



Estimation of social preferences in generalized dictator games



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HIGHLIGHTS

- Statistical analysis of social preferences requires econometric modeling of choice.
- Different choice models estimate different utility functions, preventing consensus.
- I analyze precision (in-sample fit) and robustness (out-of-sample fit) of standard models.
- Random utility model for ordered alternatives fits well, in-sample and out-of-sample.

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ABSTRACT

To statistically infer the motives underlying pro-social behavior, econometric models of choice are required. Such inference is comparable across studies if the choice model yields estimates that are precise in-sample and robust out-of-sample. Analyzing two extensive dictator game data sets, I find that structural models of choice prevent significant overfitting (contrary to regression models), structural models with generalized error structure fit the choice pattern, and random utility models yield robust identification of subject types (contrary to random behavior and random taste models). The random utility model for ordered alternatives provides robust estimates across games and is therefore suited for analyses.

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1. Introduction

In order to identify the motives shaping pro-social behavior, recent work estimates social preferences in “structural models” accounting for noisiness of choice. Structural models come in three flavors, depending on the assumed locus of noise in the choice process, and currently, these models are used interchangeably, seemingly depending on personal taste. For example, in analyses of dictator choices, Fisman et al. (2007) use *random behavior* models, which add errors to the individually optimal response, Cox et al. (2007) use *random taste* models, which add error terms to the altruism coefficient, and Cappelen et al. (2007) use *random utility* models, where the utilities of all options are perturbed independently.

The identified motives of pro-social behavior depend on the assumed model of choice, however. Convergence of research on social motives, as opposed to recent controversies (e.g. Binmore and Shaked, 2010, Fehr and Schmidt, 2010, Blanco et al., 2011), therefore requires an understanding of the relative strengths of choice models. This has previously been argued by Hey (2005) and Loomes (2005), but their main question remains unresolved: How should choice be modeled to robustly identify social motives?

This question can be addressed in several ways. One can think about it theoretically, analyzing for example invariance properties of choice models, as Wilcox (2008, 2011) does for individual choice under risk. Some of his arguments apply similarly for pro-social choice. In this paper, I focus on an econometric analysis, however, revisiting the experimental data of Andreoni and Miller (2002) and Harrison and Johnson (2006). Both experiments had been designed to analyze consistency of pro-social choice, with 8–10 observations per subject, varying budgets and transfer rates. I extend their work by analyzing the inherent choice stochastics,

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i.e. both precision (descriptive adequacy) and robustness (predictive adequacy) of utility estimates for standard choice models.¹ I particularly emphasize robustness—the avoidance of overfitting—as overfitting implies underestimation of standard errors and biased estimates that fail to be comparable across studies. I evaluate a model’s fallacy to overfit in two ways, by “k-fold cross validation” (the model is fit to a subset of the treatments, evaluated on the remaining treatments, and the data set is rotated such that all observations are used once in the evaluation stage) and by using the estimates from the larger data set (Andreoni and Miller, 2002) to predict choices in the smaller one (Harrison and Johnson, 2006).

The main results are that structural models avoid significant overfitting, that random utility models yield robustness of identified motives across treatments, and that generalized error terms are required to fit the choice patterns both descriptively and predictively. The only existing model with all three attributes is the random utility model for ordered alternatives (“ordered GEV”, Small, 1987), and it yields utility estimates that are precise in-sample, exhibit insignificant overfitting, and the identified subject types are robust across treatments. Regression models overfit subjects choosing with high precision, thus do not yield robust identification of subject types, and the inclusion of interaction terms increases overfitting further. This confirms the general arguments favoring structural modeling (e.g. Keane, 2010a,b, and Rust, 2010) in the context of pro-social choice. All three families of structural models prevent statistically significant overfitting, but random taste and random behavior models do not yield robust identification of subjects choosing with intermediate precision, contrary to random utility models.

2. The data

Dictator games are frequently used to analyze social donations. In both, Andreoni and Miller (2002, AM, 176 subjects) and Harrison and Johnson (2006, HJ, 59 subjects), each subject had to make several decisions (eight and ten, respectively) for varying transfer rates and endowments, without feedback between decisions.² These aspects of their experimental designs allow me to disentangle stochastic choice and social preferences using their data sets. Further, the choice sets are discrete and of similar cardinality (ranging from 40 to 100 options) in both experiments, which implies that a single econometric framework can be used.

Both experiments implement *generalized dictator games*: The dictator (player 1) can give between 0 and B tokens to player 2, his choice set is denoted as $S_1 = \{0, 1, \dots, B\}$. Each token has value τ_1 for player 1 and τ_2 for player 2. The two players’ payoffs are $\pi_1(s) = \tau_1(B - s)$ and $\pi_2(s) = \tau_2 s$ for all $s \in S_1$. The parameters τ_1 , τ_2 , and B vary between treatments, as shown in Table 1.³ Both data sets exhibit the typical characteristics of dictator games. A tobit regression of donations in AM on (B, τ_1, τ_2) yields

$$s_1 = -8.172 + 0.254 \cdot B - 4.348 \cdot \tau_1 + 4.878 \cdot \tau_2 + \epsilon$$

(8.86) (0.066) (1.871) (1.838)

where ϵ has standard deviation $\hat{\sigma} = 27.645$ (parentheses provide the standard errors). The donations are increasing in the budget and in the donation’s value τ_2 for player 2; they are decreasing in

Table 1
Parameters in the two dictator game experiments.

(a) Parameters in Andreoni and Miller (2002)										
Endowment B	40	40	60	60	75	75	60	100		
Hold value τ_1	3	1	2	1	2	1	1	1		
Pass value τ_2	1	3	1	2	1	2	1	1		
(b) Parameters in Harrison and Johnson (2006)										
Endowment B	75	40	75	60	40	100	60	80	40	40
Hold value τ_1	2	2	2	2	5	1	2	2	2	2
Pass value τ_2	4	6	2	4	5	2	3	4	5	8

the costs τ_1 for player 1. The estimates suggest that the average donation falls by about 4.3 per unit increase of τ_1 and that it increases by about 4.9 on average per unit increase of τ_2 . The reliability of such extra-/intrapolations is the topic of my analysis.

To see the main difference between the two experiments, look at Fig. 1. The three histograms concern choices where the transfer ratio is $\tau_1/\tau_2 = 1 : 2$. In all cases, around 30% of the subjects transferred zero tokens. The relative frequencies of the subjects making the Leontief choice (equalizing the payoffs) differ notably, however. In both AM’s treatment 4 and HJ’s treatment 4, the Leontief transfer is 20 tokens, but in HJ’s treatment 6, the exactly equalizing transfer would be 33.3 tokens. More generally, the Leontief choice is a “round number” (a multiple of 5 or even 10) in all of AM’s treatments, while this is true only in five of the ten treatments of HJ. As Fig. 1 shows, the relative height of the spike at the Leontief choice varies, depending on whether it is a round number. This variation constitutes an obstacle for models of stochastic choice: If they overfit to the “Leontief spikes” in AM, they may fail the robustness test of predicting HJ. This will also be analyzed below.

AM identified subjects with Cobb–Douglas, Leontief, and linear utility functions (with varying precision in maximizing utility). These utility functions are special cases of CES utilities $u_i = ((1 - \alpha)\pi_i^\beta + \alpha\pi_j^\beta)^{1/\beta}$, where (π_i, π_j) denotes the payoff profile. Cobb–Douglas obtains for $\beta \rightarrow 0$, Leontief for $\beta \rightarrow -\infty$, and linearity for $\beta = 1$. Since CES utility functions have also been used in many related studies (e.g. Fisman et al., 2007, Cox et al., 2007, Cap-pelen et al., 2007), my analysis is based on CES utilities, too.

3. Modeling social donations

Experimental analyses of dictator or public goods games use either structural models or regression models. A linear regression model regresses donations on treatment parameters (budget and transfer rates) using functional forms that are not derived from game-theoretic primitives such as preference orderings and utility maximization. I use an interval regression, since donations are discrete, and thus, donations s_i in dictator games are

$$s_i = \begin{cases} 0, & \text{if } 0.5 > \hat{s}_i \\ 1, & \text{if } 0.5 \leq \hat{s}_i < 1.5 \\ 2, & \text{if } 1.5 \leq \hat{s}_i < 2.5 \\ \vdots & \\ B, & \text{if } s_i \geq B - 0.5 \end{cases}$$

with $\hat{s}_i = \alpha + \beta_1 B + \beta_2 \tau_1 + \beta_3 \tau_2 + \epsilon$, (1)

where $\epsilon \sim \mathcal{N}(0, \sigma^2)$. In a second, *extended regression* model, I add the first-order interaction terms between treatment parameters, i.e. $B \times \tau_1$, $B \times \tau_2$, and $\tau_1 \times \tau_2$, reflecting common practice. Thirdly, I consider a *hurdle regression* which extends the interval model by introducing an adjustable hurdle for donating more than zero. Hurdle models are inspired by the comparatively large number of subjects donating zero in dictator games, see e.g. Fig. 1, and have been used for example by Engel (2011). In relation to the

¹ In contrast, the only related study, Conte and Moffatt (2013), use data with at most two observations per subject, which does not allow a robust separation of variance between-subjects (subject heterogeneity) and variance within-subjects (stochastic choice). Further, the transfer rate is constant for all their observations, which prevents an assessment of the robustness of fit across conditions.

² As for Harrison and Johnson’s data, I analyze the choices where the primary recipient was another subject. The amounts transferred in these cases were similar to those in other experiments. The primary recipient in the remaining cases was a charity organization, which triggered larger transfers.

³ I use the term “treatment” to refer to (within subject) variation of the economic environment.

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