The Joy of Giving and the Greater Joy of Receiving: Estimating a Multiple-Discrete Choice Models of Philanthropic Behavior*

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Abstract

This paper investigates different motives for philanthropic behavior: local public good provision, altruism, warm glow, and tangible private benefits. We develop a new framework for estimating multiple discrete choice models to quantify the importance of these motives on giving patterns. We estimate our model using a unique data set of donor lists to the ten largest cultural and environmental charitable organizations in the Pittsburgh metropolitan area. We find that altruism and warm glow play a large role in explaining observed giving patterns. However, private benefits that provide social status for donors also provide important incentives for donors to support their favorite charities.

KEYWORDS: Charitable Donations, Voluntary Public Good Provision, Altruism, Incentive Effects of Private Benefits, Multiple Discrete Choice Estimation.

JEL classification: C33, D12, H24.

1 Introduction

Most charitable organizations receive revenues from three sources. The first consists of contributions from governments, businesses, and individuals that are usually made in the form of yearly donations. These are applied to either the operating budget or the endowment which provides a second source of yearly income. Third, some organizations may provide services that are sold in the market place. This is especially true for large cultural organizations such as symphonic orchestras, public theaters, and museums. Direct revenues from ticket sales and other activities account for only a fraction of the total revenues.[1] Visitors are charged a fraction of the amount necessary to provide the services of these organizations. As a consequence most of these charitable organizations rely heavily on private donations.

The economic literature on philanthropic behavior has focused on three main causes that motivate charitable giving. The first is donating out of concern for public good provision.[2] Individuals behave in a non-cooperative, strategic way and determine their voluntary levels of donations taking donations of other individuals into consideration. Broadly speaking, individuals feel that their contributions will make an impact and improve the level of services provided by the charity.[3] In our application, we find that marginal contributions from individuals are small compared to the budgets of most large cultural organizations. For example, the median donation in our sample for the Pittsburgh Symphony or the Carnegie Museum is $1,000. The Pittsburgh Symphony had an endowment of approximately $110 million dollars and an annual budget of approximately $25 million in 2004. The value of the endowment of the Carnegie Museum has fluctuated in recent year between $180 and $250 million dollars. A single donor – with the exception of a handful of extremely wealthy patrons – is not critical for the vast majority of organizations.

Browning, Chiappori, and Lechene (2006) show that the canonical model of voluntary

[1] For example, the Western Pennsylvania Conservancy received only 31% of its total revenues from admission fees to Frank Lloyd Wright's Fallingwater in 2003.

[2] See Warr (1982), Roberts (1984) and Bergstrom, Blume, and Varian (1986).

[3] Closely related to these models are models based on pure altruism in which individuals care about other individuals' utilities.

public good provision implies that individuals will contribute to at most one public good. As we discuss below in detail, this prediction is inconsistent with our data which show that a significant fraction of individuals support more than three organizations in our sample. A small number of individuals support nine of the ten organizations. These findings suggest that other motives may be equally, if not more, important.

Andreoni (1989, 1990) has suggested that charitable donations can be attribute to a joy-of-giving or warm-glow motive. By donating to causes in which individuals receive no explicit benefit, they gain satisfaction from knowing that they contributed to a worthy cause. There are some empirical tests of these motives in the related literature. Most of these tests are based on the crowd-out hypothesis which claims that individuals are likely to donate less money if more funds are provided by the government. The empirical evidence regarding the validity of this hypothesis is mixed. Kingma (1989) analyzes donations to local public radio stations and finds support for the crowd-out hypothesis. Manzoor and Straub (2004) replicate the results of Kingma and find that the results are not robust to the use of newer data. Ribar and Wilhelm (2002) study donations to a large number of international relief organizations and find little evidence of a crowd-out effect.Andreoni and Payne (2003) find strong evidence in favor of crowd-out in their analysis.

A third motive for charitable giving is presented by Harbaugh (1998) who argues that donors receive tangible or intangible private benefits from their gifts. In the word of Thomas Hobbes: "no man giveth but with intention of good to himself" (Hobbes, 1651). One goal of this study is to attempt to document and measure the private motivations for giving. The private benefits can be broken down into a number of categories. Charitable donations are tax deductible. Thus donating to one's favorite cause effectively lowers the total tax burden of an individual. This benefit has been well documented in the past and higher marginal tax rates typically induce individuals to donate more money to charities.[4] Many of the websites for the organizations in our sample enumerate the potential tax benefits on

[4]There is a large empirical literature that has estimated the tax price elasticity of charitable giving. For surveys of the earlier literature see, for example, Clotfleter (1985) or Steinberg (1990). Recent studies include Randolph (1995) and Auten, Sieg, and Clotfelter (2002).

their on-line contribution form.

Individuals also get material benefits from donating to these organizations. Charities offer potential donors different private benefits associated with tiered levels of giving. Typical private benefits range from 10% discounts at the gift shop, to the performers' autographs, to premium seating, to free valet parking, to private tours, to exclusive dinners and parties. Moreover, individuals who donate receive a certain amount of social standing in the community. Most donors use their full names and professional titles. Judging by the way people chose to have their names listed in the brochures, they seek to make it clear who they are by using middle initials, suffixes, and professional titles. For example, there are very recognizable names on this list of sports stars, politicians, and business leaders who have an incentive to improve their reputation in the community.[5] Finally, individuals can effectively buy influence in an organization by being appointed to the board of trustees. All ten organizations list the board members and we observe how much they donate to maintain this designation.

To capture the different incentives for giving we develop and estimate a new model. Our approach differs from previous approaches in at least three ways. First, we take a market approach and focus on giving to ten large cultural and environmental local charities in Pittsburgh. One of the key features of our data set is that a significant number of individuals support multiple charities with their donations. We observe 495 individuals in our sample that give to three or more charities. Simple discrete or discrete-continuous choice models cannot be used to explain this type of behavior. Our empirical approach builds on the literature on multiple-discrete choice models that are notoriously difficult to estimate. We follow Hendel's (1999) pioneering approach and model the observed behavior as a repeated discrete choice model with multiple choice occasions.[6]

In Hendel's (1999) application multiple choice occasions arise because a number of dif-

[5] Buraschi and Cornelli (2003) also document these private benefits for donors of the English National Opera.

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

ferent agents make simultaneous decisions. In our model, we focus on one decision maker who faces a sequential decision problem. As a consequence, is 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 the previous levels of charitable giving influences contemporary behavior. To capture this type of habit formation, we assume that past charitable behavior is a state variable in our model and has a direct impact on current period utility. We therefore adopt a dynamic model to allow for state dependent choice sequences using dynamic programing techniques along the lines suggested by Rust (1994).

Estimating our model is challenging and requires some significant departures from standard dynamic discrete choice estimators.[7] Recall that the main purpose of the dynamic specification is to generate a multiple-discrete choice model that is essentially a one-period model. Since we do not observe behavior at each choice occasion, we need to integrate over all feasible choice sequences to derive a well-specified likelihood function. To our knowledge our study is the first paper that combines DP techniques with repeated discrete choice techniques to derive an empirical model of multiple discrete choices. We face two types of computational problems in estimation. First, the state space in our model is large since we control for observed heterogeneity along many dimensions and the main state variable is continuous and cannot be easily approximated on a coarse grid. Second computing the likelihood function requires integration over all feasible choice sequences. To deal with the computational complexity, we use parallel programming techniques and implement our estimator on a supercomputer provided by the Pittsburgh Supercomputing Center.

Finally, our approach also differs from previous empirical studies that have focused on charitable donations. In contrast to earlier empirical studies we adopt a differentiated product approach. The amount of giving can be interpreted as the "price" associated with a given bundle of benefits. Each tier or level of giving to a specific charity can be characterized by a vector of attributes. We thus adopt a characteristics approach based on Gorman (1980) and Lancaster (1966). Berry (1994) highlights the importance of unobserved

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

product characteristics and the potential endogeneity between prices (amount of giving) and unobserved product characteristics. Goldberg (1995) emphasizes the importance of controlling for observed and unobserved heterogeneity in modeling substitution patterns. Our two stage estimation approach is based on micro data and is thus similar in spirit to Berry, Levinsohn, and Pakes (2004). It is also consistent with the notion that unobserved characteristics associated with each tier of giving are correlated with observed levels of giving. There are 76 different combinations of levels of giving and private benefits associated with the ten charities. Moreover, there is variation in private benefits, holding giving constant. This variation arises because different charitable organization pursue different tactics to raise funds.[8] Organizations like the Opera and Symphony have much different reward structures than the Zoo or the Children's Museum. For example, the Opera and Symphony award explicit private benefits associated with each level of giving, whereas the Zoo and Children's Museum do not. It is this observed variation of private benefits at constant levels of giving that helps us separate the joy-of-giving from the joy-of-receiving motive.

The core of the empirical analysis is based on a unique data set that we assembled using publicly available donor lists of ten large cultural and environmental organizations in the Pittsburgh metropolitan area.[9] Our findings suggest that a large number of households donate money to these charities, some individuals in our sample donate to as many as eight out ten charities. Much of this giving is clearly unrelated to potential private benefits and rewards. Our findings thus support Andreoni's initial conjecture that altruism and warm-glow are important motives for charitable giving. However, we also find that households value private benefits that are affiliated with high social prestige such as invitations to dinner parties and special events. Small token gifts and extra tickets are not valued by most individuals. Individuals that are members of the board of a charity give substantially

[8]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 donor have imperfect information on charities' quality.

[9]Romano and Yildrim (2001) provide a theoretical model of giving that include warm-glow or snob appeal and show that it can be in the interest of the charity to announce donations. As we show below all charities in our sample announce donations and only a very small fraction of donors prefers to be listed anonymously.

higher amounts. This is consistent with the view that individuals value the visibility and potential power that comes with these appointments. Individuals that financially support political candidates are also more likely to be generous donors and value the private benefits associated with social functions. Our policy simulations indicate that charities have strong incentives to design a private benefit schedule that allocates different private benefits to tiers of giving to maximize donations.

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

We have assembled the data set from a number of publicly available sources. First, we use annual reports, playbills, and programs for ten large Pittsburgh cultural and environmental organizations[10] as well as the United Way. These donor lists are from the 2004-2005 donation cycle. Second, we use data from the Allegheny County Real Estate database. Third, we use socio-demographic information from the U.S. Census. Forth, we use donations to political candidates from the Federal Election Commission database. Finally, we obtained a list of the names of every physician and lawyer who practices in Allegheny County from the Allegheny County Medical Society and the Allegheny County Bar Association. We have merged these five different databases using an algorithm described in detail below.

The main sample used in this analysis is strictly speaking a choice-based sample. We

[10] 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

do not include individuals in our sample that do not show up any of the donor lists. This approach is common in this literature. As a consequence, the main focus of the analysis of this paper and most previous studies is on the sub-population of individuals that are active donors. However, we also created a random sample of 10,000 households in Allegheny County. Using this sample, we have estimated a number of logit models to predict who becomes a donor. We find that married couples, physicians, and lawyers are significantly more likely to be donors. However income, housing values, and years lived in the house do not seem to be systematically correlated with being a donor. We also find that that those who give to either political party are more likely to donate to one of these organizations. The full results are reported in Appendix A of this paper.

The donor lists do not determine the exact gift amount, instead they only identify the range of giving associated with each tier. For some calculations in this section we use the lower-bound on the giving ranges as the amount of giving since most individuals tend to give at those lower levels as reported by 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. The total giving amounts to \$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 bulk of donors give in the lowest or second-lowest range that these organizations provide.

Donors apparently do not mind being listed in the official publications. Only a small fraction of the donors prefers anonymity to publicity. This result is consistent with other evidence reported below that social prestige and private benefits are powerful explanations for the observed behavior. We consolidate the donor lists and match up names that are the same. These names are then cross-referenced with data from the Allegheny County Real Estate database, the U.S. Census, and Federal Election Commission database. We can match most individuals, with the exception of individuals with extremely common first and last names. Matching our data to professional lists, we find that 391 physicians and 500 lawyers gave money to at least one of the ten Pittsburgh cultural organizations.

Table 1: Donations by Organization

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

To determine the housing wealth of donors in our sample, we match the donors to the Allegheny County Real Estate Assessment website.[11] A subset of individuals (54 %) can be identified as owning property in Allegheny County.[12] The main part of the empirical analysis focuses on households in Allegheny County that could be 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.

We find that the Carnegie Museum and the Pittsburgh Symphony attracts donors with the highest average housing values. Maybe more surprising is the finding that donors to the Children's Museum have the third highest housing wealth. The Western Pennsylvania Conservancy and the City Theater have less wealthy donors. The real estate data base also contains the address of the house allowing 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

[11]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.

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

Table 2: Property Values of Donors

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

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 different charity that largely funds smaller charities that provide social and community outreach services. It also provides few private benefits besides the social visibility. Most donations to the United Way are, therefore, primarily driven by the warm-glow that comes with knowledge of supporting social charities. We find that 551 people who gave to one of the cultural charities also gave to the United Way as well. The minimum amount to be listed in its publication was $1,000, so the number could in fact be much higher. The maximum gift was $1,000,000 with an average gift among these individuals was $10,282 with a standard deviation $73,615.

The individuals in our sample also contributed heavily to political candidates in the 2004 elections. Of the 6,499 individual donors, 736 contributed to either the presidential campaigns of George W. Bush and John Kerry, the senatorial campaigns of Arlen Specter and Joseph Hoeffel, congressional campaigns in nearby districts, or the Republican and Democratic parties.[13] Table 3 reports the number of individuals who gave money to both the cultural organization listed and the presidential campaigns of either Bush or Kerry.

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

Table 3: Giving to Presidential Candidates

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

We find that a large number of individuals that support the cultural and environmental charities in our sample are also politically active, supporting their favorite candidates and parity.[14]

Table 4: Spread of Giving to Multiple Organizations

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

One of the striking features of our data is that many individuals donate money to

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

multiple causes. For example, 495 of the 6,499 individual donors could be identified as giving to three or more of our ten organizations. Table 4 provides a detailed analysis of the distribution of donor types. We find that the individuals who contributed to three or more organizations have different characteristics than the average donor. Of the 392 who were found in the Allegheny County Real Estate Registry, their average property value was $425,659, larger than the $292,417 of an average donor. Of the 392 with Allegheny County housing entries, 327 of them live in the city of Pittsburgh. Their average combined giving amounted to $4,630 compared to $739 for those donors who gave to only one or two organizations. They were also much more likely to donate to a political candidate, 44 % for the donors who gave to three or more places compared to 17 % for all donors. To get additional insights into the relative ranking of each organization, Table 5 reports the number of donors that gave the first, second, or third largest amounts to each organization with ties counted on the same level.

Table 5: Gift Size Ordering and Frequency among Multiple Donors

	First Choice	Second Choice	Third Choice	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 gave, for example, equal amounts to a large subset of these organizations.

Table 5 also shows in the last column the percentage of the 495 multiple donors who gave 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 because they receive less money.

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

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

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

Another potential private benefit associated with giving is the possibility of being appointed to the Board of Trustees. These individuals can gain the prestige as well as a degree

Table 7: Donations from Current Board Members

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

of influence in the organization.[15] All of these organizations have a Board of Trustees and list the names of the trustees in the same piece of literature as the names of donors. The board members who were also listed in the donation section are characterized in Table 7 with the minimum, maximum, median, and average donation of a board member along with the standard deviations.

3 A Discrete Choice Model of Charitable Giving

In this section we formalize the main ideas and provide a model of individual behavior that can explain donations to multiple organizations. We assume that there is a finite number of charitable organizations to which a donor can potentially make a contribution. Each donor makes decisions over the course of a year. The year consists of T time periods. Each donor is a characterized by a time invariant 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

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

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

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

It is plausible to assume that the willingness to donate is influenced by the total amount of previous giving.[16] 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.[17] 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.

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

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

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

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

The model can explain multiple donations to different charities in the same year. This is the central feature of the data that needs to be explained. Moreover, the model is consistent with the notation that individuals may donate to a charity because of warm glow.[18] In addition, the model incorporates the fact that the amount that a person is willing to donate to an organization may depend on the private private benefits associated with each level of giving, as well as his previous donations to other organizations.

4 Estimation

4.1 A Parametrization

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

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

where the "mean utility" associated with product il is denoted by α_{il}. The parameter δ captures the state dependence in our model and measures that the (dis-) utility of having made donations before. ψ measures the impact of observed heterogeneity on public giving. With a slight abuse of notation, we also include interactions between individual characteristics and observed product characteristics. 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:

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

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

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

such as social prestige.

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

4.2 The First Stage

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

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

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

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

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

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

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

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 that is based on the choice probabilities in equation (7) is not feasible.

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

To illustrate this procedure consider the following simple example. Let us assume that 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

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

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. It is then fairly straight forward to verify that the following six sequences of choices are elements in CS:

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

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

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

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

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

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

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

There are ten charities in our applications with 77 different levels of giving (including the outside option.) We assume that each choice occasion corresponds to one quarter of a year.[19]. We primarily restrict our attention to four choice occasions for computational reasons. We need to characterize all feasible choice sequences in the estimation procedure and then integrate over all feasible paths to compute the likelihood function.[20]

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 possible state of the world using a backward recursion algorithm.

We use the Simulated Annealing Method to compute the MLE. The main advantage of the Simulated Annealing Method is that its performance dominates simpler algorithms such as the Simplex algorithm. The main drawback is that it is computationally more expensive to use than the Simplex Method. The simulated annealing code was obtained from Goffe, Ferrier, and Rogers (1994) which we translated into FORTRAN 90.[22] Finally, we use numerical derivatives to calculate asymptotic standard errors based on the outer

[19]We also experimented with a model with six choice occasions. We found that the results are qualitatively similar to the ones reported in the next section.

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

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

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

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 3512 observations takes between 12 and 36 hours of computing time using 300 processors. Another advantage of using a super computer is that we can check for global convergence. Conducting these test would be very time consuming process on an ordinary machine. Following Goffe et al. (1994) we change the starting point and random number generators, and investigate whether the algorithm converges to the same estimates. These experiments show that our estimates are robust and that we obtain the global maximum of the likelihood function.

4.3 The Second Stage

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

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

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

5 Empirical Results

5.1 First Stage

We have estimated two versions of the model. Our baseline model does not have interactions between individual characteristics and product characteristics. The extended model allows for those interactions. Moreover, we have estimated each model using two different data sets. The first data set only contains the ten cultural and environmental charities. The second data set also includes the United Way contributions. Private Benefits are measured by two variables which measure invitations to exclusive dinner parties and special gifts. We also estimated models that include special tickets and token gifts. However, we found that the coefficients of these benefits were insignificant in almost all our specifications. We therefore focus on the private benefits that convey some social status and which seem to be the most relevant.[23]

We estimate each version of our the model using a sample of 3512 observations. The maximum likelihood estimates and corresponding standard errors for each parameter are shown in Table 8. Column I of the table reports the estimates and standard errors for the based line model and the data set which only includes the 10 cultural charities. Column II estimates the same model, but includes the data on the United Way contributions. Column III reports the estimates of the extended model which also allows for interactions between the household and product characteristics. Column IV is the extended model including the United Way data. Overall, we find that all versions of our model capture the main regularities in the data reasonably well. Most of the coefficients have the expected sign and are significant are conventional levels. Since the extended model in Column III fits the data better than the baseline model in column I, we discuss the findings of this model in detail below.[24]

[23] Additional results are available upon request from the authors.

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

Table 8: Estimation Results: First Stage

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

Note: Fixed Effects are not reported.

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

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 residential residence, which is good proxy for household wealth. We also control for the neighborhood income of each household. We find that total donations increase with house value and neighborhood income. The demand for private benefits such as private parties and dinners is also increasing in wealth.

We include a variable "years lived in the house" which measures attachment to the Pittsburgh community.[25] We find that households that have lived in a community for a longer period of time have higher valuations of the benefits associated with charitable giving. This could be due to stronger ties to the community. We also construct an indicator of whether the household lives in the city of Pittsburgh. People living in the city may have a higher demand for the services offered by these charities than people in the suburbs who face longer commuting costs. We find that city residents also have stronger tastes for charitable giving than suburban households.

We find that married couples donate larger amounts than non-married couples. Based on professional list, we have constructed two dummy variable indicating whether the household has a member that is a physician or a lawyer. We find that our professional dummies are typically insignificant. We also estimate the coefficients of two dummy variables based on a household's political donations. We find that households that are politically active are more likely to be active in the local society and thus may value private benefits such as invitations to special dinner which may allow them to social network. The coefficients of the two variables that measure political active households are typically large and significant. This result indicates that households that are politically active are also actively supporting the local charities .

We estimate the coefficients an indicator variable that measures whether the person is a member of the board of the charity as well as the interaction with total donations.[26] We

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

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

find that board members donate significantly higher amounts than non-board members.

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

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

5.2 Second Stage

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

We find that households value invitations to dinner parties as well as special events.[27] These are the private benefits that are associated with social status. We also include free parking as a private benefit in the last specification. We households seem to value this

[27]Special tickets and token gift do not seem to be useful private benefits.

Table 9: Goodness of Fit: Estimated and Simulated Moments

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

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

Table 10: Second Stage Estimates

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

Estimated std. errors are reported in parenthesis.

benefit. However, the estimate comes with a large standard error. Comparing the IV estimates with and without charity fixed effects, we find that the estimated coefficients are qualitatively and quantitatively similar. The main difference is that including fixed effects increases the estimates of the asymptotic standard errors. We would expect that one might be able to obtain more precise estimates in a larger sample. Nevertheless, we conclude that our estimates are reasonable and consistent with the view that private benefits might be important motives for philanthropic behavior.

5.3 Policy Analysis

To get some additional insights into the rule that private benefits play in attracting charitable donations, we conduct a number of counter factual policy experiments. First, we add one more dinner invitation to the highest tier at the Carnegie Museum. Our model implies that this additional dinner party for the most generous donors would raise approximately \$197,425. A dinner party for the children's museum on the contrary would only net \$11,019.

Next we considered the impact of changes in the choice set. In particular, we consider policies that eliminate choices. 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.[28]

Table 11: Policy Analysis: A Ban of Private Benefits

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

To get some additional insights into the rule that private benefits play in attracting charitable donations, we solve our model under the assumption that all charities stop using private benefits as incentives to attract donors. The results of this policy experiment is summarized in Table 11. For each charity, the first row represents the data which is, as we have seen in the previous section, close to the predictions of the model using the existing benefit structure. The second row corresponds to the predictions in the absence of private benefits.

Note that the Zoo, the Public Theater, the Western Pennsylvania Conservatory, and the Children's Museum do not use special events and dinners as fund-raising tools. As a

[28]Weissbrot (1988) provides evidence that suggests that most charities are not revenue maximizers.

consequence there overall donations are not much affected by the policy. If anything, these charities would experience a small increase in the number of donors and the total level of donations since these charities are now more attractive compared to the charities that use these incentives. The Phipps conservatory only holds one special event for their top donors. Our model predicts that this event raises approximately $15,000 in additional donations. The Ballet, the Symphony, the Opera, and the Carnegie Museum all rely heavily on special events and dinners as fund-raising tools. Top donors for the Carnegie Museum are invited to five dinners and five special events. Our model predicts that these types of events are very effective and generate a large fraction of the annual donations. Maybe most surprisingly, we find that the number of individuals that donate to multiple donations is also significantly lower in our model without private benefits. Thus private benefits not only affect giving behavior to the favorite charity, but also to charities that rank second or third.

6 Conclusions

Charitable giving is an important way for individuals to support the mission of many cultural and environmental organizations. These institutions require a significant amount of private support to balance their budgets. To attract private donors most organizations offer a variety of private benefits and perks in addition to rewarding donors by printing their names in brochures, playbills, and annual reports. Donors list their names with middle initials, suffixes, and professional titles indicating that social status and recognition is important to these individuals. More importantly, organizations sometimes host exclusive dinner parties and extend invitations to special events to important donors. The main objective of this paper has been to evaluate the importance of these benefits for annual fund-raising.[29]

Our findings indicate that private benefits for tiered donation amounts provide strong incentives for donors to support their favorite organizations. Individuals are willing to spend significant amounts of money for an invitation to a special event or dinner party. We

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

find that these benefits are particular popular among affluent donors and donors that are politically active. One plausible interpretation of these findings is that these events provide social status since additional affluent or influential people are also likely to be in attendance. These findings are also consistent with the fact that dinner parties are notoriously popular to raise political campaign contributions. Individuals often pay large amounts of money per plate at a fund-raising dinner for access to a candidate. Our findings are also consistent with the observation that most organization reward important donors by inviting them to join the board of trustees. Board membership not only provides prospects of influence in an organization, but also additional social visibility.

Individuals have a long list of causes to which they can choose to donate money. It is vitally important for cultural organizations to court potential donors. Knowing the preferences of their donor constituencies allows them to personalize the fund-raising process. Some of the large cultural organizations in our sample understand the private motivations very well. Nevertheless, private benefits can only partially explain the behavior of some donors and are clearly not the only motivation for most donors' behavior. A large fraction of the observed donations – especially donations to organizations that offer few perks – can only be explained by appealing to warm glow. Thus an incentive based theory of philanthropic behavior can only complement a theory based on warm glow or impure altruism.

A Who Chooses to Be A Donor?

We also generated a random sample of 10,000 households that own residential properties in Allegheny County. Those households were then matched against the list of donors in the same way as described in the paper. There are 90 observations that we identified as having contributed to one of the ten organizations. This implies that less than one percent of households in Allegheny County contribute to these cultural and environmental organizations. We also find that 0.9% of all households are physicians compared to the 6.0% in the donor sample. There are 1.3 % lawyers in the random sample compared to 7.7% in the donor sample. In the random sample, 147 (1.5%) contributed at least $200 to a national political cause as reported by the FEC compared to the 11.3% of donors that contributed to a national political campaign. We thus conclude that donors to these ten organizations are 6.7 times more likely to be doctors, 5.9 times more likely to be lawyers, and 7.5 times more likely to be political donors.

Table 12: Random Sample: Logit Regressions

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

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

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