Giving According to GARP: An Experimental Study of Rationality and Altruism*

by

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Abstract. This paper asks whether altruistic choices can be captured in a simple neoclassical framework with well-behaved preferences for giving. We collect data with several different prices of altruism and verify that 96 percent of subjects make choices that are consistent with the Generalized Axiom of Revealed Preference. We estimate utility functions that could have generated the data, and then use these estimates to predict data from outside our experiment. We argue that this neoclassical approach to a demand for altruism can go a long way toward understanding many anomalous results in economic laboratory experiments, and can provide an empirical foundation for theoretical models of a direct demand for giving.

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1. Introduction

Experimenters and game theorists have recently been working on ways to incorporate fairness and altruism into their models and analysis.[1] Economists, however, know very little about the nature of altruism, nor do we have a constructive notion of what a rational preference for altruism may look like.

What we do know is that it is unlikely that a single "rule" or "heuristic" governs the fair and altruistic behavior of all individuals.[2] For instance, experimental studies of distributive justice reveal that attitudes about the fair way to divide a pie are often quite varied across individuals.[3] In addition, culture may influence attitudes toward fairness, as was seen in the cross-cultural study of bargaining by Roth, et al. (1991), and other factors, such as the frame or setting, are also likely to influence attitudes toward fairness, as seen by Andreoni (1995*a*), Roth (1987), and Kahneman, et al. (1986*b*). Hence, it appears that any approach to altruism will likely have to account for a great deal of individual heterogeneity, as well as contextual factors such as culture and framing.

It is also clear that altruism is unlikely to be attributable solely to "errors" by subjects who are otherwise money-maximizers. Recent studies by Andreoni (1995*b*) and Palfrey and Prisbrey (1996, 1997) show that, while a great deal of error is present, a substantial amount of variance must be attributed to subjects who understand they are being generous to other subjects and do so willfully. Hence, altruism is volitional and seems to be a fundamental element of choice.[4]

This paper frames the approach to altruism in what is the most natural way for economists. We ask whether altruism can be modeled as a familiar neoclassical choice problem over properly defined alternatives. Clearly there is a question of "motivation" to altruism, but this is also present in most every other choice people make.[5] The essential kernel of choice theory is whether these

[1] See Rabin (1993), Palfrey and Prisbrey (1997) and Levine (1995) for recent examples.

[2] Guth's (1988) theory of hierarchical social norms is a prominent rule-based system. Similarly, Bolton (1991) and Frank (1985) assume that people care about the rank of their consumption, not simply the level. Kahneman, Knetsch and Thaler (1986a,b) explore rules of thumb for fairness.

[3] See Yaari and Ben-Hillel (1984) and Schokkaert and LaGrou (1983) for examples. Yarri and Ben-Hillel (1984) conclude, for instance, that "Sweeping solutions and world-embracing theories are not likely to be adequate for dealing with the intricacies inherent in the problem of How to Distribute."

[4] A third approach somewhere between these two considers "errors" from an evolutionary or adaptive framework. See Miller and Andreoni (1991), Binmore, Gale and Samuelson (1995), and Miller (1996).

[5] For instance, there are many possible motivations for buying a car or a necktie, but analysis would assume that personal (not strategic) motives are captured in a utility function.

considerations can be captured with a well-behaved preference ordering and a quasi-concave utility function. In other words, are choices consistent with the axioms of revealed preference?

We study this with a modification of a familiar tool in economic laboratory experiments called the dictator game. The dictator game was designed to test a simple question in bargaining theory: when given the chance to seize the entire surplus, will a bargainer so? Experimenters found that, in fact, many do not. Similar results have been found in free-riding experiments. Free-riding is analogous to taking the entire surplus in a bargaining game, but like benevolent players in dictator games, subjects give significant amounts to the public good.[6]

In our modified dictator game, subjects make choices over several different "budgets" of payoffs between themselves and another subject, with different relative prices of own-payoff and other-payoff. On some budgets giving away money is relatively expensive, while on others it is relatively cheap. We first check for rationality by conducting simple tests of the axioms of revealed preference. We then posit individual utility functions that could have generated the observed data. We next turn to a parametric analysis to estimate utility functions. These functions are then used to predict altruistic behavior in situations outside of our experiment.

We find that subjects' behavior is remarkably consistent with the axioms of revealed preference—96 percent of subjects make choices that are rationalizable with a well-behaved utility function. We estimate a family of utility functions that characterize the population of preferences, accounting for the significant heterogeneity in tastes. Moreover, we are able to use this approach to successfully predict outside of our sample. Hence, we find that using the standard tools of economists—quasiconcave utility functions and downward sloping demands—we are able to estimate a model of "rational altruism" that is sufficient to describe and predict the behavior of experimental subjects.

2. Formulating a Preference for Altruism

What would it mean in an economic laboratory experiment for subjects to have a preference for altruism? In a dictator game, subjects are typically given a budget of money m (usually \$10) which must be divided with one other person. Let π_s be the payoff an individual keeps for "self" and let π_o be the payoff that the subject gives to the "other" player. In the dictator game, the budget

[6] See Forsythe, et al. (1991) on dictator games, and also Hoffman, et al. (1995, 1996). On public goods games, see Isaac and Walker (1988); Isaac, Walker and Williams (1993); and Andreoni (1988, 1993, 1995*a*, 1995*b*).

constraint is simply $\pi_s + \pi_o = m$. Note, π represents a *change* in consumption, not consumption *per se*.

Since experimental games are framed in terms of changes in consumption, it seems natural to hypothesize that preferences are defined in terms of these changes. We explore the hypothesis that subjects have well-behaved preferences of the form

$$U_i = U_i(\pi_s, \pi_o). \tag{1}$$

Note that this does not preclude preferences over consumption, say $c_k = \bar{c}_k + \pi_k$ for $k = s, o$, where $\bar{c}_k$ is pre-experiment consumption. Since in this experiment there are no choices over pre-experiment consumption, these can be absorbed into the utility function as constants. Likewise, random components of consumption can be "integrated out" of the function. If preferences over consumption are continuous, monotonic and quasiconcave, then preferences over these marginal changes in consumption, π_s and π_o, will be as well.

Compare a dictator game experiment to a linear public goods experiment. The standard public goods experiment begins by endowing a subject with m tokens. Every token kept earns the subject one cent, while each token given to the public good earns α cents for each player in the group, where $0 < \alpha < 1$. Let x be what the subject keeps and g be what the subject gives to the public good. Then changes in payoffs are $\pi_s = x + \alpha g$ and $\pi_o = \alpha g$, where x and g must satisfy the budget $x + g = m$. Substitute π_s and π_o for x and g, and this budget can be rewritten as $\pi_s + p\pi_o = m$, where $p = (1 - \alpha)/\alpha$. Hence, public goods games are essentially multi-person dictator games in which p is the price of the other players' payoffs in terms of one's own.

Is behavior similar in dictator and public goods games? On average, subjects in the dictator game give away about 25 percent of their budget.[7] In public goods games with $p = 1$ ($\alpha = 1/2$) subjects in the first iteration of the game give about half of their tokens to the public good, hence π_o is again about 25 percent of the total. This is what would be expected if a function $U(\pi_s, \pi_o)$ generates behavior.

[7] See Forsythe, et al. (1988), and Hoffman, et al. (1996). Note that Hoffman, et al. show that the presentation of the game matters to subjects, and that increasing the anonymity of subjects decreases altruism. We view Forsythe, et al.'s original experiment, and the replication of it contained in Hoffman, et al. (1996), to be representative of most experiments of this type. Certainly the methods of Forsythe, et al, are more similar to the public goods experiments that we also consider. For that reason we will make comparisons to Forsythe, et al., rather than to the more tightly controlled versions of the dictator game presented in Hoffman, et al.

3. Experimental Design

The experiment was conducted with 70 volunteers from intermediate and upper-level economics courses at the University of Wisconsin in the Spring semester of 1995, and 72 volunteers at Iowa State University in the Fall of 1997. There were four experimental sessions of 35 or 36 subjects each, for a total of 142 subjects. Subjects earned an average of $9.40, and the experiment lasted about an hour.

In each session of the experiment subjects were assembled in one very large classroom and were asked to spread out so that there were no other subjects nearby. The experimenter then gave each subject an envelope from a stack which the experimenter had been shuffling as the subjects were assembling. The envelope contained a copy of the instructions, a "claim check," a pencil, and a credit-card size electronic calculator. Subjects were asked to remove the claim check and put it in a safe place, and were told that they would later use this to claim their earnings. Subjects were asked next to turn to the instructions, which were then read aloud by the experimenter. A copy of the instructions can be found in the appendix. They then filled out the experimental questionnaire and returned it to the blank envelope. The envelopes were then collected, shuffled, and taken to a neighboring room. Payments for each subject were calculated and put into an envelope containing the subject's number. The payment envelopes were then brought back to the room with the waiting subjects. An assistant who had remained in the room with the subjects, and hence had no knowledge of what may be in the payoff envelopes, asked subjects to present their claim checks, one at a time, and gave them their pay envelopes.[8]

Each subject's task was to make eight different allocation decisions. Each of the eight decision problems differed in the number of tokens to be divided and the number of points a token was worth to each subject. Tokens were worth either 1, 2, or 3 points each. The total number of tokens available was either 40, 60, 75, or 100. For each decision problem subjects were told they could hold tokens or pass them to the other player. Subjects made their decision by filling in the blanks in a statement like "Divide 60 tokens: *Hold* _____at 1 point each, and *Pass* _____at 2 points each." Subjects were encouraged to use the calculator to check their decisions. The decision problems were presented in random order to each subject. Subjects were told that the experimenter would choose

[8] Since we calculated payoffs in a room away from the subjects, we also used a monitor, selected randomly from among the subjects, to verify that the promised procedures for calculating payoffs were followed. Everyone was told the monitor would be paid the average amount in the experiment. The monitor viewed the entire payment procedure and when the payment envelopes were returned to the subjects the monitor announced to the group that the procedures were in fact followed.

one of the problems at random and carry out the decision of the subject with another randomly chosen subject as the recipient. Finally, subjects were told that each point earned would be worth $0.10 in payoff, hence 75 points would earn $7.50. Each of the eight problems is listed in Table 1.

TABLE 1

Allocation Choices

Condition	Token Endowment	Hold Value	Pass Value	π_s Price	π_o Price
1	40	3	1	0.33	1.00
2	40	1	3	1.00	0.33
3	60	2	1	0.50	1.00
4	60	1	2	1.00	0.50
5	75	2	1	0.50	1.00
6	75	1	2	1.00	0.50
7	60	1	1	1.00	1.00
8	100	1	1	1.00	1.00

Notice that the values of the tokens can be used to calculate the subjects' budgets in terms of the payoffs. Consider condition 1. Here transferring one token raises the other subject's payoff by 1 point, and reduces one's own payoff by 3, implying that the price of the opponents payoff π_o is 1 and the price of self payoff is 0.33. In this way we can think of the token endowment as the income variable, the inverse of the hold value as the price of self payoff π_s, and the inverse of the pass value as the price of other payoff π_o.

There are several special things to note about the budgets listed in Table 1. First, conditions 7 and 8, with relative prices of 1, are the standard dictator games with pies of six and ten dollars, respectively. As has been seen in several experiments, subjects give on average about 25 percent of their endowments away in these standard games. Hence, the remaining budgets are chosen to intersect around the area where about 25 percent of the value is given away. This is done to create the biggest possible challenge to the revealed preference test.

4. Results

The average choices across the 8 budgets are shown in Figure 1. Look first at the standard dictator game budgets—those with slopes of minus one. With the pie of six dollars an average of

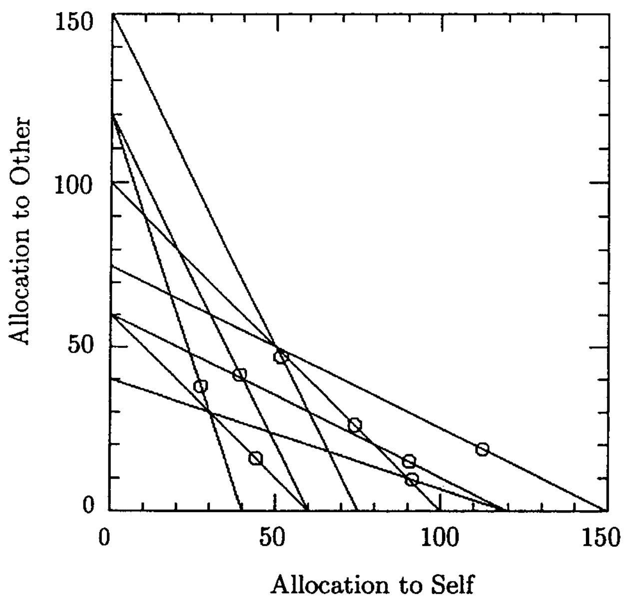

Figure 1.
Average Allocations Across Subjects

\$1.54, or 25.6 percent of the pie, is given away. With the ten dollar pie, an average of \$2.52 (25.2 percent) is given away. These results are strikingly similar to Forsythe, et al. (1994) and others.

The foremost question for this experiment is this: are subjects' choices consistent with a well-behaved underlying preference ordering over π_s and π_o? We begin answering this by conducting nonparametric demand analysis.

4.1 Nonparametric Demand Analysis: Revealed Preference

This section will apply the revealed preference techniques developed by Afriat (1967) and Varian (1982) to determine whether choices could be the result of neoclassical utility maximizers. A bundle of goods x is directly revealed preferred to a bundle y if x was purchased when y was affordable. The Weak Axiom of Revealed Preference (WARP) requires that any two distinct bundles are not directly revealed preferred to each other. The Strong Axiom of Revealed Preference (SARP) requires that any two distinct bundles are not (indirectly) revealed preferred to each other, where the (indirectly) revealed preferred relation is given by the transitive closure of the directly revealed preferred relation. The Generalized Axiom of Revealed Preference (GARP) is a generalization of SARP that allows multi-valued demand functions, that is, preferences need not be strictly convex. In particular, if x is indirectly revealed preferred to y, then y cannot be strictly directly revealed preferred to x. Afriat's theorem shows that both a necessary and sufficient condition for the existence of a well-behaved utility function that could generate the observations under the hypothesis of utility maximization is that the data satisfy GARP.[9]

The potential for violations of the revealed preference axioms depends on the price and income conditions observed. Under our conditions, there are 18 potential violations of WARP, and many more of SARP and GARP. We can set a benchmark for the likelihood of violations by analyzing the behavior of agents who randomly choose consumption bundles on the budget frontier. A Monte Carlo analysis (with 25,000 samples) of our conditions reveals that about 61 percent of random agents would exhibit violations of all three axioms. The mean (standard deviation) number of violations for the random agents is 1.2 (1.3) for WARP, 3.4 (5.2) for SARP, and 3.4 (5.2) for GARP.

One measure of the severity of a revealed preference violation is Afriat's (1972) Critical Cost Efficiency Index (CCEI), given by the lowest relative cost of foregoing a revealed preferred bundle. A

[9] For more detailed descriptions of the revealed preference axioms and proofs of these propositions, see Varian (1982, 1993).

CCEI of 0.70 indicates that the agent could have, at least once, obtained a revealed preferred bundle for 70 percent of the cost of the bundle that they actually purchased. Since there is no natural significance threshold for the CCEI, we choose, perhaps for sentimental reasons, a threshold of 0.90 (see also Varian, 1991). Over half of the random agents (54 percent) have CCEIs below 0.90. The average (standard deviation) CCEI of the random agents was 0.83 (0.19).

Of our 142 subjects, only 13 of them violated one or more of the revealed preference axioms. As seen in Table 2, only six of these 13 had CCEIs below the 0.90 threshold. We can easily reject the null hypothesis that the apparent rationalizability is due to the actions of random agents ($p < 0.00001$). If we use the 0.90 CCEI threshold, 96 percent of our subjects have rationalizable behavior. The CCEI is not, however, always a good indicator of the severity of violations. Subject 137 has a CCEI of 0.75, but would have no revealed preference violations if one of his choices was moved by just one token. Similarly, subject 38, with a CCEI of 0.75 would have no violations if one choice was moved by two tokens. Subjects 3, 41, 47, 126, and 139 would also eliminate all violations by moving just one choice by one token. Hence, using a more liberal standard, only subject 40 had severe violations of the revealed preference axioms.

TABLE 2

Violations of Revealed Preference Axioms

Subject	Number of Violations WARP	SARP	GARP	Critical Cost Effic. Index
3	1	3	3	0.83
38	2	4	4	0.75
40	3	10	10	0.50
41	1	1	1	0.92
47	1	1	3	0.96
61	1	4	4	0.90
72	1	1	1	0.98
87	1	1	1	0.95
90	1	1	1	0.98
104	1	2	2	0.87
126	1	3	1	0.90
137	1	1	1	0.75
139	1	1	1	0.67

We can conclude that the vast majority of subjects appear to be making choices that are consistent with maximizing well-behaved utility functions defined over self and other payoffs. Note that this does not tell us the form of these utility functions, but only that such functions exist. Hence, our next task will be to characterize preferences.

4.2 Individual Preferences

Now that we have learned that subjects' behavior is rationalizable, we turn to the task of trying to determine the actual form of these utility functions. We will look at each subject to identify a potential utility function based on regularities in their individual choices. To do this, we cluster the choices into groups that minimizes the within-group squared error of the final payoffs across all eight conditions.

Table 3 shows the classification of the 142 subjects. We find that six types of preferences emerge. First, 31 subjects, about 22 percent, behaved as if they were only trying to maximize their own earnings from the experiment, hence, $U(\pi_s, \pi_o) = \pi_s$ could rationalize these data. Second, 23 subjects, 16.2 percent, provided both participants with exactly equal payoffs. The utility function of these subjects is best characterized by a Leontief function, $U(\pi_s, \pi_o) = \min\{\pi_s, \pi_o\}$. Finally, 8 subjects, 4.7 percent allocated their tokens to the person with the highest redemption value, that is, the lowest price. These subjects appeared to be maximizing $U(\pi_s, \pi_o) = \pi_s + \pi_o$, a perfect substitutes utility function.[10]

Using these three extremes of utility functions we are able to classify over a third of all subjects. The remaining subjects did not fit these well-known cases as perfectly. Instead, they can be classified as weakly like one of these.[11] One group of 31 subjects is nearly complete free riders, although they do give some tokens away and display some price sensitivity. We call these weak free riders. Likewise, another group of 22 subjects is similar to the group of perfect substitutes, but shows slightly less price sensitivity. Finally, 26 subjects are classified as weak Leontief players,

[10] For these latter subjects, there is a large degree of variance in their choices in the case where the self and other prices were equal. Three of the eight subjects divided tokens evenly, while three kept all the tokens. One divided evenly when the pie was six dollars, but kept the whole pie when it was ten dollars. A final selfless subject gave all the pie to the other subject on both allocation decisions.

[11] We used several different approaches, including Baysian algorithms and adaptive search routines, each of which resulted in nearly identical classifications. The results reported here are from minimizing the Euclidian distance between the choices made and the optimal choices under one of the three strong utility functions identified.

TABLE 3

Subject Classification by Prototypical Utility Function*

Utility Function	Fit Strong	Fit Weak	Fit Total
Selfish	31	31	62
Leontief	23	26	49
Perfect Substitutes	8	22	30

*A subject exactly half way between strong Leontief and Perfect Substitutes was not listed above.

with a propensity to split equally, but a higher degree of substitutability than the strong Leontief players.[12]

4.3 Parametric Analysis: Estimating Preferences

We saw in the last subsection that the implied utility functions across subjects are often quite different. Thus a single utility function is a clear simplification. Nonetheless, it may be possible to use our data to make general statements about how the average behavior responds to prices. In this subsection we estimate an utility function over the aggregate choices as a benchmark for our more precise estimates to come.

We estimate three functional forms of utility. First is the Cobb-Douglas, $U = a_1 \ln \pi_s + (1 - a_1) \ln \pi_o$, second is the Constant Elasticity of Substitution (CES), $U = a_2 \pi_s^\rho + (1 - a_2)\pi_o^\rho$, where $\sigma = 1/(\rho - 1)$ is the elasticity of substitution, and third is the Linear Expenditure Model (LEM), $U = a_3 \ln(\pi_s - \gamma_1) + (1 - a_3) \ln(\pi_o - \gamma_2)$.

We estimate the demand functions for each utility function using tobit maximum likelihood, which accounts for the censoring of subjects' choices. Since subjects' choices are censored at both ends of the budget constraint, we estimated a two-limit tobit such that $0 \leq \pi_s/(m/p_s) \leq 1$. Furthermore, the error term was found to be heteroskedastic when demands were specified in levels. Hence, to assure homoskedasticity, demands were estimated as budget shares with an i.i.d.

[12] A final subject was exactly between a strong selfish and a strong Leontief type. In all the analysis, this subject was treated as a separate type.

error term. The decisions of all agents are pooled, for a total of 1136 observations. A detailed description of this procedure is given in Appendix 2.

The results of the estimation are listed in Table 4. Each of the coefficients for Cobb-Douglas and the CES utility functions is significant at the 95 percent confidence level or better, as are the parameters of the LEM. Note that the share parameter a is similar, at about 0.7—0.8, across all three utility functions. From the CES utility we estimate $\rho = 0.4570$ implying an elasticity of substitution of $\sigma = -1.842$. Hence, the CES indicates that π_s and π_o are more easily substitutable than in the Cobb-Douglas case, which restricts $\sigma = -1$. Testing this restriction with a likelihood ratio test, we see a significant increase in the likelihood from freeing the estimate of ρ ($\chi^2_{[1]} = 38.64$, $\alpha < 0.001$). Turning to the LEM, a test of the restriction that $\gamma_1 = \gamma_2 = 0$ can be rejected, ($\chi^2_{[2]} = 36.64$, $\alpha < 0.001$), indicating that the Cobb-Douglas function is again too restrictive.

TABLE 4

Estimates of Utility Functions

	Cobb-Douglas	CES	Linear Expenditures
Function	$\pi_s^{a_1}\pi_o^{1-a_1}$	$a_2\pi_s^\rho + (1-a_2)\pi_o^\rho$	$(\pi_s - \gamma_1)^{a_3}(\pi_o - \gamma_2)^{1-a_3}$
Parameters	$a_1 = 0.8339$	$a_2 = 0.7194^\dagger$	$a_3 = 0.8117$
(Standard Error)	(0.0142)	$\rho = 0.4570$	(0.0628)
			$\gamma_1 = -39.4865^\ddagger$
			$\gamma_2 = -11.3852$
s.e.–self	0.4340	0.4280	0.4292
	(0.0132)	(0.0129)	(0.0130)
ln Likelihood	−803.83	−784.51	−785.51
Average $\lvert\frac{\pi_s - \pi^*}{\pi^*}\rvert$	0.0504	0.1077	0.1148
Average $\frac{e(p,U)}{p\pi}$	0.9673	0.9559	0.9300

† Parameter estimates for the CES are $r = \rho/(\rho - 1) = -0.8416$ ($s.e. = 0.1600$) and $[a_2/(1-a_2)]^{(1-r)} = 5.6632$ ($s.e. = 0.7356$).

‡ Parameter estimates for the Linear Expenditures are $(1 - a_3)\gamma_1 = -7.4353$ ($s.e. = 2.7117$) and $a_3\gamma_2 = -9.2414$ ($s.e. = 2.7429$).

There are several ways to compare goodness of fit across these functional forms. Using the log of the likelihood function the CES function performs the best. Another more crude measure is to look at the average choice on each budget set, and compare this to the predicted choice. The row $|(\pi_s - \pi^*)/\pi^*|$ in Table 4 is the absolute value of the deviation between the predicted and the mean value of π_s on a budget constraint, averaged across budget constraints. With this measure all utility functions do well, although the Cobb-Douglas is slightly better. Finally, the last line of Table 4 presents a more elegant measure suggested by Varian (1993). This calculates how much of the budget the average person would have "wasted" if the true utility function were the one estimated, that is, the ratio of the value of the expenditure function $e(p, U)$ to the actual expenditures. Evaluating U at the observed mean choices, indicates that all of the utility functions performed well, wasting less than seven percent of income.

4.4 Parametric Analysis: A Distribution of Preferences

We saw above that a single utility function was capable of characterizing the average choice in the experiment. This, of course, has the advantage of being simple to apply for purposes of prediction. However, as we saw in Table 3, there appears to be important differences among subjects and their attitudes toward giving. For this reason, this subsection presents estimates of a distribution of subjects' utility functions.

An important issue in estimating a population of utility functions is the methodology applied to determine how many unique utility functions will be estimated. Ideally we would like to have enough data on individuals to estimate unique functions for each. Since this is clearly impossible we must specify a methodology for choosing classes of subjects to pool together. Here we apply the criteria used to generate Table 3. That is, we first specify three utility functions, Selfish, Leontief and Perfect Substitutes. We then choose three "strong" groups as those subjects having zero Euclidean distance to one of the three utility functions. We assume that these subjects' choices are observed without error. Clearly this is a simplifying assumption. For instance, for a person we call perfectly selfish, the range of prices considered here may not be enough to measure any elasticity of demand, or the subject may have just "erred" in being totally selfish. For the subjects who fit these strong categories we will nonetheless assume that their utility functions are known.

The remaining three categories are drawn by minimizing the Euclidean distance to the three strong utility functions. For each of these "weak" categories we estimate CES utility functions.[13]

[13] Note that we also used a general Baysian criterion, and an adaptive search algorithm to classify subjects, with similar results.

We focus on CES since it fits best in the aggregate case, and because each of the three strong types is a special case of the CES. This gives us a total of six types.

The results of the estimates from the three weak types are given in Table 5 where, as before, the decisions of the subjects are pooled. The estimated parameters are $r = \rho/(\rho-1)$ and $a = (a_2/(1-a_2))^{(1-r)}$, which are all significant beyond the 0.001 level. We also report s.e.-self, the estimated standard error for the residual in the estimation equation for payoff to self. This parameter is important for predicting the distribution of choices from these utility functions.

TABLE 5

Estimates of Utility Functions

Parameters (standard errors)

	Weak Selfish	Weak Leontief	Weak Perf. Subst.
$[a_2/(1-a_2)]^{(1-r)}$	13.8633	1.5967	2.7954
	(3.3575)	(0.0855)	(0.4702)
$\rho/(\rho-1)$	-1.4025	0.2675	-2.2745
	(0.2663)	(0.0724)	(0.2668)
a_2	0.7491	0.6545	0.5778
ρ	0.5838	-0.3652	0.6946
σ	-2.4025	-0.7325	-3.2745
s.e.–self	0.1985	0.1806	0.2585
	(0.0118)	(0.0092)	(0.0181)
ln likelihood	-41.379	-43.739	-59.817
number of cases	248	208	176

We observe from Table 5 that the share parameter a_2 differs fairly substantially for the three types, with weakly selfish having the highest (and most selfish) value. We also see that the elasticity of substitution for the weak Leontief utility function is $\sigma = -0.733$, showing a strong complementarity between π_s and π_o. The elasticities of substitution for the the weakly selfish is $\sigma = -2.403$ and for weak perfect substitutes is $\sigma = -3.275$. Hence, both the weak selfish and weak perfect substitutes have very flat indifference curves, but those for the weak selfish are much steeper.

5. Predicting Dictator and Public Goods Experiments

In this section we use our findings to predict the results of other experiments. This is the ultimate test of our approach. If our experiment is capturing preferences for altruistic behavior, then these results should, under appropriate assumptions, be generalizable to other experimental settings with similar incentives. We look at dictator games and at public goods games.

In other dictator games, Forsythe, et al. (1994) found that subjects with a five dollar pie gave 22.2 percent to their opponents, while those with a ten dollar pie gave 23.3 percent. With the six dollar pie, our subjects gave 25.6 percent, and with a ten dollar pie gave 25.2 percent. Hence, the results are quite similar.

We can also predict the results of these dictator games using our estimated utility functions. In doing so we must be careful to account for the censoring of the error term. This is because the predicted value is actually the mean of a distribution, the tails of which will be censored because of the budget constraint. Hence, using the aggregate CES utility function reported in Table 4, we must take an expectation conditional on the choice being on the budget constraint. A detailed description of this procedure is given in Appendix 2. We can also repeat this process using the six different utility functions discussed in the previous subsection, with each of the six utility functions having their own probability distribution on demands, and each represented in the population according to their empirical density. Again, we discuss this procedure in Appendix 2.

The result is that the aggregate CES utility predicts subjects offer 20.7 percent, while the disaggregated CES utilities predicts subjects offer 22.9 percent, both of which are similar to the Forsythe, et al. findings. The aggregate approach predicts 36 percent will make offers of zero, while the disaggregated approach predicts 35 percent will offer zero. Forsythe, et al. found 35.5 percent of offers to be zero. Hence, both approaches predict successfully.

Next we look at the more difficult challenge of public goods experiments. As noted earlier, public goods games are like multi-person dictator games in which each person has a budget of payoffs $\pi_s + \pi_o(1-\alpha)/\alpha = m$, where α is the marginal return to investing tokens in the public good and m is the number of tokens available. Hence, $p = (1-\alpha)/\alpha$ is the price of others' payoff in terms of own payoff.

While the allocation decisions are similar, public goods experiments differ from dictator games in three important ways. First, π_o is given to many other people at once. As Isaac and Walker

(1988), and Isaac, Walker and Williams (1994) show, there is some effect of group size on cooperation. Since we, as yet, have no theory about how to generalize preferences to account for group size, we will look only at small groups of five or fewer subjects. Second, the public goods experiments are often repeated, and repetition does in some cases have an effect. Hence, we will look only at the first iteration in these experiments. Third, public goods games constrain the payoff given away to be no greater than the payoff kept. To see this, note that the worst one can do for one's self is to give all the tokens to the public good, which is also the best thing one can do for the other players. Since this makes payoffs equal, it implies $\pi_s \geq \alpha m \geq \pi_o$. Hence, when calculating predicted values we assume that a person whom we would otherwise predict to choose $\pi_o > \pi_s$ will instead choose $\pi_o = \pi_s$.

TABLE 6

Predictions and Results for Public Goods Experiments

Price	Source	Group Size	Per Cent Contributed	Per Cent Free Riders
2.33	Prediction, Aggregate		28.5	43
	Prediction, Disaggregate		33.3	44
	Isaac, et al. (1988)	4	35.5	58
1.00	Prediction, Aggregate		41.3	36
	Prediction, Disaggregate		45.9	35
	Andreoni (1988)	5	50.8	15
	Andreoni (1995a)	5	47.5	30
	Andreoni (1995b)	5	56.0	20
	Croson (1996)	4	55.8	42
0.33	Prediction Aggregate		66.6	23
	Prediction, Disaggregate		69.9	24
	Isaac, et al. (1988)	4	49.0	34

We compare these predictions with the results of actual public goods experiment. Table 6 shows the average percentage contributions in public goods experiments conducted by Isaac and Walker (1988), Andreoni (1988, 1995*a*, 1995*b*), and Croson (1996), as well as our predictions for these experiments. The different parameters in these experiments imply prices of 2.33, 1.00 and 0.33, for marginal returns α of 0.30, 0.50, and 0.75 respectively.

Examining Table 6 and looking first at a price of 2.33, we see the aggregate prediction is for 28.5 percent and the disaggregate prediction is for 33.3 percent. Isaac and Walker find actual contributions of 35.5 percent. The number of free riders predicted is 43 or 44 percent, when the experiments show 58 percent. For a price of 1.00 the prediction is a 41.3 percent contribution with aggregate and 45.9 percent with the disaggregate approach. The experiments show contributions ranging from 47.5 percent to 56.0 percent, with an average across the four studies of 52.5 percent. The percent of free riders shows much wider variance, from 15 to 42 percent. The predicted values of 35 and 36 percent free riders is in the middle of this range. Finally for a price of 0.33, the predictions of 67 to 70 percent given is above the experimental findings of 49 percent, while the prediction is 23 or 24 percent free riding and the experiment finds 34 percent.

Overall, we find these results encouraging. By looking at individual level data in a simple dictator game we have been able to generate a predictive model of giving. Applying this model to results outside of our data set we are able to capture the choices of subjects on both the intensive and extensive margins. The fact that errors still exist suggests merit in both additional data collection and estimation on this topic, as well as further investigation into how other factors, such as the number of other subjects, may influence choices.

6. Conclusion

This paper demonstrates that the familiar tools of economics can be applied to further our understanding of altruistic behavior, without necessarily appealing to non-economic models or to other behavioral sciences. We conduct dictator game experiments under a number of different "budgets" of payoffs, and find that over 96 percent of our subjects make choices that are consistent with GARP. This means that choices can be rationalized with simple well-behaved utility functions defined over giving to self and others.

A closer examination of our results indicates that utility functions vary widely across subjects. In particular, we find that 44 percent of the subjects have utility functions that focus mainly on own returns, while the remaining subjects are divided into those who care about maximizing total social return and those who care about equalizing payoffs. We find that accurate utility functions can easily be estimated, and that they do well in explaining the results of other experiments. The successful application of our results to data from other sources suggests that the opportunity exists for unifying a number of similar areas.

An immediate question for future research is how do preferences take into account the number of others in a group. Evidence exists that groups size matters in public goods experiments (Isaac, Walker and Willaims, 1994), and a methodology like that used here could be applied to let subjects reveal how their preferences are affected by group size. Second, notions of altruism and fairness may have dynamic components, such as reciprocity. A comprehensive study of choices over repeated interactions could also reveal a preference for these sentiments, and show how they are affected by contextual factors. Finally, this study may give confidence to others who wish to examine specific functional forms of preferences for altruism in experiments.

These results demonstrate that the familiar territory of well-behaved preference orderings and utility theory need not be cast off or amended in order to deal with altruistic or moral behavior. When the consumption space is appropriately defined, these tools serve well the task of characterizing choices and predicting behavior.

Appendix 1
Subjects' Instructions

INSTRUCTIONS

Welcome

This is an experiment about decision making. You will be paid for participating, and the amount of money you will earn depends on the decisions that you and the other participants make. If you make good decisions you stand to earn a considerable amount of money.

The entire experiment should be complete within an hour. At the end of the experiment you will be paid privately and in cash for your decisions. A research foundation has provided the funds for this experiment.

Your Identity

You will never be asked to reveal your identity to anyone during the course of the experiment. Your name will never be recorded by anyone. Neither the experimenters nor the other subjects will be able to link you to any of your decisions.

In order to keep your decisions private, *please do not reveal your choices to any other participant.*

Claim Check

At the top of this page is a number on a yellow piece of paper. This is your Claim Check. Each participant has a different number. You may want to verify that the number on your Claim Check is the same as the number on the top of *page 4*.

You will present your Claim Check to an assistant at the end of the experiment to recieve your cash payment.

Please remove your claim check now and put it in a safe place.

THIS EXPERIMENT

In this experiment you are asked to make a series of choices about how to divide a set of tokens between yourself and one other subject in the room. You and the other subject will be paired randomly and you <u>will not</u> be told each other's identity.

As you divide the tokens, you and the other subject will each earn points. Every point that subjects earn will be be worth 10 cents. For example, if you earn 58 points you will make \$5.80 in the experiment.

Each choice you make is similar to the following:

Example: Divide 50 tokens: *Hold* ______@ 1 point each, and *Pass* ______@ 2 points each.

In this choice you must divide 50 tokens. You can keep all the tokens, keep some and pass some, or pass all the tokens. In this example, you will receive 1 point for every token you hold, and the other player will receive 2 points for every token you pass. For example, if you hold 50 and pass 0 tokens, you will receive 50 points, or $50 \times \$0.10 = \$5.00$, and the other player will receive no points and \$0. If you hold 0 tokens and pass 50, you will receive \$0 and the other player will receive $50 \times 2 = 100$ points, or $100 \times \$0.10 = \$10.00$. However, you could choose any number between 0 and 50 to hold. For instance, you could choose to hold 29 tokens and pass 21. In this case you would earn 29 points, or $29 \times \$0.10 = \$2.90$, and the other subject would receive $21 \times 2 = 42$ points, that is $42 \times \$0.10 = \$4.20$.

Here is another example:

Example: Divide 40 tokens: *Hold* ______@ 3 points each, and *Pass* ______@ 1 point each.

In this example every token you hold earns you 3 points, and every token you pass earns the other subject 1 point. Again, each point you earn is worth \$0.10 to you, and each point the other subject earns is worth \$0.10 to the other subject.

<u>Important Note</u>: In all cases you can choose any number to hold and any number to pass, but the number of tokens you hold plus the number of tokens you pass <u>*must*</u> equal the total number of tokens to divide.

Please feel free to use your calculator, or one provided by the experimenter, to calculate points and to assure that all of the tokens have been allocated.

EARNING MONEY IN THIS EXPERIMENT

You will be asked to make 8 allocation decisions like the examples we just discussed. We will calculate your payments as follows:

After all your decisions form have been collected, we will shuffle the forms and randomly pair your form with that of another subject in this experiment. Using a table of random numbers, we will select one of your decisions to carry out. You will then get the points you allocated in the 'hold' portion of your decision, and the other subject will get the points you allocated on the 'pass' portion of your decision. You will then be paired again with a different subject in the experiment. This time we will randomly choose one of the other subject's eight decisions to carry out. The other subject will get the points in the 'hold' portion of the decision, and you will get the points in the 'pass' portion.

We will then total the points from these two pairings and determine your monetary earnings. These earnings will be placed in your earnings envelope. The monitor chosen at the beginning of the experiment will verify that these procedures are followed.

After all the calculations have been made, another experimenter who was not involved in the experiment until this time will ask you to bring up your claim check and will hand you your earnings envelope. This will again help to guarantee your privacy.

On the following page are the 8 choices we would like you to make. Please fill out the form, taking the time you need to be accurate. When all subjects are done we will collect the forms.

Thank you very much. Good luck!

Claim Check Number ______

DECISION SHEET

Directions: Please fill in all the blanks below. Make sure the number of tokens listed under *Hold* plus the number listed under *Pass* equals the total number of tokens available. Remember, all points are worth $0.10 to all subjects.

1. Divide 75 tokens: *Hold* ______@ 1 point each, and *Pass* ______@ 2 points each.
2. Divide 40 tokens: *Hold* ______@ 1 point each, and *Pass* ______@ 3 points each.
3. Divide 75 tokens: *Hold* ______@ 2 points each, and *Pass* ______@ 1 point each.
4. Divide 60 tokens: *Hold* ______@ 1 point each, and *Pass* ______@ 2 points each.
5. Divide 40 tokens: *Hold* ______@ 3 points each, and *Pass* ______@ 1 point each.
6. Divide 60 tokens: *Hold* ______@ 1 point each, and *Pass* ______@ 1 point each.
7. Divide 100 tokens: *Hold* ______@ 1 point each, and *Pass* ______@ 1 point each.
8. Divide 60 tokens: *Hold* ______@ 2 points each, and *Pass* ______@ 1 point each.

page 4

Appendix 2
Methodology for predicting behavior based on estimated utilities

This appendix describes the methods for using an estimated CES utility function $U = U(\pi_s, \pi_o)$ to predict choices along $p_s\pi_s + p_o\pi_o = m$, although similar methods apply to all utility functions estimated. The CES utility function generates a homothetic demand function, hence the demand curve can be written as $\pi_s = f(p_s, p_o, m) = f(p_o/p_s)m/p_s$. We then estimate the demand expression

$$\frac{\pi_s}{m/p_s} = f(p_o/p_s) + \epsilon, \tag{A1}$$

where ϵ is assumed to be distributed normally with mean zero and variance σ^2. For ease of notation, let the normalized choice be $C = \pi_s/(m/p_s)$.

Note that in the estimating equation (A1) the demands are written in as a proportion of the normalized budget m/p_s. This is because the the error term was found to vary with fraction of the budget allocated rather than the level allocated, hence this formulation allows us to use an error term that is homoscedastic.

Notice that our data is subject to censoring. The experiment is structured such own payoffs must be in the range $0 \leq C \leq 1$. To account for this, equation (A1) is estimated using a two-limit tobit maximum likelihood procedure. Upon estimating the parameters of the demand curve, we can obtain an estimate of the individual's own payoff, conditional on price, income, and a set of censoring rules.

Consider a set of censoring rules that restricts choices to the range $L \leq C \leq H$. Let D be the predicted choice if censoring were ignored, that is, the value obtained simply by substituting the budget parameters into the estimated demand function. Next let $z_1 = (H - D)/\sigma$ and let $z_2 = (L - D)/\sigma$, where σ is the standard error determined in the maximum likelihood estimation. Finally, let $\phi(\cdot)$ be the standard normal distribution function and $\Phi(\cdot)$ is the standard normal density function. Then one can show (see Maddala (1983), pp. 365–67) that the expected value of C given the censoring rule is

$$\hat{C} = [1 - \Phi(z_1)]H + \Phi(z_2)L + (\Phi(z_1) - \Phi(z_2))\left[D + \sigma\frac{\phi(z_2) - \phi(z_1)}{\Phi(z_1) - \Phi(z_2)}\right]. \tag{A2}$$

Condiser the application of this to dictator games. In this case use $L = 0$ and $H = 1$ in the above to determine $\hat{C}$. Then the predicted number of people keeping the entire pie is simply $1 - \Phi(z_1)$.

Turn next to the public goods game. Let x be the *fraction* of the endowment that the individual keeps, and g be the *fraction* of the endowment given to the public good. Hence, $x + g = 1$. We would like to predict g. Since $\pi_s = x + \alpha g$, where α is the return on the contribution to the public good, we can solve for g to find

$$g = \frac{1 - \pi_s}{1 - \alpha}. \tag{A3}$$

Also using these identities one can see that the (normalized) payoffs are $\pi_s + p\pi_o = 1$, where $p = (1 - \alpha)/\alpha$. Note that in the public goods game an individual cannot allocate less to herself than the other, hence $\pi_s \geq \pi_o$. This means that the smallest π_s can be is $1/(1 + p)$ while the largest it can be is 1. Hence, in expression $(A2)$ we set $L = 1/(1 + p)$ and $H = 1$ to estimate $\hat{\pi}_s$, and convert this to g using expression $(A3)$. Finally, the measure of the percent free riders is the probability $\Pr(\pi_s = 1) = 1 - \Phi(z_1)$.

From the above we obtain the aggregate percent contributed and the aggregate percent of free riders. It is a simple extension of this method to obtain the disaggregate percent contributed and the disaggregate percent free riders. Separate the sample into six types: Strong Leontief, Strong Selfish, Strong Perfect Substitutes, Weak Leontief, Weak Selfish and Weak Perfect Substitutes. For the strong types the predictions are exact. Since there is no clear prediction for the strong Perfect Substitues at a relative price of 1, we follow our sample proportions in which the 50 percent of the players split evently, 30 percent keep everything, and 20 percent give everything. For each of the three weak types we calculate the percent contributed and percent free riding as in the aggregate case. To obtain the disaggregate percent contributed and the disaggregate percent free riders take a weighted sum of the percent contributed and percent free riders of each of the six types, where the weights are the proportion of each type within the sample as given in Table 3.

REFERENCES

Afriat, S. (1967), "The Construction of a Utility Function From Expenditure Data," *International Economic Review*, **8**, 67–77.

Afriat, S. (1972), "Efficiency Estimates of Production Functions," *International Economic Review*, **13**, 67–77.

Andreoni, James (1988), "Why Free Ride? Strategies and Learning in Public Goods Experiments," *Journal of Public Economics*, **37**, 291–304.

Andreoni, James (1993), "An Experimental Test of the Public Goods Crowding-Out Hypothesis," *American Economic Review*, **83**, 1317-27.

Andreoni, James (1995*a*), "Warm-Glow versus Cold-Prickle: The Effect of Positive and Negative Framing on Cooperation in Experiments," *Quarterly Journal of Economics*, **CIX**, 1–21.

Andreoni, James (1995*b*), "Cooperation in Public Goods Experiments: Kindness or Confusion?," *American Economic Review*, **85** September, 891–904.

Binmore, Ken, Gale, John, and Samuelson, Larry (1995), "Learning to be Imperfect: The Ultimatum Game," *Games and Economic Behavior*, **8**, 56–90.

Bolton, Gary E. (1991), "A Comparative Model of Bargaining: Theory and Evidence," *American Economic Review*, **81**, 1096–1136.

Croson, Rachel T.A. (1996), "Partners and Strangers Revisited," *Economics Letters*, **53**, 25–32.

Forsythe, Robert, Joel Horowitz, N.S. Savin, and Martin Sefton (1994), "Fairness in Simple Bargaining Games," *Games and Economic Behavior*, **6**, 347–69.

Frank, Robert H. (1985), "The Demand for Unobservable and Other Nonpositional Goods," *American Economic Review*, **75**, 101–116.

Guth, Werner (1988), "On the Behavioral Approach to Distributive Justice: A Theoretical and Experimental Investigation," in S.Matial, ed., *Applied Behavioral Economics*, New York University Press, vol 2, 703–717n.

Hoffman, Elizabeth, Kevin McCabe and Vernon Smith (1995), "On Expectations and the Monetary Stakes in Ultimatum Games," *International Journal of Game Theory*, , .

Hoffman, Elizabeth, Kevin McCabe and Vernon Smith (1996), "Social Distance and Other-Regarding Behavior in Dictator Games," *American Economic Review*, **86**, 653–660.

Isaac, R. Mark and Walker, James M. (1988), "Group Size Effects in Public Goods Provision: The Voluntary Contributions Mechanism," *Quarterly Journal of Economics*, **53**, 179–200.

Isaac, R. Mark, Walker, James M. and Williams, Arlington W. (1994), "Group Size and the Voluntary Provision of Public Goods: Experimental Evidence Utilizing Large Groups," *Journal of Public Economics*, **54**, 1–36.

Kahneman, Daniel, Jack L. Knetsch, and Richard Thaler (1986a), "Fairness as a Constraint on Profit Seeking: Entitlements in the Market," *American Economic Review*, **76**, 728–41.

Kahneman, Daniel, Jack L. Knetsch, and Richard Thaler (1986b), "Fairness and the Assumptions of Economics," *Journal of Business*, **59**, S285–S300.

Levine, David K. (1995), "Modelling Altrusim and Spitefullness in Experiments," UCLA working paper.

Maddala, G.S (1983), *Limited Dependent and Qualitative Variables in Econometrics*, Cambridge University Press: New York.

Miller, John H. (1996), "The Coevolution of Automata in the Repeated Prisoner's Dilemma," *Journal of Economic Behavior and Organization*, **792**, forthcoming.

Miller, John H., and Andreoni, James (1991), "Can Evolutionary Dynamics Explain Free Riding in Experiments?," *Economics Letters*, **36**, 9–15.

Palfrey, Thomas R. and Prisbrey, Jeffrey E. (1996), "Altruism, Reputation, and Noise in Linear Public Goods Experiments," *Journal of Public Economics*, **61**, 409–27.

Palfrey, Thomas R. and Prisbrey, Jeffrey E. (1997), "Anomalous Behavior in Public Goods Experiments: How Much and Why?," *American Economic Review*, **87**, 829–846.

Rabin, Matthew (1993), "Incorporating Fairness into Game Theory and Economics," *American Economic Review*, **83**, 1281–1302.

Roth, Alvin E. (1987), "Bargaining Phenomena and Bargaining Theory," in A.E.Roth, ed., *Laboratory Experimentation in Economics: Six Points of View*, Cambridge: Cambridge University Press.

Roth, Alvin E., Vesna Prasnikar, Shmuel Zamir, and Masahiro Okuno-Fujiwara (1991), "Bargaining and Market Behavior in Jerusalem, Ljubljana, Pittsburgh and Tokyo: An Experimental Study," *American Economic Review*, **81**, December, 1068–95.

Schokkaert, Erik and Leo LaGrou (1983), "An Empirical Approach to Distributive Justice," *Journal of Public Economics*, **21**, 33–52.

Varian, Hal R. (1982), "The Nonparametric Approach to Demand Analysis," *Econometrica*, **50(4)**, 945–972.

Varian, Hal R. (1991), "Goodness of Fit for Revealed Preference Tests," CREST working paper number 13, University of Michigan.

Varian, Hal R. (1993), *Microeconomic Analysis, Third edition*, Norton.

Yaari, M.E. and M. Bar-Hillel (1984), "On Dividing Justly," *Social Choice and Welfare*, **1**, 1–24.

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