The Richness of Giving: Charity Selection and Charitable Gifts in a Large Field Experiment*

Shachar Kariv
University of California, Berkeley

John A. List
University of Chicago

Daniel J. Lee†
Rice University

Michael K. Price
Georgia State Univeristy

This Draft: September 9, 2016

Abstract

We build on previous work in the charitable giving literature by examining not only how much subjects give to charity, but also which charities subjects prefer. We operationalize this choice in an artefactual field experiment with a representative sample of respondents. We then use these data to structurally model motives for giving. The novelty of this design allows us to ask several interesting questions regarding the choices one undertakes when deciding both whether and how much to give to charity. Further, we ask these questions in the context of a standard utility framework. Given the unique set up of this experiment, we also explore how these distributional preference parameters differ by charity choice and from what we have observed in the past. We find that there is more variation within demographics and charity types than across distributions.

*Special thanks to Susan Laury, Charles Courtemanche, the RAND American Life Panel, the John Templeton Foundation and the Science of Philanthropy Initiative

†Corresponding Author: dlee55@rice.edu

I Introduction

In 1772, Alexander Hamilton famously arrived in New York City from St. Croix as the result of charitable donations from the local populace. Over 200 years later, benevolent giving to charity now hovers at slightly above 2% of US GDP and approximately 76% of Americans contribute to at least one charitable organization each month (World Giving Index, 2013). However, we still know very little about the *decision* to donate to charity, the motivations behind it, and in particular, the mechanism behind one's charitable choice.

In this paper we examine this mechanism by means of an economic experiment. Charitable giving in many lab and field experiments (artefactual or otherwise), has previously been modeled as a 2-dimensional dictator game. That is, a game played between oneself and a charity. However, to the best of our knowledge, no one has yet examined the mechanism behind one's choice of said charity or operationalized it these experimental environments. In these giving experiments the charities to which a subject can donate tend to be either anonymous, presented without a choice, or only selected through what we call the restricted choice method (such as from an *ad-hoc* list of ten charities). Accordingly, in this paper we run an experiment where the unsure components are not only how much the subjects chose to give, but also to which charities they chose to give. In this way, our experiment examines this choice mechanism, and uses it to disentangle motives behind giving.

These charitable and philanthropic motives were first discussed by Becker (1974). In this essay he outlines the following three rationales: improvement of the general well being, receiving social acclaim, and avoidance of scorn. In the years hence, we have come to think of these motives as desires for efficiency, warm glow, and social pressures, respectively.

Whereas the formalization of social pressures remains relatively novel (DellaVigna et al. 2012; Lazear et al. 2012), the concepts of efficiency and warm glow, sometimes thought of a pure and impure altruism, have long been discussed. In an effort to improve model predictions and comment on the nature of individual donations, Andreoni (1989) introduces impure altruism, and then (1990) formalizes a theory of warm-glow giving, where a person exhibiting warm glow can have both altruistic and egoistic motives for giving. Later papers have suggested alternate reasons for this warm-glow, such as signaling benefits of giving to others (Bénabou and Tirole 2006, Ellingsen and Johannesson 2008).

Taken in the context of our model, we can think of pure altruism (as opposed to warm-glow) as dependent on the relative price of giving. One notable implication of here, is that pure altruism is only concerned with the amount of public good ultimately provided. As such, giving can be fully crowded out by what other individuals, firms, or governments provide. In a broad overview of the subject, Vesterlund (2006) further discusses these motives for giving, citing observational and experimental evidence in the context of a classical demand setting.

Distinguishing between these motives are important to both further our economic understanding of giving and, subsequently, inform optimal policies. Given these *pro forma* descriptions, economic experiments have previously tried to disentangle motives for giving by focusing on design and design choice. In particular, experiments have tended to use either linear public goods games (e.g. Andreoni 1993; Goeree et al. 2002) or dictator games, similar to the modified one we use in this paper[1].

In the first paper to introduce real charities as a dictator recipient, Eckel and Grossman (1996) vary receipts between anonymous subjects and the American Red Cross. They find that subjects are more willing to donate to charity and conclude (some form of) altruism is a motivating factor. To disentangle altruistic motives, Crumpler and Grossman (2008) extend this design, with the stipulation that the experimenter will fully crowd out any amount donated to charity. As such, any subject still opting to donate is taken as an incidence of warm glow.

As a response to Crumpler and Grossman, Tonin and Vlassopoulos (2014) use multiple to decisions to identify warm glow, noting that otherwise the observed effect could in fact be purely altruistic feelings towards the experimenter. In doing so, they are able to place bounds on the magnitudes of various motives for giving. However, these quantities are not parameter estimates, and the authors note that their results may not generalize to other settings.

As such, we design our experiment to create a richness of data and subject pool. This allows us to impose a standard utility (CES) framework and estimate a structural model, to fully quantify (rather than rule out) motives for giving.

Though this emphasis on structure is relatively novel in the literature its importance has been clearly stated. Recent papers (e.g. Huck et al. 2015) have used this methodology to focus on the fund raising side of philanthropy.

[1]For this reason I will focus on dictator games in this brief review.

However, DellaVigna et al. (2012) stress the importance of these approaches to estimate *individual* motives for giving. We extend this line of research to examine these motives inframarginally.

Further, Vesterlund (2006) cautions against interpreting aggregate elasticities when not all contributors experience the same changes in marginal tax rate. Rather, to better inform tax policy, individual elasticity estimates should be used. Chay et al. (2005) voice a similar concern that individual elasticities are necessary for unbiased welfare estimates in the market for clean air.

Taking these concerns into account, we set up our experiment such that the data act as a lens to examine charitable choices, i.e. the choices one undertakes when deciding where to give, whether to give, and how much to give to charity. Previous dictator designs have tended to not vary the price of giving, or subject income in the experiment. The novelty of our design, as well as the richness of our data and that fact that we observe it at the individual-level, allows us to impose a structure (discussed further below) that we use to recover the deep parameters of these preferences for giving. In this note we examine rationality of these choices and decompose our parameter estimates across demographics and the types of selected charities.

We also take seriously the advice of DellaVigna et al. (2013) who note the inherent difficulties of predicting which causes individuals will give to. We ask experimental subjects to choose their most preferred charity from a much richer set of organizations. In doing so we are also able to gather data that inform us of charity preference. Though non-causal, we correlate these data with subject demographics and estimated parameters. We ask if there are interesting co-movements between distributional preferences and various these chosen charities. If so, do these preference parameters for charitable giving differ from what we have observed in the past with person-to-person gifts? Finally, we ask if we can exploit this information and the in-subject heterogeneity to increase charitable giving in the naturally-occurring world.

As such, our paper speaks to the literature in both public and behavioral economics. Our contribution to these literatures is our development and estimation of the structural model in the context of a richer set of both givers and recipient organizations. In so doing, we estimate and comment on full parameter distributions, rather than simple sample averages.

This paper proceeds as follows: Section 2 presents our contextual framework, experimental design, and data. Section 3 discusses the consistency of choices and our structural estimates. Section 4 looks at the mechanism of charitable choice and selected charity. A final section concludes.

II Experimental Design

II.1 The ALP

For the purposes of structurally measuring distributional preferences in our experiment, we required a large and diverse sample of subjects that differs from the standard undergraduate population. In this sense, we classify our work as an *artefactual field experiment* to use the terminology of Harrison and List (2004). Accordingly, we chose to embed our software in the RAND Corporation's American Life Panel (ALP henceforth), and conduct and incentivized experiment. The ALP is a 6,000 member, U.S.-based, Internet panel. Its unique interface allows researchers to conduct sophisticated experiments matched with individually rich demographic data. Panelists are recruited through a number of different ways, including randomized recruitment, providing us with a representative sample, as well as HRS-style demographic data[2].

The composition of our subject pool is described in table 1, which has demographic information on those who completed the experiment, those who started but did not finish, as well as comparative US population data from the American Community Survey[3].

Subjects in our experiment hail from every state except Alaska. They range in age from 22 to 92. Our sample is 55% female and slightly less than 80% white. 45% of our subjects hold a college degree and the employment figures are roughly similar to the US population as a whole.

II.2 Charity Navigator

While there is vast anecdotal evidence that charitable givers prefer to give locally, empirical evidence on the subject remains mixed. Furthermore, local (as well as national) causes can be highly idiosyncratic in nature. As such, we required a large and diverse set of charities in addition to the diversity of our subject pool.

[2]For more information on the ALP, please visit: https://mmicdata.rand.org/alp/.

[3]For the purposes of GARP and CES analysis, we consider a "complete" experiment as completing 45 or more dictator allocations.

Table 1: Subject Demographic Averages

Variable	Completed	Started	US Adults
Female	0.55	0.566	0.58
Age (Median)	57	57	37.4
18-44	0.229	0.217	0.599
65+	0.269	0.29	0.137
Caucasian	0.799	0.783	0.763
African American	0.1	0.11	0.137
Native American	0.012	0.016	0.017
Asian or Pacific Islander	0.022	0.022	0.063
Hispanic or Latino	0.169	0.165	0.169
HS Diploma	0.955	0.955	0.862
College	0.448	0.446	0.267
Employed	0.553	0.54	0.577
Unemployed	0.059	0.051	0.058
Not in the Labor Force	0.389	0.409	0.361

Note: US Population Data come from the American Community Survey
http://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

To develop this set we turned to the website Charity Navigator, an agency used to rate charitable organizations[4]. Founded in 2001, Charity Navigator rates over 7000 charities and is the largest and most used rating agency in the United States. Using information from IRS form 990 returns, Charity Navigator assigns each charity a star rating on the bases of efficiency (financial health), and accountability (transparency)[5]. Empirical evidence suggests a positive impact of these star ratings on charitable behavior (Gordon et al. 2009; Brown et al. 2014).

The Charity Navigator website is organized as follows. Each rated charity is placed into one of nine categories, and each category has as associated list of (between 2 and 6) unique causes. For instance, "Patient and Family Support" is a cause in the "Health" category. At the time of this writing, the top rated charity in that cause is Camp John Marc.

For the purposes of this experiment, we scraped the Charity Navigator

[4]http://www.charitynavigator.com.

[5]For a more detailed yet concise description of this star rating methodology, please refer to Table I in Gordon et al. (2009).

website for the top 10 ranked charities within each cause, providing us with a list of 340 charities in total. The complete list (with associated categories and causes) can be found in appendix A.

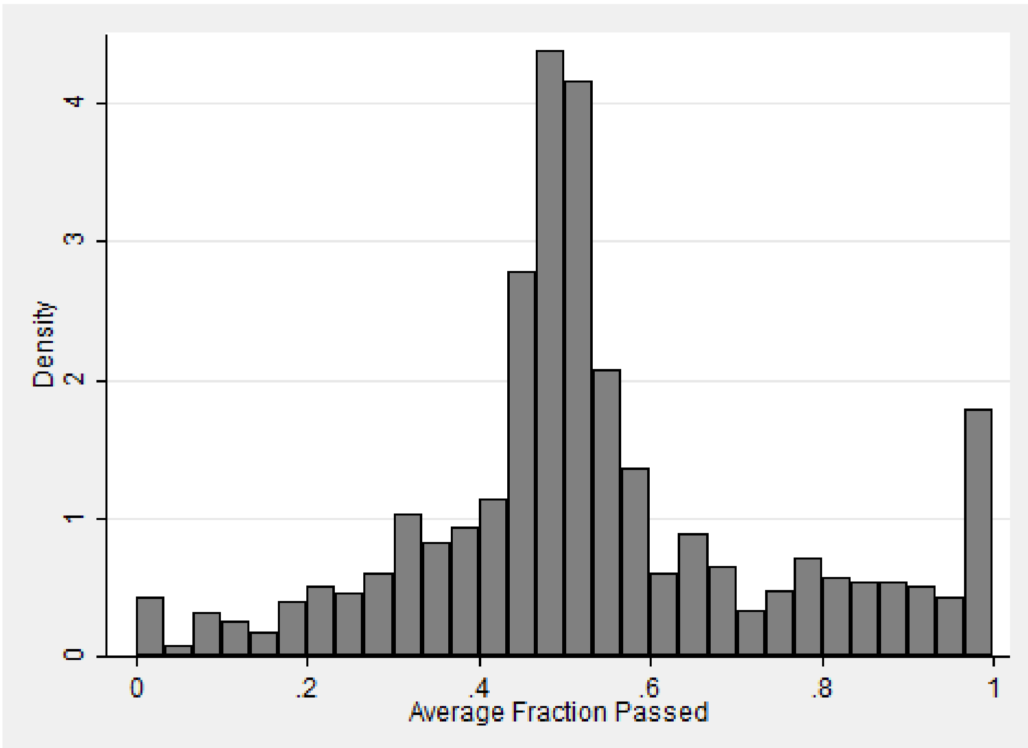
II.3 Experimental Procedures

As such, subjects in this experiment were first obliged to select their preferred charity from this list (that is, the charity to which they wish to donate). Immediately after, each subject makes a series of allocation decisions reflective of a charitable contribution. These decisions each consist of a modified dictator game played between the subject and his or her chosen charity. In the standard dictator game, an active player (the dictator) is given an endowment of wealth, w, and divides it between herself and a passive player such that total payoffs are given by $\pi_d + \pi_o = w$. This stipulation necessarily restricts the slope of the budget line to -1.

We differ from this standard dictator framework in two crucial ways. Firstly, the passive player is a charity of the dictator's own choosing. Secondly, we follow the generalization of the dictator game developed by Andreoni and Miller (2002). Budget sets are still *linear* in this game form, but the *price* of giving (donating) varies such that total payoffs are now represented as $x_i + p_g g = w$ where x_i is the payoff to oneself and p_g is the *relative price of donating to charity.* The purpose of this variation is twofold. First, we answer the seminal question: can this giving be consistent with individually rational behavior? That is, are patterns of giving are consistent with the axioms of revealed preference? Secondly, the price and income variation over several decisions allows use to trace out each subject's preferences for giving.

When subjects first log onto the experimental interface, they are given a instructions and a broad overview of the experiment. We explain to them that they will be selecting a charity of their choice and then given opportunities to allocate between themselves and that charity. To select a charity, subjects are taken through a set of expandable and collapsible tables adapted from the charity navigator website. The tables consist of populated lists. A subject is first instructed to pick a category. Each choice of category feeds into its associated list of causes. The selection of a given cause expands the list to the top 10 highest rated charities (as determined by the Charity Navigator website) for that particular cause. From there the subject is instructed to pick his or her preferred charity. If the subject so desires, or if no charity is

Figure 1: Average Fraction Donated



to his or her liking, a charity write-in option is provided.

After selecting a charity, each session consists of 50 independent dictator problems. The number number of choices allows us to generate the rich data needed for individual level statistical inference[6]. In each round, the subject is asked to allocate tokens between two accounts: the personal account of the participant (henceforth *self*), and the account of the chosen charity (henceforth *charity*). Each decision problem starts by having the computer select a budget line randomly from the set of lines that intersect at least one axis at or above the 50 token level and intersect both axes at or below the 100 token levels. The budget lines selected for each subject in his decision problems are independent of each other and of the budget lines selected for other subjects in their decision problems.

[6]This number reflects the Bronars calibration in Choi et al. 2007 who show that the distribution of consistency values is skewed to the left as the number of budget sets increases.

Next, the subject chooses an allocation along the budget line. To choose an allocation, subjects use the mouse or the arrows on the keyboard to move the pointer on the computer screen to the desired allocation. This *point-and-click* design is adapted from Fisman et al. (2007). The benefits to using this software are manifold. Among them, the ability to represent consumer choice problems graphically is simple and easy for subjects to understand, and the choice environment allows for the generalization of individual preferences. Additionally, the design can be easily adapted to many other kinds of individual choice problems. A subjects view of the computer program dialog window is shown in the attached experimental instructions located in appendix B.

The payoff for each decision round is determined by the number of tokens each account (*self* and *charity*). At the end of the experiment, the computer randomly selects one decision round for payment for each participant. The subject is then paid the amount earned in that round using to the conversion rate 2 tokens = 1 dollar.

The average subject passed 54% of her tokens. Figure 1 shows this distribution of percent of tokens donated to charity at the subject level.

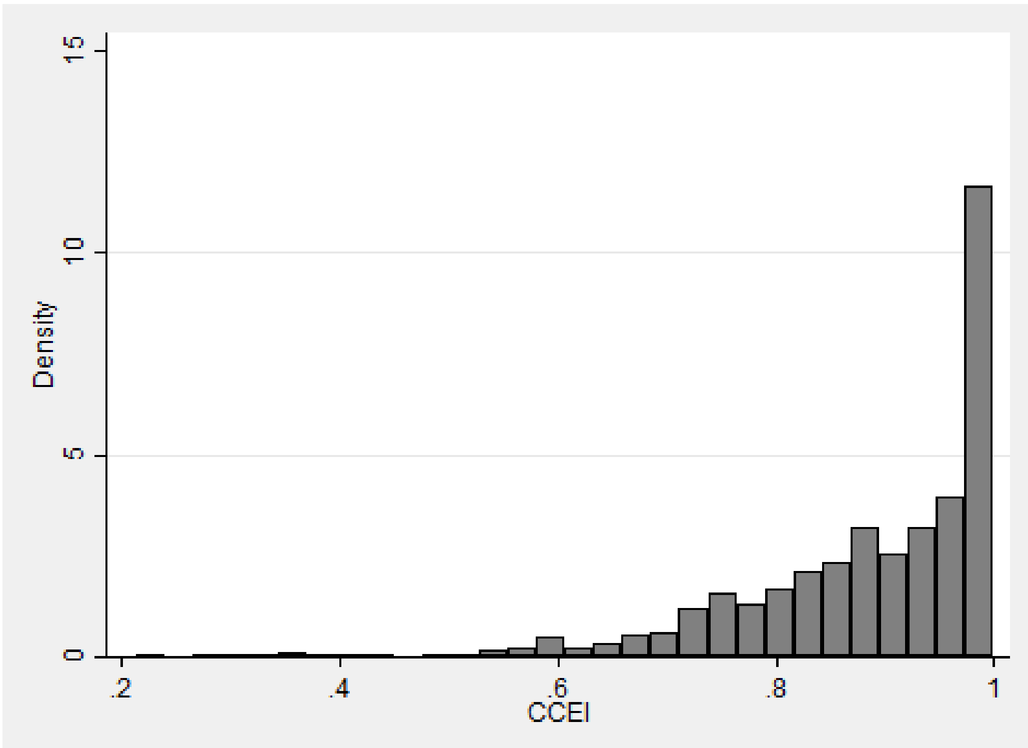
III Results

Broadly speaking, motives for giving tend to reflect either the efficiency or "warm-glow" concerns discussed above. We can think of the parameters for these concerns as boiling down to whether or not the act of giving itself is independent of the price of giving. Accordingly, in this section we examine the parameters within this analytical framework.

III.1 Rationality

However, before we can examine these equity/efficiency tradeoffs, we must first confirm that the data generated by each experimental subject are governed by the principles of utility maximization. Given that each subject has preferences over herself, x_i and the charity, g, we want to know whether observed choices can be expressed via a utility function $U_i = u_i(x_i, g)$, and subsequently, maximize said function. That is, are the data consistent with the *Generalized Axiom of Revealed Preference* or GARP. The practice of seeing if the data satisfy GARP follows Varian (1982)[7].

Figure 2: Distribution of Aftriat's CCEI



In order to see if, how, and to what extent the data comply with GARP we use Afriat's (1972) *Critical Cost Efficiency Index* (CCEI) as follows:

> Define a generalization of the revealed preference relation $R^D(e^t)$ such that $x^t R^D(e^t) x$ iff $e^t p^t x^t \geq p^t x$, that is, x would not be affordable at a fraction e^t of the income available when the person chose x^t. Define $R(e^t)$ as the transitive closure of $R^D(e^t)$. Then define GARP(e^t) as "if $x^t R(e^t) x^s$, then $e^t p^s x^s \leq p^s x^t$." Then the CCEI is the highest value of e^t such that there are no violations of GARP(e^t). (Andreoni and Miller 2002)

In short, the CCEI measures the extent to which budget constraints need to be relaxed in order for violations to no longer violate. By construct, it is

[7]Note that we restrict our analysis to *Walrasian* budget sets and therefore implicitly treat preferences as *well-behaved*.

bounded between 0 and 1, with scores closer to 1 being closer to satisfying GARP. That is, scores closer to 1 are "more rational". Among those who completed the experiment, the distribution of CCEI scores are illustrated as a histogram in figure 2.

In our data subjects exhibit significant rationality. Over 75% of the data have a CCEI score greater than 0.8. The mean CCEI score is 0.883, and the modal score in the histogram's highest bin[8].

Given this consistent behavior on the part of our panel it is appropriate to think of charitable giving as a standard utility maximizing activity. Further, we have generated enough data to estimate these standard parameters at the individual level. As such, we now test the structural properties of each subject's individual utility function.

III.2 Structural Model

Similar past experiments (e.g. Fisman et al., 2015) have shown that subjects exhibit remarkable heterogeneity. Given these demonstrations and our observed pattern of CCEI scores sufficiently close to 1, we hereby treat the data as generated by a well-behaved utility function, u_d.

Further, to maintain consistency with the previous literature, we assume u_d is both separable and homothetic. These two assumptions taken in concert with the restriction imposed by our design that choices must be budget balanced imply that u_d is of the family of CES utility functions (equation 1). In fact, we estimate these CES utility functions using non-linear tobit MLE (discussed in turn below), and find that this subject heterogeneity is more pronounced *within* demographics and charity types, rather than *across* them.

$$u_d = [\alpha \pi_d^{\rho} + (1-\alpha)\pi_o^{\rho}]^{\frac{1}{\rho}} \tag{1}$$

This utility function only has 2 components. Since people are behaving consistently (maximizing) we choose to keep the model parsimonious and do not include additional parameters. However, given that some subjects are inconsistent, future research would perhaps benefit from imposition of additional parameters or more flexible functional forms.

Within the context of a CES framework, these two parameters of interest are ρ and α. Previously, these parameters have been interpreted in terms of person-to-person giving (see e.g., Fisman et al., 2007). However, they

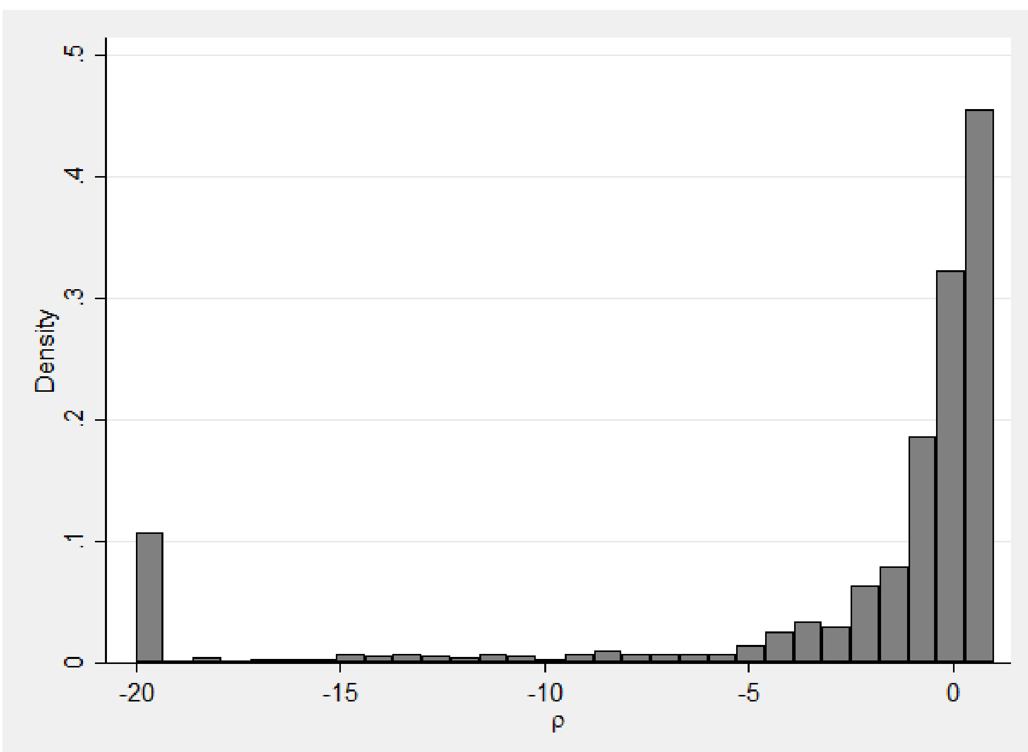
[8]i.e., the bin closest to (and inclusive of) 1.

are also immensely important in terms of charitable giving, and can easily generalize to other settings as well.

The parameter ρ represents the curvature of each individual's indifference curves, and thereby her sensitivity to price[9]. Further, α represents the relative weight one puts on *self* as opposed *charity*. As such, we interpret α as the warm-glow parameter.

For any ρ, when $\alpha = \frac{1}{2}$ the subject equally weights the payoff to herself and her selected charity. Meanwhile, when $\rho > 0$ charitable preferences are weighted towards efficiency—increasing total payoffs or the "size of the pie". When $\rho < 0$ preferences are weighted towards equity–reducing differences in payoffs or the "slices of the pie"[10]. For these reasons, we extend previous interpretations of ρ and tie it in closely with the concepts of "pure" altruism in previous giving literatures and "efficiency" in the public goods literature.

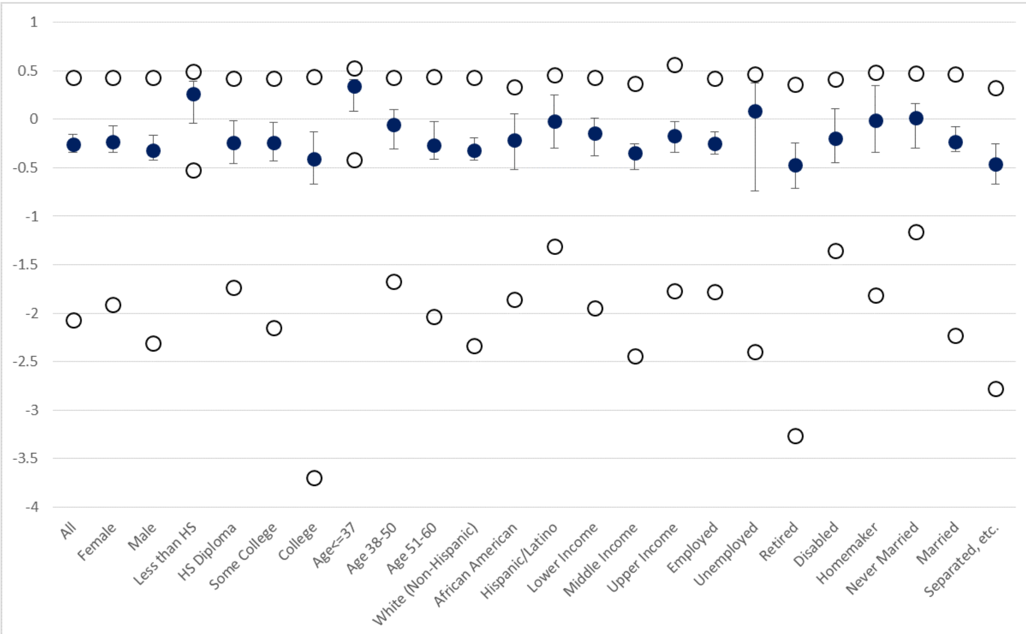
Figure 3: Distribution of Estimated Rho (ρ)



[9]It follows that $\frac{1}{\rho-1} = \sigma$ is the (constant) elasticity of substitution.

[10]i.e. the elasticity of substitution is < -1.

Figure 4: Estimated Median Rho (ρ) Values by Subgroup



Dots indicate median values, circles indicate 25th and 75th percentiles, bars indicate 95% confidence intervals for medians

III.2.1 Rho (ρ)

The mean estimated ρ is -2.70 and the median is -0.259. However, the distribution of estimated rho parameters (depicted in figure 3) is perhaps more informative. The distribution is noteworthy in that is highly skewed left with a large spike at $\rho \approx -20$. Most subjects either have a 612 subjects (58%) have a $\rho < 0$, while 441 (42%) have $\rho > 0$. In figure 4 we decompose the ρ distributions with socio-demographic data collected by the ALP. While the medians differ by subgroup, overall, the distributions appear similar.

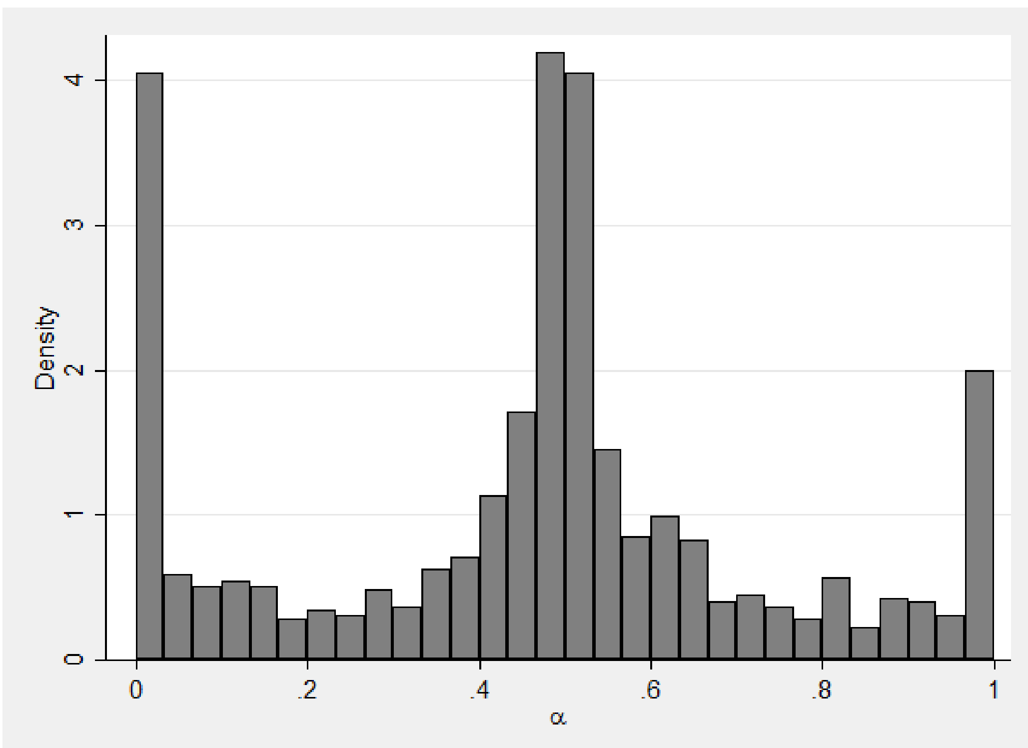
We examine this further with pairwise distributional (Kolmogorov-Smirnov) tests in table 2. In these tests, the comparison group is all subjects not in the specified subgroup. For instance, the comparison group for men is women, for a college degree it is everyone with less than a college degree. P-values for the ρ distributions are shown in the 3rd column of the table. While some subgroups (7 out of 22) exhibit statistical difference in their distributions, this is likely an artifact of multiple hypothesis testing. Further, there are *fewer* differences in distribution, then there are differences in means.

III.2.2 Alpha (α)

Similar to ρ we interpret α in a slightly different fashion than previous work. Whereas similar person-to-person giving functions have interpreted α as fair-mindedness, in our context (charitable giving and contribution to a public good) we find “warm-glow” to be a more appropriate interpretation.

The distribution of estimated alpha parameters is depicted in figure 5.

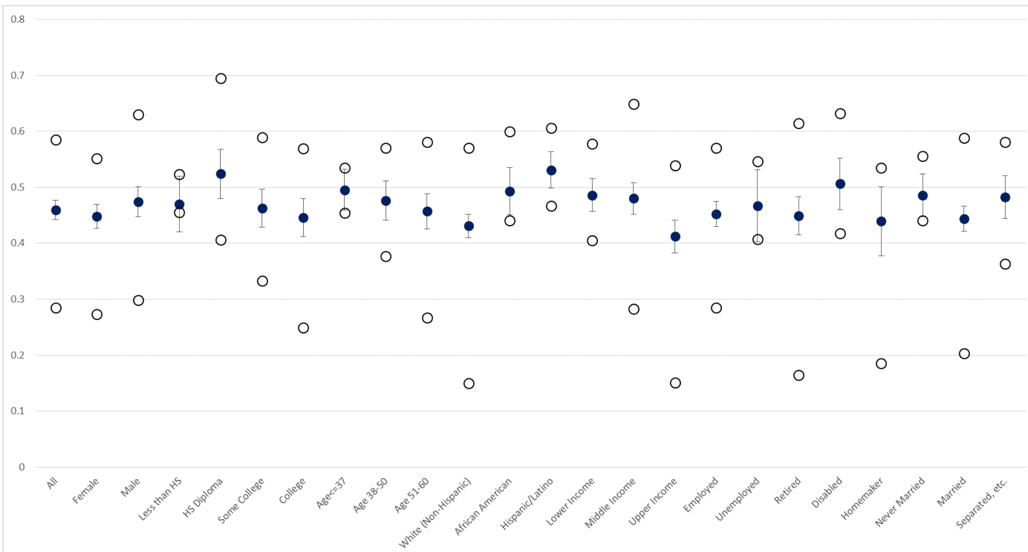
Figure 5: Distribution of Estimated Alpha (α)



Again, the full distribution appears to be more informative than the summary stats. The mean estimated α is 0.46, and the median is 0.49, both of which are in line with Fisman et al.’s (2007) interpretative definition of “fair-mindedness”. However. Interestingly however, the distribution appears to be tri-modal with large spikes at 0, 0.5, and 1. Overall, 366 subjects (34.7%)

have an α between 0.45 and 0.55, while just 75 (7%) have $\alpha > 0.95$. Again, we decompose the α distributions with socio-demographic data In figure 6. The results are striking in that the means are very close to 0.5 with tight confidence bounds.

Figure 6: Estimated Mean Alpha (α) by Subgroup



Dots indicate mean values, circles indicate 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, bars indicate 95% confidence intervals for means

P-values for the distributional tests on α are shown in table 2, column 5. The tests were calculated the same way as above. As above, there are *fewer* differences in distribution, then there are differences in means. Further, 10 out of the 22 subgroups exhibit statistical significance, although again, no corrections were made for multiple testing.

IV Charity Selection

Since Eckel and Grossman (1996), standard experimental practice has been to give to actual charities. However, within these experiments there is often not enough data to comment on charity preference. Several studies offer no choice at all (e.g. Davis et al. 2005) Furthermore, in studies that offer no choice, several conceal the charitable organization. Harrison and

Table 2: Pairwise Kolmogorov-Smirnov Tests by Subgroup

	Rho (ρ)		**Alpha (α)**	
Variable	**D**	**P-Value**	**D**	**P-Value**
Male	0.0399	0.778	0.986	0.013**
Less than HS	0.2307	0.014**	0.1833	0.086
HS Diploma	0.0669	0.604	0.1515	0.006***
Some College	0.0566	0.538	0.0549	0.577
College	0.0849	0.112	0.0607	0.448
Age<=37	0.2504	0.00***	-0.1753	0.001***
Age 38-50	0.0945	0.092	0.0854	0.161
Age 51-60	0.048	0.701	0.0343	0.957
White (Non-Hispanic)	0.0823	0.091	0.2195	0.00***
African American	0.0923	0.366	0.1308	0.069
Hispanic/Latino	0.1144	0.037**	0.2161	0.00***
Lower Income	0.0699	0.239	0.1073	0.014**
Middle Income	0.0953	0.019**	0.0963	0.017**
Upper Income	0.1439	0.00***	0.1344	0.00***
Employed	0.0646	0.228	0.0691	0.167
Unemployed	0.1317	0.241	0.1042	0.516
Retired	0.1039	0.018**	0.0749	0.182
Disabled	0.0915	0.322	0.1565	0.01***
Homemaker	0.1245	0.183	0.0864	0.606
Never Married	0.1082	0.067	0.1367	0.009***
Married	0.0836	0.056	0.0783	0.086
Separated, etc.	0.1148	0.009***	0.0606	0.428

Note: Comparison group is all subjects not in the specified subgroup, *** p<0.01, ** p<0.05

Johnson did not identify their charity (the ACLU of South Carolina) in their experiment, but afforded subjects the opportunity to examine the check written. Similarly, Buchheit and Parsons (2006) disguise the name of the charitable organization. Furthermore, in papers with choices, the choice at hand is necessarily reflective of the actual choice one makes in charitable giving. For instance, donors inMcDowell et al. (2013) are only given a choice of two charities. In what has become something of a standard, Eckel and Grossman (2003) provide a list of ten charities to choose from. They note that:

> The charities were selected to *reflect as broad a range of services and client groups as possible*. The sample included *international* charities (African Christian Relief, Doctors Without Borders USA, and Feed The Children); *national* charities (I Have A Dream Foundation); and *local* organizations (Women's Haven of Tarrant County and American Red Cross, Tarrant County Chapter). The charities covered *health* (AIDS Outreach Center and Cancer Care Services); *environmental* (Earth Share Texas); and *social service* charities (YMCA of Arlington). Charities were selected from the Texas State Employee Charitable Campaign booklet for 1997, which was provided to state employees during the workplace charity campaign. All charities included in the booklet meet state tax eligibility standards. A brief description of each charity was given to the subjects, taken verbatim from the Texas State Employee Charitable Campaign booklet.
> (Eckel and Grossman 2003)

Italics are my own. Other charitable giving papers following this procedure include Grossman et al. (2012), Tonin and Vlassopoulos (2013), and Harrison and Phillips (2013).

We account for these previous restrictions of choice by allowing subjects to not only select from a markedly broader list of charities, but also by allowing them the option to switch their charitable choice once they know the rules of the game.

Table 3: Selected Categories and Causes

Category	**N**	**Top Cause**	**N**
Animals	328	Rights,Welfare, & Services	272
Arts, Culture, & Humanities	42	Performing Arts	19
Education	131	Other Programs & Services	101
Environment	65	Protection & Conservation	59
Health	298	Medical Research	109
Human Services	307	Food Banks & Distribution	97
International	31	Development & Relief Services	13
Public Benefit	26	Advocacy & Civil Rights	12
Religion	93	Media & Broadcasting	29

Given our diverse subject pool, it follows that subjects have a wide range of charitable concerns. Table 3 gives information on the distribution of selected types and the most popular cause within each type. The three most popular charitable categories are, respectively, Animals, Human Services, and Health. Three divisions which by conventional wisdom, rely on very different donor types[11].

Figure 7: Word Cloud of Selected Charities

Excluded Words: *Association, for, foundation, in, institute, of, the, to*

Of course, the universe of selected charities within these categories presents even finer, and more diverse bins. As a means of description, figure 7 displays a word cloud comprised of the names of every selected charity in our dataset. Clearly the most prominent words are related to our top categories (e.g. *Rescue, Research and Cancer*), but an interesting observation is also the high number of geographic indicators in the cloud (e.g. *Southeastern, Greenville, Downtown*).

[11]We have more data on charitable selection than structural estimates as most subjects classified as not completing the experiment still selected a charity (*N=1321*).

IV.1 Rationality Across Type

Above, we noted that subjects exhibit rational, utility maximizing behavior. We build on this analysis further by asking the follow-up question: does this rationality differ across charity type? By way of example, we ask is a subject who prefers to donate to charities supporting education more consistent in those charitable choices (as indicated by CCEI score) than one who donates to religious causes? In this way, we follow the framework of Choi et al. (2014).

Figure 8: Distributions of CCEI Scores

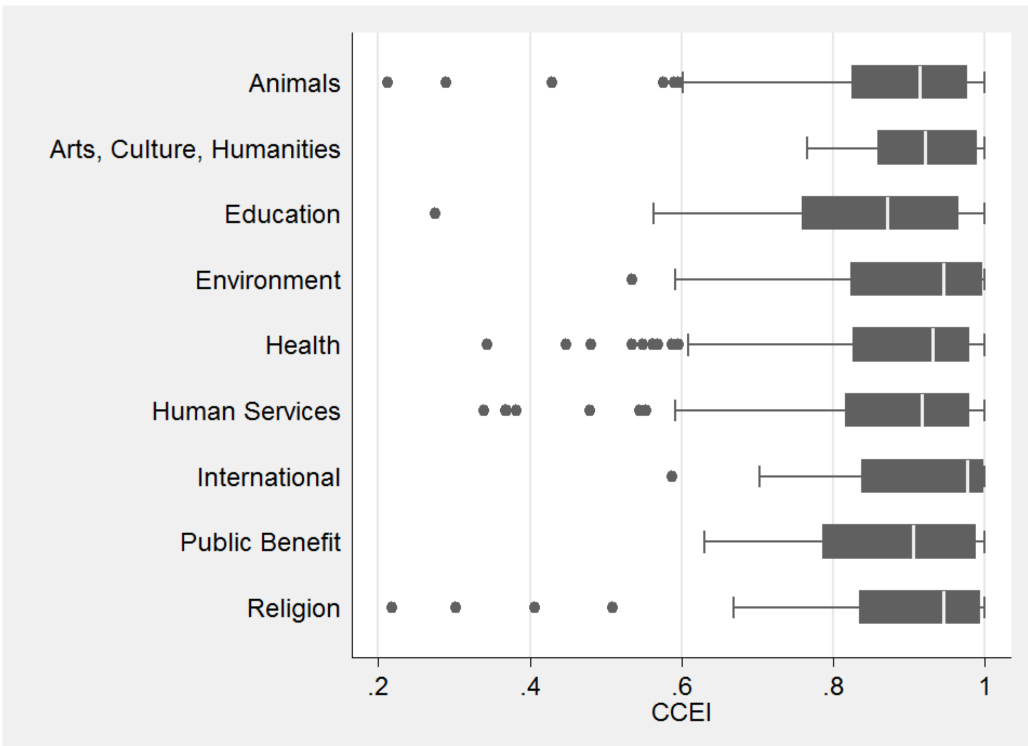


Figure 8 illustrates the distributions of these scores across all charitable categories. First we note that every type of charity has a mean CCEI greater than 0.84. Further, while that leaves the door open for some slight variation in means, the distributions of rationality are all very similar.

We continue to explore this observation using OLS in table 4, where only one category (Arts, Culture & Humanities) exhibits significantly more

Table 4: Correlation between CCEI and Selected Category (OLS)

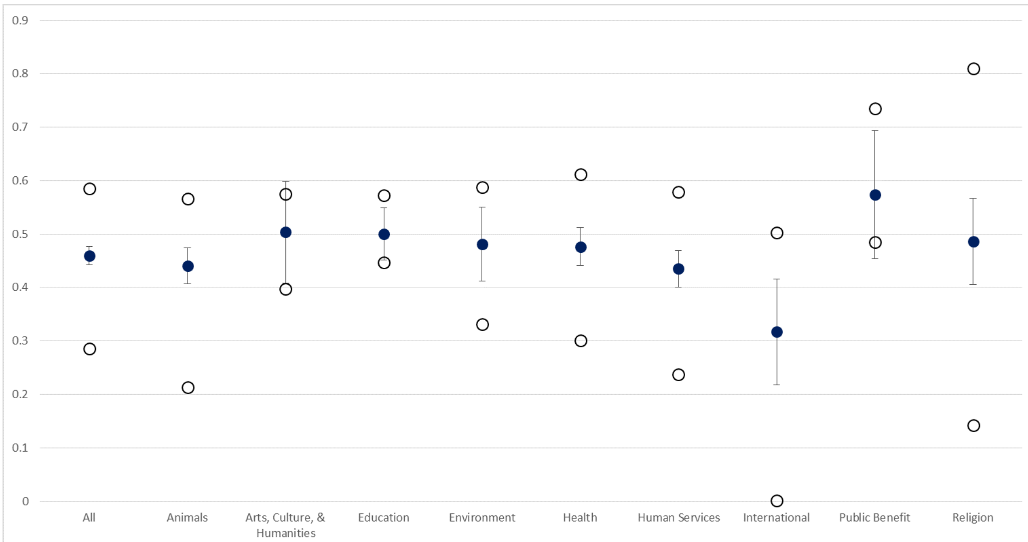
Category	**Coefficient**
Arts, Culture & Humanities	0.0414***
	(0.0140)
Education	-0.0291*
	(0.0150)
Environment	0.00620
	(0.0179)
Health	0.00225
	(0.0108)
Human Services	-0.00445
	(0.0109)
International	0.0264
	(0.0260)
Public Benefit	0.00210
	(0.0297)
Religion	-0.00179
	(0.0207)
Constant	0.884***
	(0.00730)
Observations	1051
R^2	0.01

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

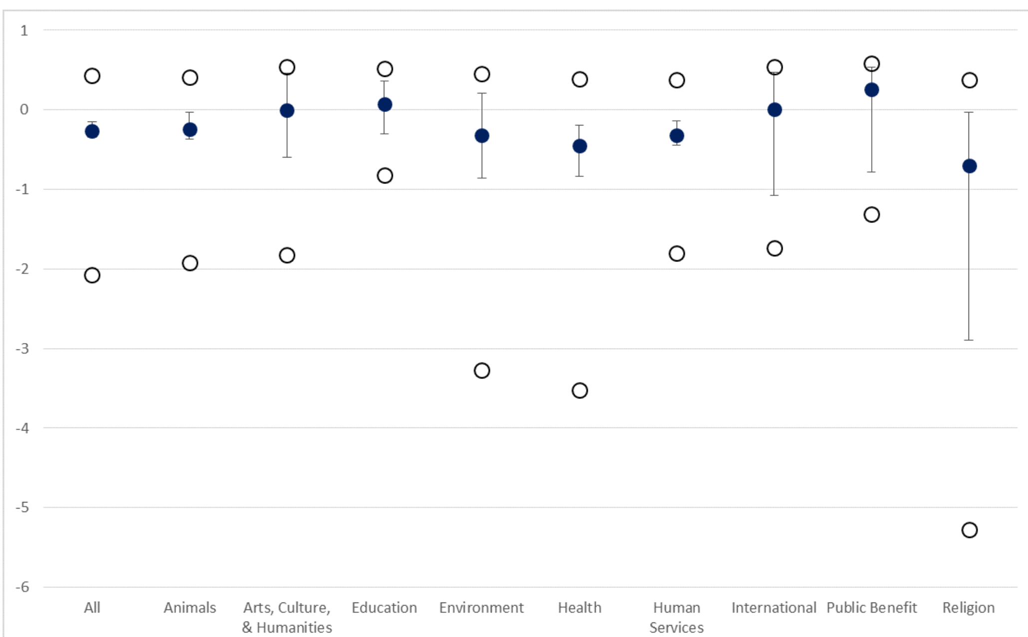
rationality than the reference group (Animals). Kolmogorov-Smirnov testing confirms this difference ($p = 0.046$).

Figure 9: CES Parameter Distributions Across Charity Types

(a) Estimated Mean $\hat{\alpha}$



(b) Estimated Median $\hat{\rho}$

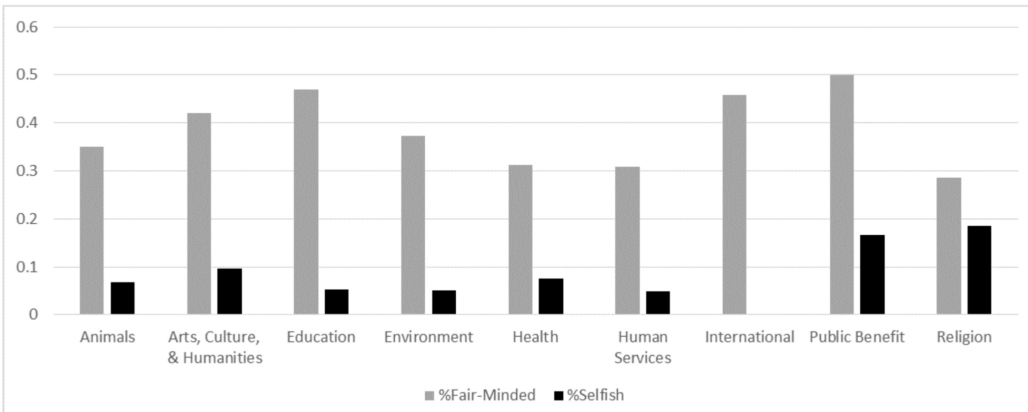


IV.2 Structural Estimates Across Type

Given the rationality exhibited both throughout the dataset and within specific charitable types, we follow the logic from the previous section and examine estimated parameters across charity type.

Again, we compare the distributions of the key parameters (namely ρ and α) across charitable categories. Figure 9 shows the distributions of our imputed parameters. An observation of note is that there appears to be more within category variation than across category variation.

Figure 10: Classifying Subjects' Preference over Own Income

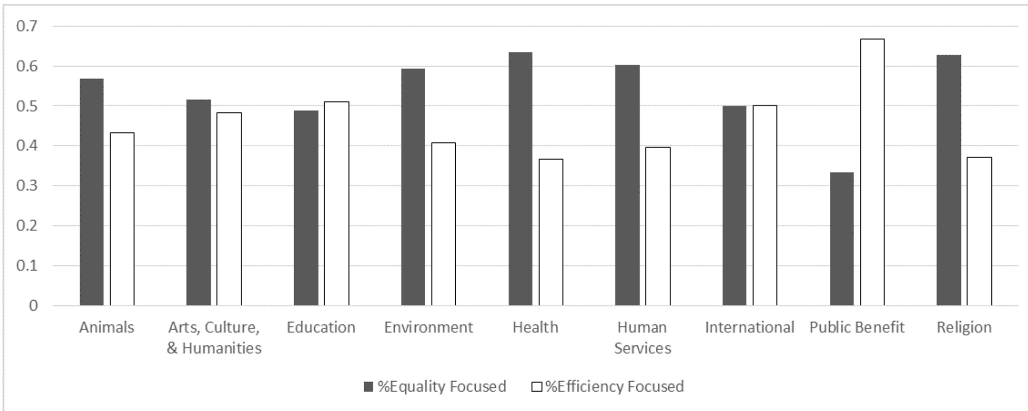


The bars indicate the percentage of subjects in each cell.
We classify a subject as fair-minded if $0.45 < \hat{\alpha}_n < 0.55$; a subject is classified as selfish if $\hat{\alpha}_n > 0.95$

Using Fisman et al.'s 2015 definitions of fair-mindedness and selfishness, we further compare $\hat{\alpha}$ distributions in figure 10. Interestingly enough, the givers to religious charitable causes have the highest number of selfish participants.

We further examine a subject's equity-efficiency trade offs by means of $\hat{\rho}$ distributions in figure 11. For the purposes of Again, Religious causes provide interesting insight into motives for giving, where givers preferences for equality vastly outnumber those who are efficiency-focused. Compare this to givers of Public Benefit causes, where we see almost the exact opposite. Public Benefit Charities (e.g. The United Way) are the only category which efficiency-focused subjects outnumber those who are equality focused .

Figure 11: Classifying Subjects' Preference over Total Income



The bars indicate the percentage of subjects in each cell. We classify a subject as equality focused if $\hat{\rho}_n < 0$; a subject is classified as efficiency focused if $\hat{\rho}_n > 0$

V Concluding Remarks

This paper examines motives for giving, and further decomposes those motives based on *where* subjects actually prefer to donate.

Our study concerns an experimental design that is strongly informed by theory. In doing so, we create a rich data set that allows us to impose the structure of a standard utility function (CES) to better understand these motives.

The benefits of this design are manifold. In particular, we are able to estimate parameters at the individual level, and thereby comment on full parameter distributions, rather than simple sample averages.

Further, decomposing by charity is a necessary step to build on previous literature. Rather than rely on conventional wisdom, we find that differences within outnumber differences across demographic and charity types. In doing so, we reveal empirical evidence for how charities can best target potential donors.

As such, our paper speaks to multiple literatures including public and behavioral economics, and structural econometrics. Of course, more work in this area is needed, and this paper is merely the first in a series of rich questions to be asked. In forthcoming projects, we aim to further disentangle motives for giving and better inform policy by adding extra dimensions to the charitable choice such as highlighting individual receivers within a charitable organization.

References

Sidney N Afriat. Efficiency estimation of production functions. *International Economic Review*, pages 568–598, 1972.

James Andreoni. Giving with impure altruism: applications to charity and ricardian equivalence. *The Journal of Political Economy*, pages 1447–1458, 1989.

James Andreoni. Impure altruism and donations to public goods: A theory of warm-glow giving. *The economic journal*, 100(401):464–477, 1990.

James Andreoni. An experimental test of the public-goods crowding-out hypothesis. *The American Economic Review*, pages 1317–1327, 1993.

James Andreoni and John Miller. Giving according to garp: An experimental test of the consistency of preferences for altruism. *Econometrica*, pages 737–753, 2002.

Gary S Becker. A theory of social interactions. *Journal of Political Economy*, 82(6):1063–1093, 1974.

Roland Bénabou and Jean Tirole. Incentives and prosocial behavior. *The American Economic Review*, 96(5):1652–1678, 2006.

Alexander L. Brown, Jonathan Meer, and J. Forrest Williams. Social distance and quality ratings in charity choice. Working Paper 20182, National Bureau of Economic Research, May 2014. URL `http://www.nber.org/papers/w20182`.

Steve Buchheit and Linda M Parsons. An experimental investigation of accounting informations influence on the individual giving process. *Journal of Accounting and Public Policy*, 25(6):666–686, 2006.

World Giving Index, volume 4, dec 2013. Charities Aid Foundation.

Kenneth Y Chay, Michael Greenstone, et al. Does air quality matter? evidence from the housing market. *Journal of Political Economy*, 113(2): 376–424, 2005.

Syngjoo Choi, Raymond Fisman, Douglas Gale, and Shachar Kariv. Consistency and heterogeneity of individual behavior under uncertainty. *The American economic review*, 97(5):1921–1938, 2007.

Syngjoo Choi, Shachar Kariv, Wieland Müller, and Dan Silverman. Who is (more) rational? *The American Economic Review*, 104(6):1518–1550, 2014.

Heidi Crumpler and Philip J Grossman. An experimental test of warm glow giving. *Journal of public Economics*, 92(5):1011–1021, 2008.

Douglas D Davis, Edward L Millner, and Robert J Reilly. Subsidy schemes and charitable contributions: a closer look. *Experimental economics*, 8(2): 85–106, 2005.

Stefano DellaVigna, John A List, and Ulrike Malmendier. Testing for altruism and social pressure in charitable giving. *The Quarterly Journal of Economics*, 127(1):1–56, 2012.

Stefano DellaVigna, John A List, Ulrike Malmendier, Gautam Rao, et al. The importance of being marginal: Gender differences in generosity. *American Economic Review*, 103(3):586–90, 2013.

Catherine C Eckel and Philip J Grossman. Altruism in anonymous dictator games. *Games and economic behavior*, 16(2):181–191, 1996.

Catherine C Eckel and Philip J Grossman. Rebate versus matching: does how we subsidize charitable contributions matter? *Journal of Public Economics*, 87(3):681–701, 2003.

Tore Ellingsen and Magnus Johannesson. Pride and prejudice: The human side of incentive theory. *American Economic Review*, 98(3):990–1008, 2008.

Raymond Fisman, Shachar Kariv, and Daniel Markovits. Individual preferences for giving. *The American Economic Review*, 97(5):1858–1876, 2007.

Raymond Fisman, Pamela Jakiela, and Shachar Kariv. Distributional preferences and political behavior. 2015.

Jacob K Goeree, Charles A Holt, and Susan K Laury. Private costs and public benefits: unraveling the effects of altruism and noisy behavior. *Journal of public Economics*, 83(2):255–276, 2002.

Teresa P Gordon, Cathryn L Knock, and Daniel G Neely. The role of rating agencies in the market for charitable contributions: An empirical test. *Journal of Accounting and Public Policy*, 28(6):469–484, 2009.

P Grossman, C Eckel, et al. Giving versus taking: a real donation comparison of warm glow and cold prickle in a context-rich environment. Technical report, Monash University, Department of Economics, 2012.

Glenn W. Harrison and Laurie T. Johnson. *Identifying Altruism in the Laboratory*, chapter 10, pages 177–223. doi: 10.1016/S0193-2306(06)11008-X.

Glenn W Harrison and John A List. Field experiments. *Journal of Economic literature*, 42(4):1009–1055, 2004.

Glenn W Harrison and Richard D Phillips. Subjective beliefs and statistical forecasts of financial risks: The chief risk officer project. 2013.

Steffen Huck, Imran Rasul, and Andrew Shephard. Comparing charitable fundraising schemes: Evidence from a natural field experiment and a structural model. *American Economic Journal: Economic Policy*, 7(2):326–69, May 2015. doi: 10.1257/pol.20120312.

Edward P Lazear, Ulrike Malmendier, and Roberto A Weber. Sorting in experiments with application to social preferences. *American Economic Journal: Applied Economics*, 4(1):136–163, 2012.

Evelyn A McDowell, Wei Li, and Pamela C Smith. An experimental examination of us individual donors information needs and use. *Financial Accountability & Management*, 29(3):327–347, 2013.

Mirco Tonin and Michael Vlassopoulos. Experimental evidence of self-image concerns as motivation for giving. *Journal of Economic Behavior & Organization*, 90:19–27, 2013.

Mirco Tonin and Michael Vlassopoulos. An experimental investigation of intrinsic motivations for giving. *Theory and decision*, 76(1):47–67, 2014.

Hal R Varian. The nonparametric approach to demand analysis. *Econometrica: Journal of the Econometric Society*, pages 945–973, 1982.

Lise Vesterlund. Why do people give. *The nonprofit sector: A research handbook*, 2:168–190, 2006.