ESSAYS IN APPLIED MICROECONOMICS

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In this dissertation, we develop empirical methods, built on the recent advances in industrial organization, to study charitable giving and fundraising in the charity market. In the first essay (joint with Holger Sieg), we propose a multiple discrete choice model with differentiated charitable products and estimate the model using a unique data set of donor lists for the ten largest charitable organizations in Pittsburgh. We find that some private benefits such as invitations to private dinner parties and special events are effective tools for fundraising. Our policy simulations suggest that the composition of private benefits has a potentially large impact on donor behavior. In the second essay, I investigate the determinants of donations to charitable organizations by incorporating their managerial capacity and fundraising productivity. Using data from environmental charities, I find that managerial capacity has a significantly positive impact on raising donations, which demonstrates the long-run benefits of managerial expenses. Fundraising productivity is a charity-specific and serially-correlated unobserved variable that causes an endogeneity problem in the estimation of the donation function. After controlling for the fundraising productivity, the estimated impact from managerial capacity on donations is significantly increased, while the impact from fundraising expenditure is significantly decreased. Finally, after estimating the donation function, I construct a measure of fundraising productivity and show that it is a key factor in explaining the variation of donations, suggesting that policy discussions should account for charities' differences in fundraising productivity and the causes of such differences.

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1.0 INTRODUCTION

In this dissertation, we study the different aspects of the charity market: charitable giving, fundraising efficiency, and the impact of government grants on donations to charities. Methodologically, we introduce the analytical tools recently developed in the literature of industrial organization into the economics of charities. In doing so, we contribute new findings and insights to the existing literature.

Private donations are an important source of revenue for most charitable organizations. Consequently, most charitable organizations need effective fundraising strategies to provide continued public services. While some individuals may support their favorite charities regardless of the incentive structures used to attract donors, others may be motivated to give conditional on the benefits the organization offers. The former set of donors might be pure altruistic or gain satisfaction from knowing that they contributed to a worthy cause–called "warm-glow" or impure altruistic, whereas these latter donors fit into the notion that 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.

In the first essay (joint with Holger Sieg), we study donors motives for giving, especially whether and which private benefits are valued by donors. After identifying donors' motives of giving, we can quantify donors' preferences for different charitable causes and conduct policy experiments to demonstrate the effectiveness of different fundraising strategies. We collected a unique data set which includes donor lists and fundraising schedules from ten large charitable organizations in Pittsburgh and the social-economic information of these donors. We develop a multiple choice model by treating different tiers of giving to different charities as differentiated products; donors make decisions by maximizing their utility from giving (or buying charitable products) in multiple periods. We find that private benefits that furnish social status to donors provide important incentives for donors to support the related charities. Our policy experiments show that the design of charitable product set and the schedules of private benefit are effective tools in fundraising.

The second essay examines the other side of the charity market, the determinants of donations received by charities and their differences in fundraising productivity. Previous studies of the determination of donations focus on the impact of government grants, also known as the crowding-out analysis (Andreoni, 2006). I introduce two new elements, managerial capacity and fundraising productivity, into the analysis. This aims to capture the dynamic impact of overhead expenditures (in fundraising and management) and the heterogeneity of charitys efficiency, which are key factors in the process of raising donations. Incorporating these factors helps to clarify the empirical challenge in estimating the donation function. That is, fundraising efficiency is unobservable for researchers but known to charities when they make expenditure decisions, which makes the explanatory variables in the donation function endogenous. The paper proposes an empirical strategy to resolve this endogeneity problem using the optimization condition of charitys expenditure which contains the information of fundraising efficiency, based on Olley and Pakes (1996).

Using the data from green charities, the paper finds that, as predicted, the estimated impact from fundraising expenditure on donations is reduced significantly, while the impact from managerial capacity is increased. Investments in management have a significant positive long-run impact on donations. Finally, I propose a new measure of efficiency, fundraising productivity, which is an important determinant of donations. In contrast to the commonly used measurethe ratio between donations and fundraising, fundraising productivity can be explained by the observed indices of the qualities of charities.

The findings have important implications on the policy discussion. First, if the estimated impact of fundraising on donations is under-estimated without controlling for productivity, the indirect crowding-out, that is, the multiplication between the estimate from fundraising on donations and the estimate from government grants on fundraising, is under-estimated. Second, government policies aiming to utilize or offset the crowding out effect should take the differences in charities' fundraising productivity into consideration.

2.0 THE EFFECTIVENESS OF PRIVATE BENEFITS IN FUNDRAISING OF LOCAL CHARITIES (JOINT WITH HOLGER SIEG)

2.1 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. While some individuals may support their favorite charities regardless of the incentive structures used to attract donors, others may be motivated to give conditional on the benefits the organization offers. The former set of donors gain satisfaction from knowing that they contributed to a worthy cause (called "warm-glow" by Andreoni (1989, 1990), whereas these latter donors fit into the framework of Harbaugh (1998) where donors receive tangible or intangible private benefits from their gifts. To attract the more fickle donors, charitable organizations rely on sophisticated fundraising strategies. The more generous the donation, the more lavish the private benefit package. The purpose of this paper is to determine whether and which private benefits are valued by donors. Using a sample of large cultural organizations that offer potential donors a variety of different private benefit packages, we find that exclusive dinner parties and special exclusive events are effective tools for attracting large annual donations.

The previous literature has set up a dichotomy in which donors are described as motivated by either warm glow or private benefits. A more compelling approach acknowledges the fact that most donors are driven by both motivations. The weight an individual donor places on each motivation depends on personal characteristics. It is, therefore, desirable to design an empirical approach that nests both hypotheses and allows us to determine the relative importance of these different incentives. Using explicit measures of private benefits we test which type of private benefits explain the observed choice behavior 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 non-market 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.[1]

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 ten 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. 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,

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

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 which assumes individuals donate to a single charity does not describe our sample well. One could in principle extend the discrete choice framework to allow consumers to choose among "tuples" of goods. But the relevant choice set gets intractably large when individuals donate to multiple organizations.

For the same reason, we cannot use a hedonic approach to identify the underlying preferences of households. We can regress the amount of donations required for each tier on the vector of 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 paper and model the observed behavior as a repeated discrete choice with multiple choice occasions. In many applications, multiple choice occasions arise because a number of different agents make simultaneous decisions. In our model, we have a single decision maker who faces a sequential decision problem. Thus, it is useful to relax the additive separability assumption in Hendel (1999) and introduce some state dependence among the choice occasions. In our context, it is plausible that previous levels of charitable giving affect contemporary behavior. To capture this type of habit formation, we assume that past charitable behavior is a state variable in our dynamic 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.[2] 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 non-marginal policy changes that cannot be evaluated with simpler approaches. Our policy experiments indicate that charities have strong incentives to redesign private benefit schedules to increase donations. We also consider the scenario in which charities stop using private incentives. Our model shows that charities that heavily rely on special events and dinners to attract wealthy donors would receive much lower donations. We then decompose the total amount of giving into a warm-glow component and a component that is due to private benefits. These types of decompositions are outside the scope of reduced form or simple experimental estimators that estimate local average treatment effects. We find that the fraction of donations that can be attributed to warm-glow varies substantially among the charities considered in the application.

The rest of the paper is organized as follows. Section 2 of the paper discusses the data set. Section 3 provides a formal model that can be used to analyze individual donations to multiple charities. Section 4 develops a new estimator for this class of models. This estimator

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

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.

2.2 DATA

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

2.2.1 The Sample and Descriptive Statistics

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

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

The main sample we use is a choice-based sample. We only include individuals in our sample that are listed in at least one of the donor lists for our ten charitable organizations. Consequently, the main focus of this paper is on the population of individuals that are active donors. In the literature of charitable giving, it is common practice to use choice-based samples. Almost all papers that have estimated the incentive effects of taxes on charitable giving use tax return data for individuals that itemize deductions. Examples are Clotfelter (1985), Randolph (1995), or Auten, Sieg, and Clotfelter (2002). Choice-based samples are also commonly used in the empirical literature that has focused on fundraising and the crowding-out effect of government grants. Kingma (1989) and Manzoor and Straub (2005) use survey data sets that only cover people who listened to public radio. Buraschi and Cornelli (2003) use data based on subscription lists from the English National Opera. Other studies have relied on aggregate data. Ribar and Wilhelm, (2002) estimate their model using a 1986-92 panel of donations and government funding from the United States to 125 international relief and development organizations. Hungermann (2005) uses a new panel data set of Presbyterian Church congregations.

To evaluate the impact of choice based sampling, we have also created a random sample of 10,000 households in Allegheny County. Those households are matched against the list of donors. There are only 90 observations that we identify as having contributed to one of the ten organizations. This implies that less than one percent of households in Allegheny County contribute to these cultural and environmental organizations. We also find that 0.9 percent of all households are physicians compared to the 6.0 percentin the donor sample. There are 1.3 percent lawyers in the random sample compared to 7.7 percent in the donor sample. In the random sample, 147 households (1.5 percent) contributed at least $200 to a national political cause as reported by the FEC compared to the 11.3 percent of donors in the choice based sample. Using the random sample, we have estimated a simple logit model which 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 Glaser and Konrad, (1996). The unit of observation in this study is a household. There are a total of 6,499 individuals and couples listed in the programs of the ten organizations and total giving is $6,732,705. The donation data are summarized in Table 1. We find that the median gift size for all organizations is close to the lowest tier, suggesting that the majority of donors give in the lowest or second-lowest range reported by these organizations.

Table 1: Donations by Organization

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

Only a small fraction of the donors are listed as "anonymous," suggesting that donors want to be recognized in official publications.[3] 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. 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

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

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

Matching our data to professional lists, we find that 391 physicians and 500 lawyers gave money to at least one of the ten Pittsburgh cultural organizations. To determine the housing wealth of donors in our sample, we match the donors to the Allegheny County Real Estate Assessment website.[4] A subset of individuals (54 percent) can be identified as owning property in Allegheny County.[5] The main part of the empirical analysis focuses on households in Allegheny County that are matched to the real estate data base. We report descriptive statistics in Table 2 that summarize the distribution of housing values, by charity, in our sample.

The Carnegie Museums and the Pittsburgh Symphony attract donors with the highest average housing values. Surprisingly, donors to the Children's Museum have the third highest housing wealth. The Western Pennsylvania Conservancy and the City Theater have donors with lower housing values. The real estate data base contains the address of the house, which allows us to match each observation in the sample to a Census Block Group and assign a (neighborhood) income level to each observation. Moreover, we can distinguish

[4]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.

[5]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 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	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

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 which measures the "attachment" to the Pittsburgh metropolitan area.

The United Way is a charity that largely funds smaller charities that provide social and community outreach services. It provides no private benefits besides social visibility. We can thus use the information about United Way donations to proxy for heterogeneity in warm glow within the population as explained in detail below. We obtained the list of United Way donors. We find that 551 people who gave to one of the cultural charities also gave to the United Way. The minimum amount of giving, such that the donor is listed in the publication, is $1,000. 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

Table 3: Giving to Presidential Candidates

	Bush number of donors	Kerry number of donors	Bush total amount	Kerry total amount
Ballet	12 (33.3%)	24 (66.7%)	$19,250	$46,550
Carnegie Museums	69 (41.1%)	99 (58.9%)	$118,025	$147,350
Children's Museum	13 (41.9%)	18 (58.1%)	$18,000	$34,350
City Theater	5 (7.0%)	66 (93.0%)	$8,500	$99,400
Opera	15 (30.0%)	35 (70.0%)	$29,000	$60,100
Phipps Conservatory	31 (36.0%)	55 (64.0%)	$54,375	$97,620
Public Theater	23 (28.0%)	59 (72.0%)	$46,950	$89,224
Symphony	31 (38.8%)	49 (61.3%)	$58,650	$77,420
WPC	40 (35.1%)	74 (64.9%)	$67,475	$115,420
Zoo	20 (54.1%)	17 (45.9%)	$46,200	$39,550

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

Table 4: Donations from Current Board Members

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

We also observe whether an individual is a member of the board of trustees of the organization. We treat board membership as a predetermined characteristic of a household in our analysis.[7] The ten organizations in our data set list the names of the trustees in the same publication as the one that lists the names of donors. Table 4 reports the minimum,

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

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

maximum, median, and average donation of board members along with standard deviations.

2.2.2 The Importance of Giving to Multiple Organizations

One of the striking features of our data is that many individuals donate money to multiple causes. For example, 495 of the 6,499 individual donors are identified as giving to three or more of our ten organizations. Table 5 provides a detailed analysis of the distribution of donor types.

Table 5: Spread of Giving to Multiple Organizations

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

We also find that individuals who contributed to three or more organizations have different characteristics than the average donor. Consider the 392 donors who are listed in the Allegheny County Real Estate Registry. Their average property value was $425,659, 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 percent for the donors who gave to three or more charities compared to 17 percent for all donors. Table 6 reports the number of donors that gave the first, second, or third largest amounts to each organization with ties counted on the same level.

Table 6: Gift Size Ordering and Frequency among Multiple Donors

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

Note: The sample size is 495.

We find that organizations like the Carnegie Museums, Opera, and Symphony are "top-heavy", i.e. they are first or second choices for many donors. The "bottom-heavy" organizations like Phipps Conservatory, WPC, Zoo, Public Theater, City Theater, and the Children's Museum rarely receive the largest share of a given donor's bankroll. The data thus suggest that individuals strategically decide how to allocate funds among the available charitable organizations. No one in our sample gives, for example, equal amounts to a large subset of these organizations. The last column of Table 6 shows the percentage of the 495 multiple donors who give any money to each organization. We find that Phipps, WPC, and the Public Theater capture about the same number of donations from the multiple donors as the Carnegie Museums and the Symphony. However these charities are the second-choice destinations for charitable giving receiving less money.

Since a significant fraction of individuals donate to more than one charity, we do not adopt a simple discrete choice approach, but a multiple discrete choice approach. These models generate the choice set from the basic options available at each choice occasion (Hendel, 1999).

2.2.3 The Importance of Private Benefits

In addition to the private good motive of prestige that comes with being listed in a playbill or annual report, some organizations provide substantial private benefits to reward donations. Organizations typically grant additional benefits to the higher levels of giving. They also offer all benefits associated with levels of giving below your current level. Only three of the ten organizations do not have these tiered privileges listed in their programs, annual reports, or websites. Table 7 summarizes the number of offerings in each category that donors at the top level are given. Appendix A.2 reports tables of private benefits for all tier of donations in our sample.

The prevalence of private incentives suggests to model behavior as choices among bundles of goods. Each tier of giving can be viewed as a differentiated product which comes with a "price" and set of characteristics. The price is equal to the minimum giving amount and a vector of private and social benefits. The observed characteristics are the private benefits. Households differ among many observed characteristics and are likely to have different tastes for these benefits.

2.3 MODEL

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 to use a multiple discrete choice model. Previous applications of multiple discrete choice

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						

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 multi-discrete choice model is then obtained by aggregating the decisions of the single individual over the relevant time horizon.

To formalize there ideas, we assume that each donor makes decisions over the course of 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.[8] At each point of time choices are mutually exclusive:

$$\sum_{i=0}^{I} \sum_{l=1}^{L_i} d_{ilt} \;=\; 1 \tag{2.1}$$

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

$$tg_t \;=\; \sum_{k=1}^{t-1} \sum_{i=0}^{I} \sum_{l=1}^{L_i} d_{ilk}\, g_{il} \tag{2.2}$$

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:

$$U_t(d_t, x, tg_t, \epsilon_t) \;=\; \sum_{i=0}^{I} \sum_{l=1}^{L_i} d_{ilt}(u_{ilt}(x, tg_t) + \epsilon_{ilt}) \tag{2.3}$$

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

where $\epsilon_t = (\epsilon_{11t}, ...\epsilon_{ILt})$ denotes a vector of idiosyncratic shocks. We thus follow McFadden (1974) and assume that the error enters the utility function in an additively separable manner. Individuals know the current period shocks, but do not have perfect foresight regarding future preference shocks.

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

$$\max_{\delta=(\delta_1,...\delta_T)} \sum_{t=0}^{T} E_\delta[U_t(d_t, s_t)|s_0 = s] \tag{2.4}$$

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

The model is sufficiently general to account for the fact that the previous donations reduce available income and thus may reduce the probability of future donations. It is also straight-forward to allow for time dependent observed characteristics such as income and impose the budget constraint.[9]

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.[10]

[9] 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.

[10] 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.

2.4 ESTIMATION

2.4.1 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:

$$u_{iltn}(x_n, tg_{tn}) \;=\; \alpha_{il} \;+\; \eta\, tg_{tn} \;+\; \omega\, x_n \;+\; \psi\, \iota(x_n, p_{il}) \tag{2.5}$$

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, Levinsohn and Pakes (2004), these interactions may be important in generating an appropriate choice model.[11] We assume that α_{il} can be decomposed into observed and unobserved characteristics as follows:

$$\alpha_{il} \;=\; \alpha \;+\; \beta\, g_{il} \;+\; \gamma\, p_{il} \;+\; \xi_{il} \tag{2.6}$$

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

It is useful to review how our model accounts for both giving due to “warm-glow” and giving that is motivate by private benefits. Consider the utility specification in equations (2.5) and (2.6). Suppose private benefits are irrelevant and donations can only be attributed to warm glow. In that case the coefficients α and β in equation (2.6) must be different from zero and γ must equal zero. Similarly in equation (2.5) 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.

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

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.

2.4.2 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:

$$P_t(d_{ilt} = 1 | tg_t, x) = \frac{\exp(v_{ilt}(tg_t, x, \theta_1))}{\sum_{j=0}^{I} \sum_{k=1}^{L_j} \exp(v_{jkt}(tg_t, x, \theta_1))} \tag{2.7}$$

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:

$$v_{ilT}(tg_T, x, \theta_1) = u_{ilT}(tg_T, x, \theta_1) \tag{2.8}$$

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

$$v_{ilt}(tg_t, x, \theta_1) = u_{ilt}(x, tg_t, \theta_1) + \log(\sum_{m=0}^{I} \sum_{n=1}^{L_m} \exp(v_{mnt}(tg_t + g_{il}, x, \theta_1))) \tag{2.9}$$

The conditional value functions can thus be computed recursively.

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

$$d_{il} \;=\; \sum_{t=1}^{T} d_{ilt} \tag{2.10}$$

As a consequence, a standard dynamic discrete choice estimator based on the conditional choice probabilities in equation (2.7) 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 household characteristics x and product characteristics, z. Let these probabilities be denoted by $P_t(d \mid x)$. These probabilities can be computed from the standard conditional probabilities in equation (2.7) by integration over all possible choice sequences.

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

$$\begin{aligned} d_{12} = d_{21} = 1 \\ d_{11} = d_{22} = d_{31} = d_{32} = 0 \end{aligned} \tag{2.11}$$

Let cs_i denote a choice sequence that is consistent with the observed behavior in equation (2.11). Let CS denote the set of all feasible choice occasions that are consistent with the observed choices d. Table 8 list the six choice sequences that are elements in CS in this example.

The probability of observing the behavior in equation (2.11), given observed characteristics x, is obtained by computing the probability of each of the six feasible 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

and summing over all possible sequences:

$$
\begin{aligned}
& P(d|\, x) && (2.12)\\
= & \sum_{i \in CS} P(cs_i|\, d, x) \\
= & P_1(d_{121} = 1 \mid tg_1 = 0, x)\ P_2(d_{212} = 1 \mid tg_2 = g_{12}, x)\ P_3(d_{003} = 1 \mid tg_3 = g_{12} + g_{12}, x) \\
+ & P_1(d_{121} = 1 \mid tg_1 = 0, x)\ P_2(d_{002} = 1 \mid tg_2 = g_{12}, x)\ P_3(d_{213} = 1 \mid tg_3 = g_{12}, x) \\
+ & P_1(d_{001} = 1 \mid tg_1 = 0, x)\ P_2(d_{122} = 1 \mid tg_2 = 0, x)\ P_3(d_{213} = 1 \mid tg_3 = g_{12}, x) \\
+ & P_1(d_{211} = 1 \mid tg_1 = 0, x)\ P_2(d_{122} = 1 \mid tg_2 = g_{21}, x)\ P_3(d_{003} = 1 \mid tg_3 = g_{21} + g_{12}, x) \\
+ & P_1(d_{001} = 1 \mid tg_1 = 0, x)\ P_2(d_{212} = 1 \mid tg_2 = 0, x)\ P_3(d_{123} = 1 \mid tg_3 = g_{21}, x) \\
+ & P_1(d_{211} = 1 \mid tg_1 = 0, x)\ P_2(d_{002} = 1 \mid tg_2 = g_{21}, x)\ P_3(d_{123} = 1 \mid tg_3 = g_{21}, x)
\end{aligned}
$$

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

To understand identification of η it is useful to consider the example above. First notice that the example involves an individual that gives to more than one charity. If all individuals only donated to only one charity, then we can easily conclude that η is not identified. In the example, the individual donates to two of the three charities. There are six possible choice sequences that are consistent with the observed behavior. In a model in which $\eta = 0$ all choice sequences are equally likely and will receive the same weight in the likelihood function. If $\eta > 0$, it is easy to verify that choice sequences 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 increasing donations. The observed behavior of individuals that 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.[12]

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:

$$P(d_n \mid x_n, \theta_1) \;=\; \sum_{cs_{in} \in CS_n} P(cs_{in} | \, d_n, x_n, \theta_1) \tag{2.13}$$

[12]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).

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

$$L(\theta_1) \quad = \quad \Pi_{n=1}^{N} P(d_n \mid x_n, \theta_1) \tag{2.14}$$

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

2.4.3 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 (2.6) can be written as:

$$\hat{\alpha}_{il}^N \quad = \quad \alpha \ + \ \beta\, g_{il} \ + \ \gamma p_{il} \ + \ \xi_{ij} \ + \ u_{ij}^N \tag{2.15}$$

Following Berry (1994), we assume that $E[\xi_{ij} + u_{ij}^N|\ p_{jk}] = 0$ for $j \neq i$ and $k \neq j$. The key identifying assumption in the second stage is that observed product characteristics are uncorrelated with unobserved product characteristics. That 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.[13]

Before we proceed, we offer the following observations. First, we treat private benefits such as the number of dinners or the number of invitations to parties as exogenous product characteristics. We, therefore, impose the same identifying assumption as Berry (1994). 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

[13] As part of our robustness analysis we also estimate the parameters using OLS. Finally, we also explore models with charity specific fixed effects α_i.

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 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.[14]

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

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

$$(Z'X)^{-1}\ Z'\ (\Sigma + \frac{\Omega}{N})\ Z\ (Z'X)^{-1} \tag{2.16}$$

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 (2.16) 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

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

[15]The first paper that modeled competition among charities is Rose-Ackerman (1982) who shows that competition can lead to excess fund-raising. Weisbrod (1988) provides a detailed institutional analysis of the non-for-profit sector. More recently, Romano and Yildrim (2001) show that a charity may prefer to announce a large donation during a fundraising campaign. Vesterlund (2003) argues that fundraisers announce past contributions to signal the quality of the charities, which could help worthwhile charities reveal their type and help them reduce free-rider problem. It assumes donors have imperfect information on the quality of programs offered by a charity. Andreoni and Payne (2003

associated with the fixed effects are relatively small compared to the variance of the residuals in the second stage.

2.4.4 Computational Considerations

There are ten charities in our applications with 76 different levels of giving and the outside option. We assume that each choice occasion corresponds to one quarter of a year.[16] We restrict our attention to four choice occasions for computational reasons. We need to characterize all feasible choice sequences in the estimation procedure and then integrate over all feasible paths to compute the likelihood function. The main disadvantage of using only four periods is that we lose information on individuals that decide to donate to more than four charities. We treat those individuals as if they had just donated money to their four most preferred charities.

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

We use parallel processing techniques and estimate the parameters of the model on a machine provided by the Pittsburgh Supercomputing Center. Estimating the model for the full sample of 3,514 observations takes between 12 and 36 hours of computing time using 300 processors. Using a supercomputer also allows us to check for global convergence. We change the starting points and the seeds of the random number generators and investigate

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

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

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

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.

2.5 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 the estimates and standard errors for the baseline model. Column II reports the estimates of an extended model which also allows for interactions between the household and product characteristics. In Column III we add a United Way dummy as well as interactions between product characteristics and the United Way dummy to the specification. 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.[19]

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

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

Table 9: First Stage Results

	I	II	III	IV
	Baseline Model	Extended Model	Extended Model with United Way	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)
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	20636.92	20363.51	20346.99	12224.56

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

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 household with higher personal wealth tend to donate more money than households with lower wealth. The same is true for households

Table 10: First Stage Results: Interactions

	I	II	III	IV
	Baseline Model	Extended Model	Extended Model with United Way	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)

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

that are members of the board of trustees.

We also find that households that are politically active value invitations to special events and dinner parties. This is especially true for Republicans for whom we consistently find large positive and significant effects. This finding is intriguing and raises some interesting research questions. We know, for example, that households that finance political campaigns often expect some favors from the politician that they support. There is a clear quid pro quo when supporting candidates that run for political office. The 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 while the interaction with dinner parties is positive and significant. The other estimates are not substantially affected by the inclusion of these interactions. Again, these findings are consistent with the view that the United Way dummy can be interpreted as a variable that captures heterogeneity in "warm glow" in the population. However, even unselfish donors may appreciate some acknowledgment. Thus it may not surprising to find that the interaction with dinners is also positive and significant.

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 eliminate all environmental and wildlife charities from our choice set (the Zoo, the WPC, and the Phipps Conservatory). We then estimate our model using this smaller choice set.[20] This test is then in the spirit of Hausman and McFadden (1984) who suggested a similar procedure to evaluate whether the IIA property holds in a logit model. We report the estimates for the arts-only-specification in the last columns 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

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

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, Sieg, and Sloan, 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 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.

Next we turn our attention to the second stage results which are based 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 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 counter-intuitive price effects without the use of appropriate instruments. This finding may be due to the fact that the correlation between

Table 11: Goodness of Fit: Estimated and Simulated Moments

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

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 12: Second Stage Estimates

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

Estimated standard errors are reported in parenthesis.

FE refers to charity level fixed effects.

prices and unobserved product characteristics is weaker in our application.[21]

Households value invitations to dinner parties as well as special events.[22] 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.

2.6 POLICY ANALYSIS

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

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

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

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 paper. 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 foregone ticket revenues.

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

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

2.6.2 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.[23]

[23]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

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

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).

2.7 CONCLUSIONS

Individuals have a long list of causes from which they can choose to donate money. It is vitally important for cultural organizations to court potential donors. A better understanding of the preferences of donors will allow these organizations to personalize the fundraising process and attract increased donations. To appeal to private donors, most organizations offer a variety of private benefits in addition to rewarding donors by printing their names in brochures, playbills, and annual reports. More importantly, organizations host exclusive dinner parties and extend invitations to special events to important donors. We have shown the importance of these benefits for annual fundraising strategies. We find that exclusive private benefits are particular popular among affluent donors and donors that are politically active.

We have distinguished in this paper between the motives for giving and the motives for participating in social events that are open to select donors. Our analysis primarily focused on the former and has less to say about the later. We have briefly discussed some possible explanations why donors may want to participate in these events. Social prestige or networking opportunities are the obvious candidates. Our findings are also consistent with the fact that dinner parties are notoriously popular to raise political campaign contributions. Individuals often pay large amounts of money per plate at a fundraising dinner for access to a candidate. More research is needed to address these open questions.

The main sample used in estimating our model is random conditional on giving to at least one of the ten charities. It is, therefore, straight forward to interpret our results. The results of our paper 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-McFadden (1984) and Hanemann (1984) have proposed estimators for these types of model that allow for one discrete and one continuous choice. Our method allows consumers to choose more than one differentiated product. We can view the techniques proposed in this paper as extensions of their methods.

Table 13: Policy Analysis: Only Give to One Charity

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

Table 14: Policy Analysis: A Ban of Private Benefits

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

3.0 MANAGERIAL CAPACITY, FUNDRAISING PRODUCTIVITY AND DONATIONS TO CHARITABLE ORGANIZATIONS

3.1 INTRODUCTION

Donations are major revenue resources of charitable organizations that account for 8 percent of wages and salaries paid in the United States and received 283 billions of dollars private contributions in 2007 (National Center for Charitable Statistics, NCCS). Understanding the determinants of donations is not only critical for the success of charities, but also has important policy implications, especially, the crowding out effects from government grants on private donations to charities[1]. Previous literature mainly focuses on the crowding out analysis, for example, Bergstrom, Blume and Varian (1986), Gruber and Hungerman (2007) and Heutel (2009). Recent developments emphasize the importance of fundraising expenditure for crowding out and donations to charities. Andreoni and Payne (2003, 2009) show that government grants crowd out charities' fundraising expenditure significantly, which will further reduces donations to charities even more than the direct impact from government grants on private donations.

Fundraising expenditure and government grants are essential components in the study of donation determination, however, they are still not sufficient for a thorough understanding for the following reasons. First of all, fundraising expenditure only accounts for a small part

[1]Theoretically, the crowding out can be complete or incomplete, depending on whether donors are pure or impure altruistic and thus whether donors see government grants as perfect or imperfect substitute of their own contributions (Warr, 1982; Robert, 1984; Andreoni,1989, 1990). Empirical studies, such as Kingma (1989), Khanna, Posnett and Sandler (1995), Payne (1998), Okten and Weisbrod (2000), Ribar and Wilhelm (2002), Hungerman (2005), find that crowding out can be positive, zero, or even negative. Some studies demonstrate the crowding in effects of government grants on private donations since government funding can serve as signals of charities' quality (Heutel, 2009). More details can be found in the survey by Andreoni (2006).

of charities' total expenditure–it is five percent for the environmental/green charities studied in this paper. Moreover, the variation of donations is very high even for charities with similar amount of fundraising expenditure and for the same charity in different years. Last, many charities do not receive government grants–it is 54 percent for green charities, so other factors might be more important for these charities to raise donations. More fundamental concerns about the impact of government grants are whether donors know about the government grants to charities and whether they care about such information (Horne, Johnson, and Van Slyke, 2005).[2]

Previous studies have modeled donations as the output of a "production" process treating fundraising expenditure and government grants as inputs. The innovation of my study is that I incorporate managerial capacity and fundraising productivity as additional factors into the production of donations. I demonstrate that failure to include these factors can cause significant bias in the estimation of the donation function and the evaluation of the crowding out effects.

Managerial capacity is an approximation to the notion of "organization capacity" that draws a lot of attention in the nonprofit practice (Backer et al., 2001) and is measured by the accumulated stock value of managerial expenses which account for a large part of the total expenses of charities–19 percent for green charities. Managerial capacity incorporates both human capital accumulated through investment in human resources and physical capital accumulated through investment in facility/infrastructure. Intuitively, better management team and better physical infrastructure can help charities to be more effective in fundraising. The public, however, impose much pressure on charities to reduce managerial expenses because of the belief that managerial spending may waste the resources for charitable causes. Despite of the importance and controversy of managerial expenses, their long-run impact on donations has not been well studied in the literature.

Fundraising productivity is employed to capture the impact of unobserved factors that affect a charity's effectiveness in fundraising, such as charities' reputation in providing public goods and donors' social preferences for different causes. It is easier to raise more donations

[2]Methodologically, the experimental approach might be an important alternative way of studying crowding out since it can better control or manipulate the impact of external funding, such as government grants, as shown in Vesterlund, Wilhelm, and Xie (2009).

using the same amount of fundraising expenditure if a charity has a prestigious establishment or deals with a significant social issue. Moreover, the heterogeneity of productivity is critical in evaluating the performance of an organization and the impact of policy changes, which has long been recognized in the literature of production function estimation (Grilliches and Mairesse, 1998; Ackerberg, Benkard, Berry and Pakes, 2006; Aguirregabiria, 2009), but not explored in the empirical study of donation function. This paper attempts to demonstrate the impact of fundraising productivity on donations.

Though not observed by researchers, fundraising productivity is known to charities when they make decisions on fundraising and managerial expenses. This generates the correlation between the unobserved productivity and other explanatory variables in the donation function. The dynamics related to managerial capacity help clarify and resolve this endogeneity problem arising from the fundraising productivity that is charity-specific and serially-correlated. I employ the methodology developed by Olley and Pakes (1996), which is close to the dynamic panel data model (Blundell and Bond, 1998, 2000). The identification strategy utilizes the fact that the observed management expenses incorporate the information of fundraising productivity and can be employed to control for the impact of the unobserved productivity on donations.

Using the data from green charities[3], the empirical analysis has the following main findings. First, managerial capacity is essential in explaining the determination of donations and has a significantly positive impact on raising donations, which demonstrates the long-run benefits of charities' investment in management. Second, after controlling for the unobserved productivity, the estimated impact from managerial capacity on donations is increased by 67 percent, while the impact from fundraising expenditure is reduced by 57 percent. This shows that the endogeneity problem caused by fundraising productivity plays an important role in the analysis. Moreover, it implies that the indirect crowding out effects, that is the multiplication of the impact from government grants on fundraising and the impact from fundraising on donations, might be overestimated. Third, after estimating the donation

[3] There is a growing literature on green charities. Heutel (2007) compares the differences between green charities and other charities of social services and finds significant differences both in the summary statistics of the data and the empirical analysis of crowding out. Straughan and Pollak (2008) investigate environmental and animal related charities based on descriptive statistics of their tax form information.

function, I compute a measure of fundraising productivity and show that it is a key factor in explaining the variation of donations. Government grants policy should take charities' differences in fundraising productivity into consideration, for instance, the matching grants policy is not effective for charities with low fundraising productivity.

The empirical framework in this paper incorporates the dynamics of managerial expenses and the heterogeneity of charities and can be used in charity evaluation.[4] The commonly used measures to evaluate charities are the ratio of donation over fundraising expenditure and the ratio of overhead-cost (sum of fundraising and management expenses) over total expenses. Such measures are designed to capture charities' efficiency in fundraising and their effectiveness in providing public goods, however, they do not reflect the corresponding long-run benefits but incorporate the sunk costs of long-run development strategies, such as investment in managerial capacity (NCCS, 2004).

The paper is structured as follows. Section 2 describes the data. Section 3 and 4 present the model and the methodology. Section 5 reports the empirical results, and section 6 provides more analysis on donation determination and fundraising efficiency. Section 7 concludes the paper.

3.2 DATA

3.2.1 Green Charities

The nonprofit sector has a long history in the United States[5] and has continued to thrive for centuries. In 2008, 1,514,821 tax-exempt organizations were registered with the Internal Revenue Service, including 956,760 public charities and 112,959 private foundations. In 2007, public charities reported nearly \$2.6 trillion total assets and \$1.4 trillion total revenues.[6]

[4] A few other papers also study the dynamics in charitable giving. For instance, Landry, Lange, List, Price, and Rupp (2009) and Card, Hallock, and Moretti (2009).

[5] As Arnsberger, Ludlum, Riley, and Stanton (2008) write, "Absent an established governmental framework, the early settlers formed charitable and other 'voluntary' associations, such as hospitals, fire departments, and orphanages, to confront a wide variety of issues and ills of the era".

[6] The statistics are obtained from the Core Files 2007 and the Business Master File 12/2008, the National Center for Charitable Statistics.

This paper focuses on green charities that preserve, protect and improve the environment. Green charities consist of an important force in resolving the environmental challenges facing us both locally and globally. Green charities have salient features, for instance, they receive respectively 46 and 16 percent of their total revenues from private contributions and government grants, compared to 12 and 9 percent for all public charities (Straughan and Pollak, 2008). Most of previous economic studies of charitable organizations mainly focus on arts, social service, or religious groups, so the analysis of green charities can be seen as an important compliment.

In the organizational classification system (NCCS, 2007), green charities, under C category, have 20 centile groups which can be further summarized into seven decile groups, as shown in Table 15. The total observations in the data from 1998 to 2003 are 28,953 from around 5000 charities; nearly half of them come from natural resources conservation & protection (C30-C36).

3.2.2 Data Resource

The data comes from the "NCCS-GuideStar National Nonprofit Research Database (NNRD)" from the National Center for Charitable Statistics. The NNRD data collects all the information in most financial sections and some information in non-financial sections of the federal tax returns Forms 990 and Forms 990-EZ of those organizations required to file tax forms with IRS, i.e., the secular charities with annual gross receipts of more than $25,000.

The main variables used in the empirical analysis are private donations, fundraising expenses, managerial and general expenses, and government grants. Private donations include contributions from individuals, cooperatives, and foundations. Donations could be financial endowment, capital campaigns, in-kind gifts, or revenues from fund-raising events for which the contributor receives nothing of value in return from the organization. Fundraising expenses are, according to the instructions for Form 990 and Form 990-EZ, "the total expenses incurred in soliciting contributions, gifts, grants, etc." Managerial and general expenses, simply called managerial expenses, are those costs associated with providing overall administration to an organization, and include personnel costs, accounting and legal fees,

Table 15: Mission and Observations of Centile Groups of Green Charities: 1998-2003

Code	**Mission Nature of Centile Groups**	**Observation Number**	**Percentage in Total**
C01	Alliances & Advocacy	316	1.1
C02	Management & Technical Assistance	113	0.4
C03	Professional Societies & Associations	383	1.3
C05	Research Institutes & Public Policy Analysis	434	1.5
C11	Single Organization Support	616	2.1
C12	Fund Raising & Fund Distribution	206	0.7
C19	Support NEC (Not Elsewhere Classified)	899	3.1
C20	**Pollution Abatement & Control**	1618	5.6
C27	Recycling	517	1.8
C30	**Natural Resources Conservation & Protection**	7681	26.5
C32	Water Resources, Wetlands Conservation & Management	2039	7.0
C34	Land Resources Conservation	2937	10.1
C35	Energy Resources Conservation & Development	424	1.5
C36	Forest Conservation	637	2.2
C40	**Botanical, Horticultural & Landscape Services**	187	0.6
C41	Botanical Gardens & Arboreta	791	2.7
C42	Garden Clubs	1493	5.2
C50	**Environmental Beautification**	1550	5.4
C60	**Environmental Education**	1837	6.3
C99	**Environment NEC**	4273	14.8
Total		28953	100

Resources: NCCS-GuideStar National Nonprofit Research Database, National Center for Charitable Statistics.

expenditure in office management and outlays for equipment and supplies. Government grants, according to the instructions, are "that encourage an organization receiving the grant to carry on programs or activities that further its exempt purposes", but are different from government contracts that are treated as part of program service revenue.

There are several issues of the data that will be carefully examined in the empirical analysis. First, 53 percent of the total observations of green charities between 1998 and 2003 come from those that never report fundraising expenses in the sample periods. Among these observations, 29 percent are from charities with positive private donations; on average they receive 35 percent of their revenues from donations. Second, 54 percent of the total observations come from green charities that never receive government grants. These charities are only a little smaller on average than those receiving government grants. The two groups of charities, with and without government grants, obtain the same proportion of revenues from donations, but receive respectively 20 and 44 percent of total revenues from other sources. The features of observations with zeros are illustrated in Table 16 using data from land conservations. Third, the main variables have large variances, are right skewed and peaked on small values. These problems alleviated by taking logarithm or focusing on a subgroup of the charities.

Table 16: Observations with and without Zeros in C34

group	**obs. #**	**donation (don.)**	**government grants**	**program revenue(prgrev)**	**other revenue(otherev)**
0 government grants	1337	366208	0	127327	147099
others	1600	1354262	218221	97210	157882
0 fundraising & positive don.	672	578718	96096	43409	41423
others	1924	1178556	145724	146055	172684

group	total rev. (tr)	don./tr	grant/tr	prgrev/tr	otherev/tr
0 government grants	640634	.513	0	.093	.394
others	1827576	.498	.203	.068	.231
0 fundraising & positive don.	759645	.51	.142	.076	.272
others	1643019	.592	.11	.072	.226

3.2.3 Summary Statistics

The salient differences in total assets, revenues, and expenses among subgroups of green charities are captured by Figure 1. Such differences are largely driven by their mission natures. For instance, Botanical Gardens & Arboreta (C41), Natural Resources Conservation & Protection (C30) and Land Resources Conservation (C34) accumulate the highest level of assets, respectively 8.72, 4.02 and 3.77 million dollars on average, because conserving natural resources leads to huge accumulated assets. Salient heterogeneity also exists in charities' financial structures which again are related to the missions and characteristics of charities. For example, the Energy Resources Conservation & Development (C35) group receives $828,316 government grants, almost 8 times the average, and earns $800,000 program service revenues, much more than other groups, through presumably their expertise in energy efficiency or clean energy.

Given the salient heterogeneity related to different groups of green charities, it seems more appropriate to start the analysis from a sample of charities within a narrower defined category. I begin with the group of land resources conservations (category C34) that preserve and protect endangered land resources from indiscriminate development, destruction or decay, for instance, conservation of forests, rangeland, vegetation, deserts, wild and scenic rivers and other wilderness areas and open land spaces. The reasons are the following. First, the group of land resources conservations is one of the largest groups of green charities and accounts for 10 percent of the whole data set. Second, it is easy to enlarge this sample by incorporating other natural resources conservations with similar mission nature, such as those in Natural Resources Conservation & Protection (category C30, accounting for 27 percent of

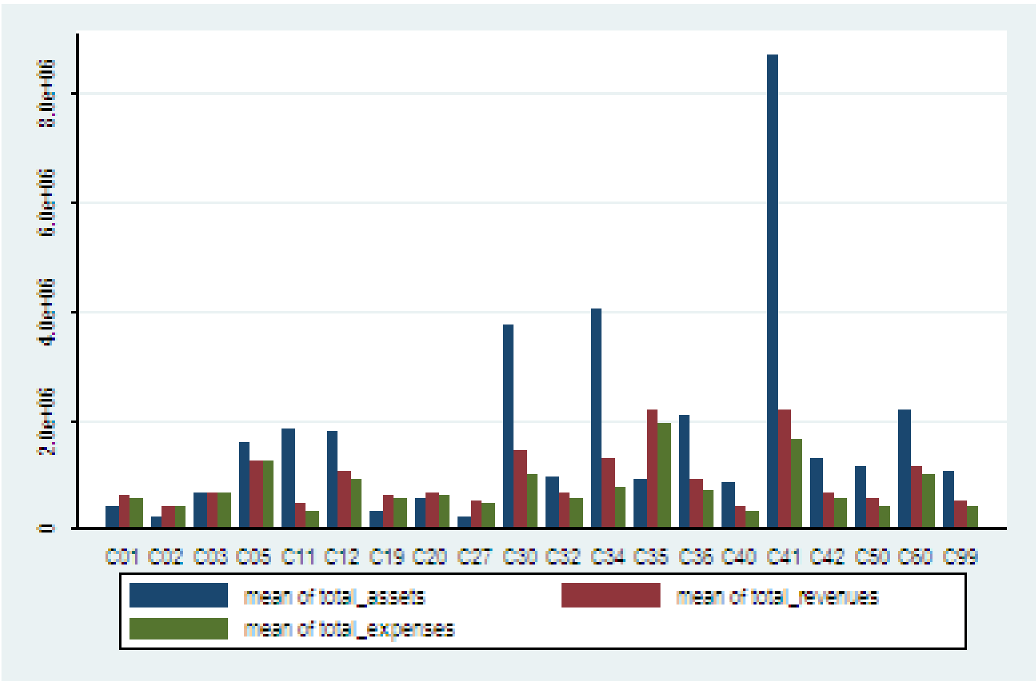

Figure 1: Total Assets, Revenues and Expenses of Centile Groups of Green Charities

total observations) and Water Resources, Wetlands Conservation & Management (category C32, accounting for 7 percent).

For land conservations, the scatter plots (in logarithm) between donations and fundraising expenditure and that between donations and government grants are shown in Figure 2 and Figure 3. The summary statistics of green charities and land resources conservations are shown in Table 17.

Several empirical regularities from the summary statistics are relevant for our analysis. First, donations are the major revenue resources for the environmental charities and account for 37 percent of the total revenues. For land resource conservations, donations account for 51 percent of their total revenues on average, so understanding the determination of donations is especially relevant for green charities. Second, managerial expenses are much larger than fundraising expenses. The percentages of managerial expenses in total expenses are 14 and 19 for all green charities and land resources conservations. Because of the importance of donations and managerial expenses in charities' total revenues and total expenses, one key part of this study is to demonstrate how managerial expenses affect donations to charities.

3.3 MODEL

This section presents a behavioral model of charities that operate along discrete time and make decisions on fundraising and management to maximize their present discounted value of current and future payoffs. The model clarifies the conditions needed for identification and estimation.

3.3.1 Per-Period Payoff Function

The per-period payoff function, π_{jt}, of charity j at time t is set as a composite of the revenue, r_{jt}, minus the disutility, c_{jt}, of overhead expenditures in fundraising expenditure, e_{jt}, and management expenditure, m_{jt}. Formally,

$$\pi_{jt} = r_{jt} - c_{jt} = (d_{jt} + g_{jt}) - c(e_{jt}, m_{jt}, g_{jt}), \tag{3.1}$$

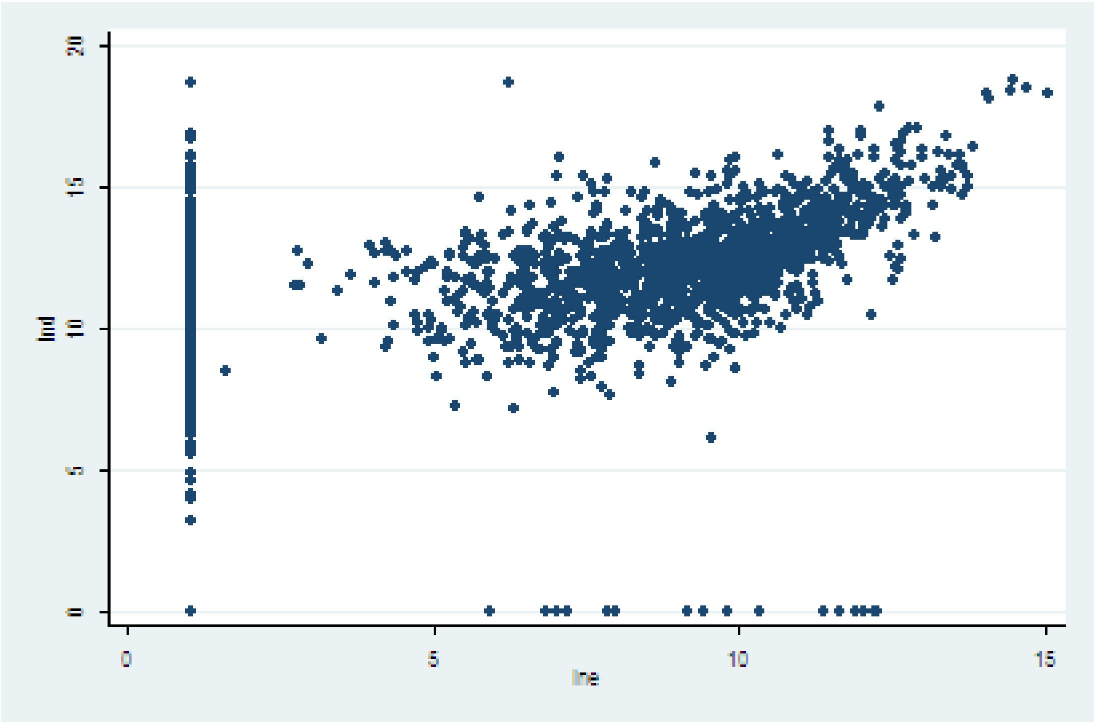

Figure 2: Donations and Fundraising Expenditure for Land Conservations

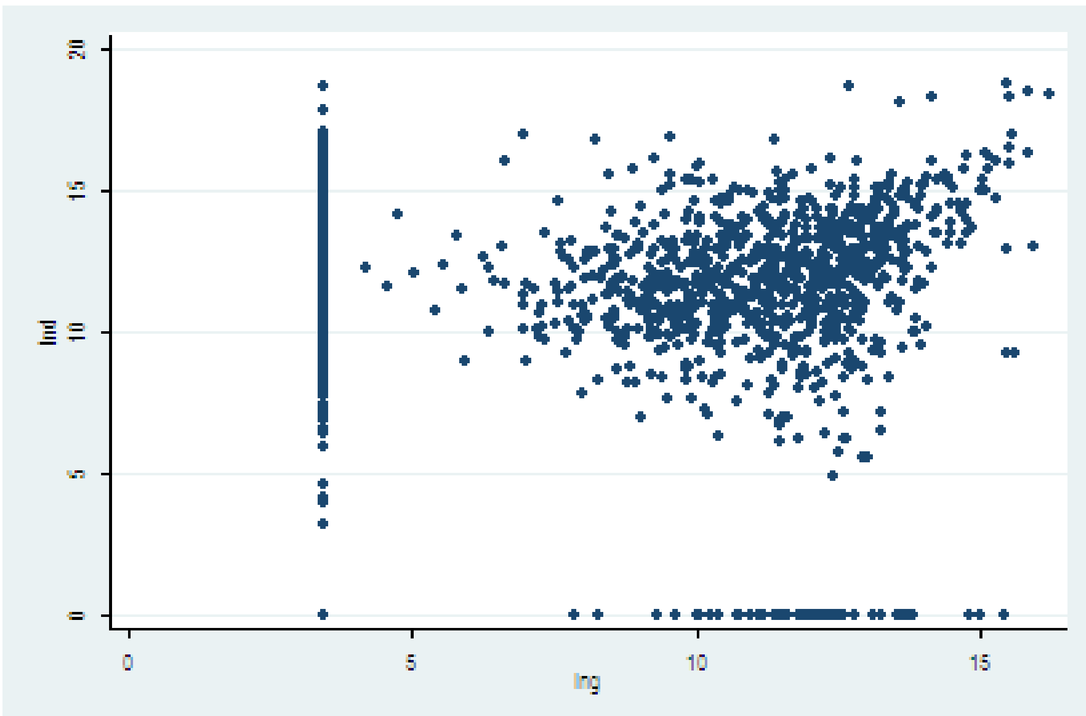

Figure 3: Donations and Government Grants for Land Conservations

Table 17: Summary Statistics of Main Variables and Financial Ratios of Green Charities and Land Conservations

		private donation	**government grants**	**total rev**	**fundraise exp**	**manage exp**	**total exp**
All	mean	534	118	998	40.5	95.7	751
	s. d.	7,584	848	12,000	719	819	7,514
	med.	26.6	0	141	0	11.0	113
Land Conserve	mean	904	119	1,287	27.3	79.7	764
	s. d.	6,300	548	7,166	125	489	5,147
	med.	92.9	0	205	0	13.1	107
		donation in total rev	**grants in total rev**	**program total rev**	**fundraise in total exp**	**management in total exp**	**donation/ fundraise**
All	mean	.368	.125	.173	.032	.143	133
	s. d.	1.84	.27	.804	.081	.194	3,007
	med.	.171	0	0	0	.083	11
Land Conserve	mean	.505	.111	.079	.049	.187	358
	s. d.	.879	.265	.207	.094	.232	7,061
	med.	.594	0	0	.0002	.116	18

Note: 1. In total revenue, except donation, grants, and program revenue, the remaining part is called other revenues which account for approximately 30 percent; in total expenditure, except fundraising and management expenditure, the remaining part is program service expenditure which account for approximately 60 percent. 2. The ratio of donation to fundraising expenditure is the commonly used measure of fundraising efficiency. 3. Resources: the NCCS-GuideStar National Nonprofit Research Database, 1998-2003.

where r_{jt} is the sum of donations, d_{jt}, and government grants, g_{jt}, and $c(e_{jt}, m_{jt}, g_{jt})$ represents the opportunity costs from overhead expenditures and the impact of government grants.

Charities are assumed to get revenues only from donations and government grants. In reality, however, charities typically receive program service revenues and other revenues. These are not specified explicitly in the model because the research objective focuses on the process of donation generation and the impact of government grants. Alternatively, one can understand other revenues as part of "government grants". Moreover, such simplification has no impact on the development of the empirical strategy and the following analysis. For similar reasons, I assume that a charity spends all net revenues on their missions or providing program services. Hence, a charity only needs to make decisions on how much to spend in fundraising and management.

The disutility function includes direct costs and indirect costs of overhead expenditures. Direct costs are just the sum of the expenditures in fundraising and management. Indirect costs reflect the observation that charities may not be net revenue maximizers (Weisbrod, 1998; Andreoni and Payne, 2003). The ultimate objective of a charity is to provide charitable services or public goods, which may conflict with the overhead expenditures. Indirect costs may come from the legal or moral restrictions imposed on charities' spending behavior. Alternatively, indirect costs can be treated as the negative social image of a charity caused by excessive spending on fundraising and management, since the public generally believes that good charities should spend most of their revenues on program services instead of on fundraising and management.

Government grants affect the cost function through the impact on fundraising and management expenditures. Given that charities see fundraising as "a necessary evil," more government grants might increase the marginal indirect-cost of fundraising expenditure and thus reduce the expenditures in fundraising. Also, government grants may alleviate the financial pressure of charities and encourage them to invest more in management to improve their managerial capacity.

3.3.2 Determination of Donations

The donation function is specified in the following log-log format:[7]

$$d_{jt} = \beta_0 + \beta_e e_{jt} + \beta_g g_{jt} + \beta_k k_{jt} + \omega_{jt} + \xi_{jt}. \tag{3.2}$$

The novel features of this specification lie in the incorporation of managerial capacity, k_{jt}, and fundraising productivity, ω_{jt}. β_0 can be interpreted as the mean fundraising productivity level of charities; ξ_{jt} represent random productivity shocks not expected by charities, such as changes in donors' preferences and time-varying economic shocks.

The impact of fundraising expenditure, e_{jt}, on donations can be interpreted as "the power of the ask", which conveys information to potential donors and alleviates the costs of giving (Andreoni and Payne, 2003). The incorporation of government grants, g_{jt}, comes from at least two considerations. One is the classical crowding out hypothesis, which predicts that donors see their contributions as perfect/imperfect substitutes for the government grants to a charitable cause (Bergstrom, Blume, and Varian, 1986; Andreoni, 1990). The other is the crowding-in effects, for example, Heutel (2009) shows that government grants can serve as a signal of a charity's quality and crowd in private donations to that charity.

Managerial capacity is a measure of the accumulated impact of a charity's investment in management, m_{jt}. It is defined by

$$k_{jt} = (1 - \delta)k_{jt-1} + m_{jt}, \tag{3.3}$$

where δ is the discount rate of the managerial capacity. Managerial investment has two categories: one consists of wages and salaries of managers and employees, the other consists of expenses on equipment, office, and other parts of operation. Correspondingly, managerial capacity has two components: human capital and physical capital[8]. Higher managerial

[7] This formalization is an aggregated representation of charities operation in raising donations, as well as donors' preferences. Ideally, it is necessary to develop a behavioral model of the giving decision of donor that accounts for the fundraising strategies and other characteristics of charities, as shown by Sieg and Zhang (2009). Unfortunately, only charity-level data are available here, so I follow this traditional donation function approach to make the analysis simple and comparable.

[8] One problem with the measurement is that initial values of management expenditure are not observed for some charities. In that case, missing observations are imputed using the average management expenditures from the observed periods. An alternative way is to estimate the investment rate using the dynamic linear panel models. Different procedures in constructing managerial capacity have no significant impact on the results.

investment can build up a better management team that likely has better abilities and strategies to raise more donations. Higher investment in office infrastructure and information technology is good for charities to be more effective in fundraising.

Fundraising productivity represents the unmeasured dynamic impact from the factors, such as social preference for different charitable causes and a charity's reputation or goodwill stock accumulated through good development practices. Productivity is known or predictable to charities and donors when they make decisions related to donations, but it is unobserved by researchers. Following the literature of productivity (Hopenhayn and Rogerson, 1993; Olley and Pakes, 1996), fundraising productivity is assumed to follow an exogenous first order Markov process[9]:

$$p(\omega_{jt+1} \mid \{\omega_{j\tau}\}_{\tau=0}^{t}, I_{jt}) = p(\omega_{jt+1} \mid \omega_{jt}) \tag{3.4}$$

where I_{jt} is the information set of charity j at time t. This is simultaneously an econometric assumption on the unobservable and an economic assumption on how charities form their perceptions on the evolution of their fundraising efficiency. It implies that a charity observes the realization of ω_{jt} at time t and forms expectations of future ω_j by $p(\omega_{jt+1} \mid \omega_{jt})$.

3.3.3 Charity's Dynamic Optimization Problem

The events related to a charity's decision problem unfold as the following.

1. Managerial capacity accumulated until last period k_{jt-1} is known at the beginning of t.
2. Government grants g_{jt} are determined exogenously.
3. Efficiency or productivity shock ω_{jt} are realized.
4. Charities make decisions on management m_{jt} and fundraising e_{jt}.
5. Donations d_{jt} are determined once the events in 1-4 are realized.
6. Period $t+1$ begins for charity j with managerial capacity k_{jt}.

Government grants g_{jt} are assumed to be pre-fixed before ω_{jt} are realized and charities make decisions on spending. This is reasonable in the following sense. The procedure of

[9]The first-order Markov process encompasses the fixed effects when $\omega_{jt} = \omega_j$.

getting government grants may take a long time, and before charities get government grants in hand they might already have information on the success of their application. Government grants, however, could happen together with or even after ω_{jt}. This could cause identification problem in our estimation procedure, so I will discuss this problem and the methods to deal with it in the estimation part.

The charity's dynamic optimization problem can be characterized by the following Bellman equation:

$$V(k_{jt-1}, g_{jt}, \omega_{jt}, \Delta_t) = max_{m_{jt}}\{r_e(k_{jt}, g_{jt}, \omega_{jt}, \Delta_t) - c_e(m_{jt}, g_{jt}, \Delta_t) - \beta E[V(k_{jt}, g_{jt+1}, \omega_{jt+1}, \Delta_{t+1})|(k_{jt-1}, g_{jt}, \omega_{jt}, \Delta_t)]\},$$

Note that in the payoff function of the current period, $r_e(k_{jt}, g_{jt}, \omega_{jt}, \Delta_t) - c_e(m_{jt}, g_{jt}, \Delta_t)$, fundraising expenses, e_{jt}, are not explicit. The reason is that fundraising expenditure is assumed to be a variable and non-dynamic input chosen at the time that it gets used. It has no impact on future payoffs and thus is not a state variable. Hence, the payoff function is denoted in a form conditional on the optimal static choice of fundraising expenses. Δ_t is used to capture some characteristics related to the charity market such as the macroeconomic environment or market competition, where t can represent time or region.

The management spending function can be derived by solving the charity's optimization problem. Under appropriate assumptions (see a discussion in Pakes (1994)), the optimal rule for management spending is strictly monotonic in ω_{jt} and can be written as

$$m_{jt} = f(g_{jt}, k_{jt-1}, \omega_{jt}, \Delta_t) = f_t(g_{jt}, k_{jt-1}, \omega_{jt}). \tag{3.5}$$

This condition provides the key identification argument in the estimation procedure proposed by Olley and Pakes (1996). The above formalization is straightforward to extend to a dynamic model of the charity market.

3.4 METHODOLOGY

3.4.1 Identification

The major challenge in the estimation of the donation function is the same endogeneity problem as that in the production function estimation. Donations can be understood as the value of output, fundraising as labor, managerial capacity as human or physical capital, government grants as intermediate inputs, and management expenditure as investment. The endogeneity problem arises from the contemporaneous correlation between fundraising productivity and other input variables, including fundraising expenditure and managerial capacity. An OLS procedure that fails to control for the dynamic heterogeneity of fundraising productivity tends to provide biased estimates. If the inputs are more variable, they are more highly correlated with productivity and their estimates are more biased (Marschak and Andrews, 1944; Griliches, 1957).

In the setting with multivariate inputs, there exist different predictions on the signs of the biases of the OLS estimates. Previous empirical practices generally reach the conclusion that the estimates on variable inputs, such as labor, is positively biased and the estimates on invariable inputs, such as capital, are negatively biased (Grilliches and Mairesse, 1998). Levinsohn and Petrin (2003) provides a formal argument for the above claim in the short panel data when the correlation between variable input and productivity is higher than the correlation between invariable input and productivity, which is close to the situation of the donation function.

According to the above arguments, it is expected that the coefficient of fundraising expenditure, the variable input, is positively biased and that on the managerial capacity is negatively biased. Intuitively, fundraising expenditure could be positively related to fundraising productivity because fundraising is more "profitable" in the case of high fundraising productivity or positive productivity shocks, so without controlling for the productivity will result in the over-estimation of the impact from fundrasing expenditure on donations. On the other hand, there could be negative relation between managerial capacity and fundraising productivity. This can come from the fact that a charity with better managerial capacity has a better chance of surviving lower productivity or negative productivity shocks in fundraising.

Different econometric techniques have been developed to deal with the endogeneity problem in the production function estimation (Ackerberg, Benkard, Berry and Pakes, 2006). I employed a procedure based on the two-stage semi-parametric approach developed by Olley and Pakes (1996) that has advantages over OLS, within, and traditional instrumental variable estimators (Grilliches and Mairesse, 1998). The identification relies on the rule of optimal management spending, m_{jt}, which is invertible in fundraising productivity, ω_{jt}, and can derived from the dynamic model presented in last section. Levinsohn and Petrin (2003) provide an alternative justification for this condition. Aguirregabiria (2009) treats this strategy as a control function approach and compares it with other available techniques. More important, this identification condition is testable.

3.4.2 Estimation

Management expenditure can be written as $m_{jt} = f(g_{jt}, k_{jt-1}, \omega_{jt}, \Delta_t) = f_t(g_{jt}, k_{jt-1}, \omega_{jt})$, which implies that, conditional on k_{jt} and g_{jt}, a charity's choices on management expenditure incorporate the information of fundraising productivity. Fundrasing productivity can be inverted as $\omega_{jt} = h'_t(k_{jt-1}, g_{jt}, m_{jt}) = h_t(k_{jt}, g_{jt}, m_{jt})$ and substituted into the production function,

$$d_{jt} = \beta_0 + \beta_e e_{jt} + \beta_k k_{jt} + \beta_g g_{jt} + h_t(k_{jt}, g_{jt}, m_{jt}) + \xi_{jt}. \tag{3.6}$$

The first stage of the estimation aims to get the consistent estimate of β_e by controlling for the impact of fundraising productivity through a semi-parametric strategy without specifying the parametric function of management and productivity. The donation function can be rewritten as:

$$d_{jt} = \beta_e e_{jt} + \phi_t(k_{jt}, g_{jt}, m_{jt}) + \xi_{jt}, \tag{3.7}$$

where $\phi_{jt} = \beta_0 + \beta_k k_{jt} + \beta_g g_{jt} + \omega_{jt}$. The semi-parametric estimation can generate a consistent estimate $\beta_e^{'}$ and an estimate $\phi_{jt}^{'}$ of ϕ_{jt}. This stage, however, can not produce consistent estimates of β_g and β_k since the non-parametric form of h_t, β_0, g_{jt} and k_{jt} are incorporated together as ϕ_{jt}.

The objective of the second stage estimation is to estimate β_g and β_k as the following. First, note that $\omega_{jt} = E(\omega_{jt} \mid I_{jt-1}) = E(\omega_{jt} \mid \omega_{jt-1}) + \eta_{jt} = g(\omega_{jt-1}) + \eta_{jt}$. The second equality follows from the assumption of the first order Markov process. η_{jt} is treated as the innovation component of ω_{jt} from time $t-1$ to time t and is unexpected by charities. Then, one can rewrite the donation function as $d_{jt} - \beta_e e_{jt} = \beta_k k_{jt} + \beta_g g_{jt} + E[\omega_{jt} \mid \omega_{jt-1}] + \xi_{jt} + \eta_{jt}$. Finally, the residual for any given (β_g, β_k) is computed by:

$$\widehat{\xi_{jt} + \eta_{jt}} = d_{jt} - \widehat{\beta}_e e_{jt} - \beta_k k_{jt} - \beta_g g_{jt} - E[\omega_{jt} \mid \omega_{jt-1}], \tag{3.8}$$

where the estimator $\widehat{\beta}_e$ is from the first stage. A consistent approximation to $E[\omega_{jt} \mid \omega_{jt-1}]$ is given by the predicted values from the non-parametric regression based on the computed productivity index $\omega_{jt} = \phi'_{jt} - \beta_k k_{jt} - \beta_g g_{jt}$ for any set of (β_k, β_g) and ϕ'_{jt}.

The identification of β_k and β_g needs at least two instruments which interact with the residual $\widehat{\xi_{jt} + \eta_{jt}}$ and form the moment condition. Given that the innovation part η_{jt} is uncorrelated with k_{jt-1} and g_{jt}, so the moments for estimation can be $E[\xi_{jt} + \eta_{jt} \mid k_{jt-1}] = 0$ and $E[\xi_{jt} + \eta_{jt} \mid g_{jt}] = 0$.Over-identification conditions and additional instrumental variables can be used to improve efficiency and test the specification. Let Z_{jt} denotes all instrumental variables, the estimators solve

$$min_{(\beta_k, \beta_g)} \sum_i [\frac{1}{J}\frac{1}{T} \sum_j \sum_t (\widehat{\xi_{jt} + \eta_{jt}}) Z_{j,it}]^2, \tag{3.9}$$

where i is the index for the elements of Z_{jt}, and J and T are the number of charities and periods.

The analytic derivation of the covariance of the estimators must account for the sampling variation in the above two-stage procedure and is difficult to calculate. Instead of deriving the covariance, this paper employs a bootstrapping procedure to get the standard errors, as suggested by Levinsohn and Petrin (2003). The bootstrapped sample is constructed as the following. If a charity's ID number is drawn randomly, all the observations of that charity will be included. This procedure continues until the total number of observations is no less than the number in the true sample. The variation from the point estimates of all bootstrapped samples provides the estimates of the standard errors of the point estimates from the true sample.

3.5 EMPIRICAL RESULTS

3.5.1 Estimation of the Donation Function

Table 3 shows the estimates of the donations function using the procedure documented in Section 3.2, called base-case, and the estimates from the OLS and the fixed effects model. All estimations use the same benchmark sample of land conservations. As a first step, I followed the literature (Andreoni and Payne, 2003) to screen the data.[10] The main findings are not affected by different screening procedures, as shown in the robustness check,.

Table 18: Estimates from the Base-Case, Fixed Effects and OLS

	Base-Case	**Fixed Effects**	**OLS**
fundraising expenditure	0.131 (0.036)	0.308 (0.067)	0.305 (0.064)
management capacity	0.927 (0.396)	0.754 (0.128)	0.556 (0.077)
government grants	0.029 (0.019)	0.063 (0.017)	0.025 (0.015)

Note: in all tables, the parameters in prentheses are standard errors.

After controlling for fundraising productivity, the estimated impact of fundraising expenditure on donations is significantly reduced by 57 percent, from 0.305 to 0.131, comparing to OLS estimate. An intuitive explanation is that the OLS estimate of the impact from fundraising expenditure actually incorporates the impact from the unobserved productivity in a positive correlation. In other words, a charity is more willing to increase its fundraising expenditure if its perceived fundraising productivity is higher.

This finding highlights the importance of incorporating fundraising productivity into the analysis of crowding out. It implies that without controlling the impact of fundraising productivity might cause the over estimation of the indirect crowding out that is the multi-

[10] The procedure is the following sequentially: drop 437 observations from charities that have no more than 3 observations between 1998 and 2003; drop 185 observations from charities never receiving donations; drop 507 observations from charities never reporting fundraising expenditure; drop 575 observations from charities never receiving government grants; drop 56 and 178 observations from charities that only report donations or fundraising in no more than 2 years between 1998 and 2003. Finally, 999 observations remains from 176 charities.

plication between the estimated impact from government grants on fundraising expenditure and the estimated impact from fundraising expenditure on donations.

In the base-case estimation, compared to OLS, the estimated impact from managerial capacity on donations is increased by 67 percent, from 0.556 to 0.927. Among all the specification and robustness checks, the impact from managerial capacity on donations is positive and significant. Table 19 further demonstrates the effects of incorporating managerial capacity in the analysis by comparing the results from the estimations with and without managerial capacity. Incorporating managerial capacity reduces the impact of government grants on donations.

Table 19: Estimates from the Model with and without Managerial Capacity (k)

	Base-Case	**Fixed Effects**	**OLS**
fundraising expenditure with k	0.131 (0.036)	0.308 (0.067)	0.305 (0.064)
fundraising expenditure without k	0.128 (0.036)	0.344 (0.069)	0.438 (0.062)
government grants with k	0.029 (0.019)	0.063 (0.017)	0.025 (0.015)
government grants without k	0.038 (0.015)	0.076 (0.017)	0.038 (0.017)

The importance of managerial capacity has important implication on the discussion of the overhead expenditure of charities. Generally, the public impose high pressure on charities to reduce overhead spending in management and fundraising, since people think charities should spend more resources on program services. Charities, however, need to do necessary investment in management, so that they could build up a sustainable organization in the long term.

Compared to OLS, the base-case estimate on government grants, g_{jt}, is decrease from 0.029 to 0.025. Such positive impact supports the crowding-in hypothesis (Heutel, 2009). A robustness check is to use the government grants lagged one period as the instrumental variables to construct the moment in the second stage; doing this increases the estimate of government grants from 0.029 to 0.094, but the results are not significant.

The fixed effects model can control for the unobserved characteristics of charities that do not vary across time. The results from fixed effects model are closer to those from the base-case estimation than OLS, but only controlling the fixed effects is still not sufficient. This is reasonable since fixed effects model can be treated as a special example of the base-case model.

3.5.2 Specification Tests

A major concern related to the methodology is whether management expenditure can be expressed as a function of government grants, managerial capacity, and fundraising productivity and used to resolve the endogeneity problem.[11] One specification test proposed in Olley and Pakes (1996) is the following. If the proxy of fundraising productivity is conditioning out all of the variation in inputs that is correlated with the productivity shock, the error term in the donation function, ξ_{jt}, should be mean independent of e_{t-1}. Moreover, since e_t and e_{t-1} are highly correlated, if there were an error in the first stage estimation of β_e, one would expect a significant coefficient for e_{t-1} if it is added to the regression:

$$d_{jt} - \beta_e e_{jt} = \beta_k k_{jt} + \beta_g g_{jt} + \beta_e' e_{jt-1} + E[\omega_{jt} \mid \omega_{jt-1}] + \xi_{jt} + \eta_{jt}. \tag{3.10}$$

The results in Table 20 show that lagged fundraising expenditure has no impact on donations in later periods, so this rules out the possible dynamic impact of fundraising and validates the identification strategy. Similarly, one can add lagged government grants, g_{t-1}, into the last step of the estimation to test whether the index restriction in the bias term for the inversion is consistent with the data. If so, the estimate on g_{t-1} is not significant, which is also shown in Table 20.

Another simple check for the identification power of the management spending function, $m_{jt} = f_t(g_{jt}, k_{jt-1}, \omega_{jt})$, is to run the regression of m_{jt} on fundraising productivity, ω_{jt}, after controlling for the impact from g_{jt} and k_{jt-1}. Here, fundraising productivity is computed after estimating the donation function as documented in Section 5. The results show a significant positive relation between managerial expenditure and fundraising productivity.

[11] Another restriction in the first stage identification is that fundraising expenses chosen in this period should not be correlated with the innovation in productivity next period. If this is not the case, Ackerberg, Caves and Frazer (2006) propose an alternative procedure for the estimation. In this paper, if the impacts from past fundraising are included in the model as another state variable, the estimates of such dynamic impacts are not significant.

Table 20: Specification Tests

	specification test of fundraising expenditure	**specification test of government grants**
fundraising expenditure	0.1319 (0.0365)	0.1319 (0.0317)
managerial capacity	1.4082 (0.3683)	1.3408 (0.4223)
government grants	0.0429 (0.0193)	0.0537 (0.0168)
lagged fundraising expenditure	0.0012 (0.0028)	-
lagged government grants	-	-0.0035 (0.0029)

I also conducted two other specification tests within the current empirical framework. One is incorporating alternative instrumental variables for government grants. The other is adding more control variables that are typically used in the estimation of the donation function. In both cases, there are no significant impact on the estimates.

3.5.3 Data Issues

This section focuses on the robustness of the empirical results related to the issues of data reporting, sample selection, and screening procedure as documented in the data analysis of Section 2.

There are large amount of observations from charities that never report fundraising expenditure but receive positive donations, which is more likely misreporting because charities facing pressure in reducing fundraising expenses. To deal with this problem, one approach I used is substituting those zeros with an imputation procedure. First, I estimate a model of the determination of fundraising spending, using the observed information such as managerial expenditure, total expenditure and total assets. I assume charities with similar size in expenditure and total assets should spend similar amounts in fundraising, after controlling fixed effects and other observed characteristics. Then I use the estimates from the fixed effects model to impute the zero observations by the predicted value of fundraising expenditure.

The second column in Table 21 shows the results from the estimation using the data that substitutes the zero fundraising expenditures with imputed values. Compared to the results without imputation, the salient difference is that the estimate on fundraising is much higher in the base-case estimation, from 0.13 to 0.32. The reason is that the substitution of zeros increase the impact of fundraising expenditures. The results have no impacts on the bias of the estimate on fundraising expenditure which is over estimated and that of managerial capacity which is under estimated.

Table 21: Estimates after Substituting or Deleting Observations with Zeros

	Base-Case	**Substituting Zero Fundraising Expenditure**	**Deleting Zero Government Grants**
fundraising expenditure	0.131 (0.036)	0.3225 (0.0739)	0.1305 (0.0536)
managerial capacity	0.927 (0.396)	0.9662 (0.4307)	0.9549 (0.2104)
government grants	0.029 (0.019)	0.0296 (0.0202)	0.2911 (0.1296)

The results in the third column of Table 21 are obtained from the estimation without observations with zeros in government grants. Compared to the estimation that keeps zero government grants, the estimate of government grants after deleting zeroes is much higher that is 0.2911 compared to 0.0296 for the base-case estimation. This is intuitive since dropping observations with zero government grants give more weight on the impact of government grants.

Using the data from other subgroups of green charities generates similar results and conclusions as those using the bench march sample (land resources conservation). The results from three other groups are shown in Table 22. The first group is Water Resources, Wetlands Conservation & Management (C32). The second group includes general natural resources conservations that can not be categorized into other more specific groups (C30). The third group includes all natural resources conservations. Overall, the key conclusions still hold.

Table 22: Estimates from Different Samples and Data Screening Procedure

	Water Conservations	**Other Conservations**	**All Conservations**	**All Conservations Different Screening**
fundraising expenditure	0.170 (0.050)	0.257 (0.033)	0.173 (0.020)	0.197 (0.012)
managerial capacity	0.947 (0.386)	0.544 (0.103)	0.700 (0.351)	1.718 (0.239)
government grants	-0.033(0.035)	0.187 (0.011)	0.016 (0.011)	-0.018 (0.012)

For data screening, I try an alternative procedure that I only drop those observations from the charities that never receive private donations and the charities that have fewer than 4 observations in the sample period. The results are shown in the last column of Table 22 using the observations from all natural resource conservations. The estimates give the similar results and conclusions.

3.5.4 Alternative Approaches

Dynamic panel data models (for example, Blundell and Bond, 1998, 2000) can also deal with the problem of the unobserved dynamic heterogeneity in the empirical analysis. Essentially, such models extend the fixed effects model to allow for more sophisticated error structures by adding a serially correlated unobservable that follows AR(1) or MA(0) to capture the impact of productivity. I estimated the donation function using the system GMM estimation from Blundell and Bond (1998). The estimates from the dynamic panel data model are very close to the base-case estimates. Such findings are reasonable because of the similar assumptions of these two approaches, as documented in Ackerberg, Caves, and Frazer (2005).[12]

[12] Assuming ω_{jt} follow an AR(1) process: $\omega_{jt} = \rho\omega_{jt-1} + \eta_{jt}$, ω_{jt} is correlated with g_{jt}, k_{jt} and e_{jt} for all t, and the innovation or changes from ω_{jt-1} to ω_{jt} is uncorrelated with these variables before t. Thus, the donation function can be written as $d_{jt} = \beta_g g_{jt} + \beta_k k_{jt} + \beta_e e_{jt} + \varpi_{jt}$, where $\varpi_{jt} = \beta_j + \omega_{jt} + \xi_{jt}$. The estimates for β and ρ can be derived by the sample analogue of $E[(\varpi_{jt} - \rho\varpi_{jt-1}) - (\varpi_{jt-1} - \rho\varpi_{jt-2}) | \{k_{j\tau}, e_{j\tau}, g_{j\tau}\}, \tau = 1, ..., t-2]$.

Table 23: Estimates from Base-Case and Dynamic Panel Model

	Base-Case without K	**Dynamic Panel without K**	**Base-Case**	**Dynamic Panel**
fundraising expenditure (β_e)	0.128 (0.036)	0.158 (0.090)	0.131 (0.036)	0.161 (0.074)
management capacity (β_k)	-	-	0.927 (0.396)	1.010 (0.128)
government grants (β_g)	0.038 (0.015)	0.073 (0.017)	0.029 (0.019)	0.040 (0.020)

Instrumental variables are also employed to deal with the endogeneity problem related to fundraising expenditure and government grants.[13] Andreoni and Payne (2009) use total occupancy costs and total liabilities as instrumental variables for fundraising expenditure and find that the impact from fundraising is increased, different from the predictions and results of our base-case estimation. For the instrumental variables for government grants, Andreoni and Payne use the measures of local politician's power and find that there are crowding out effects; Heutel (2009) employs the instruments–social security income transfers from federal to local or state governments–and find that there are crowding in effects. Both paper used the data from social service organization. I estimated the donation function using the same instrumental variables strategy and have similar findings: the estimate of the impact fundraising expenditure on donations is over-estimated and the impact of government grants is not significant. The results are shown in Table 24 and Table 25.

[13] Those instrumental variables have two major problems. First, they cannot resolve the endogeneity problem related to the unobservable that is time-varying and serially correlated, such as fundraising productivity. Second, the results are not consistent across different data sets and instrumental variables.

Table 24: Estimation Using Instrumental Variables for Fundraising Expenditure

Variable	OLS	FE	2SLS	FEIV
fundraising expenditure	0.329 (0.025)	0.314 (0.026)	1.154 (0.237)	0.626 (0.139)
managerial capacity	0.636 (0.056)	0.628 (0.112)	-0.106 (0.227)	0.431 (0.149)
government grant	0.031 (0.013)	0.067 (0.014)	-0.064 (0.033)	0.046 (0.017)
program revenue	-0.060 (0.014)	0.004 (0.022)	-0.078 (0.021)	-0.018 (0.026)
other revenue	-0.069 (0.039)	-0.217 (0.051)	-0.057 (0.058)	-0.152 (0.062)
population	-0.067 (0.064)	-0.280 (0.664)	-0.133 (0.097)	-0.564 (0.735)
income/capital	1.925 (0.474)	1.627 (0.862)	1.053 (0.746)	-0.873 (1.437)
cons.	-16.670 (4.876)	-9.051 (12.391)	-3.932 (8.074)	20.603 (18.664)

Table 25: Estimation Using Instrumental Variables for Government Grants

Variable	OLS	FE	2SLS (A&P)	2SLS (Heutel)
government grant	0.031 (0.013)	0.067 (0.014)	-0.095 (0.060)	0.023 (0.082)
fundraising expenditure	0.329 (0.025)	0.314 (0.026)	0.382 (0.035)	0.333 (0.042)
managerial capacity	0.636 (0.056)	0.628 (0.112)	0.677 (0.062)	0.639 (0.062)
program revenue	-0.060 (0.014)	0.004 (0.022)	-0.052 (0.015)	-0.060 (0.015)
other revenue	-0.069 (0.039)	-0.217 (0.051)	-0.079 (0.041)	-0.070 (0.039)
population	-0.067 (0.064)	-0.280 (0.664)	-0.070 (0.067)	-0.067 (0.064)
income/capital	1.925 (0.474)	1.627 (0.862)	1.961 (0.498)	1.927 (0.475)
cons.	-16.670 (4.876)	-9.051 (12.391)	-17.010 (5.122)	-16.692 (4.882)

3.6 DETERMINANTS OF DONATIONS

3.6.1 Interpretation and Decomposition

The estimated parameters of the donation function are elasticities so the marginal impact from fundraising expenditure, managerial capacity, and government grants on donations can be computed by multiplying their estimates with the inverse of their ratios to donation: $\widehat{\beta}_e * (d/e)$, $\widehat{\beta}_k * (d/k)$, and $\widehat{\beta}_g * (d/g)$. Using the base-case estimates and the median ratios, the marginal impact of fundraising expenditure, managerial capacity, and government grants are respectively 2.16, 1.08, and 0.10. For managerial capacity, it means that one dollar of marginal spending on management capacity leads to 1.08 dollar increase in donations. Fundraising expenditure remains the most important determinant of donations, followed by managerial capacity and government grants.

After estimating the donation function, donations can be decomposed into the contribution from fundraising productivity, fundraising expenditure, managerial capacity, and government grants, as shown in Table 26. Fundraising productivity is computed by $w_{jt} = d_{jt} - \widehat{\beta}_e * e_{jt} - \widehat{\beta}_k * k_{jt} - \widehat{\beta}_g * g_{jt}$.[14] The decomposition shows that fundraising productivity is a key determinant of donations and its variance is much higher than other determinants. Government policies should account for charities' differences in fundraising efficiency and the causes of such differences. For example, the matching grants policy may not be effective if the fundraising productivity of a grant recipient is very low. Furthermore, the causes of low fundraising productivity may not be related to bad performance because not all charitable causes are well recognized by society at the beginning.

3.6.2 Fundraising Efficiency

In this subsection, I investigate the determinants of fundraising efficiency using the computed fundraising productivity and compare it with the commonly used measure of fundraising efficiency–the ratio between donations and fundraising expenditure. The analysis is con-

[14]An alternative way to compute the fundraising productivity is using $W_{jt} = exp(d_{jt} - \widehat{\beta}_e * e_{jt})$. Fundraising productivity is a relative efficiency measure since its absolute value depends on the different ways to measure it. The robust checks show that different relative measures have no impact on the following analysis.

Table 26: Decomposition of the Donation Function in the Log-Linear Form

	donation	**productivity**	**fundraising** ($\widehat{\beta}_e$·e)	**management** ($\widehat{\beta}_k$·k)	**grant** ($\widehat{\beta}_g$·g)
mean	12.2	-.62	1.14	11.5	.203
s.d.	2.78	2.24	.441	1.57	.166
median	12.4	-.403	1.24	11.5	.276

ducted based on the following regression:

$$w_{jt} = \beta_j + \beta^{pe} x_{jt}^{pe} + \beta^{as} x_{jt}^{as} + \beta^{pr} x_{jt}^{pr} + \beta^{or} x_{jt}^{or} + \mu_{jt} \tag{3.11}$$

where w_{jt} is the measure of fundraising efficiency, β_j is the fixed effect. Other explanatory variables are four ratios: program service expenditure over total expenditure x_{jt}^{pe}, total assets over total expenditure x_{jt}^{as}, program service revenue over total revenue x_{jt}^{pr}, and other revenue over total revenue x_{jt}^{or}. The control variables include age and expenditure variables.

It is expected that fundraising efficiency is positively determined by the asset scale relative to total expenditure and the ratio of program service expenditure in total expenditure, because the relatively high asset and program service provision indicate good charities. Fundraising efficiency should be negatively related to the ratios of program service revenue and other revenues in total revenue, since if charities have other revenue resources they might not have strong incentives to improve their fundraising efficiency, considering that their main objective is not to maximize their total revenue but to provide public services.

Table 27 shows the estimates from the fixed effects model. In the first column, the efficiency measure is the computed fundraising productivity incorporating the impact of managerial capacity. It can be seen that the coefficients have the expected signs. In this case, managerial capacity as an explanatory variable has strong predictive power. These results are robust to alternative computation of fundraising productivity. For instance, the results are similar if using the productivity measure without incorporating the impact of managerial capacity, as shown in column 3.

Table 27: Determinants and Comparison of Fundraising Efficiency

Variable	**Fundraising Productivity 1**	**Fundraising Productivity 2**	**Donation/ Fundraising**
managerial capacity	0.516 (0.076)	-	-
age	0.031 (0.034)	0.017 (0.032)	11.3 (25.4)
(program expenditure)/(total expenditure)	5.365 (0.773)	5.326 (0.761)	983 (842)
(total asset)/(total expenditure)	0.013 (0.003)	0.013 (0.002)	-15.1 (20.5)
(program revenue)/(total revenue)	-2.155 (0.965)	-2.364 (0.960)	-280 (157)
(other revenue)/(total revenue)	-0.154 (0.137)	-0.162 (0.138)	1.40 (14.2)
Intercept	-0.187 (0.769)	-4.747 (0.778)	-209 (661)

Note: The estimates are obtained from the estimation of the fixed effects models. Fundraising productivity 1 incorporates the impact of managerial capacity, but fundraising productivity 2 does not.

In the last column of Table 27, the results are obtained using the alternative measure of fundraising efficiency–the donation-fundraising ratio. It shows that only some parameters have the expected signs and most of them are not significant, which implies that the donation-fundraising ratio as a measure of efficiency may be problematic.

3.7 CONCLUSIONS

I incorporate managerial capacity and fundraising productivity into the analysis of donations to charitable organizations and demonstrate that both have important impact on the estimation of the donation function. More works can be done by applying this productivity approach to study whether and why there are differences in fundraising efficiency across different groups of charities. Policy design should also account for charities' differences in fundraising productivity.

This paper provides the evidence that supports necessary managerial investment, however, the public might impose too much pressure on charities to reduce their overhead expenditures in management. It seems interesting to further investigate the micro-structure and compensation scheme of charities, as well as their relation to charities' performance.

APPENDIX A

APPENDIX FOR CHAPTER 2

A.1 ANONYMOUS DONATIONS

The number of donors listed as anonymous does not constitute a large percentage for any charity as shown in Table 28. 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.

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 28: 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%

Table 29: Perks of Different Charity-Ties: Part 1

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

Table 30: Perks of Different Charity-Ties: Part 2

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

APPENDIX B

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