributions. In order to control the variable "others' behaviour" without using deception, a "Conditional Information Lottery" (CIL) was deployed. This experimental procedure, its justification and the basic results of the experiment are set out in detail in Bardsley (2000). In a CIL, the real

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[1] In "strangers" treatments (after Andreoni (1988)), where group composition changes between rounds, there is only one independent observation per *session*.

game task is camouflaged amongst a set of controlled dummy tasks; conditional on a task's being the real one, the task information describes the real situation (so "others' behaviour" is as shown). Subjects are told that only one task will constitute the real game, that in the other tasks "others' behaviour" is an artefact of the design, and that only the real task is to be paid out. In the other tasks, subjects "played" against a computer program, but these did not determine payoffs. The procedure is analogous to the random lottery design used in parametric (non-interactive) choice tasks, with the difference that there is only subjectively a lottery over the task set; each task, from a subject's point of view, has a chance of being the real one. It is also has affinities with the strategy method.[2]

In this environment, subjects ought to disregard information about others' behaviour from task to task. For in the experiment, subjects only see real behaviour once, and do not know at which point this is to occur. It is therefore impossible for them to learn anything useful about others' behaviour. For if one believes the real task has already occurred, behaviour in the current task would have, *ex hypothesi*, no consequences. Whilst the event that the task is real *is* the event that all previous and subsequent tasks are fictional. So if one believes there is any possibility the task is real, determining consequences, *and* therefore wishes to behave as if it is real, one must regard the previous tasks as containing no information about others' actions. This point was emphasised to subjects before play. Given that they understood this, contributions should be independent across subjects in the dummy tasks modelled below.[3]

The payoff function was, in units of 40 pence tokens,

$$C_i = 10 - w_i + \frac{2\sum_{h=1}^{n} w_h}{n} \qquad (1)$$

where C_i is an individual *i*'s monetary payoff, w_i is their contribution to the public good and $n = 7$ is the number of players in a group. The game was a *sequential* contribution public good game, in the sense that subjects decided one at a time how many tokens to contribute, after seeing the (supposed) contributions of any group members who came earlier in the sequence. Others' contributions, in 16 tasks, were randomly generated as follows. For each dummy

[2] For discussion and an experimental exploration of the validity of the random lottery incentive system, see for example Cubitt et al (1998). See also Brandts and Charness (2000) on the validity of the strategy method.
[3] And if not, since subjects only interacted once over a total of 30 tasks, the effects of this should be very dilute.

contribution, a draw was taken of a random variable with a beta distribution, which was then multiplied by ten and rounded to the nearest integer. The distribution used (for an entire task) was either $b(3,1)$ or $b(1,3)$ with equal probability, implying a mean contribution of 75% or 25% of the endowment respectively, and a standard deviation of approximately 2 tokens. Hence roughly half of these tasks showed high contributions from others and half of them low ones. In these random stimuli tasks, a subject's order in the sequence was determined with uniform probability. In four other tasks, all subjects were placed in last position, and stimuli were used which were chosen to test specific conjectures about voluntary contributions.[4]

3. Expected Determinants of Contributions

For a set of standard economic agents, who maximise a utility function of the form $U_i(C_i)$, the sequential game has a unique Nash equilibrium consisting of a vector of zero contributions. If, on the other hand, an agent i suspects that for some other(s) j, $\partial w_j / \partial w_i > 0$, then there may be a self-interested contribution motive early in the sequence. Let K_i denote the set of agents following agent i in the sequence. There *is* an egoistic contribution incentive if $\sum_{l:l \in K_i}^{n} \left(\partial w_l / \partial w_i \right) > \frac{n}{2} - 1$ (which equals 2.5 in this experiment). However, since as the sequence progresses there are less agents left to play, there should be less reason for egoists to contribute the later a subject's position within the game. Hence there should be an inverse relationship between contributions and subjects' position in the sequence, *ceteris paribus*.

Note that any such egoistic incentive is dependent on a belief that some agents exhibit reciprocity. There is evidence that this is indeed the case in public good games (see Weimann (1994), Fehr and Gächter (1996), Croson (1999) and Fischbacher et al. (1999) for examples). In the model below, reciprocity is represented as an influence on contributions from the median of previous contributions within a task. It is perhaps likely that these previous contributions give rise to two effects: reciprocity plus an impact on expectations (relevant both for forward looking reciprocity and egoism early in the sequence). It would

[4] The experiment also included the real sequential game, six binary contribution tasks and three simultaneous play tasks.

not be possible to separate these, however, without independent data on expectations which would have made the experiment considerably more cumbersome.

There is another potential influence on a subject's contribution decision (which varies in the experiment) to be expected from the existing literature. Most repeated game experiments report that contributions decay over the course of play. Candidate explanations comprise strategic reasoning and learning (either about the selfishly rational strategy or about others' behaviour). In the present context, the only of these which could provide a plausible explanation is learning about the (individually) cash maximising strategy. For, as discussed above, subjects only interact once, and so ought not to make inferences about others' behaviour, or (for the same reason) signal their own behaviour, across tasks. Hence, the decay effect here is in agreement with the results of Andreoni (1988) (and others) who find declining contributions in repeated games in which group composition changes randomly between rounds - another setting where strategic factors are irrelevant.

To summarise, the existing literature suggests that contributions in the game just defined should be affected by others' contributions (reciprocity), a subject's order in the sequence (egoism) and the position of the choice task within the experiment (learning), all of which were controlled experimental variables. These presence of these effects was confirmed by the basic hypothesis testing reported in Bardsley (2000).

The literature also suggests that there should be a distinct class of free-riders, who conform to the (game theoretic) cash maximising strategy of zero contribution. The fact that the game is both one-shot and sequential enables an operational distinction to be made for the first time between egoistic contributors and full free-riders. For some subjects may contribute at the start of a sequence but not at the end, whereas a full free rider *never* contributes (which is the nash equilibrium strategy). One cannot observe such a distinction in one-shot simultaneous play games since there is no egoistic contribution motive, nor in repeated games since subjects might decrease contributions at the end of the game in the expectation of similar behaviour by others, even if they are in fact *bona fide* reciprocators.

4. Exploratory data analysis

98 subjects were observed over the 20 tasks. It is revealing to examine the pooled distribution of contributions. A histogram of this variable is shown below (figure 1). The histogram clearly reveals censoring at zero, and to a lesser extent, censoring at the upper limit, 10.

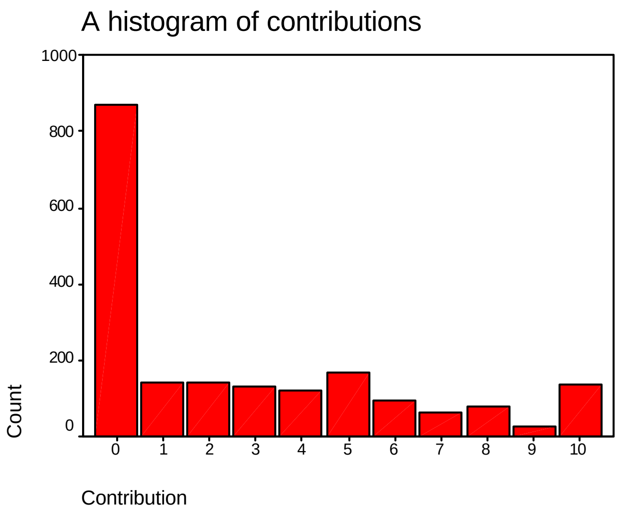


Figure 1

The overall mean contribution was 2.711, compared with a median of 1.0, this difference confirming the clear positive skew evident in the histogram. It is useful to investigate how the mean varies at different positions of the ordering within the group, and these means are shown in table 1 below:

Position in group (ORD)	*MEAN*
1	4.10
2	3.25
3	3.40
4	3.02
5	2.96
6	2.27
7	1.72
overall:	2.71

Table 1

The numbers in table 1 clearly reveal that contributions tend to fall as the task progresses, with the subject in seventh place typically contributing less than half of the contribution of the first mover. The precise dynamics of this downward trend will be revealed in the estimation of our econometric model in the following section.

5. The Random Effects 2-Limit P-Tobit model

For the purpose of the theoretical model, let us assume that there are n subjects, each of whom has been observed over T tasks. Let w_{it} be the observed contribution by subject i in task t. The variable w_{it} has a lower limit of 0 and an upper limit of 10. The two-limit tobit model (see Nelson, 1976), with limits 0 and 10, is therefore appropriate.

The underlying *desired* contribution is $w_{it}*$ and this is assumed to depend linearly on a set of explanatory variables which are contained in the vector:

$$x_{it} = \begin{pmatrix} ORD_{it} - 1 \\ I_{ORD_{it}>1} \\ I_{ORD_{it}>1} * MED_{it} \\ TSK_{it} - 1 \end{pmatrix} \qquad (2)$$

where ORD_{it} is subject i's position in the group for the t'th task solved, $I_{(.)}$ is the indicator function (taking the value 1 if the subscripted expression is true, 0 otherwise), MED_{it} is the median of previous contributions by other subjects in the group (not defined when $ORD=1$), and TSK_{it} is the task number (TSK is not the same as t, since some of the tasks are part of a separate experiment). The reasons for choosing this set of explanatory variables will become clear when the results are interpreted. Let $\underline{\boldsymbol{b}} = (\boldsymbol{b}_1, \boldsymbol{b}_2, \boldsymbol{b}_3, \boldsymbol{b}_4)'$ be the parameter vector associated with the vector x_{it} defined in (2).

The intercept in this linear equation is assumed to vary randomly with a normal distribution across the population of subjects. This assumption leads us to a model similar to the random effects tobit model (Kim and Maddala, 1992).

A proportion of the population p are assumed to be "free-riders". Their contribution is always zero, whatever the values contained in x_{it}. Let $d_i* = 1$ if subject i is a free-rider, 0 otherwise, so $P(d_i* = 1) = p$. With the parameter p, the model may be referred to as the <u>random effects 2-limit p-tobit model</u>. The "p-tobit model" was introduced by Deaton and Irish (1984) in models of household consumption, in which the parameter p would represent the probability of abstention by the consumer from the good in question.

We specify the following latent model for the desired contribution:

$$\begin{aligned} &w_{it}* = \mathbf{a}_i + x_{it}'\mathbf{b} + \mathbf{e}_{it} \quad \mathrm{i} = 1,...,\mathrm{n} \quad \mathrm{t} = 1,...,\mathrm{T} \\ &\mathbf{e}_{it} \sim N(0, \mathbf{s}^2) \\ &\mathbf{a}_i \sim N(m, \mathbf{h}^2) \\ &P(d_i* = 1) = p \end{aligned} \tag{3}$$

The relationship between *desired* contribution $w_{it}*$ and *actual* contribution w_{it} is specified by the following censoring rules:

$If\ d_i* = 0:$

$$\begin{aligned} &w_{it} = 0 \quad if\ w_{it}* \le 0 \\ &w_{it} = w_{it}* \quad if\ 0 < w_{it}* < 10 \\ &w_{it} = 10 \quad if\ w_{it}* \ge 10 \end{aligned} \tag{4a}$$

$If\ d_i* = 1:$

$$w_{it} = 0 \quad \forall t \tag{4b}$$

The likelihood function may now be constructed. Conditional on $d_i* = 0$, we have the following likelihood contributions for a single response, where $F(.)$ and $f(.)$ are the standard normal c.d.f. and p.d.f. respectively:

Regime 1 (w = 0):

$$P(w_{it} = 0 \mid d_i* = 0, \mathbf{a}_i) = \Phi\left(-\frac{\mathbf{a}_i + x_{it}'\mathbf{b}}{\mathbf{s}}\right) \tag{5a}$$

Regime 2 (0 < w < 10):

$$f\left(w_{it} \mid d_i{*}=0, \boldsymbol{a}_i\right)=\frac{1}{\boldsymbol{s}}\,\boldsymbol{f}\left(\frac{w_{it}-\boldsymbol{a}_i-x_{it}'\boldsymbol{b}}{\boldsymbol{s}}\right) \tag{5b}$$

Regime 3 (w = 10):

$$P(w_{it}=10 \mid d_i{*}=0, \boldsymbol{a}_i)=1-\Phi\left(\frac{10-\boldsymbol{a}_i-x_{it}'\boldsymbol{b}}{\boldsymbol{s}}\right) \tag{5c}$$

In addition we know that:

$$P(w_{it}=0 \mid d_i{*}=1, \boldsymbol{a}_i)=1 \tag{6}$$

Let $d_i=1$ if $y_{it}=0\ \forall t$; $d_i=0$ otherwise. Thus d_i is an indicator of whether subject *i* chooses to donate zero on *every* occasion. Note the distinction between d_i and d_i*. d_i could, possibly as a result of extreme values in the explanatory variables, take the value one in a situation in which subject *i* is *not* a free-rider.

The Likelihood contribution (conditional on a_i) for subject *i* is:

$$G_i(\boldsymbol{a}_i)= pI(d_i=1)+(1-p)\prod_{t=1}^{T}P(w_{it}=0 \mid \boldsymbol{a}_i)^{I(w_{it}=0)}\, f(w_{it} \mid \boldsymbol{a}_i)^{I(0<w_{it}<10)}\, P(w_{it}=10 \mid \boldsymbol{a}_i)^{I(w_{it}=10)} \tag{7}$$

where *I(.)* is the indicator function, and the three terms appearing in the product are defined above.

The *marginal* likelihood for subject *i* is:

$$F_i=\int_{-\infty}^{\infty} G_i(\boldsymbol{a}_i)\, f(\boldsymbol{a}_i \mid m, \boldsymbol{h})\, d\boldsymbol{a}_i \tag{8}$$

where $f(\boldsymbol{a}_i \mid m, \boldsymbol{h})$ is the normal $(m, \boldsymbol{h}^2)$ density function evaluated at a_i.

The sample log-likelihood is:

$$LogL = \sum_{i=1}^{n} \ln\left(F_i\right) \tag{9}$$

LogL is maximised using the MAXLIK routine in GAUSS, to obtain MLEs of the parameters: b, s, m, h and p. The GAUSS quadrature routine INTQUAD1 is used to evaluate the integral appearing in (8).

The results are contained in table 2 below. Three models, of varying generality, have been estimated. According to the maximised likelihood, and Wald tests of the significance of added parameters, the most general of the three, the random effects 2-limit p-tobit model, is clearly superior. The results from this model are interpreted below.

	Pooled 2-limit tobit	*Random effects 2-limit tobit*	*Random effects 2-limit p-tobit*
ORD-1	-0.759(0.081)	-0.740(0.058)	-0.748(0.059)
$I_{ORD>1}$	-1.556(0.562)	-1.542(0.406)	-1.531(0.409)
$I_{ORD>1}$ * *MED*	0.378(0.045)	0.360(0.033)	0.364(0.033)
TSK-1	-0.070(0.016)	-0.075(0.011)	-0.076(0.011)
s	5.522(0.145)	3.615(0.093)	3.629(0.093)
m	4.518(0.451)	4.105(0.531)	5.624(0.486)
h	-	4.659(0.267)	3.343(0.298)
p	-	-	0.138(0.036)
n	98	98	98
T	20	20	20
LogL	-3770.37	-3248.99	-3235.39

Results of maximum likelihood estimation
Asymptotic standard errors in parentheses
Table 2

The regression part of the model is estimated as:

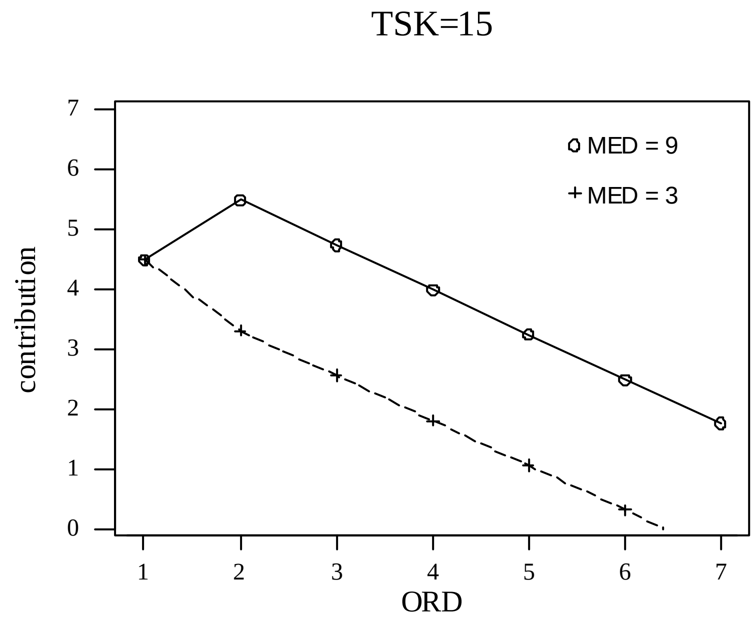
$$\begin{aligned} E\left(w^* \mid ORD, MED, TSK\right) &= 5.624 - 0.748\left(ORD - 1\right) \\ &\quad - 1.531 I_{ORD>1} + 0.364\left(I_{ORD>1} * MED\right) - 0.076\left(TSK - 1\right) \end{aligned} \tag{10}$$

The explanatory variable vector (x_{it} defined in (2)) was chosen so that the parameter m, estimated as 5.624, can be conveniently interpreted as the intercept (i.e. expected contribution) of a first mover in task 1. Note that a different intercept applies to other players due to the presence of the parameter b_2, estimated as -1.556. The presence of this shift parameter is essential because, otherwise, a zero effect of the variable *MED* would be erroneously imposed upon first-movers, for whom *MED* is not defined. The second mover's (task 1) expected contribution is, in fact: $3.345 + 0.364MED$, where *MED* is the first mover's contribution. The third mover's (task 1) expected contribution is: $2.597 + 0.364MED$, where *MED* is computed from the first two movers, and so on.

All of the explanatory variables show impressively strong significance. As anticipated, the effect of *ORD* is significantly negative, each subject being predicted to donate 0.748 LESS than the previous player, *ceteris paribus*. The effect of *MED* is significantly positive, and implies that if all of the previous contributions were raised by one, the current subject's contribution is expected to rise by 0.364. The effect of *TSK* is significantly negative, simply implying a diminution of contributions with experience.

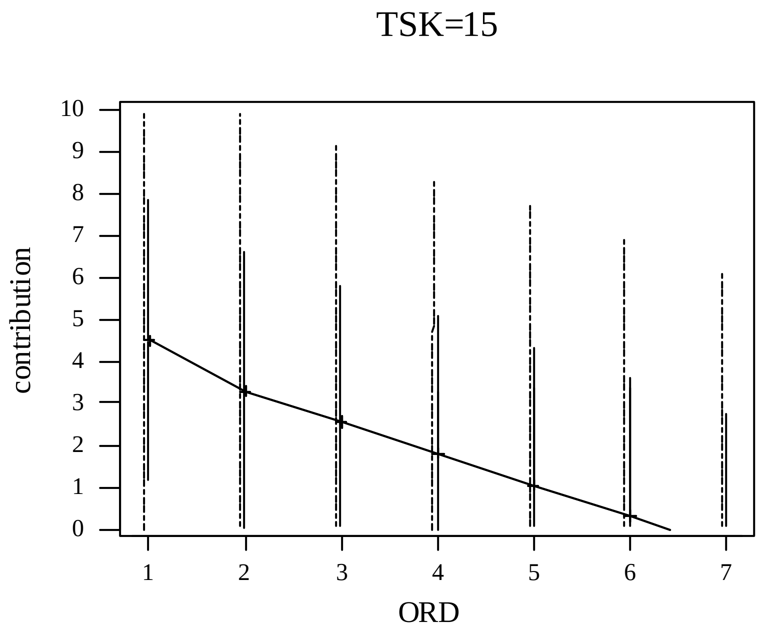
The proportion of free-riders in the population (p) is estimated as 0.138.

A diagrammatic representation of the model is useful for presenting the predictions of contributions against position in the group; this is given in figures 2 and 3 below.



Estimated Comparative Static Effects of ORD and MED

Figure 2



Estimated Distribution of Contributions By ORD (MED = 3)

Figure 3

Figure 2 shows, for a representative task,[5] the predicted response of a non-free-rider against position in the sequence, for a median contribution from others of 3 and 9 tokens. It shows the *comparative static* effects of MED and ORD. Hence if ORD = 3 and MED = 3 the expected contribution is approximately 2.6 tokens given TSK = 15. Suppose instead that MED = 9. Then if ORD = 3 the predicted response is 4.8 for that task, whilst if ORD = 7 (and MED = 9) it is lower (1.8 tokens).

Figure 3 mainly serves to illustrate the rôle of the model' s random effect term, a_i, which represents *between-subject* variation. It shows the distribution of subjects around the representative response when the median is 3 tokens. Since $a_i \sim N(m, h^2)$, 50% of non-free riders' mean responses lie above the line, 50% below, 68% within the bold lines and 99% within the dotted lines.

6. Comparison of Real and Simulated Games

A rough check on the performance of the model can be obtained by comparing predictions from the model with actual behaviour in the real game task. Recall that the model was estimated only for the tasks in which subjects were playing with experimenter-generated "others". The difference between a real task and a task with artificial stimuli is that a subject's decision in the latter cannot affect what another subject does. Whereas in the real task, it may indeed affect the decision of a player coming later in the sequence; this is what the model estimated from the dummy tasks actually predicts. The experiment produced data for one real game per group, hence 14 independent observations of the real game.

In order to compare the model's predictions with the results of the real game, we simulated the former as follows. A value is drawn from the model for a first mover's contribution; with probability p = 0.138 (from table 2) this is 0 (from a free-rider). Otherwise, it is determined by a draw from the distribution of the intercept, a_i, and from the distribution of the "within" parameter, e_{it}, then adjusted by the determinants ORD-1 and TSK-1 using the coefficients from table 2. The resulting value determines MED for the second mover. With probability p the second mover is a free-rider; otherwise their contribution is drawn from the model. The

[5] There were 30 tasks in total. The median value of TSK is therefore 15.5.

first and second movers' simulated contributions determine MED for the third mover, and so on. The results of a computed simulation of 10 000 independent groups are given in table 3 below (figures in experimental tokens, 1 d.p.):[6]

	Real (N=14)		Simulated	
ORD	Mean	Median	Mean	Median
1	4.9	5	5.2	6
2	2.1	0.5	3.7	3
3	1.9	0.5	3.1	2
4	2.8	3	2.5	1
5	2.4	0.5	2.1	0
6	1.8	0.5	1.6	0
7	1.6	0	1.3	0
Mean group total		15		19.5
Standard deviation of group total		11		10.8

Contributions By Order in the Sequence: Real and Simulated

Table 3

Although the low sample size for the real data allows only tentative conclusions to be drawn, the model's prediction concerning total contributions is consistent with the real data (the simulated mean group total of 19.5 tokens falls within the 90% confidence interval for group total constructed from the real sample), and also the diminution effect which it predicts is clearly observed within the real game.[7] There is perhaps a suggestion that the diminution is not monotonic across the values of ORD as predicted by the model, a matter which might be investigated by further experimentation.

7. Conclusions

The model confirms the existence of a distinctive class of free-riders, who constitute appromimately 14% of all subjects, and reports highly significant effects for ORD, MED and TSK, as expected. Those coefficients are plausibly interpretable as effects of egoism,

[6] The simulation used 19 for the value of TSK since this was its mean value for the real tasks in the experiment.
[7] The difference between contributions in first and last positions is significant at the 5% level (2 sample t-test) - see Bardsley (2000).

backward-looking reciprocity and learning (about the mapping from actions to payoffs) respectively. The coefficient for MED is less than one, implying a decay during sequential public good games independently of the effect of a subject's position in the sequence. This is also consistent with the biased reciprocity observed in Fischbacher et al (1999) (biased in the sense that subjects, although influenced positively by the contributions of others, tend to donate less than the levels contributed by others), which, as the authors point out, may be responsible for the usually-observed decay of contributions in (simultaneous play) repeated game public good experiments. The model was estimated for controlled tasks but predicts behaviour consistent with that found in the real game tasks, in particular anticipating the observed decay of contributions across the sequence.

A novel observation made possible by the use of panel data techniques is the substantial amount of intra-individual variation (ó). This might be interpreted as error, but other possibilities include subjects' experimentation or, more subversively, a stochastic element distinguishable from error. The latter might be seen as a response to value conflict, since in the public good game there are various reasons for action (the literature suggests, say, considerations of egoism, equity, collective rationality and reciprocity) which might appeal to subjects at different times during the trial. This would be a radical "random preferences" process, in which the underlying model of choice is the object of randomisation.[8]

The sequential game enables observation of both egoistic contribution and pure free-riding. Egoistic contributors give at the start of a sequence but not at the end, even if others have given large amounts to the public good. The model reports a high degree of egoism, distinct from complete free riding. For by the end of the experiment (TSK = 30), first movers' contributions are centred on 3.4. However, even f the median of others' contributions is as high as 8, a typical "non-free-rider" would give 0 tokens in last position (that is, with ORD = 7); of the ≈84 non-free riders observed, roughly half would give nothing, whilst ≈14 subjects would free-ride anyway. Notwithstanding this, there should still be many subjects contributing in such a task, because of the within- and between- subject variation; 34% of the

[8] We owe this suggestion to Michael Bacharach. The term "random preferences" is taken from Loomes and Sugden (1995). There, however, the phrase refers to the incorporation of a stochastic element into a *given* model of choice.

≈84 non-free riders would be predicted to have contributions centred between 0 and 3.2 tokens, with 16% having donations centred higher than 3.2. However, it is estimated that virtually no one's donation in this situation is centred as high as the representative contribution from others (8 tokens). It is an open question whether the class of "free-riders" identified by the parameter p have "solved" the game as envisaged by game theory, or simply overlooked the possibility of triggering reciprocal contributions from subsequent players.

To sum up, estimation of laboratory contributions as a function of others' donations, experience and position within a sequential game confirms the importance of reciprocity, learning and egoism in laboratory public goods settings. The censoring of contributions, particularly at zero, is a marked feature of the data, necessitating a tobit model. A fruitful distinction can be made in a sequential context between egoistic contributors and full free-riders. There is substantial variation in behaviour both between and within individuals. Positive reciprocity has a relatively weak impact on contributions. In the sequential game studied here, this contributes to a diminution of contributions across the sequence, whilst in the more usual repeated game settings, with simultaneous play, it is a probable cause of their decay across stage games.

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