The Effectiveness of Private Benefits in Fundraising

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Abstract:

This paper provides an empirical analysis of the role that private benefits play in explaining charitable donations to large cultural organizations. We use a multiple discrete choice model with differentiated products, and estimate the model using a unique data set of donor lists for the ten largest cultural and environmental charitable organizations in the Pittsburgh metropolitan area. We find that private benefits that furnish social status to donors provide important incentives for donors to support the related charities.

KEYWORDS: Charitable Donations, Incentive Effects of Private Benefits, Multiple Discrete Choice Models, Theory based Estimation.

JEL classification: C33, D12, H24.

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1 Introduction

Private donations are the main source of revenue for most charitable organizations, particularly large cultural organizations such as symphonic orchestras, public theaters, and museums. In contrast, direct revenues from ticket sales and other activities account for a much smaller fraction of total revenues. Consequently, most charitable organizations must have effective fundraising strategies to provide continued levels of service. While some individuals may support their favorite charities regardless of the incentive structures to attract donors, others may be motivated to give conditional on the benefits offered. The former set of donors gain satisfaction from knowing that they contributed to a worthy cause (called "warm-glow" by Andreoni (1989, 1990)), whereas these latter donors fit into the framework of Harbaugh (1998) in which donors receive tangible or intangible private benefits from their gifts. To attract the more fickle donors, charitable organizations rely on sophisticated fundraising strategies with private benefits in return for donations. The more generous the donation, the more lavish the benefit package.[1] The purpose of this paper is to determine whether and which private benefits are effective tools to raise funds from donors. We focus on donations to large cultural organizations that offer potential donors social networking opportunities as part of the private benefit package.[2] We find that social networking opportunities offered by attending private tours, exclusive dinner parties, and special exclusive events are useful tools for attracting large annual donations.

Our approach differs from previous empirical studies in the charitable donations literature. We adopt a differentiated product approach (Gorman (1980) and Lancaster (1966)) whereby the amount of giving is interpreted as the "price" associated with a bundle of benefits. Each tier or level of giving to a specific charity can be characterized by a vector of attributes.[3] Our two stage estimation is based on cross sectional data on individual donors.

[1] In the words of Thomas Hobbes: "no man giveth but with intention of good to himself" (Hobbes, 1651).

[2] Typical private benefits include, but are not limited to, discounts at the gift shop, performers' autographs, premium seating, free valet parking, private tours, and exclusive dinners and parties. Buraschi and Cornelli (2003) also document these private benefits for donors of the English National Opera.

[3] Berry (1994) highlights the importance of unobserved product characteristics and the potential endo-

It is thus similar in spirit to Berry, Levinsohn, and Pakes (2004) and controls for the fact that unobserved characteristics associated with each tier of giving are correlated with observed levels of giving. Adopting a differentiated product approach is central to identifying and estimating the role that private benefits play in explaining donations.

To implement our empirical analysis we assemble a novel and extensive data set that allows us to compare the private benefits offered to donors among a collection of organizations. The core of the empirical analysis is based on data that we assemble using publicly available donor lists of *ten* large cultural and environmental organizations in the Pittsburgh metropolitan area. By using a larger number of charitable organizations, we have 76 different combinations of levels of giving and private benefits in our sample.[4] Holding giving constant, the variation in private benefits arises because different charitable organizations pursue different tactics to raise funds and appeal to donors.[5] Organizations like the Opera and Symphony have much different reward structures than the Zoo or the Children's Museum. For example, the Opera and Symphony award explicit private benefits associated with each level of giving, whereas the Zoo and Children's Museum do not. It is this observed variation of private benefits at constant levels of giving that allows us to identify more precisely the effects of private benefits.

A key feature of our data set is that a significant number of individuals support multiple charities. In our sample, a large number of individuals give to three or more charities. Some individuals give to nine charities. Given that there are a large number of tiers of giving, a simple discrete choice model cannot be used to describe this type of behavior. The relevant choice set gets intractably large when individuals donate to multiple organizations since we need to keep track of a large number of possible permutations of the different products. As a consequence we adopt a different approach that builds on the literature on multiple-discrete choice models.

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geneity between prices (amount of giving) and unobserved product characteristics.

[4]Previous empirical studies such as Buraschi and Cornelli (2003) typically focus on a single cultural organization.

[5]Vesterlund (2003) argues that fundraisers announce past contributions to signal the quality of the charities, which could help worthwhile charities reveal their type and help them reduce free-rider problem. It assumes donors have imperfect information on the quality of programs offered by a charity.

We follow Hendel's (1999) pioneering approach and model the observed behavior as a repeated discrete choice with multiple choice occasions.[6] In most previous applications of these models, multiple choice occasions arise because a number of different agents make simultaneous decisions. In our model, we focus on a single decision maker who faces a sequential decision problem. Thus, it is useful to relax the additive separability assumption in Hendel (1999) and introduce some state dependence among the choice occasions. In our context, it is plausible that previous levels of charitable giving affects contemporary behavior. To capture this type of habit formation, we assume that past charitable behavior is a state variable in our model and has a direct impact on current period utility. We adopt a dynamic model to allow for state dependent choice sequences using dynamic programming techniques.[7] Since we do not observe behavior at each choice occasion, we integrate over all feasible choice sequences to derive a well-specified likelihood function.

Our findings provide some important new insights in the quantitative importance of private benefits in fundraising. We find that households value private benefits that are affiliated with high social prestige such as invitations to dinner parties and special events. Small token gifts and extra tickets are not valued by most individuals. Individuals that are members of the board of a charity give substantially higher amounts than other donors. This is consistent with the view that individuals value the visibility and potential power that comes with board appointments. Individuals with high levels of wealth or those that support political candidates are more likely to be large donors and place a higher value on the private benefits associated with social functions. Our policy simulations indicate that charities have strong incentives to design a private benefit schedule that allocates different private benefits to tiers of giving to maximize donations. We also consider the scenario in which charities stop using private incentives. Our model predicts that charities that heavily rely on special events and dinners to attract wealth donors would receive much

[6] Kim, Allenby, and Rossi (2002) propose a Bayesian estimator for a multiple-discrete choice model. Dube (2005) estimates a differentiated demand model for the carbonated soft drink industry. Ackerberg, Benkard, Berry, and Pakes (2006) also discuss the difficulties associated with estimating these types of models.

[7] Dynamic discrete choice estimation was first used by Wolpin (1984), Miller (1984), Pakes (1986) and Rust (1987).

lower donations.

The rest of the paper is organized as follows. Section 2 of the paper discusses the data set. Section 3 provides a formal model that can be used to analyze individual donations to multiple charities. Section 4 develops a new estimator for this class of models. This estimator combines previous work on dynamic discrete choice estimation and multiple discrete choice estimators. Section 5 reports the results from this estimation exercise, discusses the fit of the model, and discusses the policy implications of our results. The conclusions are offered in Section 6.

2 The Data Set

In this section we discuss our sample and present some descriptive statistics. We document the importance of giving to multiple organization. This discussion motivates the use of a multiple-discrete choice model. Finally, we document the prevalence and importance of private benefits. This evidence suggests to treat donations as bundles of goods with different characteristics.

2.1 The Sample and Descriptive Statistics

We assemble our data set from a number of publicly available sources. We use annual reports, playbills, and programs for ten large Pittsburgh cultural and environmental organizations. These are the Pittsburgh Ballet Theater, Carnegie Museums of Pittsburgh, Pittsburgh Children's Museum, City Theater, Pittsburgh Opera, Phipps Conservatory, Pittsburgh Public Theater, Pittsburgh Symphony, Western Pennsylvania Conservancy, and Pittsburgh Zoo & PPG Aquarium. The sample is representative and includes all the large organizations in the Pittsburgh market. The donor lists are from the 2004-2005 donation cycle.[8]

[8]Romano and Yildrim (2001) provide a theoretical model of giving that includes warm-glow or snob appeal. They show that it is in the interest of the charity to provide information about its donations. All charities in our sample announce donations and very few donors choose to be listed anonymously.

For individual characteristics on our donors, we use data from the Allegheny County Real Estate database, socio-demographic information from the U.S. Census and political contribution data from the the Federal Election Commission database. For professional memberships, we use lists from the Allegheny County Medical Society (physicians) and the Allegheny County Bar Association (attorneys). We merge these five different databases using an algorithm we describe in detail below.

The main sample we use is a choice-based sample which is common in this literature. Specifically, we do not include individuals in our sample that are not present on at least one of the donor lists for our ten charitable organizations. Consequently, the main focus of the analysis of this paper (and most previous studies) is on the sub-population of individuals that are active donors. However, we also create a random sample of 10,000 households in Allegheny County. Using this sample, we estimate a number of logit models which predict who will donate to a charitable organization. Based on these models, married couples, physicians and lawyers, and individuals that donate to either political party are significantly more likely to donate to one of these organizations. Income, housing values, and years lived in the house, in contrast, do not seem to be systematically correlated with donating. The full results are reported in Appendix A of this paper.

The donor lists do not provide exact gift amounts; instead they identify the range of giving associated with each tier. For some calculations in this section we use the lower-bound on the giving ranges since most individuals tend to give at those lower levels as reported by Harbaugh (1998) and Glazer and Konrad (1996). The unit of observation in this study is a household. There are a total of 6,499 individuals and couples listed in the programs of the ten organizations and total giving is $6,732,705. The donation data are summarized in Table 1. We find that the median gift size for all organizations is close to the lowest tier, suggesting that the majority of donors give in the lowest or second-lowest range reported by these organizations.

Only a small fraction of the donors are listed as "anonymous," suggesting that donors do not mind being recognized in official publications. This result is consistent with other

Table 1: Donations by Organization

	# of Donors	Total Donations	Median	Average	Standard Deviation
Ballet	559	$399,750	$250	$715.12	$1,069
Carnegie Museums	1,236	$2,303,005	$1,000	$1,863.27	$3,678
Children's Museum	185	$79,350	$100	$428.92	$1,396
City Theater	170	$185,200	$100	$1,089.41	$638
Opera	556	$1,125,000	$250	$2,023.38	$5,552
Phipps Conservatory	984	$189,200	$100	$192.28	$463
Public Theater	1,082	$410,200	$50	$379.11	$1,019
Symphony	668	$1,361,500	$1,000	$2,038.17	$3,882
WPC	2,082	$523,350	$100	$251.37	$875
Zoo	649	$155,650	$50	$239.83	$531
United Way	4,180	$16,383,500	$1,000	$3,919.50	$40,999

evidence reported below that social prestige and private benefits are powerful explanations for observed donation behavior. We consolidate the donor lists and match on names. These names are then cross-referenced with data from the Allegheny County Real Estate database, the U.S. Census, and Federal Election Commission database. We can easily match most individuals, with the exception of individuals with extremely common first and last names. Matching our data to professional lists, we find that 391 physicians and 500 lawyers gave money to at least one of the ten Pittsburgh cultural organizations.

To determine the housing wealth of donors in our sample, we match the donors to the Allegheny County Real Estate Assessment website.[9] A subset of individuals (54 %) can be identified as owning property in Allegheny County.[10] The main part of the empirical analysis focuses on households in Allegheny County that are matched to the real estate data base. We report descriptive statistics in Table 2 that summarize the distribution of housing values, by charity, in our sample.

[9] The site was established to provide transparency to the assessment of property taxes and has every residential property listed with the deeded owner's name.

[10] It is certain that individuals donate to these organizations from surrounding counties. For example, the WPC's Fallingwater attraction is located outside of Allegheny County.

Table 2: Property Values of Donors

	Number	Average	Median	Standard Deviation
Ballet	327	$322,450	$243,600	$280,154
Carnegie Museums	806	$389,524	$323,350	$325,356
Children's Museum	126	$383,075	$311,700	$311,661
City Theater	383	$295,484	$236,100	$283,174
Opera	373	$331,953	$260,000	$264,489
Phipps	631	$327,004	$265,000	$280,950
Public Theater	730	$287,289	$230,450	$218,276
Symphony	444	$363,339	$281,500	$312,028
WPC	850	$263,428	$190,650	$242,911
Zoo	419	$292,641	$218,800	$262,995

The Carnegie Museums and the Pittsburgh Symphony attract donors with the highest average housing values. Surprisingly, donors to the Children's Museum have the third highest housing wealth. The Western Pennsylvania Conservancy and the City Theater have donors with lower housing values. The real estate data base contains the address of the house, which allows us to match each observation in the sample to a Census Block Group and assign a (neighborhood) income level to each observation. Moreover, we can distinguish among households that live in the City of Pittsburgh and households that live in one of the surrounding suburbs. Finally, we know how long the household has owned the property which we use to construct a variable which measures the "attachment" to the Pittsburgh metropolitan area.

The United Way is a charity that largely funds smaller charities that provide social and community outreach services. It provides few private benefits besides social visibility. We find that 551 people who gave to one of the cultural charities also gave to the United Way. The minimum amount of giving, such that the donor is listed in the publication is $1,000, suggesting that the number could, in fact, be much higher. The maximum gift was $1,000,000 with the average gift at $10,282 with a standard deviation of $73,615.

The individuals in our sample also contributed significantly to political candidates in the 2004 election. Of the 6,499 individual donors, 736 contributed to at least one of: a presidential campaign (either George W. Bush or John Kerry), a senatorial campaign (Arlen Specter or Joseph Hoeffel), a congressional campaign in nearby districts, or the Republican or Democratic parties.[11] Table 3 reports the number of individuals who gave money to both the cultural organization listed and the presidential campaigns of either G.W. Bush or J.F. Kerry.

Table 3: Giving to Presidential Candidates

	Bush number of donors	Kerry number of donors	Bush total amount	Kerry total amount
Ballet	12 (33.3%)	24 (66.7%)	$19,250	$46,550
Carnegie Museums	69 (41.1%)	99 (58.9%)	$118,025	$147,350
Children's Museum	13 (41.9%)	18 (58.1%)	$18,000	$34,350
City Theater	5 (7.0%)	66 (93%)	$8,500	$99,400
Opera	15 (30.0%)	35 (70.0%)	$29,000	$60,100
Phipps Conservatory	31 (36.0%)	55 (64.0%)	$54,375	$97,620
Public Theater	23 (28.0%)	59 (72.0%)	$46,950	$89,224
Symphony	31 (38.8%)	49 (61.3%)	$58,650	$77,420
WPC	40 (35.1%)	74 (64.9%)	$67,475	$115,420
Zoo	20 (54.1%)	17 (45.9%)	$46,200	$39,550

A large number of individuals that support the cultural and environmental charities in our sample are also politically active, supporting their favorite candidates and party.[12] We will document in a later section of this paper that these individuals are most receptive to private benefits that convey social status.

2.2 The Importance of Giving to Multiple Organizations

One of the striking features of our data is that many individuals donate money to multiple causes. For example, 495 of the 6,499 individual donors are identified as giving to three or more of our ten organizations. Table 4 provides a detailed analysis of the distribution of

[11] The FEC requires political contributions of $200 or more to be reported.

[12] An analysis of the political contributions to the both parties as well as Senate and House candidates are available upon request from the authors.

donor types.

Table 4: Spread of Giving to Multiple Organizations

# of Organizations	# of Donors	% of Individuals	Sum of Donations	% of Total Donations
1	5264	81.00%	$3,076,945	45.70%
2	740	11.39%	$1,363,360	20.25%
3	304	4.68%	$1,034,195	15.36%
4	118	1.82%	$569,485	8.46%
5	44	0.68%	$327,205	4.86%
6	13	0.20%	$141,160	2.10%
7	11	0.17%	$115,160	1.71%
8	2	0.03%	$10,095	0.15%
9	3	0.05%	$94,600	1.41%
10	0	0.00%	$0	0.00%

We find that the individuals who contributed to three or more organizations have different characteristics than the average donor. Of the 392 who were found in the Allegheny County Real Estate Registry, their average property value was $425,659, substantially larger than the $292,417 of an average donor to fewer charities. Of the 392 with Allegheny County housing entries, 327 live in the city of Pittsburgh. Their average combined giving amounted to $4,630 compared to $739 for those donors who gave to fewer organizations. They were also much more likely to donate to a political candidate, 44 % for the donors who gave to three or more charities compared to 17 % for all donors. Table 5 reports the number of donors that gave the first, second, or third largest amounts to each organization with ties counted on the same level.

We find that organizations like the Carnegie Museums, Opera, and Symphony are "top-heavy", i.e. they are first or second choices for many donors. The "bottom-heavy" organizations like Phipps Conservatory, WPC, Zoo, Public Theater, City Theater, and the Children's Museum rarely receive the largest share of a given donor's bankroll. The data thus suggest that individuals strategically decide how to allocate funds among the available charitable organizations. No one in our sample gives, for example, equal amounts to a large

Table 5: Gift Size Ordering and Frequency among Multiple Donors

	Largest Donation	Second Largest	Third Largest	Gift Frequency
Ballet	50	52	11	23.4%
Carnegie Museum	180	78	7	53.7%
Children's Museum	6	18	15	10.5%
City Theater	18	77	46	31.5%
Opera	88	47	18	32.3%
Phipps Conservatory	22	104	76	49.1%
Public Theater	48	101	76	48.9%
Symphony	142	60	14	43.6%
WPC	34	103	83	48.7%
Zoo	11	36	40	22.0%

Note: The sample size is 495.

subset of these organizations.

Table 5 also shows the percentage of the 495 multiple donors who give any money to each organization (last column). We find that Phipps, WPC, and the Public Theater capture about the same number of donations from the multiple donors as the Carnegie Museums and the Symphony. However these charities are the second-choice destinations for charitable giving receiving less money.

Since a significant fraction of individuals donate to more than one charity, the challenge is to model their behavior since their potential choice set is very large. As a consequence we do not adopt a simple discrete choice approach, but a multiple discrete choice approach which generates the choice set from the basic options available at each choice occasion (Hendel, 1999).

2.3 The Importance of Private Benefits

In addition to the private good motive of prestige that comes with being listed in a playbill or annual report, some organizations provide substantial private benefits to reward donations. Organizations typically grant additional benefits to the higher levels of giving. They also offer all benefits associated with levels of giving below your current level. Only three of the ten organizations do not have these tiered privileges listed in their programs, annual reports, or websites. Table 6 summarizes the number of offerings in each category that donors at the top level are given.

Table 6: Private Benefits Explicitly Offered to Donors in the Top Tier

	Exclusive Party	Special Tickets	Events	Token Gifts	Autographs	Free Parking
Ballet	2	3	3	3	1	
Carnegie Museums	5	7	5	3		1
Children's Museum						
City Theater	2	2			1	1
Opera	2	3	6	1		1
Phipps Conservatory	1	3	1	5		
Public Theater						
Symphony	1	4	7	3	1	1
WPC		3		2		
Zoo						

Another potential private benefit associated with giving is the possibility of being appointed to the Board of Trustees. Board membership is likely to provide both prestige as well as a degree of influence in the organization.[13] All of the ten organizations in our data set have a Board of Trustees and the names of the trustees are listed in the same piece of literature as the names of donors. The board members who were also listed in the donation section are characterized in Table 7 with the minimum, maximum, median, and average donation of a board member along with the standard deviations.

Based on our analysis thus far, we conclude that is useful to model behavior as choices among bundles of goods. Each tier of giving is thus a differentiated product which comes with a "price" which is equal to the minimum giving amount and a vector of private and social benefits. This recognition motivates our use of a differentiated product model in the empirical analysis. This allows us to determine the quantitative importance of private

[13]Individuals who give a lot of money to an organization and do not value the benefits of board membership can clearly refuse to serve on the board.

Table 7: Donations from Current Board Members

	# of Contributing Board Members	Range	Median	Average	Standard Deviation
Ballet	44	\$250 - \$5,000	\$5,000	\$3,494	\$1,762
Carnegie Museums	99	\$500 - \$25,000	\$2,500	\$7,449	\$8,691
Children's Museum	33	\$50 - \$10,000	\$500	\$1,782	\$2,961
City Theater	39	\$250 - \$2,500	\$2,500	\$1,878	\$858
Opera	69	\$250 - \$50,000	\$5,000	\$8,272	\$9,359
Phipps Conservatory	44	\$50 - \$5,000	\$475	\$722	\$867
Public Theater	41	\$150 - \$10,000	\$2,500	\$3,662	\$2,488
Symphony	29	\$500 - \$25,000	\$1,000	\$4,345	\$6,835
WPC	28	\$100 - \$10,000	\$1,000	\$2,461	\$3,383
Zoo	49	\$100 - \$5,000	\$1,000	\$980	\$1,031

benefits. Moreover, we can study which types of households prefer what types of private benefits which may help these organizations to devise effective fundraising strategies.

3 A Multiple-Discrete Choice Model of Charitable Giving

As seen in the previous section, the challenge is to develop an empirical model that treats charitable donations as a differentiated product and can explain donations by a single individual to multiple organizations. In principle, one could use standard discrete choice techniques from the recent literature surveyed by Ackerberg et al. (2006). The main problem with this approach is the dimensionality of the choice set. If there are J differentiated products and I charities, the relevant choice set is of the order of approximately J^I which quickly becomes intractable. We, therefore, follow the literature on multiple-discrete choice models pioneered by Hendel (1999) to deal with this curse of dimensionality problem.

In most applications of multiple discrete choice models, one assumes that multiple individuals make simultaneous discrete decisions. Aggregating over decision makers then yields a well defined multiple-discrete choice model. We follow a different approach since it is more reasonable to assume that a single decision maker makes a sequence of discrete choice over time. The multi-discrete choice model is then obtained by aggregating the decisions of the single individual over the relevant time horizon. To formalize there ideas, we assume that there is a finite number of charitable organizations to which a donor can potentially make a contribution. Each donor makes decisions over the course of a year. The year consists of T time periods. Each donor is a characterized by a vector of observed characteristics x such as wealth, occupational status, party affiliation, marital status, and others.

There are I charities and an outside option denoted by 0. Each charity has L_i tiers of giving that are associated with an amount of giving g_{il} and private benefits p_{il}. We treat each tier of giving to each charity, i.e. each pair il, as a separate differentiated product. Let d_{ilt} denote an indicator function that is equal to one if a donor chooses to give to charity i at level l at time t. At each point of time choices are mutually exclusive:

$$\sum_{i=0}^{I} \sum_{l=1}^{L_i} d_{ilt} \ = \ 1 \tag{1}$$

It is plausible to assume that the willingness to donate is influenced by the total amount of previous giving.[14] Define the total amount of giving up to time t as

$$tg_t \ = \ \sum_{k=1}^{t-1} \sum_{i=0}^{I} \sum_{l=1}^{L_i} d_{ilk} \, g_{il} \tag{2}$$

We assume that tg_t is a sufficient statistic that characterizes the history of giving.[15]

It is plausible that preferences depend on the a vector of observed characteristics of the household, x. The per-period utility at time t is given by:

$$U_t(d_t, x, tg_t, \epsilon_t) \ = \ \sum_{i=0}^{I} \sum_{l=1}^{L_i} d_{ilt}(u_{ilt}(x, tg_t) + \epsilon_{ilt}) \tag{3}$$

where $\epsilon_t = (\epsilon_{11t}, ...\epsilon_{ILt})$ denotes a vector of idiosyncratic shocks. We thus follow McFadden

[14]Our model is thus slightly more general than a two stage budgeting model in which households first determine the total amount of giving per year, and then allocate that amount among the preferred charities.

[15]It is also possible to treat the total amount of giving to each charity as a state variable. But that would obviously increase the relevant state space and thus impose significant additional computational burden.

(1974) and assume that the error enters the utility function in an additively separable manner.

Let $s = (tg, x, \epsilon)$ denote the vector of state variables. Individuals are rational and forward looking and behave according to an optimal decision rule which solves the following maximization problem:

$$\max_{d_1, d_T} \sum_{t=0}^{T} E[\beta^t \, U_t(d_t, s_t)|s_0] \tag{4}$$

The model can explain multiple donations to different charities in the same year. This is the central feature of the data that needs to be explained.[16] In addition, the model treats donations as a differentiated product, thus allowing for the fact that individuals also receive tangible private and social benefits. The model thus allows us to analyze how the willingness to donate to an organization depends on the private benefits associated with each level of giving.

The model is sufficiently general to account for the fact that the previous donations reduce available income and thus may reduce the probability of future donations. It is also straight-forward to allow for time dependent observed characteristics such as income and impose the budget constraint.[17] We primarily use the time structure to generate multiple choice occasions which is a central component in any multiple-discrete choice model. Allowing for multiple choice occasions is essential to reduce the complexity of the model and avoid the curse of dimensionality of simpler discrete choice models as discussed above. If $\beta = 0$ or if previous donations do not matter, the model is essentially equivalent to the Hendel model.

[16] We do not model explicitly the strategic interactions that would arise in a dynamic public provision game. We leave this for future research.

[17] In practice, this would require observing income at the different points in time. Unfortunately, we do not have access to quarterly income measures in our application.

4 Estimation

4.1 A Parametrization

We assume that the utility of giving at level l to charity i in period t is given by

$$u_{ilt}(x_t, tg_t) \;=\; \alpha_{il} \;+\; \delta tg_t \;+\; \psi x \tag{5}$$

where the "mean utility" associated with product il is denoted by α_{il}. The parameter δ captures the state dependence in our model and measures that the (dis-) utility of having made donations before. ψ measures the impact of observed heterogeneity on public giving. With a slight abuse of notation, we also include interactions between individual characteristics and observed product characteristics in x. As discussed in detail in Berry et al. (2004), these interactions may be important in generating an appropriate choice model. We assume that α_{il} can be decomposed into observed and unobserved characteristics as follows:

$$\alpha_{il} \;=\; \alpha \;+\; \beta\, g_{il} \;+\; \gamma\, p_{il} \;+\; \xi_{il} \tag{6}$$

where α denotes an intercept, g_{il} denoted the level of giving associated with the level l of charity i. p_{il} denotes the private benefits associated with giving at level l to charity i such as invitations to special events and dinners. ξ_{ij} denotes an unobserved product characteristic such as social prestige.

Estimation of the parameters of the model proceeds in two stages. In the first stage we estimate the parameters $\theta_1 = (\alpha_{ij}, \delta, \psi)$ using a maximum likelihood estimator. In the second stage we estimate the remaining parameters $\theta_2 = (\alpha, \beta, \gamma)$ using a linear instrumental variable estimator. We discuss both stages in detail below.

4.2 The First Stage

Since this model yields deterministic decision rules, we rely on unobserved state variables to generate a properly defined econometric model. Note that we assume that each individual knows the level of previous giving tg_t, and the realizations of ϵ_t when making decisions. In contrast, tg_t and ϵ_t are unobserved by the econometrician.

Rust (1987) shows that if the unobserved state variables satisfy the assumptions of additive separability (AS) and conditional independence (CI), conditional choice probabilities are well defined. If we additionally assume that the idiosyncratic shocks in the utility function follow a Type I extreme value distribution (McFadden, 1974), we obtain Rust's multinomial dynamic logit specification:

$$P_t(d_{ilt} = 1 | tg_t, x) \;\; = \;\; \frac{\exp(v_{ilt}(tg_t, x, \theta_1))}{\sum_{j=0}^{I} \sum_{k=1}^{L_j} \exp(v_{jkt}(tg_t, x, \theta_1))} \tag{7}$$

To evaluate these conditional choice probabilities we must compute the conditional value functions, $v_{ilt}(\cdot)$. Since this is a finite horizon model, we can compute the conditional or choice specific value functions recursively using backward induction. To see how it works, consider the decision problem in the last period T. In the last period, the donor solves a static decision problem and the last period conditional value function is simply given by:

$$v_{ilT}(tg_T, x, \theta_1) \;\; = \;\; u_{ilT}(tg_T, x, \theta_1) \tag{8}$$

For all other periods the conditional value function is defined as:

$$v_{ilt}(tg_t, x, \theta_1) \;\; = \;\; u_{ilt}(x, tg_t, \theta_1) \; + \; \log(\sum_{m=0}^{I} \sum_{n=1}^{L_m} \exp(v_{mnt}(tg_t + \; g_{il}, x, \theta_1))) \tag{9}$$

The conditional value functions can thus be computed recursively.

Estimation of the model is not straight-forward, since we do not observe choices at each point of time. Instead, we observe for each charity, i, whether an individual donates at a given level, l:

$$d_{il} \;\; = \;\; \sum_{t=1}^{T} d_{ilt} \tag{10}$$

As a consequence, a standard dynamic discrete choice estimator based on the choice probabilities in equation (7) is not feasible.

A feasible maximum likelihood estimator for this model must be based on the probability of observing the outcomes $d = (d_{11}, ..., d_{LI})$ conditional on the observed time-invariant characteristics x. Let these probabilities be denoted by $P_t(d \mid x)$. These probabilities can be computed from the standard conditional probabilities in equation (7) by integration over all possible choice sequences.

To illustrate this procedure, consider the following simple example. Assume there are three choice occasions ($T = 3$), three charities ($I = 3$), and each charity has two tiers of giving ($L = 2$). Suppose we observe that an individual donates to the first charity at level 2, to the second charity at level 1, and not to the third charity. Using our notation, we observe $d = (d_{11}, d_{12}, d_{21}, d_{22}, d_{31}, d_{33})$ where

$$d_{12} = d_{21} = 1 \tag{11}$$
$$d_{11} = d_{22} = d_{31} = d_{32} = 0$$

Let cs_i denote a choice sequence that is consistent with the observed behavior in equation (11). Let CS denote the set of all feasible choice occasions that are consistent with the observed choices d. It is then fairly straight forward to verify that the following six sequences of choices are elements in CS:

Feasible Choice Sequences			
Choice Sequence	Period 1	Period 2	Period 3
cs_1	12	21	0
cs_2	12	0	21
cs_3	0	12	21
cs_4	21	12	0
cs_5	0	21	12
cs_6	21	0	12

The probability of observing the behavior in equation (11), given some observed characteristics x, is obtained by computing the probability of each of the six feasible choice sequences and summing over all possible sequences:

$$\begin{aligned}
P(d|\, x) &= \sum_{i\in CS} P(cs_i|\, d, x) \qquad (12)\\
&= P_1(d_{121}=1 \mid tg_1=0,x)\; P_2(d_{212}=1 \mid tg_2=g_{12},x)\; P_3(d_{003}=1 \mid tg_3=g_{12}+g_{12},x)\\
&+ P_1(d_{121}=1 \mid tg_1=0,x)\; P_2(d_{002}=1 \mid tg_2=g_{12},x)\; P_3(d_{213}=1 \mid tg_3=g_{12},x)\\
&+ P_1(d_{001}=1 \mid tg_1=0,x)\; P_2(d_{122}=1 \mid tg_2=0,x)\; P_3(d_{213}=1 \mid tg_3=g_{12},x)\\
&+ P_1(d_{211}=1 \mid tg_1=0,x)\; P_2(d_{122}=1 \mid tg_2=g_{21},x)\; P_3(d_{003}=1 \mid tg_3=g_{21}+g_{12},x)\\
&+ P_1(d_{001}=1 \mid tg_1=0,x)\; P_2(d_{212}=1 \mid tg_2=0,x)\; P_3(d_{123}=1 \mid tg_3=g_{21},x)\\
&+ P_1(d_{211}=1 \mid tg_1=0,x)\; P_2(d_{002}=1 \mid tg_2=g_{21},x)\; P_3(d_{123}=1 \mid tg_3=g_{21},x)
\end{aligned}$$

The algorithm in the example above can be generalized to deal with arbitrary number of T, I and L. We observe a sample of individual donors with size N. The probability of observing a vector of indicators d_n, for donor n, with observed characteristics x_n, is given by:

$$P(d_n \mid x_n, \theta_1) = \sum_{cs_{in}\in CS_n} P(cs_{in}|\, d_n, x_n, \theta_1) \qquad (13)$$

where the conditional choice probabilities $P(cs_{in}|\, d_n, x_n, \theta_1)$ associated with a feasible choice sequences can be computed from the underlying conditional choice probabilities of the dynamic logit model described above. The parameters of the model can be consistently estimated using a MLE. The likelihood function is:

$$L(\theta_1) = \Pi_{n=1}^{N} P(d_n \mid x_n, \theta_1) \qquad (14)$$

4.3 The Second Stage

The first stage of our algorithm yields an estimator of the product specific fixed effects or "mean utilities" denoted by $\hat{\alpha}_{ij}^N$. Given standard regularity assumptions, $\hat{\alpha}_{ij}^N$ converges almost surely to α_{ij}. Accounting for the sequential nature of our estimation algorithm, equation (6) can be written as:

$$\hat{\alpha}_{il}^N \;=\; \alpha \;+\; \beta\, g_{il} \;+\; \gamma p_{il} \;+\; \xi_{ij} \;+\; u_{ij}^N \tag{15}$$

Following Berry, Levinsohn, and Pakes (1995), Berry et al. (2004), we assume that $E[\xi_{ij} + u_{ij}^N |\, p_{jk}] = 0$ for $j \neq i$ and $k \neq j$. The key identifying assumption in the second stage is that observed product characteristics are uncorrelated with unobserved product characteristics. That allows us to use observed product characteristics of other products, especially those of close substitutes, as instruments for the amount of donations required at each tier. Following this logic, g_{il} is the "price" associated with "buying" the bundle of warm-glow and private benefits that are associated with given to a charity i at level l. Under these assumptions, we can estimate the remaining parameters of the model using a linear IV estimator. As part of our robustness analysis we also estimate the parameters using OLS. Finally, we also explore models with charity specific fixed effects α_i.

5 Empirical Results

5.1 First Stage

We estimate two versions of the model. Our baseline model does not have interactions between individual characteristics and product characteristics. The extended model allows for those interactions. We estimate each model using two different samples. The first sample contains the ten cultural and environmental charities only. The second sample includes the United Way contributions.

We estimate each version of our the model using a sample of 3,514 observations. The maximum likelihood estimates and corresponding standard errors for each parameter are shown in Table 8. Column I of the table reports the estimates and standard errors for the based line model and the data set which only includes the 10 cultural charities. Column II estimates the same model, but includes the data on the United Way contributions. Column

Table 8: Estimation Results: First Stage

	I	II United Way	III	IV United Way
Lawyer	-73.46	63.18	-72.78	67.88
	(73.5)	(66.7)	(73.56)	(66.8)
Physician	-52.04	-105.7	-43.89	-94.11
	(80.3)	(77.0)	80.80	(77.6)
Republican	218.37	339.4	67.23	220.88
	(67.6)	(66.4)	(84.06)	(79.8)
Democrat	295.11	355.63	323.08	370.76
	(61.7)	(61.9)	(75.81)	(73.3)
House value	516.8	583.73	203.8	144.69
	(93.3)	(82.8)	(123.39)	(115.5)
Mean income	-5.66	51.93	17.42	70.52
	(83.9)	(79.8)	(83.91)	(80.6)
Membership	372.49	388.84	59.66	348.94
	(70.5)	(64.8)	(76.60)	(66.6)
Married	175.11	204.34	185.29	209.57
	(56.6)	(52.1)	(56.87)	(52.5)
Pittsburgh	111.2	86.24	115.63	81.44
	(62.2)	(57.1)	(62.18)	(6.6)
Years House	7.01	5.51	7.04	4.96
	(2.8)	(2.6)	(2.81)	(2.6)
Amount * House value			36.18	47.4
			(20.36)	(8.8)
Amount * Membership			330.75	39.22
			(16.29)	(12.9)
Dinner * Republican			225.49	311.41
			(69.74)	(64.3)
Dinner * Democrat			100.91	154.22
			(75.43)	(69.3)
Dinner * House value			127.83	220.18
			(100.24)	(54.4)
Event * Republican			67.12	40.79
			(23.94)	(24.1)
Event * Democrat			-19.21	-22.85
			(24.73)	(25.1)
Event * House value			138.17	181.79
			(24.74)	(31.3)
Lagged Giving	28.55	78.03	-40.79	67.40
	(6.4)	(8.2)	(19.64)	(8.3)
log likelihood	20636.92	22398.98	20363.51	22273.83

Note: Fixed effects are not reported.

Note: All coefficients and standard errors are inflated by a factor of 10^3 .

III reports the estimates of the extended model which also allows for interactions between the household and product characteristics. Column IV is the extended model including the United Way data. Overall, we find that all versions of our model capture the main regularities in the data reasonably well. Most of the coefficients have the expected sign and are significant at conventional levels. Since the extended model in Column III fits the data better than the baseline model in column I, we discuss the findings of this model in detail below.[18]

One key advantage of our data set is that we observe many characteristics of our donors. Most importantly, we know the value of the donor's main residence, which is good proxy for household wealth. We also control for the neighborhood income of each household. We find that total donations increase with house value and neighborhood income. The demand for benefits such as private parties and dinners is also increasing in wealth.

We include a variable "years lived in the house" which measures attachment to the Pittsburgh community.[19] We find that households that have lived in the community for a longer period of time have higher valuations of the benefits associated with charitable giving. This could be due to stronger ties to the community. We also construct an indicator of whether the household lives in the city of Pittsburgh. People living in the city may have a higher demand for the services offered by these charities than people in the suburbs who face higher commuting costs. We find that city residents also have stronger tastes for charitable giving than suburban households.

Married couples donate larger amounts than singles. Based on professional lists, we have two dummy variables indicating whether the household has a physician or a lawyer. Our professional dummies are typically insignificant. We also estimate the coefficients of two dummy variables based on a household's political donations. We find that households that are politically active are more likely to be active in the local society and thus may value

[18]We do not report the estimates of the fixed effects. However we find that all of the fixed effects are negative. That is not surprising. Everything else equal, individual prefer not to donate in any given time period.

[19]Note that this variable is also positively correlated with age.

private benefits such as invitations to special dinner which may allow them to build social networks. The coefficients of the two variables that measure politically active households are typically large and significant. This result indicates that households that are politically active are also actively supporting the local charities .

We estimate the coefficients on an indicator variable that measures whether the person is a member of the board of the charity as well as the interaction with total donations.[20] We find that board members donate significantly higher amounts than non-board members.

We also find that total past donations are significant in all our model specifications. Accounting for state dependence typically improves the fit of our model. The finding is robust across all those models, including those for which we do not report the estimation results. In our preferred model, the sign is positive, which may indicate that previous giving discourages current giving. We also estimate restricted versions of these models by setting $\delta = 0$. In that case, there is no habit formation and individual donors solve repeated static decision problems. We find that standard likelihood ratio tests typically reject the hypothesis that $\delta = 0$. However, the improvements in the fit of the model are smaller compared to those gained by including interactions between household and product characteristics.

We also consider the within sample fit of the model. Table 9 reports selected moments from the data with moments predicted by the baseline and the extended model. Table 11 reports number of donors, median and average donation levels for the data and a simulated sample of the same size. We find that our model fits the distribution of donors among charities and the median and average level of donations very well.

[20] Of course, board membership may be endogenous since households that donate large amounts may be asked to join the board. None of the main results reported in this paper crucially depend on including this variable.

Table 9: Goodness of Fit: Estimated and Simulated Moments

		mean	S.D.	# Donors	median
Ballet	Data	818.11	1201.94	323	250
	Model I	794.43	1165.13	322	312
	Model II	829.10	1215.98	321	381
Carnegie M	Data	1930.97	3709.59	804	1000
	Model I	1825.06	3486.76	816	750
	Model II	1897.89	3704.03	802	850
Children M	Data	610.27	1756.10	112	100
	Model I	624.72	1699.90	109	103
	Model II	563.19	1607.00	113	107
City Theater	Data	363.64	665.19	374	100
	Model I	375.06	674.13	377	100
	Model II	363.63	667.05	368	100
Opera	Data	2029.13	5340.50	369	500
	Model I	2130.59	5454.45	379	462
	Model II	1977.20	5276.78	370	443
Phipps	Data	176.89	258.07	608	100
	Model I	176.19	253.32	607	100
	Model II	175.86	250.01	592	100
Public Theater	Data	402.09	1054.36	718	50
	Model I	392.63	1007.05	713	100
	Model II	386.12	1018.65	711	90
Symphony	Data	2161.40	4213.06	443	1000
	Model I	2180.97	4268.37	444	1000
	Model II	2136.88	4109.60	445	1000
WPC	Data	343.99	1272.57	832	100
	Model I	356.47	1355.26	837	100
	Model II	355.82	1314.65	847	100
Zoo	Data	234.24	460.17	406	50
	Model I	234.48	456.17	403	63
	Model II	231.80	446.47	406	65

Note: The simulated moments are averages over 20 simulated samples with 3512 observations.
Model I has no interactions while model II accounts for interactions.

5.2 Second Stage

Next we turn our attention to the second stage results. Table 10 reports the results of least squares and two stage least squares regressions in which we regress the mean product utilities on observed characteristics. The IV estimators use characteristics of close substitutes as instruments for the total amount of donations. We use estimators with and without charity specific fixed effects.

Table 10: Second Stage Estimates

	IV no FE	OLS no FE	IV FE	IV no FE
Amount	-433	-397	-459	-254
	(26)	14	(36)	(44)
Event	148	97	229	218
	(64)	(53)	(222)	(105)
Dinner	149	64	162	263
	(144)	(129)	(220)	(217)
Free Parking				665
				(897)

Estimated std. errors are reported in parenthesis.

We find that households value invitations to dinner parties as well as special events. These are the private benefits that are associated with social status. Special tickets and token gifts do not seem to be useful private benefits. We also include free parking as a private benefit in the last specification. Households seem to value this benefit, but the estimate comes with a large standard error. Comparing the IV estimates with and without charity fixed effects, we find that the estimated coefficients are qualitatively and quantitatively similar. The main difference is that including fixed effects increases the estimates of the asymptotic standard errors. We would expect that one might be able to obtain more precise estimates in a larger sample. Nevertheless, we conclude that our estimates are reasonable and consistent with the view that private benefits might be important motives for philanthropic behavior.

5.3 Policy Analysis

To get some additional insights into the role that private benefits play in attracting charitable donations, we conduct a number of counter-factual policy experiments. First, we add one more dinner invitation to the highest tier at the Carnegie Museum. We chose the Carnegie Museum since it is the largest organization in our sample. Our model implies that an additional dinner party for the most generous donors would raise approximately $197,425. We repeated the exercise for the Children's Museum which is one of the smaller organizations in our sample. A dinner party for the Children's Museum, in contrast, would only net $11,019. There are thus some important quantitative differences among the organizations in our sample. The intuition for this finding is that attractiveness of dinners depends on overall appeal of the charity. These findings also suggest that charities may not be behave as revenue maximizers. While this finding may be surprising at first sight, there is some evidence in the literature that supports this view of charitable organizations.[21]

Next, we consider the impact of changes in the choice set. Looking at these changes is interesting since it helps to understand the impact of changes in fundraising strategies. We consider policies that eliminate choices and thus simplify the menu for potential donors. In principal we could also look at policies that add new choices. This would require additional assumptions about the unobserved characteristics of the new choice. First, we eliminate the $2000-2500 tier of giving at the Carnegie Museum. Our model predicts that the total amount of donations would decline by $182,675. Eliminating the lowest tier for the Pittsburgh Opera reduces the number of donors by 28 percent with a reduction in total donations of approximately $50,400.

To further our understanding of the role that private benefits play in attracting charitable donations, we solve our model under the assumption that all charities eliminate all private benefits as incentives to attract donors. The results of this policy experiment is summarized in Table 11. For each charity, the first row represents the data which is, as we have seen in the previous section, close to the predictions of the model using the existing

[21] Weissbrod (1988) provides a discussion of these issues.

Table 11: Policy Analysis: A Ban of Private Benefits

Charity		Number of Donors	Median Donations	Average Donations
Ballet	status quo	323	250	818.11
	no private benefits	202	250	629.66
Carnegie M	status quo	804	1000	1930.97
	no private benefits	402	500	1116.73
Children M	status quo	112	100	610.27
	no private benefits	122	107	657.34
City Theater	status quo	374	100	363.64
	no private benefits	399	100	297.81
Opera	status quo	369	500	2029.13
	no private benefits	192	215	913.12
Phipps	status quo	608	100	176.89
	no private benefits	555	100	167.01
Public Theater	status quo	718	50	402.09
	no private benefits	793	95	404.71
Symphony	status quo	443	1000	2161.40
	no private benefits	165	1000	1627.12
WPC	status quo	832	100	343.99
	no private benefits	919	100	389.58
Zoo	status quo	406	50	234.24
	no private benefits	458	76	233.88

benefit structure. The second row corresponds to the predictions in the absence of private benefits.

Note that the Zoo, the Public Theater, the Western Pennsylvania Conservatory, and the Children's Museum do not use special events and dinners as fundraising tools. As a consequence their overall donations would not be significantly affected by eliminating these benefits. If anything, these charities would experience a small increase in the number of donors and the total level of donations since these charities are now more attractive compared to charities that use these incentives. The Phipps conservatory holds a single special event for their top donors. Our model predicts that this event raises approximately $15,000 in additional donations. The Ballet, the Symphony, the Opera, and the Carnegie Museums all rely heavily on special events and dinners as fundraising tools. Top donors for the Carnegie Museum are invited to five dinners and five special events. Our model predicts that these types of events are very effective and generate a large fraction of the annual donations. Perhaps most surprisingly, we find that the number of individuals that donate to multiple charities would be significantly lower without private benefits. Thus, private benefits affect both giving behavior to the favorite charity as well as charities that rank second or third.

6 Conclusions

Charitable giving is an important way for individuals to support the mission of many cultural and environmental organizations. These institutions rely on a significant amount of private support to balance their budgets. To attract private donors, most organizations offer a variety of private benefits and perks in addition to rewarding donors by printing their names in brochures, playbills, and annual reports. Donors list their names with middle initials, suffixes, and professional titles indicating that social status and recognition is important to these individuals. More importantly, organizations host exclusive dinner parties and extend invitations to special events to important donors. We have shown the importance of these benefits for annual fundraising strategies.[22]

Our findings indicate that private benefits for tiered donation amounts provide strong incentives for donors to support their favorite organizations. Individuals are willing to spend significant amounts of money for an invitation to a special event or dinner party. We find that these benefits are particular popular among affluent donors and donors that are politically active. One plausible interpretation of these findings is that these events provide social status since other affluent and/or influential people are also likely to attend. These findings are also consistent with the fact that dinner parties are notoriously popular to raise political campaign contributions. Individuals often pay large amounts of money per plate at a fundraising dinner for access to a candidate. Our findings are also consistent with

[22] Different strategies for effective fundraising are also analyzed by List and Lucking-Reiley (2002), Karlan and List (2007) and Huck and Rasul (2008).

the observation that most organizations reward important donors by inviting them to join the board of trustees. Board membership not only provides prospects of influence in the organization, but also social visibility. Individuals have a long list of causes from which they can choose to donate money. It is vitally important for cultural organizations to court potential donors. Knowing the preferences of their donor constituencies will allow these organizations to personalize the fundraising process and attract increased donations.

A Who Chooses to Be A Donor?

We generate a random sample of 10,000 households that own residential property in Allegheny County. Those households are matched against the list of donors in the same way as described in the paper. There are 90 observations that we identify as having contributed to one of the ten organizations. This implies that less than one percent of households in Allegheny County contribute to these cultural and environmental organizations. We also find that 0.9% of all households are physicians compared to the 6.0% in the donor sample. There are 1.3 % lawyers in the random sample compared to 7.7% in the donor sample. In the random sample, 147 (1.5%) contributed at least $200 to a national political cause as reported by the FEC compared to the 11.3% of donors that contributed to a national political campaign.

Table 12: Random Sample: Logit Regressions

Variable	Model 1	Model 2
Constant	-5.790	-5.788
	(0.479)	(0.488)
Married	1.100	1.047
	(0.347)	(0.351)
Lawyer	1.791	1.057
	(0.532)	(0.595)
Physician	2.314	1.744
	(0.489)	(0.551)
Mean Income	0.00000544	0.00000451
	(0.00000576)	(0.00000591)
House Value	0.0000000276	0.0000000324
	(0.000000105)	(0.0000000998)
Years in House	-0.0195	-0.0225
	(0.0140)	(0.0148)
Republican Donor		2.397
		(0.500)
Democratic Donor		3.198
		(0.545)

We estimate a number of logit models. The dependent variable is one if the person is listed a donor to one of the 10 charitable organizations and zero otherwise. The results are summarized in Table 12. The results from model 1 show that married couples, physicians, and lawyers are significantly more likely to be donors. However income, housing values, and years lived in the house do not seem to be systematically correlated with being a donor. In model 2 we add the political donations as regressors. We find that those individuals who give to either political party are more likely to donate to one of these organizations.

B Computational Considerations

There are ten charities in our applications with 77 different levels of giving (including the outside option.) We assume that each choice occasion corresponds to one quarter of a year.[23]. We primarily restrict our attention to four choice occasions for computational reasons. We need to characterize all feasible choice sequences in the estimation procedure and then integrate over all feasible paths to compute the likelihood function.[24]

In our application almost all donation amounts can be expressed in increments of $50. This imposes a natural way to discretize the choice space.[25] We compute the value function for every possible state of the world using a backward recursion algorithm.

We use the Simulated Annealing Method to compute the MLE. The main advantage of the Simulated Annealing Method is that its performance dominates simpler algorithms such as the Simplex algorithm. The main drawback is that it is computationally more expensive to use than the Simplex Method. The simulated annealing algorithm is code from Goffe, Ferrier, and Rogers (1994) which we translated into FORTRAN 90.[26] Finally,

[23]We also experiment with a model with six choice occasions. We find that the results are qualitatively similar to the ones reported in the next section.

[24]The main disadvantage for setting $T = 4$ is that we lose information on individuals that decide to donate to more than four charities. Fortunately, we only have a small number of individuals in our sample that donate to more than four charities per year. We treat those individuals as if they had just donated money to their four most preferred charities.

[25]Alternatively, one could pick a coarser grid and use interpolation techniques as suggested, for example, by Keane and Wolpin (1994, 1997).

[26]The sample code is available upon request from the authors. To test code for the likelihood function, we have conducted a number of Monte Carlo experiments. We set up these problems so that the simulated choice data captured some of the main characteristics of the field data. The results from these experiments

we use numerical derivatives to calculate asymptotic standard errors based on the outer product of the score vector.

We use parallel processing techniques and estimate the parameters of the model on a machine provided by the Pittsburgh Supercomputing Center. Estimating the model for the full sample of 3,514 observations takes between 12 and 36 hours of computing time using 300 processors. Another advantage of using a super computer is that we can check for global convergence. Conducting these test would be very time consuming process on an ordinary machine. Following Goffe et al. (1994) we change the starting point and random number generators, and investigate whether the algorithm converges to the same estimates. These experiments show that our estimates are robust and that we obtain the global maximum of the likelihood function.

showed that our programs can recover the true parameter values.

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