1-1-2006

Altruism Spillovers: Are Behaviors in Context-Free Experiments Predictive of Altruism Toward a Naturally Occurring Public Good?

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Abstract: This paper addresses the external validity of experiments investigating the characteristics of altruism in the voluntary provision of public goods. We conduct two related experiments that allow us to examine whether individuals who act more altruistically in the context-free environment are also more likely to act altruistically toward a naturally-occurring public good. We find that laboratory behavior can be predictive of contributions toward naturally-occurring goods, but not in a uniform way. In fact, parametric measures of altruism do a poor job of predicting which subjects are most likely to contribute to a naturally-occurring public good.

JEL Classification Code: C91, D64, H41

Keywords: altruism, experiments, external validity

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[†]This material is based upon work supported by the National Science Foundation under Grant No. 0096320 and the EPA STAR program, grant number R830820. The authors would also like to thank Peter Grigelis, Ikuho Kochi, Eunice Heredia, Viviane Malafaia, and Angelino Viceisza for research assistance and Ronald Cummings, Ragan Petrie, and participants at the 2004 Meeting of the Economic Science Association and the 2004 American Economiccs Association Annual Meetings for comments on earlier versions of this paper.

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A common criticism of using experiments to test economic hypotheses is that the laboratory environment is so sterile as to lose its relevancy for more complex "naturally occurring" markets and behaviors. For example, experiments investigating the characteristics of altruism in the voluntary provision of public goods typically use induced-values with neutral-contexts in which lab contributions to the "public good" are framed as an "investment" decision, with the internal and external benefits specified, rather than as a "contribution" decision. Because the external validity of this type of experiment has not been addressed, the question remains: are decisions that are made in the sterile lab environment using tokens, anonymous partners, and benefits that only accrue to a small number of subjects (those who are in the experiment concurrently) predictive of altruistic behavior toward naturally-occurring public goods that involve benefits that accrue to the general public?

We address this issue directly by conducting two related experiments. First, we conduct a context-free laboratory public goods experiment that is used to estimate the level of altruism exhibited by each subject. Subjects are paid their earnings from these induced-value experiments, and a follow-up experiment is immediately conducted in which subjects are given the opportunity to contribute to a naturally-occurring local public good. Contributions to this local public good can be made in cash (either from money brought into the lab or experiment-earnings) or paid by check. To address potential ordering effects, we also reverse the sequence of the experiments, allowing subjects to contribute to the local public good first, followed by the context-free laboratory public goods.

Our experimental design allows us to examine whether those individuals who are estimated to be more altruistic in the context-free environment are also more likely to contribute to a naturally-occurring public good – i.e., to test for altruism spillovers.[1] Results indicate that altruistic behavior in the lab can be predictive of contributions to naturally occurring public

[1] Our use of the phrase "altruism spillovers" is related to the use of the phrase "rationality spillovers" by Cherry et. al (2003), who examine whether or not rational behavior induced in market settings can spillover and result in subjects behaving more rationally in non-market valuation settings.

goods, but not in a uniform manner. While there is some degree of correlation between some simple, non-parametric measures of altruism estimated with the induced-value lab game (such as average tokens contributed across rounds) and the likelihood of exhibiting altruistic behavior toward the naturally occurring public good, other non-parametric measures are inconsistent with our priors. For instance, the more often a subject acts as a weak free-rider in the induced-value public goods game, the *more* likely she is to contribute to the naturally occurring public good. Furthermore, as describe in Section IV, our parametric estimates of altruism do a poor job of predicting giving to the naturally-occurring public good.

The next section presents the experimental design. Section III provides a parametric model that formally incorporates altruism and error in the public goods decision. Results follow in Section IV. The final section concludes.

II. Experimental Design

Two treatments are conducted with a total of 193 subjects. In "base treatment," subjects first participated in an induced-value, context-free, public-good experiment. Next, an experiment was conducted in which subjects were given the opportunity to contribute to a naturally-occurring local public good. In this treatment, there were 125 subjects participating in 10 experimental sessions.[2] In the reverse order treatment, an additional 68 subjects in 4 experimental sessions participated in the contribution experiment first, followed by the induced value experiments. We describe each component of these experiments in turn next. Experiment instructions are available from the authors upon request.

Laboratory Public Goods Experiment

The design for the laboratory experiment follows that of Goeree et al. (2002a). Subjects are given an endowment of tokens and must chose how many of these tokens to "keep" and how many to "invest" in a public good. Each token kept earns a return only to the person who keeps it. A token invested earns a return to the person making the investment and to all others in this person's group. The return to a token invested may not be the same for all. For example, in one

[2] There were an additional 3 subjects who participated in the base induced-value experiments, but could not be included in our analysis because they did not complete the portion of the experiment involving the naturally occurring public good. These subjects are also not included in the analysis of the induced-value experiments for consistency.

treatment used in this experiment, a token kept earned 5-cents. A token invested earned an "internal return" of 4-cents to the individual making the investment and an "external return" of 2-cents to each of the three other people in the group.

In this framework, individual *i*'s earnings in decision *t* are calculated as

$$E_{it} = v(X_{it} - x_{it}) + m_i x_{it} + m_e \sum_{i \neq j} x_j , \qquad (1)$$

where v is the value of a token kept, X_{it} is the individual *i*'s token endowment in decision *t*, x_{it} is individual *i*'s contribution (or investment) to the public good in decision *t*, m_i is the internal return from one's own contribution, and m_e is the external return from the sum of all others' contributions.

In this experiment, each subject made an investment decision under a number of treatment conditions. Group size, internal return to the person contributing the tokens, and external return to all others in the group were varied between each treatment. All choices were presented to the subject at one time, with the order of presentation varied between subjects. A subject was able to complete the decisions in any order and change any decisions until they were all submitted. Half of the 128 subjects completed the same 10 decisions as those reported in Goeree et al. (2002a). In these sessions group size was either 2 or 4, a token kept earned 5-cents, and a token contributed earned either 2-cents or 4-cents to the person contributing it, and the external return to each other person in the group was 2-cents, 4-cents, 6-cents, or 12-cents. In order to test the robustness of our results we conducted additional sessions that included more variation in group size (2, 4, or 8) and higher per-token earnings. In these sessions, a token kept earned 10-cents; a token contributed earned either 4 or 8 cents; the external return to each other person in the group was 4-cents, 8-cents, or 12-cents. All remaining subjects made decisions under these treatments.

Subjects were paid for this experiment before the next experiment was conducted. Average earnings in the base treatment were $38.35, with a range of $23.20 to $59.02.[3] Average earnings in the reverse-order treatment were $35.37, with a range of $28.50 to $43.82. Results from these experiments are discussed more fully in Section III.

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[3] After participating in the one-shot public goods experiment, subjects then participated in a repeated public-goods experiment. Earnings are the sum of earnings from both the one-shot and repeated experiment. The effect of their

Local Public Good Experiment

In the base treatment, after subjects were paid for the laboratory public goods experiment, they were then given instructions for a choice-experiment involving the naturally-occurring public good; subjects were explicitly told that they would not have the opportunity to earn more money in this part of the experiment. In the reverse-order treatment, subjects participated in the choice-experiment involving the naturally-occurring public good first. Subjects were told that this part of the experimental session was unlike the rest of the session in that they would not have the opportunity to earn money in this part of the experiment.

The format of the choice experiment follows a standard choice-modeling (conjoint) format that is commonly used to elicit values for non-marketed, public goods (see Holmes and Adamowicz 2003 and Hanley et al. 1998 for a discussion of choice experiments and their use in valuation of environmental goods). Briefly, in a choice experiment, subjects are asked to choose between different bundles of goods. The goods are described in terms of their characteristics, and the characteristics (one of which is price) vary across the bundles. For example, a subject may be asked to consider a choice over two computers, each with different levels of characteristics (e.g., differing in storage capacity, memory, and monitor size) and with different prices. By observing the tradeoffs made between computer characteristics and the cost of the computer, one can infer the marginal value of the computer attributes. The logic follows for public goods in which the characteristics of the public good are varied and the "price" of the public good varies with its attributes.[4]

In our choice experiment, subjects are given the opportunity to contribute to a naturally occurring local public good. The public good chosen must have the following characteristics. First, it must be "deliverable." If subjects were to choose to purchase "the good," it must be credible that it could actually be provided in return for their payment. Second, the good must be divisible in provision. Subjects must be able to connect their specific payment with a specific amount of the public good provided (this rule may be relaxed, but for acceptability of the survey

experience in the repeated experiment (in particular, their contributions relative to others in their cohort) for the base treatment is captured in our parametric models by a measure of subjects' earnings relative to those in their group.

[4] Public good choice experiments often involve hypothetical situations and hypothetical choices in which subjects are often confronted with a tax-price for the public good (e.g., increased taxes to provide increased services at national parks). Other payment vehicles are plausible, such as variations in entry or license fees required to use the public good.

instruments we feel it is important). Third, we must be able to alter the attributes of the public good and still be able to provide or deliver any combination of the attributes we offer to subjects.

The public good we offered subjects that satisfied the above criteria was planting shade trees in an urban area. More specifically, we used *Trees Atlanta's* "gift trees" program. *Trees Atlanta* is a local non-profit organization that seeks to protect the Atlanta metropolitan environment by planting and conserving trees. It focuses on planting and maintaining trees in downtown Atlanta, which is ranked among cities having the least downtown tree cover. The lack of trees, along with increased asphalt and reflective buildings has contributed to an 8-10 degree increase in downtown Atlanta summer temperatures since 1970. *Trees Atlanta* seeks to alleviate this "urban heat-island" effect through the planting and maintaining of trees in the downtown area. The organization will plant a tree in the metro-area for a contribution to their gift-trees program. Each donation leads directly to the planting of a tree during the current planting cycle (from October through April each year).

There are three possible trees that subjects could choose to have planted: an Oak, Dogwood, or Crepe Myrtle. Further, each tree could be planted in one of two sizes: a small tree (5-feet) or a medium tree (8-feet). The cost to the subject for having a tree planted varied between \$8 and \$26.[5] Subjects did not know the actual cost of tree planting and were only told,

> For *Trees Atlanta* to plant a tree, you will need to make a contribution. The amount of a contribution ranges from \$8 to \$26 per tree and varies by the size and type of tree. Each contribution leads to a tree being planted that would not have been planted otherwise.

The choice of trees results in an experimental design with two attributes (apart from cost): type of tree, which has three "levels" (crepe myrtle, dogwood, oak) and tree size, which has two levels (small or medium). An orthogonal fractional factorial experimental design was selected from Sloane (2004) to develop 36 choice questions (or choice sets). The design was modified so that there was a correlation between size and cost (medium sized trees cost more than small trees), but orthogonality between all three attributes was maintained. Each choice question

[5] The cost could be \$8, \$12, \$15, \$19, \$22 or \$26. The cost of planting trees as subjects saw them were allocated through the process of developing an orthogonal attribute design for the survey.

presents the subject with a decision to purchase one of two trees that differ by tree-type, size, and/or cost. The subjects are also given the option to purchase neither tree in each question. To illustrate, a sample choice question is presented below. A color photograph of each tree at maturity is also presented to subjects in the column "Type of Tree" in the actual experimental questions.

Suppose Option A and B are the only two available, which do you choose, if any?

	Cost	**Type of Tree**	**Size at Planting**
Option A:	$19	Dogwood	Medium (8 feet)
Option B:	$12	Oak	Small (5 feet)

I choose the following option (please check one box only):

□ I choose to contribute $19 to have the tree planted in Option A.
□ I choose to contribute $12 to have the tree planted in Option B.
□ I will not contribute, and neither tree will be planted.

Of the 36 choice questions, 4 combinations were implausible. For example, there were combinations in which there were two identical trees offered for different prices. The 32 plausible combinations were split into four different questionnaires, each containing eight questions. Each subject is presented with only one of the four questionnaires and thus answers 8 choice questions.

The design for this portion of the experiment was as follows. Subjects were given an experiment packet that contained the instructions, the eight choice questions, and a demographic survey. Subjects read the instructions as the experimenter read them aloud. First, *Trees Atlanta* was introduced to subjects, and its effort to increase tree cover in Atlanta was described. The "Gift Trees" program was introduced, and a table shown to subjects that described each of the three trees that could be planted and a few of the important characteristics of each tree. The attributes of the trees that were described are flowering habit, mature height, growth rate (years to reach maturity), and shade potential. Color photographs of each tree type (at maturity) were also shown to subjects.

After describing the good, the choice questions were introduced. Subjects were told that they would answer eight questions in which they could choose one of three options: the option to purchase one of two trees, or the option to purchase neither tree. A sample question was then provided, and the experimenter described in detail what it would mean if they checked the first option, the second option, or the third option (which was always the option not to purchase either tree).

Subjects were then told how contributions would work. To determine which tree, if any, is planted as a result of their contribution, one of the eight questions would be drawn at random to be the "binding" question. By randomly choosing one question to be binding, we avoid sequencing effects in the choice questions. If a subject chose a tree in the binding question, the subject then paid the specified cost for the tree, received a receipt for the payment, and that specific tree was planted by *Trees Atlanta*. Subjects who chose to purchase a tree also completed a form (which could not be matched to their experiment ID number) that was given to *Trees Atlanta* with their name and mailing address so *Trees Atlanta* could mail a confirmation directly to the subject when the tree had been planted. Finally, all subjects completed a demographic survey.[6]

III. Measuring Altruism in Context-free Environments

We are interested in whether altruistic behavior in the context-free environment is predictive of contributions to the naturally-occurring local public good. We consider three ways to model altruistic behavior in the context-free experiments, varying from very simple measures summarizing overall behavior across treatments to more complicated parametric models that formally incorporate altruism and noisy decision-making. Each of these is explained in turn below, with summary results presented for each measure.

Nonparametric Measures: Average Contributions

[6] In the reverse-order treatment, the demographic survey was completed at the end of the experimental session rather than at the end of the choice-experiment to avoid potential confounds associated with being asked attitudinal and personal information prior to being in the induced-value public goods experiments.

Perhaps the simplest way to summarize a subject's behavior in the context-free experiment is simply to compute the average number of tokens contributed across decisions. Because endowments varied across treatments, we compute the average percentage of each subject's endowment contributed in each decision:

$$\frac{\sum_{t=1}^{T}\left(\frac{x_{it}}{X_{it}}\right)}{T}, \tag{2}$$

where x_{it} is individual i's contribution in decision t, X_{it} is the individual's token endowment in decision t, and T is the total number of decisions made by individual i.

In the base treatment and reverse-order treatment, subjects contributed an average of 27 and 29 percent of their endowment across decisions, respectively. The mean and variance of the average contributions is not significantly different across the two treatments. Considering each subject separately, Figure 1 displays a histogram of the average contribution (across all decisions) made by each individual in both treatments. The minimum average contribution was 0 percent of their endowment (29 subjects contributed nothing in all decisions), and the maximum average contribution was 92 percent of the endowment. As in previous public goods experiments, positive contributions are commonly observed, but few subjects (less than 20 percent of the total subject pool) contributed more than 50 percent of their endowment across decisions.

Nonparametric Measures: Strong and Weak Free-riding Behavior

Although average contributions are a simple, commonly reported summary measure of decision-making in public goods experiments, it may mask important differences in decision-making across subjects and across decisions. For instance, consider two subjects both with an endowment of 100 tokens in each of four decisions. Suppose subject-1 contributes 25 tokens in each decision, and subject-2 contributes 0 tokens in 3 decisions and 100 tokens in the 4th decision. Both subjects contributed 25 percent of their endowment on average. However, the behavioral motives underlying these two subjects' observed contributions could be very different (this point is discussed more fully below).

In order to address this concern, we have created two summary measures that better reflect the heterogeneity of contributions across decisions. First, we calculate the percentage of decisions in which a given subject behaved as a strong free-rider (i.e., contributed nothing). The second measure uses the percentage of decisions in which the subject behaved as weak free-rider (i.e., contributed more than 0 tokens, but less than 30% of their endowment).[7]

The strong and weak free-rider measures better reflect differences in contribution decisions compared to the subject's average contribution across all rounds. For example, consider the two subjects in the example above. Both contribute an average of 25 percent of their endowment across decisions; however they are categorized very differently using the new weak and strong free-rider measures. Subject-1 is categorized as a weak free-rider in 100% of the decisions and a strong free-rider in 0% of the decisions. Subject-2, on the other hand, would be categorized as a strong free rider in 75% of the decisions, and a weak free-rider in 0% of the decisions.

Averaging across all subjects in the context-free experiments, subjects in the base and reverse-order treatments behaved as strong free-riders in 32.3 and 27.8 percent of their decisions, respectively. Similarly, on average across subjects in the base and reverse-order treatments, they behaved as weak free-riders in 31.7 and 33.7 percent of their decisions, respectively. Again, the mean behavior is not significantly different across treatments. While the average behavior is similar between weak and strong free-riding, the distribution across subjects is rather different. The top panel of Figure 2 presents a histogram that shows the frequency with which each subject behaved as a strong free-rider (subjects from both treatments are pooled in Figure 2). Forty percent of subjects did not behave as a strong free-rider in any decision. At the other extreme, 15 percent of subjects acted as a strong free-rider in all decisions. The bottom panel of Figure 2 presents corresponding information for weak free-riding behavior. Less than 30 percent of subjects never behaved as a weak free rider, while only 5 percent of subjects always acted as a weak free-rider.

Parametric Models: Incorporating Altruism and Noisy Decision Making

[7] Isaac and Walker (1988) defined a "strong free-rider" as one who contributed less than 30 percent of their endowment. We wanted to distinguish between perfect-Nash players and those who contributed a low number of tokens; therefore we kept Isaac and Walker's cut-off contribution level but made a distinction between those who contributed nothing ("strong free-rider" in this paper) and those who contributed a positive amount, but less than 30 percent ("weak free-rider" in this paper).

The summary statistics created thus far have the advantage that they do not require restrictive assumptions regarding motivations for contributing or the parametric form that preferences take. They simply summarize the observed behavior. However, they do not distinguish between warm-glow giving (utility is based on the act of contributing independent of the benefit others receive from the contribution; see Andreoni 1990, Palfrey and Prisbrey 1997, and Goeree et al. 2002a) and altruism based on the benefit that others receive. Because subjects faced different parameters in each decision (i.e., group size, internal and external returns from a token contributed), differences in contributions between treatments yield important information about the underlying motives for contributions.

Again, consider the two subjects described above. Suppose the external return to a token contributed was constant in the first three decisions, but increased substantially in the fourth decision. Because subject-1 contributes the same amount, no matter the external benefit, this subject's behavior might best be described by a model of "warm-glow giving." Subject-2, on the other hand, responds to the change in the external benefit. As such, this behavior is more consistent with altruistic giving. We examine this idea using a formal model of altruistic preferences.

The most common specification of altruism assumes that one's utility is a linear function of own-earnings and others' earnings (see Holt and Laury 2004 for a survey of other theoretical explanations of contributions). This is specified as

$$U_i = E_i + \alpha_i \sum_{j \neq i} E_j, \tag{3}$$

where U_i represents the utility of subject i, E_i represents own earnings as defined by (1), and α_i is interpreted as an altruism parameter that determines the weight subject i places on others' earnings.[8]

If the altruism parameter is set equal to zero, the model reduces to the standard game theoretic model: the subject acts as a Nash player and maximizes own earnings only. If α_i is positive in equation (3), this indicates that an individual values both one's own earnings and the earnings of others in the group. In this case, increasing the external benefit of a contribution or increasing the number of others in the group who will benefit from a contribution should

[8] Other specifications could include non-linear functions of own and others' earnings.

increase contributions. On the other hand, a negative estimate for α_i indicates an individual's utility is decreased when the earnings of others are increased.

An important feature of the linear altruism specification is that it predicts an all-or-nothing contribution decision. According to this model, a subject will compare the marginal cost of contributing with the marginal benefit to all in the group to determine whether or not to contribute one's full endowment. In other words, a person will contribute fully if

$$\alpha_i \geq \frac{v - m_i}{(n-1)m_e}, \tag{4}$$

where v, m_i and m_e are defined in equation (1), and n is the number of subjects in the group. If equation (4) does not hold, a subject will contribute nothing. Equation (4) makes apparent how changes in the experiment parameters will affect the level of contributions to the public good. For example, consider a decision in which a subject is paired with one other participant; if a token kept earns 5-cents, and the internal and external return are both 4-cents, then only those with an altruism parameter greater than 0.25 will contribute to the public good. If we hold all parameters at these values, but increase the external return to 12-cents, those with an altruism parameter greater than 0.08 will contribute to the public good. Given that the altruism parameter differs across participants, we would expect to see more contributors (and therefore a higher level of contributions) as the external return to the public good increases. In addition, by observing an individual's contribution decisions across treatments, one can estimate an individual-level altruism parameter. Based on the example above, if one does not contribute when the external return is 4-cents but does contribute when the external return is 12-cents, we can infer that this subject's linear altruism parameter is between 0.08 and 0.25.

Even with no altruism, some investment in the public good may be observed if the net loss from investing a token is small. This type of "noisy" decision-making also implies that we may observe the level of investment increasing as the internal return increases (thereby decreasing the net opportunity cost of the investment).[9] We introduce this model formally using a logit probabilistic choice rule (See Anderson et al. 1998 and Goeree et al. 2002a, 2002b for details). According to this specification, choice probabilities are given by

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[9] The opportunity cost of a contribution is the difference between the value of a token kept and the internal return to the person contributing a token.

$$P(x_i) = \frac{\exp(U_i(x_i)/\mu)}{\sum_{x=0}^{X_i} \exp(U_i(x_i)/\mu)}, \tag{5}$$

where X_i represents the individual's token endowment, x_i is the number of tokens subject i contributes, $U(x_i)$ is defined by equations (1) and (3), μ is an noise parameter to be estimated, and the denominator ensures that the choice probabilities add up to 1. This choice rule implies that the probability of choosing any given level of contribution is proportional to an exponential function of the expected utility associated with that level of contribution. The noise parameter, μ, represents the sensitivity of choices to changes in utility. If μ is very large, choices are close to random. If μ is very small, one is very sensitive to changes in utility, so the optimal decision is very likely to be chosen.

In the absence of altruism ($\alpha = 0$), utility in equation (4) is simply one's own earnings. Therefore, the earnings-maximizing decision to contribute zero tokens is most likely to be chosen. The presence of some noise ($\mu > 0$) implies that positive contributions will be observed with some positive probability. Moreover, the model predicts that contributions will be higher when the opportunity cost of a contribution is smaller.[10] When there is some altruism ($\alpha > 0$) positive contributions are more likely to be observed, with higher contributions more likely when the benefit to others is larger.

The parameterization in (5), with U_i determined by linear altruism model in (3), can be used to estimate the effects of altruism and noise. The probability that individual i contributes x_i tokens is given by (5); assuming that decisions are independent, the likelihood function is given by the product of these choice probabilities. Therefore the log likelihood can be expressed as

$$\ln(L) = \sum_i \ln(P(x_i)), \tag{6}$$

where $P(x_i)$ is given in equation (5). Estimates of μ and α_i can be obtained by maximizing the log-likelihood function with respect to these parameters. We estimate a separate altruism parameter for each individual but constrain the error term (μ) to be identical for all subjects.

Based on the estimated altruism parameter and a specified level of significance, we classify subjects into one of three categories: those with a positive altruism parameter that is

[10] When this opportunity cost falls, the utility-loss from deviating from the optimal decision is smaller; therefore the optimal decision is less likely to be chosen.

significantly different than zero, those with a negative altruism parameter that is significantly different than zero, and those with an altruism parameter that is not significantly different than zero. For the purposes of discussion, we use a 95% level of confidence for the altruism parameters to classify subjects into one of the three categories. In our parametric models, we examine the sensitivity of our results to this assumption, using both a 10 and 1 percent test size to classify subjects. For ease of exposition, we simply refer to subjects as having a positive, negative, or a "zero" altruism parameter. There were 29 subjects who chose to contribute 0-tokens in all decisions; these subjects have no variation in their decisions and altruism parameters could not be directly estimated for these subjects. However, as described in the next section, we do incorporate the decisions of these subjects into our parametric analysis as well.

Across both treatments, there are 27, 46, and 11 percent of subjects categorized as having a positive, zero and negative altruism parameter, respectively.[11] There are 29 subjects (15% of the total sample) who acted as pure Nash players. The only significant difference between the two treatments is for the proportion of subjects who are categorized as having a zero altruism parameter. In the base treatment, 42% of subjects are classified as having a zero altruism parameter, while 54% of subjects are classified as such in the reverse-order treatment.[12] There were no significant differences across treatments in the proportion of subjects placed in each of the remaining altruism categories, and this is robust to our decision about which confidence level is used to categorize the altruism parameters (99, 95, or 90 percent level).

We use each of these measures from the context-free public goods experiment to predict the probability that a contribution is made to the naturally-occurring local public good. These results are described below.

IV. Testing for Altruism Spillovers

In this section, we relate the decisions subjects made in the context-free experiments to their choices over whether or not to contribute to the naturally-occurring local public good. First, we briefly summarize the results of the choice experiments and provide an overview of the

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[11] If a 10% test size is used to categorize subjects, there are 32, 39, and 14 percent of subjects categorized as having a positive, zero and negative altruism parameter, respectively. If instead a 1% test size is used is used to categorize subjects, there are 20, 65, and 0 percent of subjects categorized as having a positive, zero and negative altruism parameter, respectively

various measures of altruism and their relationship to the decision to purchase a tree. Parametric models are then presented that provide a better understanding of the relationship between altruism in the context-free environment and altruism toward the naturally-occurring public good.

Altruism Measures and Choice Experiment Results

Table 1 defines the variables used in our analysis, and Table 2 reports summary statistics for the altruism measures for each treatment. The summary statistics for the non-parametric measures of altruism (avgcont, %strong, and %weak) are reported by altruism parameter category (altpos, altneg, altzero, altnash).

There is a strong correlation between the estimated level of altruism and subjects' average contribution in the context-free experiment. The Pearson correlation coefficient is 0.46, which is significantly different from zero at any standard level. This correlation is reflected in the consistency between the average contribution and altruism parameter category reported in Table 2. Average contributions are highest among those with positive altruism parameters and lowest for those with negative estimated altruism parameters. Because we define those subjects who never contribute as Nash players, by definition they will have the lowest average contribution (zero) of any altruism category. Those with a positive altruism parameter contributed, on average, almost 60% of their tokens, compared with approximately 26 percent for those with a zero altruism parameter and just 3 to 5 percent for those with a negative altruism parameter.

Figure 3 shows frequency histograms of the percent of the endowment contributed by each individual in each decision.[13] Contributions by those with a positive altruism parameter (top panel of Figure 3) are more uniformly distributed than those with a zero or negative altruism parameter (see the middle and bottom panels of Figure 3, respectively). In fact, the modal outcome (with over 19 percent of all contribution decisions) by those with a positive altruism parameter is to contribute over 95 percent of one's endowment. In contrast, only about 8 percent

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[12] If, instead, a 10% test size is used to categorize subjects, there are 36 and 44 percent of subjects categorized as having a zero altruism parameter, and these proportions are not significantly different from each other.

[13] The number of data points graphed in the histograms corresponds to the total number of decisions made by all subjects. For example, if there are 10 subjects making 10 decisions, the histogram is comprised of 100 data points, each one representing the percentage of endowment contributed in a given decision.

of contribution decisions made by those with a zero altruism parameter exceed 55 percent of one's endowment. Those with negative altruism parameters appear very similar to Nash players. They contribute less than 5 percent of one's endowment in 83 percent of all decisions and never contribute more than 50 percent of one's endowment. A Kolmogorov-Smirnov test confirms that the distribution of contributions is significantly different among those with positive, zero, and negative altruism parameters ($p < 0.01$).

A consistent relationship is found between the parametric measure of altruism and the percent of rounds in which subjects are classified as a strong free-rider (%strong). Subjects with a negative altruism parameter behaved as strong free-riders in at least 50% of rounds, on average, while subjects with positive altruism parameters only did so in approximately 7% of rounds. The relationship between the sign of the altruism parameter and the number of rounds in which one is a weak free-rider is not as strong. While subjects with a positive altruism parameter acted as weak free-riders in the fewest rounds (on average), there is little difference in the percentage of rounds in which subjects with negative altruism parameters acted as weak free-riders as compared to subjects with a zero altruism parameter. Those with a negative altruism parameter were much more likely to contribute nothing than those with a zero altruism parameter. In contrast, those with a zero altruism parameter were much more likely to contribute more than 30 percent of their endowment than those with a negative altruism parameter. However, there is little difference between these two groups in the percentage of contributions that fall ***between*** zero and 30 percent of one's endowment (i.e., behave as a weak free-rider).

Turning to the decisions made in the choice experiment, across both treatments 77% of all subjects chose not to purchase a tree for *Trees Atlanta* in any of the eight choice questions. Of the 23% who chose to purchase a tree at least once, almost half chose a tree in just one of the eight questions. Slightly fewer subjects chose a tree in the reverse-order treatment (19%) versus the base treatment (25%). The difference in proportion choosing a tree across treatments is not statistically significant (Pearson X^2 statistic p-value = 0.369). Table 2 also reports the percentage of subjects within each altruism parameter category who chose a tree in at least one question. Surprisingly, Pearson X^2 statistics indicate no significant differences in the percentage of subjects choosing a tree across any of the four altruism categories in the base or reverse-order treatments. However, these non-parametric tests are not particularly informative because there is variation across subjects in the tree-types and costs presented to them (recall, there were four different versions of the questionnaire administered to subjects). Thus, we now turn to parametric tests that allow us to incorporate the features of the trees and their costs to understand better the relationship between the altruism parameter estimates and the likelihood that a subject chooses to have a tree planted.

Parametric Analysis

Conditional logit models (see McFadden 1974) are used to relate subjects' choices to the characteristics of the trees presented, the tree costs, subjects' earnings in the context-free experiments, and the various altruism measures computed for each subject in the context-free experiment. Demographic variables are also included. We include demographic characteristics that indicate a subject's gender, ethnic background (Caucasian, Hispanic, African-American, and other), personal income, maritial status, whether or not raised in the U.S., whether or not employed, and whether or not personally responsible for tuition and expenses while in college. Also included are the student's major (business, hard-sciences, other), the class standing (undergraduate versus graduate student), the number of economics courses taken, and a categorical variable indicating whether or not a subject reported typically favoring environmental preservation over development. Given our design, there are 24 observations for each subject (8 choice questions with 3 alternatives in each question), and the conditional logit model incorporates this structure of the data (see Greene 2003 or Wooldridge 2004 for standard introductions to the conditional logit model).

Subjects in the base treatment completed the context-fee experiment before the naturally-occurring contribution decision. As such, there is a concern that one's prior experience in the experiment may affect a subject's contribution decision. We control for this prior experience in two ways. It is possible that subjects view their earnings from the context-free experiment as "found money," and therefore they would be more likely to contribute than in the absence of these earnings. We address this by including each subject's total earnings from the context-free experiment in the regression analysis. However, this does not explicitly address how *differences* in experiences among subjects may contribute to one's contribution decision. For example, a subject who contributed a lot relative to the others in one's group in the context-free experiment may be less likely to contribute in a follow-up experiment. We control for these differences in prior experience by including a second variable in the regression analysis: one's own earnings relative to the average earnings of all others in one's group in the context-free experiment. If one contributed more than the others in one's group, this subject would have earned less than the others, and therefore this measure will be less than one. On the other hand, if one contributed less than the others in one's group, this measure will be greater than one.

In addition to controlling for total and relative earnings, we conducted the reverse-order treatment in which a subject's decision to contribute to a tree is not affected by any prior experience in an induced-value experiment.[14] Because earnings (or relative earnings) would not affect contribution decisions of subjects in the reverse-order treatment, in the parametric analysis we interact both the earnings and relative earnings variables with a categorical variable equal to one if the experiment was the base treatment and equal to zero if the experiment was a reverse-order treatment.

Results from the parametric models are presented in Tables 3 and 4. First, we briefly discuss the results for covariates related to the types of trees offered to subjects. As all models in Table 3 and 4 indicate, the subjects were price-responsive. The higher the price of a tree, the less likely it was to be chosen. Oak trees (of either size) were more likely to be chosen as compared to small-crepe myrtle trees (the category left out of the models). There was no significant difference between the likelihood of purchasing a dogwood (of any size) as compared to a small crepe myrtle, but larger crepe myrtles were preferred over small crepe myrtles. These results are consistent with subjects having internalized the information provided during the discussion of the naturally occurring public good. Recall, the issue presented to subjects was the loss of tree-cover in downtown Atlanta that helps to create an "urban heat island" effect, increasing temperatures due to loss of shade. Oak trees provide the greatest shade potential (up to 70 feet at maturity) and the dogwood and crepe myrtle both provide relatively little shade potential (up to 20 feet at maturity).

Although not reported for succinctness, demographic variables were generally significant. All demographic variables are interacted with an attribute-specific constant indicating whether or not the subject chose either of the two trees (i.e., was "in the market" or not). Briefly, the results were that older subjects and females were less likely to choose a tree. Caucasians were more likely to choose a tree, and African-Americans were less likely to choose

[14] Subjects in the reverse-order treatment had not participated in any economics experiment previously.

a tree as compared to the base-category (which included Asian and other ethnic backgrounds). There was no significant difference between Hispanic students and the base category. Graduate students (as compared to undergraduates) and subjects that were raised primarily outside the US were more likely to give to a tree. Students majoring in hard-sciences were less likely to give to a tree as compared to any other major, although this was only significant in two of the four models estimated. Whether or not a student was married, working, or responsible for their own tuition and books was not a significant predictor of whether or not they choose a tree, after controlling for the subject's income. Subjects with higher incomes (personal income, not laboratory earnings) were more likely to choose a tree, athough this was only significant in two of the four models. Lastly, subjects who indicated they typically favor environmental preservation over development were significantly more likely to choose a tree in all four models.

Table 3 reports models that include the non-parametric measures of altruism. The variables related to altruism (avgcont, %weak, %strong) and earnings are interacted with an attribute-specific constant indicating whether or not the subject chose either of the two trees (i.e., was "in the market" or not). Model 1 in Table 3 indicates that the average contributions of subjects are related to the decision of whether or not to purchase a tree. The higher the average percentage of tokens contributed in the context-free experiments, the more likely a subject would choose to contribute to the naturally-occurring local public good. However, this relationship is non-linear. The likelihood that a subject contributes to *Trees Atlanta* increases at a decreasing rate as the percentage of tokens they contributed in the context-free experiments increases. This relationship is consistent with the notion of altruism spillovers: people who behave altruistically in context-free, sterile laboratory environments that involve small benefits to few people (as measured by average token contributions) are also those who behave more altruistically in situations that involve benefits to the general public. However, these results should be interpreted with caution because, as discussed earlier, the measure of "altruism" that we use here, an individual's average contribution across all decisions (Avgcontr), is at best a rough proxy for altruism since it does not capture any differences in contributions between treatments

In Model 2 we instead measure altruistic behavior using the percentage of rounds in which subjects were either strong or weak free-riders. Results are presented in the last column of Table 3. As expected, there is a negative correlation between the percent of rounds in which one is a strong free-rider (perfect Nash player) and the probability of purchasing a tree. However, there is a *positive* relationship between the percentage of rounds in which one is a weak free-rider and the probability of purchasing a tree. In other words, the more frequently a subject makes a low (but non-zero) contribution decision, the *more* likely one is to contribute to the naturally occurring public good.

While the results for strong free-riders are consistent with our notion of altruism spillovers, the results for weak free-riders raise interesting questions. One way to interpret these results comes when we classify subjects who are weak free-riders in most rounds as exhibiting behavior consistent with "warm-glow giving." When we look at the contribution decisions made by these subjects, we see that they contributed small amounts across decisions regardless of the external or internal return of the contribution or the number of subjects who benefit from their contribution. In this context, Model 2 in Table 3 suggests that subjects who exhibit behavior more consistent with "warm-glow giving" in the laboratory (i.e., contribute small, positive amounts in more rounds) are also more likely to give to the naturally-occurring public good. This raises the question: are the contributions of these subjects to the naturally-occurring local public good an extension of their warm-glow behavior? To examine this hypothesis more closely, we turn now to our parametric measure of altruism. This parametric measure explicitly models the subject's response to differences in the parameter values in the context-free experiments. In this way we can more clearly distinguish those whose behavior is consistent with "altruism," which is associated with positive contributions and responsiveness to external benefits to the pubic good, with those who are warm-glow givers.

Table 4 reports four models in which the decision to purchase a tree is related to the subject's estimated altruism parameter. In model A, the estimated value of the subject's altruism parameter is entered directly as an explanatory variable. For this one regression we omit Nash players (those who never contributed in the laboratory experiment) because we were unable to estimate an altruism parameter for these subjects. They are, however, included in all other regressions reported in Table 3 and 4. Results suggest that the likelihood of choosing a tree increases as the subject's altruism parameter increases. While these results are supportive of altruism spillovers being present, the model does not distinguish between altruism parameters that are significantly different than zero and imposes a specific interpretation on the altruism parameters that may not be reasonable: that a subject with altparam=2 cares twice as much about others as a subject with altparam=1. The next model we present considers these two aspects of the data directly.

Models B through D use categorizations of the subjects based on the sign and significance of their altruism coefficient. The four categories are Nash players who contributed nothing in all decisions (Altnash), those with a statistically significant, positive altruism parameter (Altpos), those with a statistically significant, negative altruism parameter (Altneg), and those whose altruism parameter is not significantly different from zero (Altzero). We test the robustness of our results by presenting estimation results using different cut-off values used to determine whether an altruism parameter is significantly different than zero. Test sizes of 10%, 5%, and 1% are used as the cut-off for Models B, C, and D, respectively. If we use a 1% test size for categorizing the altruism parameters, there are no subjects who are categorized as having a negative altruism parameter (the largest z-statistic for those with a negative altruism parameter is 2.437 in absolute value), which is reflected in Model D having no entry for the coefficient estimate of altneg.

Two findings emerge from these models. First, supportive of the previous analyses, subjects who are strong free-riders. i.e., are pure Nash-players in all rounds. are significantly less likely to choose a tree in all models. While this is consistent with the notion of altruism spillovers, the results for our other categories are less promising. All models indicate that subjects who are estimated to have a positive altruism parameter are no more likely to choose a tree than subjects who are estimated to have a zero altruism parameter (the "warm glow givers"). In addition, if one is most generous about who is categorized as having a negative altruism parameter (i.e., use the 90% level of confidence to categorize subjects), then there is also no significant difference in the probability that a subject with a positive or zero altruism parameter chooses a tree when compared to those with a negative altruism parameter. This latter result is sensitive to the cutoff-level for categorizing subjects. If instead, a more stringent rule is applied (the 5% test size), the probability that a subject with a negative altruism parameter chooses a tree is not statistically different than subjects who are pure Nash players (see model C) and is statistically different than subjects with a positive or zero altruism parameter.[15]

The results in Models B through D are consistent with our earlier hypothesis that subjects who act as warm-glow givers in the laboratory may extend that behavior to non-laboratory public

[15] The coefficients for the positive and zero altruism parameter categories are significantly different than the coefficient for the negative altruism category at the 90% level of confidence only.

goods and that Nash players in the laboratory may also extend their non-altruistic behavior beyond the laboratory, thus indicating some degree of relationship between altruism in laboratory contexts and in naturally occurring contexts. However, the results are also not wholly supportive of our notion of altruism spillovers. Subjects who acted the most altruistically in the lab were no more likely to contribute to the naturally-occurring public good than the warm-glow givers or those who behaved 'spitefully' in the laboratory experiments (although this latter result is sensitive to choices made about the categorization of altruism parameters).

VI. Summary

Laboratory public-goods experiments have traditionally been used to study the question of whether altruism exists and the nature of altruism (e.g., warm glow versus pure altruism). However, most experiments are careful to use a neutral setting, even referring to the decision as an "investment" rather than a "contribution." Our results suggest that further investigation into the external validity of decisions made in these context-free situations is warranted.

Results indicate that altruistic behavior in the lab can be predictive of contributions to naturally occurring public goods, but not in a uniform manner. We observe a positive relationship between a crude measure of altruism (the average contributions to the laboratory public good across rounds) and the likelihood that a subject contributes to a naturally occurring public good. In addition, the more often a subject behaves as a pure Nash player across rounds (i.e., contributes zero tokens to the laboratory public good), the less likely he is to contribute to a naturally-occurring public good. However, contrary to expectations, acting as a weak free-rider more often in the induced-value public goods game *increases* the likelihood of contributing to the naturally occurring public good.

Parametric estimates of altruism also do a poor job of predicting contributions to the naturally-occurring public good. Subjects are categorized into four categories based on individual-level altruism parameter estimates: those who are Nash players and contribute nothing in all decisions, those with a statistically significant, positive altruism parameter, those with a statistically significant, negative altruism parameter, and those whose altruism parameter (positive or negative) is not significantly different from zero. Supportive of the notion of altruism spillovers, we find that the pure Nash players are less likely to give to the naturally occurring public good. However, we cannot distinguish between the contribution behavior toward the naturally occurring public good of the other subjects based on whether they have a positive, negative, or “zero” altruism parameter with any degree of confidence.

Overall, while our results indicate there is some relationship between altruism in laboratory games and altruism toward a naturally occurring public good, the relationship is far from being incontrovertible. The question this naturally raises is whether subjects in the laboratory experiment view their investment decision as a contribution to a public good that benefits others (in this case, other participants) or as a different sort of game. At the very least our results suggest that one should be cautious when using the results from laboratory public goods experiments to make inferences about altruism outside of the lab and that further testing of the notion of altruism spillovers is certainly warranted.

References

Anderson, S.P., Goeree, J.K., Holt, C.A., 1998. A theoretical analysis of altruism and decision error in public goods games. Journal of Public Economics 70, 297-323.

Andreoni, J., 1990. Impure altruism and donations to public goods: a theory of warm-glow giving. The Economic Journal 100, 464-477.

Cherry, T.L., Crocker, T.D., Shogren, J.F., 2003. Rationality spillovers. Journal of Environmental Economics and Management 45, 63-84.

Goeree, J.K., Holt, C.A., Laury, S.K., 2002a. Private costs and public benefits: unraveling the effects of altruism and noisy behavior. Journal of Public Economics 83, 255-276.

Goeree, J.K., Holt, C.A., Laury, S.K., 2002b. Incentives in public goods experiments: implications for the environment. In: List, J., de Zeeuw, A. (Eds.). Recent Advances in Environmental Economics. Northampton, MA, Edward Elgar Publishing, Inc., 309-339.

Greene, W.H., 2003. Econometric Analysis. New Jersey: Prentice Hall Publishers.

Hanley, N., Wright, R., Adamowicz, W., 1998. Using choice experiments to value the environment. Environmental and Resource Economics 11, 413-418.

Holmes, T.P., Adamowicz, W., 2003. Attribute-based methods. In: Champ, P., Boyle, K., Brown, T. (Eds.). A Primer on Nonmarket Valuation. Dordrecht, The Netherlands: Kluwer Academic Publishers, 171-219.

Holt, C.A., Laury, S.K., 2004. Theoretical explanations of treatment effects in voluntary contributions games. Forthcoming in: Plott, C., Smith, V.L. (Eds.). Handbook of Experimental Economic Results. Burlington, MA, Elsevier Press.

Isaac, R.M., Walker, J., 1988. Group size effects in public goods provision: the voluntary contribution mechanism. Quarterly Journal of Economics 103, 179-199.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembaka, P. (Ed.) Frontiers in Econometrics. New York: Academic Press, 105-142.

Palfrey, T.R. and Prisbrey, J., 1997, Anomalous behavior in linear public goods experiments: how much and why? American Economic Review 87, 829-846.

Sloane, N.J.A., 2004. A library of orthogonal arrays, http://www.research.att.com/~njas/oadir/.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge, Mass: MIT Press.

Table 1. Variable Definitions

Context-free Experiment Variables	
Avgcontr	Average contributions of subject across decisions, measured as a percentage of their total endowment in each decision (see equation 2).
%Strong	Percentage of decisions in which the subject was a strong free-rider (contributed 0 tokens).
%Weak	Percentage of decisions in which the subject was a weak free-rider (contributed more than 0 tokens, but less than 30% of their endowment).
Altparam	Altruism parameter as estimated by equation 6.
Altpos	=1 if altruism parameter is positive and significantly different than zero (the level of significance will vary as noted in the text where appropriate), =0 otherwise.
Altzero	=1 if the estimated altruism parameter is not significantly different than zero (the level of significance will vary as noted in the text where appropriate), =0 otherwise.
Altneg	=1 if altruism parameter is negative and significantly different than zero (the level of significance will vary as noted in the text where appropriate), =0 otherwise.
Altnash	=1 if subject contributed zero tokens in all rounds, =0 otherwise.
Earnings	Earnings of the subject in the context-free experiment.
Relearn	Earnings of the subject in the context-fee experiment relative to the other subjects in one's decision-making group.
Trees Atlanta Experiment Variables	
Price	Price of the tree offered in the alternative.
Oakmed	=1 if the alternative was a medium-sized Oak tree, = 0 otherwise.
Oaksm	=1 if the alternative was a small-sized Oak tree, = 0 otherwise.
Dogmed	=1 if the alternative was a medium-sized Dogwood tree, = 0 otherwise.
Dogsm	=1 if the alternative was a small-sized Dogwood tree, = 0 otherwise.
Crepemed	=1 if the alternative was a medium-sized Crepe Myrtle tree, = 0 otherwise.
Crepesm	=1 if the alternative was a small-sized Crepe Myrtle tree, = 0 otherwise. This is the category not included in the model.

Table 2. Contribution Characteristics by Altruism Parameter Category.[1]

	Positive Altruism Parameter (altpos)		Zero Altruism Parameter (altzero)		Negative Altruism Parameter (altneg)		Nash Players (altnash)	
	Base (N=37)	Rev. Order (N=16)	Base (N=52)	Rev. Order (N=37)	Base (N=14)	Rev. Order (N=8)	Base (N=22)	Rev. Order (N=7)
Average percentage contribution (avgcont)	58.1 (14.3) [35 – 92]	56.8 (16.7) [37 – 92]	24.9 (11.0) [7 – 46]	27.5 (12.5) [0.5 – 57]	4.9 (2.8) [2 - 11]	2.7 (2.5) [0.5 – 8]	0.00 (0.00) [NA]	0.00 (0.00) [NA]
Strong free-riders (%strong)	6.7 (9.8) [0 - 30]	7.8 (12.4) [0 - 40]	17.4 (23.7) [0 - 90]	12.8 (20.8) [0 - 90]	48.1 (29.3) [0 - 90]	73.9 (28.0) [10 - 92]	100 (0.00) [NA]	100 (0.00) [NA]
Weak free-riders (%weak)	16.6 (14.9) [0 – 50]	17.2 (16.9) [0 – 50]	50.3 (24.3) [0 – 100]	49.3 (28.4) [8 – 100]	49.9 (31.4) [0 – 100]	23.9 (29.4) [0 – 90]	0.00 (0.00) [NA]	0.00 (0.00) [NA]
Number of subjects who chose a tree at least once	8 {22%}	4 {25%}	15 {29%}	9 {24%}	3 {21%}	0 {0%}	5 {23%}	0 {0%}
Earnings	$36.57 (5.53)	$35.29 (2.22)	$39.42 (8.09)	$35.74 (3.23)	$41.41 ($9.78)	$34.00 ($2.72)	$36.34 ($6.56)	$35.18 ($3.22)
Relative Earnings (relearn)	0.90 (0.15) [0.5 – 1.1]	1.00 (0.06) [0.9 – 1.1]	1.05 (0.21) [0.7 – 1.9]	1.01 (0.10) [0.8 – 1.3]	1.16 (0.14) [1.0 – 1.5]	0.96 (0.08) [0.9 – 1.1]	1.03 (0.16) [0.6 – 1.4]	0.99 (0.10) [0.9 – 1.1]

[1] In parentheses is the standard deviation. In brackets is the range of outcomes, and in curly brackets is the percent of total subjects in each category (e.g., 19 percent of those with a positive altruism parameter chose a tree at least once).

Table 3. Conditional logit models including non-parametric measures of contribution behavior in the context-free experiments.*

	Model 1: Average Contributions	Model 2: %Strong and %Weak
	Coefficient (std. error)	Coefficient (std. error)
Price	-0.288[a] (0.045)	-0.290[a] (0.045)
Oakmed	2.148[a] (0.538)	2.170[a] (0.546)
Oaksm	0.642[b] (0.304)	0.653[b] (0.308)
Dogmed	1.063 (0.679)	1.060 (0.685)
Dogsm	-0.110 (0.332)	-0.145 (0.339)
Crepemed	1.356[b] (0.675)	1.361[b] (0.687)
Earnings	-0.281[b] (0.119)	-0.289[b] (0.127)
$(\text{Earnings})^2$	0.003[b] (0.001)	0.003[b] (0.002)
RelEarn	11.472[b] (4.700)	12.060[b] (5.076)
$(\text{RelEarn})^2$	-5.561[b] (2.325)	-5.892[b] (2.522)
AvgContr	0.007[a] (0.012)	
$(\text{AvgContr})^2$	-0.001[a] (0.0001)	
%Strong		-0.029[a] (0.011)
$(\%\text{Strong})^2$		0.0002 (0.0001)
%Weak		0.035[a] (0.012)
$(\%\text{Weak})^2$		-0.003[b] (0.0001)
	N=4200 (175 subjects[d])	N=4200 (175 subjects[d])

	Ln(L) = -427.32	Ln(L) = -421.66
	Psuedo R^2=0.7469	Psuedo R^2=0.7503

[*] Included in all models are a combined alternative-specific constant that is equal to one if the choice involved one of the two trees (i.e., the subject was "in the market"), and equal to zero if the choice involved neither tree (i.e., the subject was "out of the market"). Earnings of the subject and the variables related to the subject's estimated altruism parameter are interacted with this alternative-specific constant.
[a] Coefficient significant at the 1% level of significance.
[b] Coefficient significant at the 5% level of significance.
[c] Coefficient significant at the 10% level of significance.
[d] 18 subjects were dropped from this analysis because they did not answer some of the included demographic questions.

Table 4. Conditional logit models including parametric measures of altruism in the context-free experiments *

	Model A: Continuous Altruism Parameter, Nash Players Excluded	Model B: Altruism Parameter Categories (10% level)	Model C: Altruism Parameter Categories (5% level)	Model D: Altruism Parameter Categories (1% level)
	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)
Price	-0.285[a] (0.046)	-0.293[a] (0.045)	-0.294[a] (0.045)	-0.291[a] (0.045)
Oakmed	2.176[a] (0.552)	2.158[a] (0.536)	2.172[a] (0.537)	2.151[a] (0.533)
Oaksm	0.666[b] (0.322)	0.655[b] (0.308)	0.654[b] (0.309)	0.651[b] (0.308)
Dogmed	1.107 (0.691)	1.088 (0.677)	1.092 (0.677)	1.074 (0.675)
Dogsm	-0.010 (0.347)	-0.094 (0.338)	-0.105 (0.338)	-0.092 (0.335)
Crepemed	1.376[b] (0.694)	1.381[b] (0.678)	1.382[b] (0.680)	1.373[b] (0.675)
Earnings	-0.332[a] (0.101)	-0.328[a] (0.118)	-0.333[a] (0.119)	-0.371[a] (0.113)
$(\text{Earnings})^2$	0.004[a] (0.001)	0.004[a] (0.001	0.004[a] (0.001)	0.004[a] (0.001)
Relearn	13.077[a] (3.757)	13.821[a] (4.551)	13.816[a] (4.556)	15.308[a] (4.421)
$(\text{Relearn})^2$	-5.843[a] (1.716)	-6.532[a] (2.197)	-6.469[a] (2.179)	-7.262[a] (2.137)
Altparam	0.674[c] (0.364)			
$(\text{Altparam})^2$	-0.538 (0.394)			
Altpos		1.678[a] (0.487)	1.708[a] (0.490)	1.882[a] (0.515)
Altzero		1.874[a] (0.482)	1.811[a] (0.479)	1.690[a] (0.472)
Altneg		1.180[c] (0.614)	0.877 (0.647)	
	N=3600 (150 subjects)[d]	N=4200 (175 subjects)[d]	N=4200 (175 subjects)[d]	N=4200 (175 subjects)[d]

Ln(L) = -385.09	Ln(L) = -412.49	Ln(L) = -428.33	Ln(L) = -428.33
Psuedo R^2=0.7232	Psuedo R^2=0.7557	Psuedo R^2=0.7463	Psuedo R^2=0.7463

[*] Included in all models are a combined alternative-specific constant that is equal to one if the choice involved one of the two trees (i.e., the subject was "in the market"), and equal to zero if the choice involved neither tree (i.e., the subject was "out of the market"). Earnings of the subject and the variables related to the subject's estimated altruism parameter are interacted with this alternative-specific constant.

[a] Coefficient significant at the 1% level of significance.

[b] Coefficient significant at the 5% level of significance.

[c] Coefficient significant at the 10% level of significance.

[d] 18 subjects were dropped from this analysis because they did not answer some of the included demographic questions.

Figure 1. Average Individual Contribution Over All Decisions

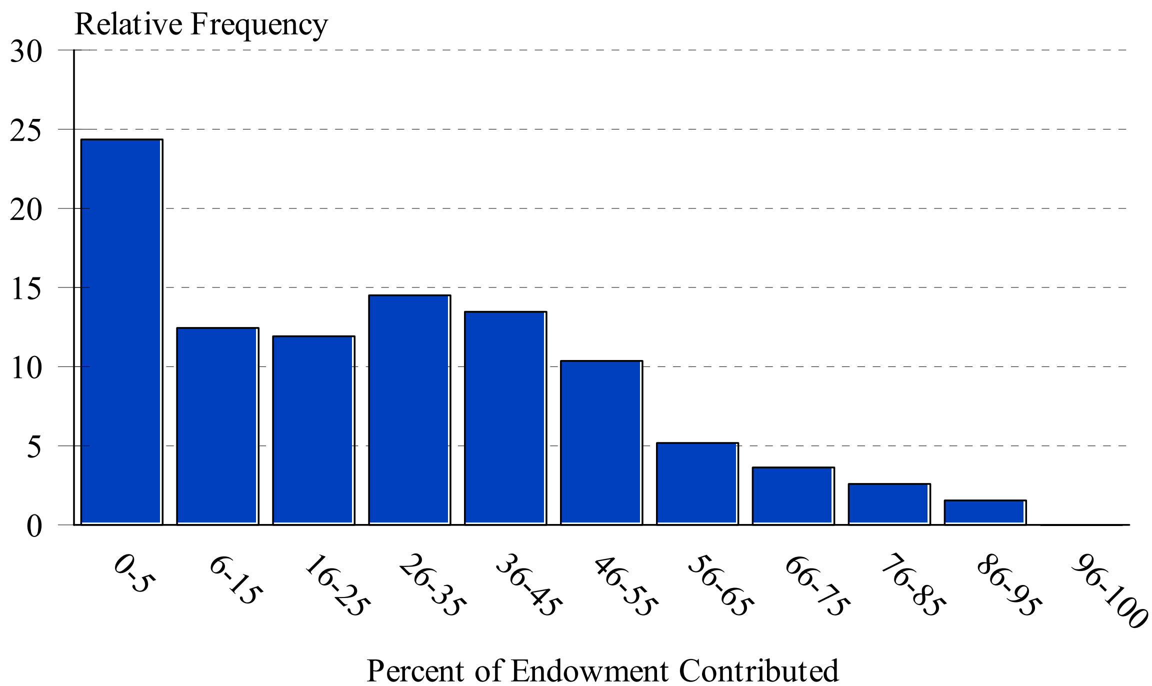
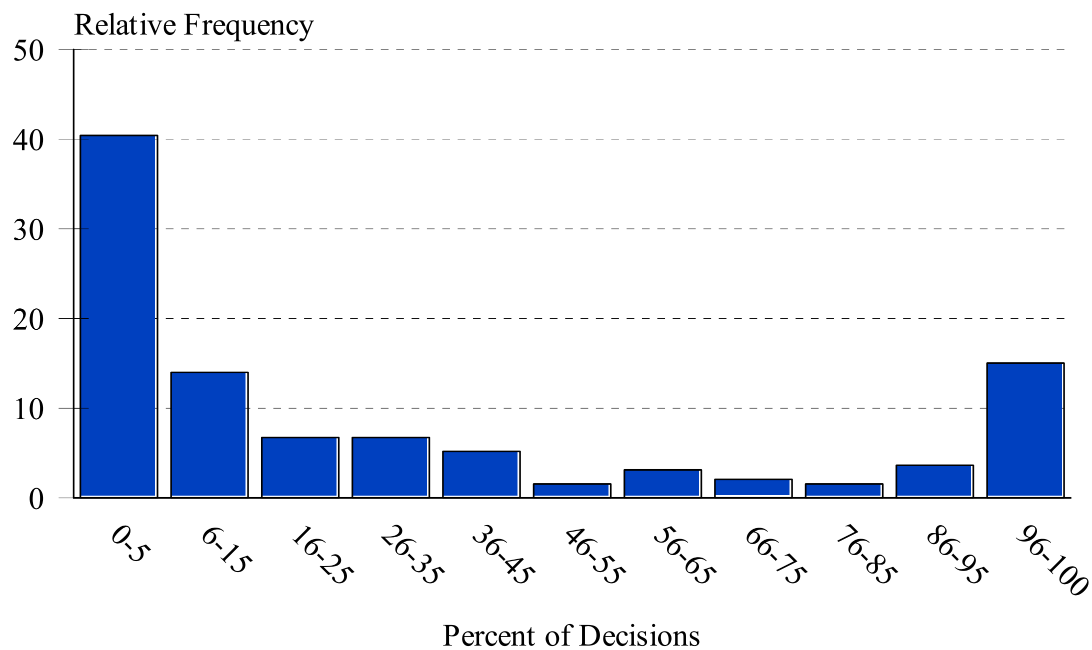


Figure 2. Free-Riding Behavior

(a) Percent of Decisions in which an Individual Contributes Nothing



(b) Percent of Decisions in which an Individual Contributes a Positive Amount, But Less than 30 Percent of the Endowment

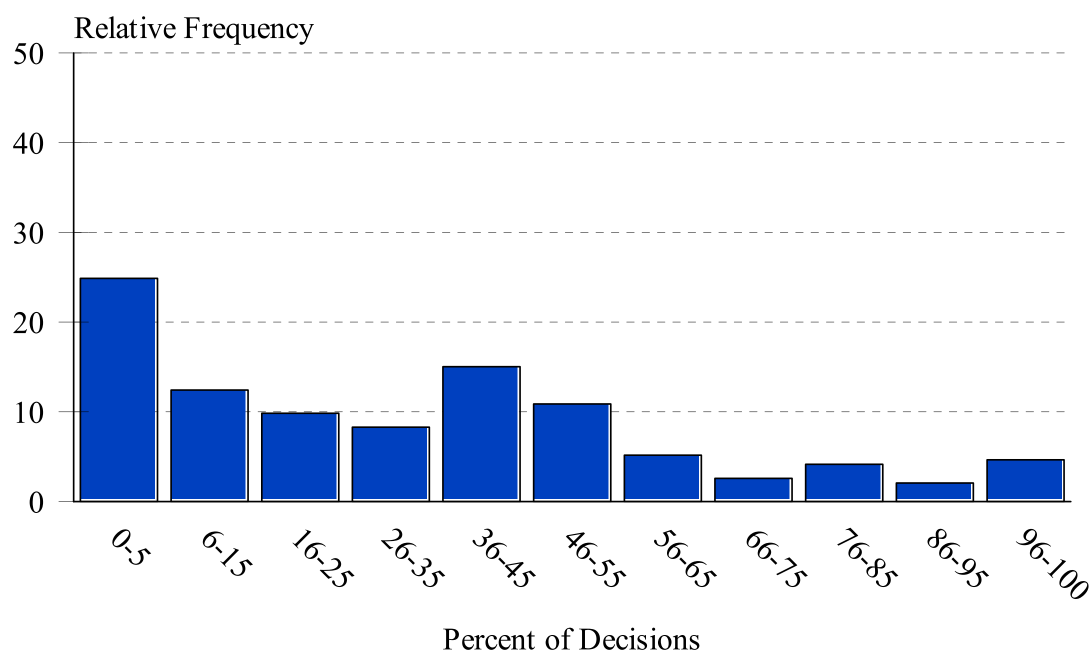
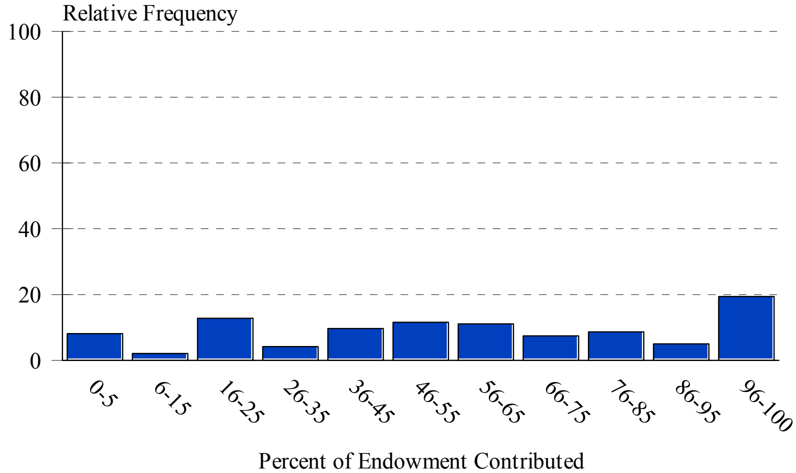
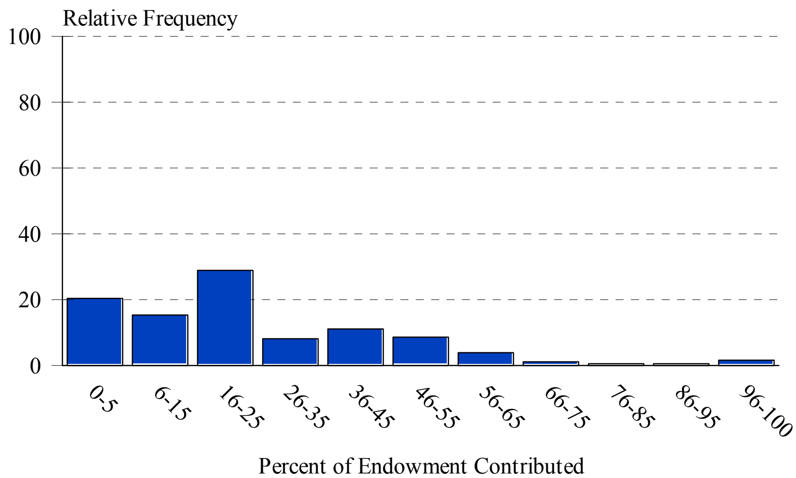


Figure 3. Percentage of Endowment Contributed in Each Decision

(a) Contributions by Individuals with Positive Altruism Parameters



(b) Contributions by Individuals with Zero Altruism Parameters



(c) Contributions by Individuals with Negative Altruism Parameters