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THE EFFECTIVENESS OF PRIVATE BENEFITS IN FUNDRAISING OF LOCAL CHARITIES*

BY HOLGER SIEG AND JIPENG ZHANG[1]

University of Pennsylvania, U.S.A.; Nanyang Technological University, Singapore

This article provides an empirical analysis of the role that private benefits play in explaining charitable donations to large cultural and environmental 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 10 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. Our policy simulations suggests that the composition of private benefits has a potentially large impact on donor behavior.

1. INTRODUCTION

Private donations are an important source of revenue for most charitable organizations, particularly symphonic orchestras, public theaters, and museums. Direct revenues from ticket sales and other activities rarely cover costs. Consequently, most charitable organizations need effective fundraising strategies to provide continued levels of service. Although 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.[2] The purpose of this article 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

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

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 of donors. Our preference specification also nests the special case in which all donations are driven almost exclusively by warm glow.

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 often standard market goods. In addition, each organization offers a second set of products that cannot 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 nonmarket goods that are offered by large cultural and environmental organizations.

Our modeling approach is rooted in the literature on characteristic models or differentiated products (Gorman, 1980; Lancaster, 1966). We interpret the amount of giving as the "price" associated with these product bundles. One component 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.[3]

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 have assembled using publicly available donor lists of 10 large cultural and environmental organizations in the Pittsburgh metropolitan area. By focusing on a larger number of charitable organizations, we generate 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 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 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 that 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 observed 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 article and model the observed behavior as a repeated discrete choice with multiple choice occasions.[5] In many applications, multiple choice occasions

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

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

[5] 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

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 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 fixed effects for each tier of giving. In the second stage, we then decompose these fixed effects into parts that can be explained by observed and unobserved characteristics.[6] We thus control for the fact that unobserved characteristics associated with each tier of giving are correlated with observed amounts 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 nonmarginal 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 warm glow varies substantially among the charities considered in the application.

The rest of the article is organized as follows. Section 2 of the article 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 and discusses the fit of the model. Section 6 explores the policy implications of our results. Conclusions are offered in Section 7.

2. THE DATA SET

In this section we discuss our sample and present some descriptive statistics. We document the importance of giving to multiple organizations. This discussion motivates the use of a multiple discrete choice model. Finally, we document the prevalence and importance of private benefits. This evidence suggests treating 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 10 large Pittsburgh

for online and print newspapers and develops new methods to deal with the fact that some products are potentially complements.

[6] Our estimation approach thus combines microlevel data with aggregate data and is similar in spirit to Berry et al. (2004) and Epple et al. (2006).

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, sociodemographic information from the U.S. Census, and political contribution data from the Federal Election Commission (FEC) 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 listed in at least one of the donor lists for our 10 charitable organizations. Consequently, the main focus of this article 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 articles 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 et al. (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. Hungerman (2005) uses a new panel data set of Presbyterian Church congregations.

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 10 organizations. This implies that less than 1% 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 simple logit model that predicts 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 becoming a donor.

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 10 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 want to be recognized in official publications.[7] Most donors are listed by name in each of the donor lists. The Allegheny County Real Estate database lists the name of the owners of a property.

[7] Appendix A.1 provides a table that list the number of anonymous donors by charity.

TABLE 1
DONATIONS BY ORGANIZATION

	# of Donors	Total Donations (in dollars)	Median (in dollars)	Average Standard (in dollars)	Deviation (in dollars)
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

The Federal Election Commission maintains a database that lists the names 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 differently in different organizations. Some appeared more formally printed (Mr. & Mrs. John A. Doe, Jr.), whereas 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 10 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.[8] A subset of individuals (54%) can be identified as owning property in Allegheny County.[9] The main part of the empirical analysis focuses on households in Allegheny County that are matched to the real estate database. We report descriptive statistics in Table 2 that summarizes 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 database 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 a household has owned the property, which we use to construct a variable that measures the "attachment" to the Pittsburgh metropolitan area.

[8] 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.

[9] Observations are lost because donors live outside the Allegheny county. The number of donors in our sample that are renters and live in Allegheny county appears to be small. The Western Pennsylvania Conservancy (WPC) attracts a large number of donors from outside of Allegheny county since its main attraction — Frank Lloyd Wright's Falling Water — is located an hour and a half outside of Pittsburgh in the Laurel Highlands. The WPC accounts for a large number of the dropped observations, as is evident from a comparison of the number of households reported in Table 1 with the ones in Table 2. We do not have access to real estate data outside of Allegheny county. Omitting all donors to the WPC does not affect our main results.

TABLE 2
PROPERTY VALUES OF DONORS

	Number	Average (in dollars)	Median (in dollars)	Standard Deviation (in dollars)
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

TABLE 3
GIVING TO PRESIDENTIAL CANDIDATES

	Bush Number of Donors	Kerry Number of Donors	Bush Total Amount (in dollars)	Kerry Total Amount (in dollars)
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

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. 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 the following: 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.[10] Table 3 reports the number of individuals who gave money to both the cultural organizations listed and the presidential campaigns of either G.W. Bush or J.F. Kerry. We will document in a later section of this article that these individuals are most receptive to private benefits such as special events and dinner parties.

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

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

Table 4
DONATIONS FROM CURRENT BOARD MEMBERS

	# of Contributing Board Members	Range (in dollars)	Median (in dollars)	Average	*SD* (in dollars)
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

Table 5
SPREAD OF GIVING TO MULTIPLE ORGANIZATIONS

# of Organizations	# of Donors	% of Individuals (%)	Sum of Donations (in dollars)	% 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

analysis.[11] The 10 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 10 organizations. Table 5 provides a detailed analysis of the distribution of donor types.

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, 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.

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

[11] 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 article, but view them as interesting topics for future research.

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

NOTES: The sample size is 495.

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						

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 generate 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 10 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 A.2 reports tables of private benefits for all tier of donations in our sample.

The prevalence of private incentives suggests modeling behavior as choices among bundles of goods. Each tier of giving can be viewed as a differentiated product that 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) suggested using a multiple discrete choice model. Previous applications of multiple discrete choice models assume that different individuals make simultaneous discrete decisions. Aggregating simple discrete choices 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 agent makes a sequence of discrete choices over time. The multiple 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 one year. The year consists of T time periods. 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.[12] 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 a vector of observed, time-invariant characteristics of the household, x, such as wealth, occupational status, party affiliation, marital status, and others. 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 $\epsilon_t = (\epsilon_{11t}, \dots \epsilon_{ILt})$ 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.

[12] 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% of the cases that households make donations twice to the same charity and in less than 0.4% of the cases at the same tier. As a consequence, there is little need to impose these constraints in estimation.

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 $\delta_t(s_t) = d_t$ that solves the following intertemporal 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 straightforward to allow for time-dependent observed characteristics such as income and impose the budget constraint.[13]

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.[14]

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 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.[15] 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 motivated 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

[13] 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.

[14] One advantage of using static models is that it is easier to account for unobserved heterogeneity in preferences. We discuss these issues in detail below.

[15] Our approach can be extended to deal with observed differences among charities or firms. Suppose there is a vector z that measures observed differences among charities. We can then interact individual characteristics with charity-level characteristics.

that case the coefficients α and β in Equation (6) must be different from zero and γ must be equal to 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:

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

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

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

For all other periods the conditional value function is defined as

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

The conditional value functions can thus be computed recursively.

Estimation of the model is not straightforward, 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 conditional choice probabilities in Equation (7) is not feasible. A feasible maximum likelihood estimator for this model must be based on the probabilities of observing the outcomes $d = (d_{11}, \ldots, d_{LI})$ conditional on the observed time-invariant household characteristics x and product characteristics, z. Let these probabilities be denoted by $P_t(d\,|x)$. These probabilities can be computed from the standard conditional probabilities in Equation (7) by integration over all possible choice sequences.

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

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

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

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 lists the six choice sequences that are elements in CS in this example.

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:

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

The algorithm in the example above can be generalized to deal with an 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 who 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 3 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 more than one large donation. The observed behavior of individuals who donate to multiple charities then allows us to identify η.

Observing the order of donations is not necessary for establishing identification. Note that η primarily affects the probabilities that are assigned to different feasible choice sequences. We do not observe the choice sequences. We need to aggregate over the choice sequences to generate the conditional choice probabilities. But the aggregation is linear in the conditional choice probabilities and η enters into the conditional choice probabilities in a highly nonlinear way. Aggregation will, therefore, not cause a lack of identification of η. Our empirical estimates support that assessment.

It is often hard to distinguish between state dependence and unobserved heterogeneity. Nevertheless, these two approaches rely on different assumptions about the functional form of the utility function and thus have different implications for conditional choice probabilities implied of the model and the shape of the likelihood function. In principle, one should be able to differentiate among these competing explanations. In practice, it might be hard due to small sample estimation problems and lack of power.[16]

We observe a sample of donors with size N. The probability of observing a vector of choice indicators, denoted by d_n, for a donor with observed characteristics x_n is given by

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

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

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

The parameters of the model can, therefore, be estimated using a Maximum Likelihood Estimator (MLE).

4.3. *The Second Stage.* The first stage of our algorithm yields an estimator of the product-specific fixed effects 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

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

Following Berry (1994) and Berry et al. (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 assumption justifies the use of observed product characteristics of other products, especially those of close substitutes, as instruments for the endogenous price. We can then estimate the remaining parameters of the model using a linear IV estimator.[17]

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

[16] If the model is misspecified and unobserved heterogeneity is important, one would expect that this heterogeneity might be captured by the state-dependence variable. For a discussion of these types of identification problems see also Gentzkow (2007).

[17] As part of our robustness analysis we also estimate the parameters using Ordinary Least Squares (OLS). Finally, we also explore models with charity-specific fixed effects α_i.

characteristics. We, therefore, impose the same identifying assumption as Berry (1994). We observe the full set of benefits that are explicitly offered by each charity. The unobserved characteristics are not directly chosen when the private benefits are determined. Maybe more importantly, unobserved characteristics such as reputation are only partially under the control of the charity. It thus seems reasonable to assume that the observed benefits are orthogonal to the unobserved characteristics. But this is ultimately an identifying assumption that cannot be tested within our framework.

Our findings raise the interesting question of why donors like invitations to special 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.[18]

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 fundraising strategies. These strategies may include private benefits or direct solicitations.[19]

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

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

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 $\sqrt{N}(\alpha^N - \alpha) \to N(0, \Omega)$. The formula in Equation (16) converges to standard IV formula if the sampling error of 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 10 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 an year.[20] 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 who 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.[21] We compute the value function for every

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

[19] The first article that modeled competition among charities is Rose-Ackerman (1982), who shows that competition can lead to excess fundraising. Weisbrod (1988) provides a detailed institutional analysis of the not-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 fundraising activities in game with two charities.

[20] 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.

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

Table 9
FIRST STAGE RESULTS

	I Baseline Model	II Extended Model	III Extended Model with United Way	IV Extended Model Arts Only
Lawyer	−73.46	−72.78	−120.53	−124.91
	(73.5)	(73.56)	(122.3)	(101.76)
Physician	−52.04	−43.89	−28.81	−102.92
	(80.3)	80.80	(50.70)	(120.97)
Republican	218.37	67.23	30.21	−168.50
	(67.6)	(84.06)	(45.8)	(125.34)
Democrat	295.11	323.08	306.88	381.03
	(61.7)	(75.81)	(74.8)	(102.80)
House value	516.8	203.8	187.29	−61.24
	(93.3)	(123.39)	(122.0)	(158.86)
Mean income	−5.66	17.42	−0.01	16.20
	(83.9)	(83.91)	(82.3)	(115.95)
Membership	372.49	59.66	55.08	−15.62
	(70.5)	(76.60)	(75.1)	(97.6)
Married	175.11	185.29	174.33	101.76
	(56.6)	(56.87)	(60.0)	(79.40)
Pittsburgh	111.2	115.63	120.05	121.32
	(62.2)	(62.18)	(63.3)	(93.67)
Years house	7.01	7.04	7.34	5.42
	(2.8)	(2.81)	(2.7)	(4.29)
United Way			226.37	−14.65
			(74.1)	(102.21)
Lagged giving	28.55	−40.79	−45.61	−171.18
	(6.4)	(19.64)	(21.9)	(28.7)
Log likelihood	20, 636.92	20, 363.51	20, 346.99	12, 224.56

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

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 et al. (1994), which we translated into FORTRAN 90.[22] 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 352 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 four of the most interesting specifications are reported in Table 9. Column I reports

[22] 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.

the estimates and standard errors for the baseline model. Column II reports the estimates of an extended model that 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. In Column IV we restrict the choice set to include only cultural charities.

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.[23]

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 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.

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 households 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.

[23] 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. Eighty-one percent of the households in our sample only give to one charity. The model thus needs to generate choice sequences if the outside option is the preferred choice in more than 80% 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 10
FIRST STAGE RESULTS: INTERACTIONS

	I Baseline Model	II Extended Model	III Extended Model with United Way	IV Extended Model Arts Only
Amount * House value		36.18	39.82	69.32
		(20.36)	(21.9)	(20.22)
Amount * Membership		330.75	327.94	321.20
		(16.29)	(15.6)	(17.00)
Amount * United Way			−10.76	−24.62
			(8.5)	(27.33)
Dinner * Republican		225.49	177.74	216.61
		(69.74)	(67.6)	(71.83)
Dinner * Democrat		100.91	68.32	84.49
		(75.43)	(74.3)	(78.69)
Dinner * House value		127.83	113.43	138.56
		(100.24)	(98.4)	(102.91)
Dinner * United Way			222.26	197.16
			(68.8)	(89.20)
Event * Republican		67.12	68.19	78.64
		(23.94)	(23.7)	(28.82)
Event * Democrat		−19.21	−19.74	−56.04
		(24.73)	(24.8)	(27.99)
Event * House value		138.17	123.03	102.72
		(24.74)	(24.6)	(29.96)
Event * United Way			8.99	86.54
			(6.5)	(27.41)

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

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 same types of households also place higher values on private benefits such as invitations to special dinner. This finding 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 whereas 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 be surprising to find that the interaction with dinners is also positive and significant.

It is possible that there is heterogeneity in tastes for the different charities that is not captured by the logit errors in our model. In particular, there may be heterogeneity in tastes between environmental and art charities. To test this hypothesis, we eliminated all environmental and wildlife charities from our choice set (the Zoo, the WPC, and the Phipps Conservatory). We then estimated our model using this smaller choice set.[24] This test is then in the spirit of Hausman and McFadden (1984), who suggested a similar procedure to evaluate whether the IIA

[24] Notice that we also dropped all observations in the sample that only donated to these three charities.

property holds in a logit model. We report the estimates for the arts-only specification in the last column of Tables 9 and 10. Comparing the estimates in column III with those in column IV, we find that the estimates are both qualitatively and quantitatively similar to our previous estimates that are based on the full sample. A small number of estimates change sign, but these estimates are typically not significant in both specifications. Most importantly, the key parameter estimates in Table 10 that capture the interactions between individual heterogeneity and donation characteristics are virtually unchanged. These findings suggest that unobserved heterogeneity in tastes between arts and environmental charities is not a substantial problem in this application.

The test above cannot rule out the possibility that there are other potential unobserved correlations in tastes that we have not modeled. One procedure to capture unobserved heterogeneity is to use discrete types as suggested by Heckman and Singer (1984). This approach has been successfully applied in dynamic discrete choice models since the work by Keane and Wolpin (1997). However, this approach is computationally expensive, even if one uses an EM algorithm in estimation (Arcidiacono et al., 2007). Alternatively, one can use a random coefficient logit type specifications of the utility function. But, this approach is even more difficult to implement in our application. It increases the state space requirements even more than the Heckman and Singer approach. In contrast to a simple static model, our approach requires the repeated numerical computation of value functions as part of a nested fixed-point algorithm.

Next, 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.[25]

Next, we turn our attention to the second stage results, which are based on the specification of the model reported in Column II of Table 9. Table 12 reports the results of ordinary least squares and two-stage-least squares (2SLS) regressions. 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.

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 counterintuitive 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.[26]

Households value invitations to dinner parties as well as special events.[27] 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.

6. POLICY ANALYSIS

6.1. *The Importance of the Composition of the Choice Set*. To get some additional insights into the role that private benefits play in attracting charitable donations, we conduct a number of

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

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

[27] We estimated additional versions of the model that are not reported in this article and found that special tickets and token gifts are, surprisingly, not valued by donors.

TABLE 11
GOODNESS OF FIT: ESTIMATED AND SIMULATED MOMENTS

		Mean	*SD*	# Donors	Median
Ballet	Data	818.11	1,201.94	323	250
	Model I	794.43	1,165.13	322	312
	Model II	829.10	1,215.98	321	381
Carnegie M	Data	1,930.97	3,709.59	804	1,000
	Model I	1,825.06	3,486.76	816	750
	Model II	1,897.89	3,704.03	802	850
Children M	Data	610.27	1,756.10	112	100
	Model I	624.72	1,699.90	109	103
	Model II	563.19	1,607.00	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	2,029.13	5,340.50	369	500
	Model I	2,130.59	5,454.45	379	462
	Model II	1,977.20	5,276.78	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	1,054.36	718	50
	Model I	392.63	1,007.05	713	100
	Model II	386.12	1,018.65	711	90
Symphony	Data	2,161.40	4,213.06	443	1,000
	Model I	2,180.97	4,268.37	444	1,000
	Model II	2,136.88	4,109.60	445	1,000
WPC	Data	343.99	1,272.57	832	100
	Model I	356.47	1,355.26	837	100
	Model II	355.82	1,314.65	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

NOTES: The simulated moments are averages over 20 simulated samples with 3,512 observations.
Model I has no interactions whereas model II accounts for interactions.

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)

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

counterfactual 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

TABLE 13
POLICY ANALYSIS: ONLY GIVE TO ONE CHARITY

Charity	Policy Regime	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	1,000	1,930.97
	only give to one	476	975	1,630.94
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	2,029.13
	only give to one	217	375	1,446.20
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	1,000	2,161.40
	only give to one	252	1,000	1,730.13
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

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 party depends on the overall appeal of the charity. These simulations also suggest that charities may not behave as revenue maximizers. Although this finding may be surprising at first sight, there is some evidence in the literature that supports this view of charitable organizations (Weisbrod, 1988).

We do not know how much money the organizations in our sample spend when organizing a dinner party or a special event. As a consequence we do not perform a complete benefit–cost analysis in the article. But the costs for hosting a special event such as a meeting with the conductor or the director of a show are probably small. Dinners are typically catered by an outside company and are thus more expensive than other social functions. The opportunity costs of having a free, special performance are the forgone ticket revenues.

Next, we consider the impact of changes in the choice set. Looking at these changes is interesting since it helps us 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 $2,000–2,500 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% with a reduction in total donations of approximately $50,400.

Recall that 19% of donors in our sample give to multiple charities. Their donations account for 54.3% 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 fewer donations, measured both 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 14
POLICY ANALYSIS: A BAN OF PRIVATE BENEFITS

Charity	Policy Regime	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	1,000	1,930.97
	no private benefits	402	500	1,116.73
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	2,029.13
	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	1,000	2,161.40
	no private benefits	165	1,000	1,627.12
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

6.2. *The Importance of Private Benefits*. We can 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.[28]

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 top donors. Our model predicts that this event raises approximately $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. Note that we do not

[28] When we eliminate private benefits, we do not reduce the number of elements in the choice set. We keep all the tiers of each charity and just remove private benefits. Each tier has a separate logit error. Alternatively, we could assume that each charity only offers one tier of donations. Since each donation tier has a separate logit error, charities that offered multiple tiers would be less attractive after the policy change under this alternative scenario. For a discussion of alternative approaches for dealing with the logit errors in these types of simulations see, Ackerberg and Rysman (2005) and Gowrisankaran and Rysman (2009).

eliminate the benefit of being listed in the program, which may provide social prestige. We find that the contributions attributed to altruism or warm glow are 48% for Ballet, 29% for Carnegie Museum, 87% for City Theater, 23% for Opera, 86% for Phipps, and 28% for Symphony. Note that the Children's 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 charitable 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.[29] We find that exclusive private benefits are particular popular among affluent donors and donors that are politically active.

We have distinguished in this article between the motives for giving and the motives for participating in social events that are open to select donors. Our analysis primarily focuses on the former and has less to say about the later. We have briefly discussed some possible explanations for 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.

The main sample used in estimating our model is random conditional on giving to at least one of the 10 charities. It is, therefore, straightforward to interpret our results. The results of our article cannot be used to infer anything about the behavior of those households that did not support one of these charities. Studying these participation decisions is an important area for future research.

Our methodological approach is flexible and has many other potential applications. 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 article as extensions of their methods.

APPENDIX

A.1. *Anonymous Donations*. The number of donors listed as anonymous does not constitute a large percentage for any charity as shown in Table A1. 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.

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

TABLE A1
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

A.2. *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 A2
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	1,000	1	1	3	3	1	0
Artistic Director's Circle	2,500	2	3	3	3	1	0
Chairman's Circle	5,000	2	3	3	3	1	0
Carnegie Museum:	500	0	3	3	1	0	0
	1,000	0	4	4	1	0	0
1895 Society	2,000	1	5	4	2	0	0
Curator's Society	2,500	1	6	4	2	0	0
Director's Society	5,000	3	6	4	2	0	0
President's Society	10,000	5	7	4	3	0	1
Carnegie Founder's Society	25,000	5	7	5	3	0	1
Symphony: Symphony Club	500	0	0	5	3	0	0
Encore Club	1,000	0	2	5	3	0	0
Ambassador's Circle	2,500	0	3	6	3	0	1
Director's Circle	5,000	0	3	7	3	0	1
	7,500	0	3	7	3	0	1
Guarantor's Circle	10,000	1	4	7	3	0	1
Chairman's Circle	15,000	1	4	7	3	1	1
	20,000	1	4	7	3	1	1
Founder's Circle	25,000	1	4	7	3	1	1
	50,000	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	1,000	0	0	0	0	0	0
New Play Circle	2,500	2	2	0	0	1	1

TABLE A3
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	1,000	0	3	0	2	0	0
	2,500	0	3	0	2	0	0
	5,000	0	3	0	2	0	0
	7,500	0	3	0	2	0	0
	10,000	0	3	0	2	0	0
	20,000	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	1,000	0	2	6	1	0	0
	3,000	2	3	6	1	0	1
	5,000	2	3	6	1	0	1
	10,000	2	3	6	1	0	1
	25,000	2	3	6	1	0	1
Galaxy	50,000	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	1,000	1	3	1	5	0	0
	2,000	1	3	1	5	0	0

REFERENCES

ACKERBERG, D., AND M. RYSMAN, "Unobservable Product Differentiation in 2 Discrete Choice Models: Estimating Price Elasticities and Welfare Effects," *RAND Journal of Economics* 36 (2005), 771–88.

——,L. BENKARD, S. BERRY, AND A. PAKES, "Econometric Tools for Analyzing Market Outcomes," in J. Heckman and E. Leamer, eds., *Handbook of Econometrics, Volume 6* (Amsterdam: Elsevier-North Holland, 2006, pp. 4171–276).

ANDREONI, J., "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence," *Journal of Political Economy* 97 (1989), 1447–58.

——, "Impure Altruism and Donations to Public Goods: A Theory of Warm Glow Giving," *Economic Journal* 100 (1990), 464–77.

——, AND A. PAYNE, "Do Government Subsidies to Nonprofits Crowd Out Giving or Fundraising?" *American Economic Review* 93 (2003), 792–812.

ARCIDIACONO, P., H. SIEG, AND F. SLOAN, "Living Rationally Under the Volcano? Heavy Drinking and Smoking Among the Elderly," *International Economic Review* 48 (2007), 37–65.

AUTEN, J., H. SIEG, AND C. CLOTFELTER, "Charitable Giving, Income and Taxes: An Analysis of Panel Data," *American Economic Review* 92 (2002), 371–82.

BERRY, S., "Estimating Discrete-Choice Models of Product Differentiation," *Rand Journal of Economics* 25 (1994), 242–62.

——, J. LEVINSOHN, AND A. PAKES, "Automobile Prices in Market Equilibrium," *Econometrica* 63 (1995), 841–90.

——, ——, AND ——, "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Vehicle Market," *Journal of Political Economy* 112 (2004), 68–104.

BURASCHI, A., AND F. CORNELLI, "Donations," Working Paper, London Business School, 2003.

CLOTFLETER, C., *Federal Tax Policy and Charitable Giving* (Chicago, IL: Chicago University Press, 1985).

DUBE, J., "Product Differentiation and Mergers in the Carbonated Soft Drink Industry," *Journal of Economics, Management and Strategy* 14 (2005), 879–904.

DUBIN, J., AND D. MCFADDEN "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption," *Econometrica* 52 (1984), 345–62.

Ekeland, I., J. Heckman, and L. Nesheim, "Identification and Estimation of Hedonic Models," *Journal of Political Economy* 112 (2004), S60–101.

Epple, D., "Hedonic Prices and Implicit Markets: Estimating Demand and Supply Functions for Differentiated Products," *Journal of Political Economy* 95 (1987), 59–80.

——, R. Romano, and H. Sieg, "Admission, Tuition, and Financial Aid Policies in the Market for Higher Education," *Econometrica* 74 (2006), 885–928.

Gentzkow, M., "Valuing New Goods in a Model with Complementarities: Online Newspapers," *American Economic Review* 97 (2007), 713–44.

Glazer, A., and K. Konrad, "A Signaling Explanation for Charity," *American Economic Review* 86 (1996), 1019–28.

Goffe, W., G. Ferrier, and J. Rogers, "Global Optimization of Statistical Functions with Simulated Annealing," *Journal of Econometrics* 60 (1994), 65–99.

Gorman, W., "A Possible Procedure for Analyzing Quality Differentials in the Egg-Market," *Review of Economic Studies* 47 (1980), 843–56.

Gowrisankaran, G., and M. Rysman, "Dynamics of Consumer Demand for New Durable Goods," Working Paper, Boston University, 2009.

Hanemann, M., "Discrete Continuous Models of Consumer Demand," *Econometrica* 52 (1984), 541–61.

Harbaugh, W., "What Do Donations Buy? A Model of Philanthropy Based on Prestige and Warm Glow," *Journal of Public Economics* 67 (1998), 269–84.

Hausman, J., and D. McFadden, "Specification Tests for the Multinomial Logit Model," *Econometrica* 52 (1984), 1219–40.

Hendel, I., "Estimating Multiple Discrete Choice Models: An Application to Computerization Returns," *Review of Economic Studies* 66 (1999), 423–46.

Heckman, J., and B. Singer, "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models of Duration Data," *Econometrica* 52 (1984), 271–320.

Hobbes, T., "*Leviathan or The Matter, Forme, Power of a Commonwealth Ecclesiasticall and Civil*," (London: Andrew Crooke, 1651).

Huck, S., and I. Rasul, "Comparing Charitable Fundraising Schemes: Evidence from a Natural Field Experiment," Working Paper, University College London, 2008.

Hungerman, D., "Are Church and State Substitutes: Evidence from the 1996 Welfare Reform," *Journal of Public Economics* 89 (2005), 2245–67.

Karlan, D., and J. List, "Does Price Matter in Charitable Giving? Evidence from a Large-Scale Natural Field Experiment," Working Paper, University of Chicago, 2007.

Keane, M., and K. Wolpin, "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence," *Review of Economics and Statistics* 76 (1994), 648–72.

——, and ——,"The Career Decisions of Young Men," *Journal of Political Economy* 105 (1997), 473–523.

——, and ——, "Exploring the Usefulness of a Non-Random Holdout Sample for Model Validation: Welfare Effects on Female Behavior," *International Economic Review* 48 (2007), 1351–78.

Kim, J., G. Allenby, and P. Rossi, "Modeling Consumer Demand for Variety," *Marketing Science* 21 (2002), 229–50.

Kingma, B., "An Accurate Measurement of the Crowd-Out Effect, Income Effects, and the Price Effect to Charitable Contributions," *Journal of Political Economy* 97 (1989), 1197–207.

Lancaster, K., "A New Approach to Consumer Theory," *Journal of Political Economy* 74 (1966), 132–57.

List, J., and D. Lucking-Reiley, "The Effects of Seed Money and Refunds on Charitable Giving: Experimental Evidence from a University Capital Campaign," *Journal of Political Economy* 110 (2002), 215–33.

Manzoor, S., and J. Straub, "The Robustness of Kingma's Crowd-Out Estimate: Evidence from New Data on Contributions to Public Radio," *Public Choice* 123 (2005), 463–76.

McFadden, D., "The Measurement of Urban Travel Demand," *Journal of Public Economics* 3 (1974), 303–28.

Randolph, W., "Dynamic Income, Progressive Taxes, and the Timing of Charitable Contributions," *Journal of Political Economy* 103 (1995), 709–38.

Ribar, D., and M. Wilhelm, "Altruistic and Joy-of-Giving Motivations in Charitable Behavior," *Journal of Political Economy* 110 (2002), 425–57.

Romano, R., and H. Yildrim, "Why Charities Announce Donations: A Positive Perspective," *Journal of Public Economics* 81 (2001), 423–47.

Rose-Ackerman, S., "Charitable Giving and Excessive Fundraising," *Quarterly Journal of Economics* 97 (1982), 193–212.

Rosen, H., and J. Meer, "Altruism and the Child-Cycle Alumni Donations," *American Economic Journal: Economic Policy* 1 (2009), 258–86.

Rust, J., "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurchner," *Econometrica* 55 (1987), 999–1033.

Todd, P., and K. Wolpin, "Assessing the Impact of a School Subsidy Program in Mexico: Using Experimental Data to Validate a Dynamic Behavioral Model of Child Schooling and Fertility," *American Economic Review* 96 (2006), 1384–417.

Vesterlund, L., "The Information Value of Sequential Fundraising," *Journal of Public Economics* 87 (2003), 627–57.

Weisbrod, B., "*The Nonprofit Economy*" (Cambridge, MA: Harvard University Press, 1988).