The Effectiveness of Private Benefits in Fundraising of Local Charities

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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 develop a multiple discrete choice model with differentiated products. We 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 some private benefits such as invitations to private dinner parties and special events are effective tools for fundraising.

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 symphonic orchestras, public theaters, and museums. In contrast, direct revenues from ticket sales and other activities often account for a much smaller fraction of total revenues and rarely cover costs. Consequently, most charitable organizations need effective fundraising strategies to provide continued levels of service. While some individuals may support their favorite charities regardless of the incentive structures used to attract donors, others may be motivated to give conditional on the benefits the organization offers. 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) where donors receive tangible or intangible private benefits from their gifts. To attract the more fickle donors, charitable organizations rely on sophisticated fundraising strategies. The more generous the donation, the more lavish the private benefit package.[1] The purpose of this paper is to determine whether and which private benefits are valued by donors. Using a sample of large cultural organizations that offer potential donors a variety of different private benefit packages, we find that exclusive dinner parties and special exclusive events are effective tools for attracting large annual donations.

The previous literature has set up a dichotomy in which donors are described as motivated by either warm glow or private benefits. A more compelling approach acknowledges the fact that most donors are driven by both motivations. The weight an individual donor places on each motivation depends on personal characteristics. It is, therefore, desirable to design an empirical approach that nests both hypotheses and allows us to determine the relative importance of these different incentives. Using explicit measures of private benefits we test which type of private benefits explain the observed choice behavior. Our preference specification also nests the special case in which all donations are driven exclusively by warm-glow.

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

Our approach differs from previous empirical studies in the charitable donations literature since we view each organization as a multi-product firm. Each organization offers "core" products such as concerts, opera performances or museum exhibitions that are closely related to the mission of the organization. These goods are standard market goods. In addition, each organization offers a second set of products that can not be purchased in the marketplace, but can be obtained only by donating money to the charity. Thus, by donating money to the organization, a donor not only obtains warm glow, but may also receive a number of exclusive private benefits in return for the donation. We focus on the second type of non-market goods that are offered by large cultural organizations.

Our modeling approach is rooted in the literature on characteristic models or differentiated products (Gorman (1980) and Lancaster (1966)). We interpret the amount of giving as the "price" associated with these product bundles. One components of the bundle may be warm glow. Others are private benefits that can be explicitly measured. We thus assume that each tier or level of giving to a specific charity can be characterized by a vector of observed and unobserved attributes.[2]

To implement our empirical analysis we assemble a novel and extensive data set that allows us to compare the private benefits offered to donors by charities. 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 generate 76 different combinations of levels of giving and private benefits in our sample.[3] Holding giving constant, the variation in private benefits arises because different charitable organizations pursue different strategies to raise funds and appeal to donors. 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. This observed variation of private benefits

[2]Berry (1994) discusses the endogeneity of prices (amount of giving) when unobserved product characteristics are important.

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

at constant levels of giving allows us to identify the effects of private benefits.

A key feature of our data set is that a significant number of individuals support multiple charities. A large number of individuals give to three or more charities. Some individuals give to nine charities. A simple discrete choice model which assumes individuals donate to a single charity does not describe our sample well. One could in principle extend the discrete choice framework to allow consumers to choose among "tuples" of goods. But the relevant choice set gets intractably large when individuals donate to multiple organizations.

For the same reason, we cannot use a hedonic approach to identify the underlying preferences of households. We can regress the amount of donations required for each tier on the vector of characteristics and thus implement the first stage of a hedonic price regression. However, to learn more about the underlying household preferences, one would need to implement the second stage of the hedonic which is challenging as explained by Epple (1987) and Ekeland, Heckman, and Nesheim (2004). More importantly, the hedonic approach suffers from similar problems as the pure discrete choice approach. Hedonic models typically assume that consumers purchase one unit of a differentiated product. Since simple discrete choice or hedonic approaches are not feasible, we adopt a different approach that builds on the literature on multiple-discrete choice models.

We follow Hendel's (1999) pioneering approach and model the observed behavior as a repeated discrete choice with multiple choice occasions.[4] In many applications, multiple choice occasions arise because a number of different agents make simultaneous decisions. In our model, we have 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 affect contemporary behavior. To capture this type of habit formation, we assume that past charitable behavior is a state variable in our dynamic

[4]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. Gentzkow (2007) considers the market for on-line and print newspapers and develops new methods to deal with the fact that some products are potentially complements.

decision model and has a direct impact on current period utility. Since we do not observe behavior at each choice occasion, we integrate over all feasible choice sequences to derive a well-specified likelihood function. Based on this likelihood function, we can estimate specific fixed effects for each tier of giving. In the second stage, we then decompose these fixed effects into the observed and unobserved characteristics.[5] We thus control 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.

Our theory-based estimation approach has many advantages over simpler approaches. Simple reduced form approaches such as hedonic price regressions typically do not allow researchers to identify the underlying preferences of households. Our findings provide some important new insights in the quantitative importance of private benefits in fundraising. 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. Members of the board of a charity or households that also support the United Way give substantially higher amounts than other donors. Individuals with high levels of wealth or those that support political candidates are more likely to make large donations and place a higher value on the private benefits associated with social functions.

Our approach also allows us to evaluate non-marginal policy changes that cannot be evaluated with simpler approaches. Our policy experiments indicate that charities have strong incentives to redesign private benefit schedules to increase donations. We also consider the scenario in which charities stop using private incentives. Our model shows that charities that heavily rely on special events and dinners to attract wealthy donors would receive much lower donations. We then decompose the total amount of giving into a warm-glow component and a component that is due to private benefits. These types of decompositions are outside the scope of reduced form or simple experimental estimators that estimate local average treatment effects. We find that the fraction of donations that can be attributed to

[5] Our estimation approach thus combines micro level data with aggregate data and is similar in spirit to Berry, Levinsohn, and Pakes (2004) and Epple, Romano, and Sieg (2006).

warm-glow varies substantially among the charities considered in the application.

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 have assembled 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. We thus have cross-sectional data for one year.

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. We only include individuals in our sample that are present on at least one of the donor lists for our ten charitable organizations. Consequently, the main focus of the analysis of this paper is on the population of individuals that are active donors. In the literature of charitable giving, it is common practice to use choice-based samples. Almost all papers that have estimated the incentive effects of taxes on charitable giving use tax return data for individuals that itemize deductions. Examples are Clotfleter (1985), Randolph (1995), or Auten, Sieg, and Clotfelter (2002). Choice based samples are also commonly used in the empirical literature that has focused on fundraising and the crowding-out effect of government grants. Kingma (1989) and Manzoor and Straub (2005) use survey data sets that only cover people who listened to public radio. Buraschi and Cornelli (2003) use data based on subscription lists from the English National Opera. Other studies have relied on aggregate data. Ribar and Wilhelm (2002) estimate their model using a 1986-92 panel of donations and government funding from the United States to 125 international relief and development organizations. Hungermann (2005) uses a new panel data set of Presbyterian Church congregations. Again all the data sets use choice-based sampling and typically do not deal with the extensive margin.

To evaluate the impact of choice based sampling, we have also created a random sample of 10,000 households in Allegheny County. Those households are matched against the list of donors. There are only 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 households (1.5%) contributed at least $200 to a national political cause as reported by the FEC compared to the 11.3% of donors in the choice based sample. Using

the random sample, we have estimated a number of logit models which predict who will donate to a charitable organization. We find that 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 being in the choice based sample.

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.

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

Only a small fraction of the donors are listed as "anonymous," suggesting that donors want to be recognized in official publications.[6] Most donors are listed by name in each of

[6]Appendix A provides a table that list the number of anonymous donors by charity.

the donor lists. The Allegheny County Real Estate database lists the name of the owners of a property. The Federal Election Commission maintains a database that lists the name of donors that support candidates running for federal offices. Finally, we also collected a list of lawyers that are members of the American Bar Association and a list of members of the Allegheny County Medical Society. We consolidated the donor lists and matched up names that appeared to be the same. We wrote a simple Excel program that suggested the most likely matches for each individual in the sample. We then inspected each case individually and chose the most likely match by hand. This procedure worked well for the vast majority of observations in our sample. It proved to be a more challenging task if individuals have their names listed slightly different in different organizations. Some appeared more formally printed (Mr. & Mrs. John A. Doe, Jr.), while some appeared more casual (John and Jane Doe). Matching is most difficult for individuals with extremely common last and first names. Knowing the names of both spouses can be helpful in that case.

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.[7] A subset of individuals (54 %) can be identified as owning property in Allegheny County. 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.

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

[7]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.

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

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 no private benefits besides social visibility. We can thus use the information about United Way donations to proxy for heterogeneity in warm glow within the population as explained in detail below. We obtained the list of United Way donors. 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

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 (93.0%)	$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

or Democratic parties.[8] 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. We will document in a later section of this paper that these individuals are most receptive to private benefits such as special events and dinner parties.

Table 4: 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

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

We also observe whether an individual is a member of the board of trustees of the organization. We treat board membership as a predetermined characteristic of a household in our analysis.[9] The ten organizations in our data set list the names of the trustees in the same publication as the one that lists the names of donors. Table 4 reports the minimum, maximum, median, and average donation of board members along with standard deviations.

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 5 provides a detailed analysis of the distribution of donor types.

Table 5: 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 also find that individuals who contributed to three or more organizations have different characteristics than the average donor. Consider the 392 donors who are listed in the Allegheny County Real Estate Registry. Their average property value was $425,659,

[9] This assumption rules out the case that a households donates a large amount in the current period and is therefore put on the board. Board membership is likely to provide both prestige as well as a degree of influence in the organization. We do not explore these issues in this paper, but view them as interesting topics for future research.

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. The multiple donors 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 6 reports the number of donors that gave the first, second, or third largest amounts to each organization with ties counted on the same level.

Table 6: 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.

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 subset of these organizations. The last column of Table 6 shows the percentage of the 495 multiple donors who give any money to each organization. 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, we do not adopt a simple discrete choice approach, but a multiple discrete choice approach. These models 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 7 summarizes the number of offerings in each category that donors at the top level are given. Appendix B reports tables of private benefits for all tier of donations in our sample.

Table 7: 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						

The prevalence of private incentives suggests to model behavior as choices among bundles of goods. Each tier of giving is thus viewed as a differentiated product which comes with a

"price" and set of characteristics. The price is equal to the minimum giving amount and a vector of private and social benefits. The observed characteristics are the private benefits. Households differ among many observed characteristics and are likely to have different tastes for these benefits.

3 A Multiple Discrete Choice Model of Charitable Giving

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. Since simple discrete choice models cannot explain this behavior, Hendel (1999) has suggested to use multiple discrete choice model. Previous applications of multiple discrete choice models assume that different individuals make simultaneous discrete decisions. Aggregating over decision makers then yields a well defined multiple-discrete choice model. We follow a different approach. It is more reasonable to assume in our application 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 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 (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.[10] At each point of time choices are mutually exclusive:

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

Habit formation implies that the willingness to donate is influenced by the total amount of previous giving. 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. Preferences also depend on the a vector of observed, time-invariant 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 (1974) and assume that the error enters the utility function in an additively separable manner. Individuals know the current period shocks, but do not have perfect foresight regarding future preference shocks.

Let $s_t = (tg_t, x, \epsilon_t)$ denote the vector of state variables at time t. Individuals are rational and forward looking with a discount factor equal to one. Individuals, therefore, behave according to an optimal decision rule $\delta_t(s_t) = d_t$ which solves the following intertemporal

[10] We thus implicitly assume that the choice set does not depend on earlier choices. In principle it is easy to relax this assumption and introduce another set of state variables to account for the fact that households do not give twice to the same organization. But the additional computational burden of keeping track of this large vector of state variables does not justify the gains. When we simulate our model we find that our model predicts in 2 percent of the cases that households make donations twice to the same charity and in less than 0.4 percent of the cases at the same tier. As a consequence, there is little need to impose these constraints in estimation.

maximization problem:

$$\max_{\delta=(\delta_1,\ldots\delta_T)} \sum_{t=0}^{T} E_\delta[U_t(d_t, s_t)|s_0 = s] \tag{4}$$

where E_δ denotes the expectation with respect to the controlled stochastic process $\{s_t, d_t\}$ induced by the decision rule, δ.

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.[11] 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. If previous donations do not matter, the model is essentially equivalent to Hendel's model.

4 Estimation

4.1 A Parametrization

We assume that household n obtains utility of giving to charity i at level l in period t according to the following function:

$$u_{iltn}(x_n, tg_{tn}) \;=\; \alpha_{il} \;+\; \eta\, tg_{tn} \;+\; \omega\, x_n \;+\; \psi\, \iota(x_n, p_{il}) \tag{5}$$

The fixed effect associated with product il is denoted by α_{il}. The parameter η captures the state dependence in our model and measures the effect of prior donations on preferences. Note that ω measures the impact of observed heterogeneity on public giving and ψ the importance of interactions between individual characteristics and observed product

[11] 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.

characteristics, denoted by $\iota(x_n, p_{il})$. 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 and g_{il} the level of giving associated with the level l of charity i. p_{il} denotes the observed vector of private benefits such as invitations to special events and dinners. ξ_{ij} denotes an unobserved product characteristic such as social prestige.

It is useful to review how our model accounts for both giving due to "warm-glow" and giving that is motivate by private benefits. Consider the utility specification in equations (5) and (6). Suppose private benefits are irrelevant and donations can only be attributed to warm glow. In that case the coefficients α and β in equation (6) must be different from zero and γ must equal zero. Similarly in equation (5) ψ must be equal to zero. We can thus test the hypothesis that giving is only motivated by warm-glow, by testing the null hypothesis that $\psi = 0$ and $\gamma = 0$. If the alternative hypothesis is true, these coefficients are different from zero. Then part of the giving must be attributed to private benefits.

Estimation of the parameters of the model proceeds in two stages. In the first stage we estimate the parameters $\theta_1 = (\alpha_{ij}, \eta, \omega, \psi)$ 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. 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 the idiosyncratic shocks in the utility function follow a Type I extreme value distribution (McFadden, 1974), we obtain Rust's multinomial dynamic logit specification:

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

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 value functions recursively using backward induction. 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:

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

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

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

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:

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

As a consequence, a standard dynamic discrete choice estimator based on the conditional 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 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. Table 8 list the six choice sequences that are elements in CS in this example.

Table 8: Possible Choice Sequences

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 observed characteristics x, is obtained by computing the probability of each of the six feasible choice sequences and summing over all possible sequences:

$$P(d|\, x) \quad = \quad \sum_{i \in CS} P(cs_i|\, d, x) \tag{12}$$

$$
\begin{aligned}
= \quad & P_1(d_{121} = 1 \mid tg_1 = 0, x)\ P_2(d_{212} = 1 \mid tg_2 = g_{12}, x)\ P_3(d_{003} = 1 \mid tg_3 = g_{12} + g_{12}, x) \\
+ \quad & P_1(d_{121} = 1 \mid tg_1 = 0, x)\ P_2(d_{002} = 1 \mid tg_2 = g_{12}, x)\ P_3(d_{213} = 1 \mid tg_3 = g_{12}, x) \\
+ \quad & P_1(d_{001} = 1 \mid tg_1 = 0, x)\ P_2(d_{122} = 1 \mid tg_2 = 0, x)\ P_3(d_{213} = 1 \mid tg_3 = g_{12}, x) \\
+ \quad & P_1(d_{211} = 1 \mid tg_1 = 0, x)\ P_2(d_{122} = 1 \mid tg_2 = g_{21}, x)\ P_3(d_{003} = 1 \mid tg_3 = g_{21} + g_{12}, x) \\
+ \quad & P_1(d_{001} = 1 \mid tg_1 = 0, x)\ P_2(d_{212} = 1 \mid tg_2 = 0, x)\ P_3(d_{123} = 1 \mid tg_3 = g_{21}, x) \\
+ \quad & P_1(d_{211} = 1 \mid tg_1 = 0, x)\ P_2(d_{002} = 1 \mid tg_2 = g_{21}, x)\ P_3(d_{123} = 1 \mid tg_3 = g_{21}, x)
\end{aligned}
$$

The algorithm in the example above can be generalized to deal with arbitrary number of time periods, charities, and tiers.

To understand identification of η it is useful to consider the example above. First notice that the example involves an individual that gives to more than one charity. If all individuals only donated to only one charity, then we can easily conclude that η is not identified. In the example, the individual donates to two of the three charities. There are six possible choice sequences that are consistent with the observed behavior. In a model in which $\eta = 0$ all choice sequences are equally likely and will receive the same weight in the likelihood function. If $\eta > 0$, it is easy to verify that choice sequences 2 and 5 will receive more weight than the other choice sequences because of the crowding in effect. Similarly if $\eta < 0$, choice sequences 1 and 4 will receive more weight. Different parameters values of η thus yield different weighting schemes for the different choice sequences and thus yield different likelihood functions. This also implies that models with $\eta < 0$ put more weight on choice sequences in which there is one large donation and a few small donations, indicating that large donations are crowding out other donations. Similarly, a model with $\eta > 0$ places more weight on observations with many large donations. The observed sequences of donations of individuals that donate to multiple charities then allows us to identify η.[12]

We observe a sample of donors with size N. The probability of observing a vector of

[12] We find in our application that that the point estimate of η is negative and significantly different from zero. Moreover, we also conducted some tests with simulated data that suggests that our approach yields accurate estimates of η. Note that η may also capture other aspects of the choice behavior that we may not have adequately modeled. For a discussion of the main identification challenges in these types of models see Gentzkow (2007).

choice indicators, denoted by d_n, for a donor with observed characteristics x_n is given by:

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

where the conditional choice probability $P(cs_{in} \mid d_n, x_n, \theta_1)$ that is associated with a feasible choice sequence can be computed from the underlying conditional choice probabilities of the dynamic logit model as described above. The likelihood function is then given by:

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

The parameters of the model can, therefore, be estimated using a MLE.

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} for fixed J and large N. Accounting for the sequential nature of our estimation algorithm, equation (6) can be written as:

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

Following Berry (1994) and Berry, Levinsohn, and Pakes (1995), we assume that $E[\xi_{ij} + u_{ij}^N \mid p_{jk}] = 0$ 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. We can then estimate the remaining parameters of the model using a linear IV estimator.[13]

[13] 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.

Before we proceed, we offer the following observations. First, we treat private benefits such as the number of dinners or the number of invitations to parties as exogenous product characteristics. We, therefore, impose the same identifying assumption as Berry (1994). However, our findings raise the interesting question why donors like these dinners and parties. One view that is consistent with our findings is that these events provide social networking opportunities. One could address this point and include characteristics of the network as potential product characteristics in the model specification. But this approach then leads us outside the standard approach since network characteristics should be viewed as endogenous.[14]

Second, the IV strategy relies on the assumption that a charity sets its rewards to donors in response to what other charities are offering. This underlying assumption of strategic competition among charities is common in the theoretical literature. Charities that differ in quality strategically compete for donations and government grants using fund-raising strategies. These strategies may include private benefits and / or direct solicitations.[15]

Third, one convenient way to approximate the standard errors for the second stage is given by the following equation:

$$(Z'X)^{-1}\ Z'\ (\Sigma + \frac{\Omega}{N})\ Z\ (Z'X)^{-1} \tag{16}$$

where Z is a $J \times k$ matrix of instruments, X is a $J \times k$ matrix of regressors, and Σ is the covariance matrix of the residuals of the regression. Ω is the asymptotic covariance matrix of the fixed effects that are estimated in the first stage. Note that $\sqrt{N}(\alpha^N - \alpha) \rightarrow N(0, \Omega)$. The formula in equation (16) converges to standard IV formula if the sampling error of

[14]There are some obvious similarities with the literature on peer effects. We view these extensions of our model as interesting future research.

[15]The first paper that modeled competition among charities is Rose-Ackerman (1982) who shows that competition can lead to excess fund-raising. Weisbrod (1988) provides a detailed institutional analysis of the non-for-profit sector. More recently, Romano and Yildrim (2001) show that a charity may prefer to announce a large donation during a fundraising campaign. 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. Andreoni and Payne (2003) consider the impact of government grants on fund-raising activities in game with two charities.

the first stage is negligible, i.e. if $N \to \infty$. In practice, we find that the first stage errors associated with the fixed effects are relatively small compared to the variance of the residuals in the second stage.

4.4 Computational Considerations

There are ten charities in our applications with 76 different levels of giving and the outside option. We assume that each choice occasion corresponds to one quarter of a year.[16] We 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. The main disadvantage of using only four periods is that we lose information on individuals that decide to donate to more than four charities. We treat those individuals as if they had just donated money to their four most preferred charities.

In our application almost all donation amounts can be expressed in increments of $50. This imposes a natural way to discretize the choice space.[17] We compute the value function for every possible state using a backward recursion algorithm. We use a simulated annealing method to compute the MLE. We find that this method performs better in our application than simpler algorithms such as the simplex algorithm. The code of the simulated annealing algorithm is taken from Goffe, Ferrier, and Rogers (1994) which we translated into FORTRAN 90.[18] 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

[16] 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.

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

[18] The sample code is available upon request from the authors. To test the 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 show that our estimator works well in practice.

full sample of 3,514 observations takes between 12 and 36 hours of computing time using 300 processors. Using a supercomputer also allows us to check for global convergence. We change the starting points and the seeds of the 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.

5 Empirical Results

We start with the discussion of the first stage estimation results. We estimated a number of different versions of our model. The maximum likelihood estimates and corresponding standard errors of three of the most interesting specifications are reported in Table 9. Column I reports the estimates and standard errors for the baseline model. Column II reports the estimates of an extended model which also allows for interactions between the household and product characteristics. In Column III we add a United Way dummy as well as interactions between product characteristics and the United Way dummy to the specification.

We find that the extended versions of our model capture the main regularities in the data reasonably well. We can clearly rule out the baseline model that does not include interactions between household and product characteristics using standard likelihood ratio tests. Since the extended models in Columns II and III fit the data better than the baseline model in Column I, we primarily discuss the findings of these two models in detail below.[19]

We find that total past donations are significant in all our model specifications. In our two preferred models the sign is negative, which indicates that previous giving discourages current giving. We also estimate restricted versions of these models by setting $\eta = 0$. In

[19] We do not report the estimates of the fixed effects. We find that all estimates of the fixed effects are negative. This is not surprising since we have normalized the mean utility of the outside option (no giving) equal to zero. 81 percent of the households in our sample only give to one charity. The model thus needs to generate choice sequences in the outside option is the preferred choice in more than 80 percent of the data points. As a consequence the mean utilities of the other choices are negative. Everything else equal, most individuals prefer not to donate at any given point of time.

Table 9: First Stage Results

	I	II	III
	Baseline Model	Extended Model	Extended Model with United Way
Lawyer	-73.46	-72.78	-120.53
	(73.5)	(73.56)	(122.3)
Physician	-52.04	-43.89	-28.81
	(80.3)	80.80	(50.70)
Republican	218.37	67.23	30.21
	(67.6)	(84.06)	(45.8)
Democrat	295.11	323.08	306.88
	(61.7)	(75.81)	(74.8)
House value	516.8	203.8	187.29
	(93.3)	(123.39)	(122.0)
Mean income	-5.66	17.42	-0.01
	(83.9)	(83.91)	(82.3)
Membership	372.49	59.66	55.08
	(70.5)	(76.60)	(75.1)
Married	175.11	185.29	174.33
	(56.6)	(56.87)	(60.0)
Pittsburgh	111.2	115.63	120.05
	(62.2)	(62.18)	(63.3)
Years House	7.01	7.04	7.34
	(2.8)	(2.81)	(2.7)
United Way			226.37
			(74.1)
Lagged Giving	28.55	-40.79	-45.61
	(6.4)	(19.64)	(21.9)
log likelihood	20636.92	20363.51	20346.99

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

that case, there is no habit formation and individual donors solve repeated static decision problems. We find that standard likelihood ratio tests reject the hypothesis that $\eta = 0$. We thus conclude that accounting for state dependence improves the fit of our model. However, the improvements in the fit are smaller compared to those gained by including interactions between household and product characteristics.

Table 9 also reports the estimates that measure the impact of personal characteristics on giving. Most of the coefficients have the expected sign, but not all are statistically significant. 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 a 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, but only house value is typically significant.

We include a variable called "years lived in the house" which measures attachment to the Pittsburgh community. We find that households that have lived in the community for a longer period of time tend to give more. This could be due to stronger ties to the community. We also construct an indicator that equals one if the household lives in the City of Pittsburgh and zero otherwise. City residents may have a higher demand for the services offered by these charities than suburban residents who face higher commuting costs to attend events. We find that city residents also have stronger tastes for charitable giving than suburban households. Married couples donate larger amounts than singles. We also include two dummy variables indicating whether an individual in the household is a physician or a lawyer. These variables are typically insignificant.

We also estimate the coefficients of two dummy variables based on a household's political affiliations. We find that households that are politically active – especially those who donate to Democratic candidates – are more likely to support local cultural charities. Finally, we find that households that support the United Way typically donate more as well. The United Way offers few if any private benefits. Individuals who support the United Way may be less selfish or may have an active interest in public welfare or the good of the

local community. We can thus interpret the United Way dummy as a proxy that captures heterogeneity in warm glow or public spirits in the population.

Table 10: First Stage Results: Interactions

	I	II	III
	Baseline Model	Extended Model	Extended Model with United Way
Amount * House value		36.18	39.82
		(20.36)	(21.9)
Amount * Membership		330.75	327.94
		(16.29)	(15.6)
Amount * United Way			-10.76
			(8.5)
Dinner * Republican		225.49	177.74
		(69.74)	(67.6)
Dinner * Democrat		100.91	68.32
		(75.43)	(74.3)
Dinner * House value		127.83	113.43
		(100.24)	(98.4)
Dinner * United Way			222.26
			(68.8)
Event * Republican		67.12	68.19
		(23.94)	(23.7)
Event * Democrat		-19.21	-19.74
		(24.73)	(24.8)
Event * House value		138.17	123.03
		(24.74)	(24.6)
Event * United Way			8.99
			(6.5)

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

To get additional insights into the effectiveness of private benefits in fundraising and the importance of heterogeneity among donors, we turn to the estimates of the interaction effects reported in Table 10. The estimates reveal that household with higher personal wealth tend to donate more money than households with lower wealth. The same is true for households that are members of the board of trustees.

We also find that households that are politically active value invitations to special events

and dinner parties. This is especially true for Republicans for whom we consistently find large positive and significant effects. This finding is intriguing and raises some interesting research questions. We know, for example, that households that finance political campaigns often expect some favors from the politician that they support. There is a clear quid pro quo when supporting candidates that run for political office. The fact these types of households also place higher values on private benefits such as invitations to special dinner is consistent with a number of potential explanations. One of them focuses on the role that social networks play in the local society. One function of these charities may be to provide social networking opportunities to interested individuals.

Adding interactions between the observed characteristics and the United Way dummy does not alter the main findings. Note that the interactions with the amount given and invitations to special events are insignificant while the interaction with dinner parties is positive and significant. The other estimates are not substantially affected by the inclusion of these interactions. Again, these findings are consistent with the view that the United Way dummy can be interpreted as a variable that captures heterogeneity in "warm glow" in the population. However, even unselfish donors may appreciate some acknowledgment. Thus it may not surprising to find that the interaction with dinners is also positive and significant.

We consider the within sample fit of the model. Table 11 compares selected moments from the data with moments predicted by the baseline and the extended model. We focus on the number of donors, median and average donation levels for the data and a simulated sample of the same size. We find that our models fit the distribution of donors among charities and the median and average level of donations very well.[20] For the remainder of the empirical analysis we focus on the specification of the model reported in Column II.

Next we turn our attention to the second stage results. Table 12 reports the results of ordinary least squares and two stage least squares regressions. The IV estimators use

[20]For a discussion of different strategies for model validation see, among others, Keane and Wolpin (1997, 2007), Todd and Wolpin (2006) and Arcidiacono, Sieg, and Sloan (2007).

Table 11: 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.

characteristics of close substitutes as instruments for the total amount of donations. We use estimators with and without charity specific fixed effects.

Table 12: Second Stage Estimates

	IV no FE	OLS no FE	IV FE	IV no FE
Amount	-433	-397	-459	-265
	(30	(25)	(40)	(42)
Event	148	97	229	221
	(65)	(51)	(207)	(74)
Dinner	149	64	162	272
	(126)	(123)	(187)	(248)
Free Parking				782
				(721)

Estimated standard errors are reported in parenthesis.
FE refers to charity level fixed effects.

We find that the results are quite similar across IV and OLS specifications. In particular, the price effect is negative even when we use OLS. Thus in contrast to many applications in industrial organization, we do not obtain counter-intuitive price effects without the use of appropriate instruments. This finding may be due to the fact that the correlation between prices and unobserved product characteristics is weaker in our application.[21] We find that households value invitations to dinner parties as well as special events. Special tickets and token gifts are, surprisingly, not valued by donors. We also estimate a model that includes free parking as a private benefit. The point estimate suggests that households value free parking, 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 expect that one might be able to obtain more precise estimates in a larger sample. We conclude that our estimates are reasonable and consistent with the view that private benefits are important motives for philanthropic behavior.

[21] The R^2 of our first stage of the 2SLS estimation for our model without fixed effects is 0.52.

6 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 additional 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 the attractiveness of a dinner parties 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 (Weisbrod, 1988).

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. 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.

Recall that 19 percent of donors in our sample give to multiple charities. Their donations account for 54.3 percent of total donations To highlight the importance of these donors we solve our model assuming that each donor gives to, at most, one charity. The results are summarized in Table 13. We find that this restriction results in less donations, both measured by the average donations to charities and the number of donors. There are important differences among the charities. Larger charities such as the Symphony, Opera, and Carnegie Museum, more heavily rely on these donors than smaller charities.

Table 13: Policy Analysis: Only Give to One Charity

Charity		Number of Donors	Median Donations	Average Donations
Ballet	status quo	323	250	818.11
	only give to one	186	331	770.18
Carnegie M	status quo	804	1000	1930.97
	only give to one	476	975	1630.94
Children M	status quo	112	100	610.27
	only give to one	69	100	571.82
City Theater	status quo	374	100	363.64
	only give to one	227	100	386.44
Opera	status quo	369	500	2029.13
	only give to one	217	375	1446.20
Phipps	status quo	608	100	176.89
	only give to one	324	100	168.34
Public Theater	status quo	718	50	402.09
	only give to one	436	65	370.40
Symphony	status quo	443	1000	2161.40
	only give to one	252	1000	1730.13
WPC	status quo	832	100	343.99
	only give to one	518	100	316.03
Zoo	status quo	406	50	234.24
	only give to one	246	76	232.29

We then solve our model under the assumption that all charities eliminate all private benefits as incentives to attract donors. The results of this policy experiment are summarized in Table 14. For each charity, the first row reports the sample statistics. The second row shows the predictions of our model 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 are not significantly affected by eliminating private benefits. If anything, these charities 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 heavily rely on private incentives. The Phipps conservatory holds a single special event for their top donors. Our model predicts that this event raises approximately

Table 14: 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

$15,000 in additional donations which may not be enough to cover costs. 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 special events generate a large fraction of the annual donations. Perhaps most surprisingly, we find that the number of individuals that donate to multiple charities will 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.

It is important to distinguish the impact of altruism and private benefits on charitable giving, as argued by Rosen and Meer (2009). Based on the policy experiment above, we can compare the total donations to charities with and without providing private benefits. We

find that the contributions attributed to altruism or warm-glow are 48 percent for Ballet, 29 percent for Carnegie Museum, 87 percent for City Theater, 23 percent for Opera, 86 percent for Phipps, 28 percent for Symphony. Note that the Children Museum, the Public Theater, WPC, and Zoo, do not use private benefits. Hence all donations to those organizations are primarily driven by altruism or warm-glow.

7 Conclusions

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. A better understanding of the preferences of donors will allow these organizations to personalize the fundraising process and attract increased donations. To appeal to private donors, most organizations offer a variety of private benefits in addition to rewarding donors by printing their names in brochures, playbills, and annual reports. 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] We find that exclusive private benefits are particular popular among affluent donors and donors that are politically active.

We have distinguished in this paper between the motives for giving and the motives for participating in special, social events that are open to some donors. Our analysis primarily focused on the former and has less to say about the later. We have briefly discussed some possible explanations why donors may want to participate in these events. Social prestige or networking opportunities are the obvious candidates. Our 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. More research is needed to address these open questions.

Our methodological approach is flexible and has many other potential applications. Re-

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

sponding to concerns that simple discrete choice models do not match the reality (Ackerberg, Benkard, Berry, and Pakes, 2006), we have modeled the observed behavior as a repeated discrete choice with multiple choice occasions. Our approach extends to other settings where consumers demand multiple units of different products. Our methods can also be used to study topics outside of industrial organization. Consider, for example, demand models in recreational and environmental economics where individuals take multiple trips to different beaches which vary by amenities. Other applications arise in transportation economics when commuters use different means of transportation. Dubin and McFadden (1984) and Hanemann (1984) have proposed estimators for these types of model that allow for one discrete and one continuous choice. Our method allows consumers to choose more than one differentiated product. We can view the techniques proposed in this paper as extensions of their methods.

A Anonymous Donations

The number of donors listed as anonymous does not constitute a large percentage for any charity as shown in Table 15. The number of anonymous givers for the Pittsburgh Opera is the largest, but 87 of the 105 listed anonymously give between $120 and $249 which is the lowest tier.

Table 15: Anonymous Donors

	# of Anonymous Donors	% of Donors
Ballet	10	1.76%
Carnegie Museums	4	0.32%
Children's Museum	7	3.65%
City Theater	6	3.41%
Opera	105	15.89%
Phipps Conservatory	2	0.20%
Public Theater	66	5.75%
Symphony	34	4.84%
WPC	5	0.24%
Zoo	4	0.61%

B Private Benefits

The next two tables report the bundles of private benefits received in each tier for those organizations that actively use these benefits.

Table 16: Perks of Different Charity-Ties: Part 1

Charity-Tie	*Giving*	*Dinner*	*Ticket*	*Event*	*Gift*	*Autograph*	*Parking*
Ballet: Pointe Club	100	0	0	1	2	0	0
Master's Club	250	0	0	2	2	0	0
Choreographer's Club	500	0	0	3	2	0	0
Principal's Circle	1000	1	1	3	3	1	0
Artistic Director's Circle	2500	2	3	3	3	1	0
Chairman's Circle	5000	2	3	3	3	1	0
Carnegie museum:	500	0	3	3	1	0	0
	1000	0	4	4	1	0	0
1895 Society	2000	1	5	4	2	0	0
Curator's Society	2500	1	6	4	2	0	0
Director's Society	5000	3	6	4	2	0	0
President's Society	10000	5	7	4	3	0	1
Carnegie Founder's Society	25000	5	7	5	3	0	1
Symphony: Symphony Club	500	0	0	5	3	0	0
Encore Club	1000	0	2	5	3	0	0
Ambassador's Circle	2500	0	3	6	3	0	1
Director's Circle	5000	0	3	7	3	0	1
	7500	0	3	7	3	0	1
Guarantor's Circle	10000	1	4	7	3	0	1
Chairman's Circle	15000	1	4	7	3	1	1
	20000	1	4	7	3	1	1
Founder's Circle	25000	1	4	7	3	1	1
	50000	1	4	7	3	1	1
City Theater: Dressing Room	50	0	0	0	0	0	0
Green Room	100	0	0	0	0	0	0
Backstage	250	0	0	0	0	0	0
Wings	500	0	0	0	0	0	0
Center Stage	1000	0	0	0	0	0	0
New Play Circle	2500	2	2	0	0	1	1

Table 17: Perks of Different Charity-Ties: Part 2

Charity-Tie	*Giving*	*Dinner*	*Ticket*	*Event*	*Gift*	*Autograph*	*Parking*
WPC: Contributing	100	0	1	0	2	0	0
Patron	250	0	1	0	2	0	0
Benefactor	500	0	1	0	2	0	0
Leadership Circle	1000	0	3	0	2	0	0
	2500	0	3	0	2	0	0
	5000	0	3	0	2	0	0
	7500	0	3	0	2	0	0
	10000	0	3	0	2	0	0
	20000	0	3	0	2	0	0
Opera: Friend	150	0	1	1	0	0	0
Sponsor	250	0	1	3	0	0	0
Patron	500	0	2	5	1	0	0
Benefactor	1000	0	2	6	1	0	0
	3000	2	3	6	1	0	1
	5000	2	3	6	1	0	1
	10000	2	3	6	1	0	1
	25000	2	3	6	1	0	1
Galaxy	50000	2	3	6	1	0	1
Phipps:	50	0	0	0	0	0	0
Contributing Membership	100	0	2	1	3	0	0
Supporting Membership	150	0	2	1	4	0	0
Sustaining Membership	250	0	3	1	4	0	0
Benefactor Membership	500	0	3	1	5	0	0
Henry Phipps Associate	1000	1	3	1	5	0	0
	2000	1	3	1	5	0	0

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