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The importance of managerial capacity in fundraising: Evidence from land conservation charities ☆

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ABSTRACT

The objective of this paper is to show the importance of incorporating managerial capacity into the empirical analysis of the determinants of donations to charitable organizations. We adopt a production function approach to model the outcome of the fundraising process. The empirical findings suggest that managerial capacity is an important factor determining charitable donations. This finding is qualitatively robust using a variety of different estimation strategies including Olley and Pakes style estimators, dynamic panel data estimators, standard IV estimators, and fixed effects estimators. In contrast, estimates of the two other input factors, fund-raising expenditures and government grants, are sensitive with respect to different identification strategies, sample selection rules, and missing data imputation mechanisms.

1. Introduction

The protection of the environment for the benefit of current and future generations has been a policy objective of all U.S. administrations for the past decades. Green charities play an increasingly important role in the U.S. Traditional green charities, including the Conservation Fund or the Sierra Club, focus primarily on preserving, restoring and improving the natural environment. These efforts complement efforts by the U.S. government. More recently established charities pursue a variety of other objectives that are often different from government objectives. EarthJustice, for example, advocates that new and more stringent environmental laws are passed. Similar charities monitor firms to make sure that current laws are abided by, thus acting as a public watch dog. EnviroCorp provides individuals with self-directed opportunities to serve local communities focusing on volunteering to improve local environmental conditions. The Environmental Defense Fund supports research of scientists and identifies promising business practices to bring about environmental progress. Despite the significance of these charities, there are few papers investigating the inner workings of these organizations and, in particular, the impact managerial ability has on performance. This paper addresses this gap in the literature.

In contrast to the government, charities cannot rely on taxes to fund their activities, but must instead successfully raise large amounts of donations from private households, firms, and the government. Previous research has investigated the fundraising process of charities trying to isolate the different input factors that are important in explaining differences in fundraising productivity. A charity's fundraising process is modeled as a firm's production process, in which output (donations) is produced from a variety of input factors.[1] While this approach abstracts from many potentially important details of the fundraising process, it provides a compelling framework to isolate the impact of the most important input factors. Andreoni and Payne (2003, 2011), for example, have argued that fundraising expenditures and government grants are the two most important input factors that explain donations to a charity. This finding is surprising since most studies outside this area suggest that the quality and quantity of labor inputs largely determines firm productivity. All previous studies on charitable donations have overlooked this well-known fact. The key robust finding of this paper is that managerial

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[1] Prominent examples of this approach are Okten and Weisbrod (2000), Ribar and Wilhelm (2002), Andreoni and Payne (2003, 2011), Hungerman (2005), Gruber and Hungerman (2007) and Heutel (2009).

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capacity is potentially the most important factor in determining giving to charitable organizations.

The purpose of this paper is then to quantify the impact of managerial capacity on charitable donations for green charities. Green charities are well suited to study the role of managerial capacity in charitable organizations. Green charities derive a large share of revenue from private donations, 37% in our sample. The financial success of a charity rests, at least partially, on the ability of its management team. It is, therefore, not surprising that managerial expenses account for a large share of charities' total expenditures.

While fundraising expenditures and government grants are potentially important factors in the fundraising process, there are some doubts that they are sufficient to explain observed differences among charities. First of all, fundraising expenditures only account for a small part of charities' total expenditures. In our sample of green charities, fund raising expenditures account for 5%. Moreover, the variation of donations is very high even for charities with similar amounts of fundraising expenditures indicating that there may be some other important factors. Last, many charities receive few or no government grants.[2] It is, therefore, essential to measure and incorporate other potential input factors into the analysis.[3] This paper focuses on the importance of managerial capacity as an input factor into the process of raising donations for a charity.

Most charities have a core mission that is explicitly stated in a mission statement. The core mission of charities in our application is environmental conservation. To achieve this mission a charity must define management objectives. Instead, it is common practice in the non-for-profit management literature to focus on long-term sustainability and development of the charity as the main management objectives (Backer et al., 2001). This approach suggests to define managerial capacity as the ability of a charity to accomplish the goal of long term sustainability and program development.

While most for-profit firms typically invest in tangible physical assets, charities primarily invest in intangible assets such as reputation, goodwill, and organizational knowledge. Most intangible assets are created through time and effort of the management team. These intangibles directly impact effectiveness and productivity within an organization and, therefore, costs, donor satisfaction, and thus revenues. It makes sense to treat managerial expenditures as investments into intangible assets of a charity. Salaries are a large component of managerial expenditures. If labor markets are competitive managers that are more capable in building up a charitable organization will receive higher salaries. Thus accumulated managerial expenses are a good measurement of the investment into intangible assets.

Accumulated managerial expenses account for 19% of total expenses in our sample of green charities. Managerial expenses are controversial because some watch dog organizations hold the belief that managerial spending wastes resources for charitable causes. Despite the importance and controversy of managerial expenses the impact of managerial capacity on donations has not been well studied in the literature.

The key econometric challenge encountered in the estimation of production functions is to deal with unobserved productivity differences among organizations (Marschak and Andrews, 1944). Fundraising productivity captures the impact of unobserved factors that affect a charity's effectiveness in fundraising, such as donors' social preferences for different causes. It is easier to raise more donations 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.[4]

Most of the previous empirical literature on charitable donations has adopted a standard IV approach to deal with the potential endogeneity of fund raising expenditures and government grants. It is, however, difficult to find good instruments in many applications.[5] As a consequence, it is useful to explore alternative estimators that primarily rely on timing assumptions and control function approaches. We explore two such estimators in this paper. First, we adapt and implement the estimator developed by Olley and Pakes (1996) (OP). This identification strategy utilizes the fact that the observed investment in managerial capacity is a monotonic function of the unobserved fundraising productivity. Under some regularity and timing assumptions, this function can be inverted to control for the impact of the unobserved productivity in the estimation. One nice feature of our application is that investments into managerial capacity are always positive in our sample which makes it straight forward to invert the investment function. Our application thus avoids the well-known problem of lumpy investments into capacity that can be a problem in many applications when using the OP estimator. The second technique is based on dynamic panel data models pioneered by Blundell and Bond (1998, 2000). Both of these techniques use identification strategies that differ from standard IV estimators. At minimum, it is useful to explore how sensitive the estimates of charitable production functions are to these different identifying assumptions. In the absence of convincing standard instruments, they provide a clean approach to identify and estimate the parameters of interest.

The applications studied in this paper focuses on green charities.[6] Green charities are an important force in resolving the environmental challenges of our times. The data come from the GuideStar National Nonprofit Research Database (NNRD) collected by the National Center for Charitable Statistics. Implementing a variety of different estimators discussed above, we find that managerial capacity has a significantly positive impact on raising donations, which demonstrates the long-run benefits of charities' investments in management. After controlling for unobserved productivity, the estimated impact from managerial capacity on donations increases by 67%, while the impact from fundraising expenditures is reduced by 57%.

We also find that estimates of fund raising expenditures and government grants are sensitive to sample selection criteria. The estimates of managerial capacity in contrast are robust. It matters whether or not charities with zero government grants are excluded from the sample. It also matters, whether reported zero fundraising expenditures are treated as missing data or not. These robustness checks demonstrate the importance of controlling for managerial capacity.

Finally we explore the policy implications and propose a new method for charity evaluation.[7] A commonly used measure to evaluate charities is the ratio of donations over fundraising expenditures. Alternatively, analysts frequently use the ratio of overhead-costs (sum of fundraising and management expenses) over total expenses. Such measures are designed to capture the efficiency in fundraising and their effectiveness in providing public goods. These measures do not reflect the corresponding long-run benefits of development strategies, such as investment in managerial capacity. The paper develops a new set of measures that do not suffer from these drawbacks. The new measure yields

[2] 54% for green charities in our sample do not receive grants, but are successful in raising private donations.

[3] 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). 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 et al. (2009).

[4] For a recent discussion of these issues see Griliches and Mairesse (1998), Ackerberg, Benkard, Berry and Pakes (2007) and Aguirregabiria (2009).

[5] We implement the Andreoni and Payne (2003) approach as one of our estimators.

[6] 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.

[7] A few other papers also study the dynamics in charitable giving. Auten et al. (2002) study the impact of transitory and permanent tax and income changes on donations. Other studies include Landry et al. (2010) and Card et al. (2009).

a better ranking of charities and can be used to target efficient charities for public subsidies.

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 reviews the Olley and Pakes techniques and shows how this technique can be used to study charitable giving. Section 4 reports the main empirical results. Section 5 explores the policy implications of our work. Section 6 concludes the paper.

2. Data

The non-for-profit sector plays an important role in the U.S. economy.[8] Charitable organizations accounted for 8% of wages and salaries paid in the United States in 2007. They received 283 billions of dollars private contributions.[9] 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. Public charities reported nearly $2.6 trillion total assets and $1.4 trillion total revenues.[10]

This paper focuses on green charities that preserve, protect and improve the environment. Green charities receive respectively 46% and 16% of their total revenues from private contributions and government grants, compared to 12% and 9% for all public charities (Straughan and Pollak, 2008). Most of the 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 complement.

The data comes from the NCCS-GuideStar National Nonprofit Research Database (NNRD) assembled by the National Center for Charitable Statistics. The NNRD data contain information in financial and 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., secular charities with annual gross receipts of more than $25,000. In the organizational classification system (NCCS, 2007), green charities are listed under the 'C' category and are broken down into a variety of groups, as shown in Table 1. There are 28,953 observations in the data from 1998 to 2003. Nearly half of them come from natural resources conservation and protection.

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 are obtained from capital campaigns, annual giving campaigns, in-kind gifts, or revenues from other fund-raising events. 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, expenditure in office management and outlays for equipment and supplies. Government grants are meant to "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.

Table 2 summarizes the number of green charities in different years by decile groups. In 1998, there were 3778 charities in the sample. The number increased to 5512 in 2003. The full sample of the green charities is, therefore, unbalanced. When we apply the standard data screening procedure proposed by Andreoni and Payne (2003), we obtain a bench-mark sample that is even more balanced. For the sample of land conservation charities 70% of the 176 organizations have complete information for the whole sample period.

Table 1
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, Wettlands 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.

Most land conservations charities in our sample are well establish organizations that have existed on average for 18 years in 2003. 75% of the charities are, at least, 10 years old. In our bench-march sample of 176 charities, we observe 4 charities entering the market and 6 charities exiting. We conclude that entry and exit is not an important concern in our application. However, it is a bigger problem for larger sample as can be seen from Table 2. According to the National Center for Charity Statistics, the number of reporting public charities grew from 187,038 in 1995 to 310,683 in 2005, which is an increase of 66% for the full period.

The land conservation charities in our sample are not located in the same geographic area. Local differences in factor prices may affect both spending and donations. However, most charities are located in large metropolitan areas which are likely to have similar labor market conditions.[11]

There are two basic data issues that will be carefully examined in the empirical analysis. First, 53% of the total observations of green charities between 1998 and 2003 never report fundraising expenses in the sample periods. Among these observations, 29% are from charities with positive private donations; on average they receive 35% of their revenues from donations. Second, 54% 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% of total revenues from other sources. The features of observations with zeros are illustrated in Table 3 using data from land conservation charities (C34). We will explore how sensitive the estimation results are to different approaches that can be used to deal with these issues.

There are salient differences in total assets, revenues, and expenses among the set of green charities. 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. Heterogeneity also exists in charities' financial structures which are related to the missions and characteristics of charities. For example, the Energy

[8] As Arnsberger et al. (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."

[9] See the 2007 report by the National Center for Charitable Statistics.

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

[11] Unfortunately, our data set does not contain detailed price data which would allow us to control for regional price differences.

Table 2
Distribution of charities by years and decile groups.

Year	General	Pollution abatement	Conservation	Botanical gardens	Beautification	Education	Other	All
	C01-19	C20-27	C30-36	C40-42	C50	C60	C99	
1998	436	301	1909	343	215	272	302	3778
1999	485	344	2181	396	254	302	454	4416
2000	493	350	2281	413	260	306	663	4766
2001	509	368	2400	435	265	313	912	5202
2002	513	386	2434	429	268	313	935	5279
2003	531	386	2513	455	288	331	1007	5512

Note: Data are from environmental charities that file Form990 with IRS during 1998–2003.

Resources Conservation and 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 large amount of heterogeneity among different groups of green charities, it is appropriate to focus the analysis on a sample of charities within a narrower defined category. Ignoring these differences raises a variety of econometric problems. If there is heterogeneity in the effectiveness of fundraising and government grants, the pooled estimates are hard to interpret since estimates will be weighted averages of the underlying group specific structural parameters. Differences in entry and exit rates among groups may also give rise to complicated sample selection problems.

We analyze charities in the group of land resources conservations (category C34). These charities 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.

We chose this sample for the following reasons. First, the group of land resources conservations is one of the largest groups of green charities and accounts for 10% of all green charities in the 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% of total observations) and Water Resources, Wetlands Conservation & Management (category C32, accounting for 7%).

Summary statistics of green charities and land resources conservations are shown in Table 4. Donations are the major revenue resources for the environmental charities and account for 37% of the total revenues. For land resource conservations, donations account for 51% of their total revenues on average. 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.

3. Estimation

3.1. A Model

This section presents a behavioral model of a charity.[12] While the ultimate objective of a charity is to provide charitable services or public goods, we focus on the intermediate goal of raising funds to accomplish this task. We assume that the charity determines fundraising expenditures and investments into management to maximize the present discounted value of current and future payoffs.[13] Charities obtain revenues, r_{jt}, from donations, d_{jt}, and government grants, g_{jt}.[14] Costs, c_{jt}, are a function of fundraising expenditures, e_{jt}, management expenditure, m_{jt}, and grants. The per-period payoff function, π_{jt}, of charity j at time t is the difference between revenues and costs:

$$\pi_{jt} = r_{jt} - c_{jt} = \left(d_{jt} + g_{jt}\right) - c\left(e_{jt}, m_{jt}, g_{jt}\right) \tag{1}$$

The cost function includes direct costs and indirect costs of overhead expenditures. Direct costs are the sum of the expenditures in fundraising and management. 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. It is costly to write grant applications since charities need to devote resources to these activities. As a consequence g enters into the cost function of the charity.

The donation function is specified in the following log-log format[15]:

$$d_{jt} = \beta_0 + \beta_e e_{jt} + \beta_g g_{jt} + \beta_k k_{jt} + \omega_{jt} + \xi_{jt}. \tag{2}$$

The novel feature of this specification lies in the incorporation of managerial capacity, k_{jt}. ω_{jt} denotes the productivity shock; β_0 can be interpreted as the mean fundraising productivity level of the charity; 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.

Government grants, g_{jt}, enter into the production function since they may crowd-out or crowd-in private donations. The classical crowding out hypothesis predicts that donors see their contributions as perfect/imperfect substitutes for the government grants to a charitable cause (Bergstrom et al., 1985). Crowding-in may arise if government grants serve as a positive signal of a charity's quality (Heutel, 2009).[16]

[12] Our model is similar to the traditional dynamic investment model described in Olley and Pakes (1996).

[13] There is some evidence that charities may not be net revenue maximizers (Weisbrod, 1998). With costs of fund raising broadly defined, our model could generate this result.

[14] In practice, charities also receive program service revenues and other revenues. These are not specified explicitly in the model. This simplification has no impact on the development of the empirical strategy and the following analysis.

[15] This formalization is an aggregated representation of charities operation in raising donations, as well as donors' preferences. Ideally, it is useful 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 (2012). In this application, we only have access to charity-level data. Hence, we follow this traditional donation function approach which is consistent with the previous literature. See, for example, Okten and Weisbrod (2000) and Andreoni and Payne (2003, 2011).

[16] 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; Roberts, 1984; Bergstrom et al., 1985; Andreoni, 1989). Empirical studies, such as Kingma (1989), Khanna et al. (1995), Payne (1998), Okten and Weisbrod (2000), find that crowding out can be positive, zero, or even negative. Recent developments emphasize the importance of fundraising expenditure for crowding out and donations to charities. Andreoni and Payne (2003, 2011) 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.

Table 3
Observations with and without zeros in fundraising and grants for C34.

Group	Obs.	Donation	Grants	Program revenue	Other revenue	Managerial expenses
Zero government grants	1337	366208	0	127327	147099	23992
Nonzero government grants	1600	1354262	218221	97210	157882	96238
Zero fundraising expenses with positive donations	672	578718	96096	43409	41423	50869
Nonzero fundraising expenses with positive donations	1924	1178556	145724	146055	172684	103807

Group	Total revenue ($)	Donation/total rev	Grants/total rev	Program/total rev	Other/ total rev
Zero government grants	640634	.513	0	.093	.394
Nonzero government grants	1827576	.498	.203	.068	.231
Zero fundraising expenditure with positive donations	759645	.51	.142	.076	.272
Nonzero fundraising expenditure with positive donations	1643019	.592	.11	.072	.226

Table 4
Summary statistics and financial ratios of green charities and land conservations.

Sample	Stat	Private donation	Government grants	Total rev	Fundraise exp	Manage exp	Total exp
All	mean	534	118	998	40.5	95.7	751
Organization	s. d.	7,584	848	12,000	719	819	7,514
(thousand $)	med.	26.6	0	141	0	11.0	113
Land	mean	904	119	1,287	27.3	79.7	764
Conservation	s. d.	6,300	548	7,166	125	489	5,147
(thousand $)	med.	92.9	0	205	0	13.1	107

Sample	Stat	Donation/total rev	Grants/total rev	Program/total rev	Fundraise/total exp	Management/total exp	Donation/fundraise
All	mean	.368	.125	.173	.032	.143	133
Organization	s. d.	1.84	.27	.804	.081	.194	3,007
	med.	.171	0	0	0	.083	11
Land	mean	.505	.111	.079	.049	.187	358
Conservation	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%; in total expenditure, except fundraising and management expenditure, the remaining part is program service expenditure which account for approximately 60%. 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.

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

$$k_{jt} = (1-\delta)k_{jt-1} + m_{jt}, \tag{3}$$

where δ is the depreciation 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 includes human capital, physical assets as well as intangible assets.[17]

Fundraising productivity represents the unmeasured dynamic impact from the factors, such as social preference for different charitable causes. Productivity is known to charities and donors when they make decisions related to donations, but it is unobserved by researchers. Following Hopenhayn and Rogerson (1993) and Olley and Pakes (1996), productivity evolves according to an exogenous first-order Markov process:

$$p\left(\omega_{jt+1}\middle|\left\{\omega_{j\tau}\right\}_{\tau=0}^{t}, I_{jt}\right) = p\left(\omega_{jt+1}\middle|\omega_{jt}\right) \tag{4}$$

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_{jt+1} by $p(\omega_{jt+1}|\omega_{jt})$.

We treat productivity as a one dimensional index. This is a plausible starting point for our analysis that is common in the literature. Ackerberg, Benkard, Berry and Pakes (2007) discuss how to relax this assumption and incorporate two different productivity shocks. Finally, we are assuming that the productivity shock is Hicks neutral, i.e. the productivity shock does not affect the balance of input factors used in production. An different approach would be to assume that productivity shocks affect the effectiveness of fundraising expenditures, but not the effectiveness of managerial capacity or government grants. Alternatively one could bias the productivity shock towards the effectiveness of managerial capacity. We do not have any strong prior knowledge regarding appropriate functional form specifications. The previous literature on charitable donations has adopted the Hicks neutral specification. We, therefore, follow this approach while acknowledging that it would be fruitful to explore alternatives in future research.

There are some economic shocks that affect charities in a similar way than firms. For, example, donations respond to local, regional and business cycle shocks just as output of manufacturing or service sector firms. However, donations also respond to other shocks that do not affect most firms. For example, individual generosity is often tricked by media coverage of accidents or natural disasters. The recent oil spill in the Gulf of Mexico can be viewed as an example illustrating this type of shock, that affected donations to a variety of green charities. This event had a much smaller impact on most traditional firms.

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}.

[17] One problem with the measurement is that initial values of management expenditure are not observed for some charities. 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.

In our baseline model we assume that government grants g_{jt} are determined before ω_{jt} is realized and charities make decisions on spending. As a consequence, we can treat grants in the baseline model as exogenous. Government grants often serve as seed money or initial capital for new initiatives taken by green charities. Thus a successful grant applications often precedes fundraising efforts by the charity. In those cases, it is reasonable to treat government grants as predetermined. This is especially true for small or mid sized charities who do not have significant endowments.[18] We relax this assumption in Section 4 and explore alternatives. It is also important to understand that investments into managerial capacity and fundraising expenditures are determined after the productivity shock is realized. This allows us to invert the investment equation and use a control function approach in estimation.

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

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

Note that in the payoff function of the current period, $r_e(k_{jt},g_{jt},\omega_{jt}) - c_e(m_{jt},g_{jt})$, 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.

3.2. The Olley and Pakes estimator

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

$$m_{jt} = f_t\left(g_{jt}, k_{jt-1}, \omega_{jt}\right). \tag{5}$$

This condition provides the key identification argument in the estimation procedure proposed by Olley and Pakes (1996) which relies on the idea that investment into management capacity is given by an invertible function in fundraising productivity, ω_{jt}.[19] More formally, management expenditure can be written as $m_{jt} = f_t(g_{jt},k_{jt-1},\omega_{jt})$, which implies that, conditional on k_{jt} and g_{jt}, a charity's choices on management expenditure incorporate the information of fundraising productivity. If this function is monotonic in productivity, it can be inverted and hence we have:

$$\omega_{jt} = h_t^{'}\left(k_{jt-1}, g_{jt}, m_{jt}\right) = h_t\left(k_{jt}, g_{jt}, m_{jt}\right) \tag{6}$$

Substituting into the production function, yields:

$$d_{jt} = \beta_0 + \beta_e e_{jt} + \beta_k k_{jt} + \beta_g g_{jt} + h_t\left(k_{jt}, g_{jt}, m_{jt}\right) + \xi_{jt} \tag{7}$$

The first stage of the estimation yields a consistent estimator 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:

$$d_{jt} = \beta_e e_{jt} + \phi_{jt} + \xi_{jt} = \beta_e e_{jt} + \phi_t\left(k_{jt}, g_{jt}, m_{jt}\right) + \xi_{jt}, \tag{8}$$

where $\phi_{jt} = \beta_0 + \beta_k k_{jt} + \beta_g g_{jt} + \omega_{jt}$. We can, therefore, consistently estimate β_e and ϕ_{jt}. This stage, however, does not produce a consistent estimator 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. First, note that $\omega_{jt} = E(\omega_{jt}|I_{jt-1}) = E(\omega_{jt}|\omega_{jt-1}) + \eta_{jt} = g(\omega_{jt-1}) + \eta_{jt}$. 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 $d_{jt} - \beta_e e_{jt} = \beta_k k_{jt} + \beta_g g_{jt} + E[\omega_{jt}|\omega_{jt-1}] + \xi_{jt} + \eta_{jt}$. Finally, the residual for any given (β_g,β_k) is computed by:

$$\widehat{\xi_{jt} + \eta_{jt}} = d_{jt} - \hat{\beta}_e e_{jt} - \beta_k k_{jt} - \beta_g g_{jt} - E\left[\omega_{jt}\middle|\omega_{jt-1}\right]\left(\beta_k, \beta_g\right), \tag{9}$$

where the estimator $\hat{\beta}_e$ is from the first stage. A consistent estimator of $E[\omega_{jt}|\omega_{jt-1}]$ can be obtained 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}.

Identification of β_k and β_g requires two moment conditions. Given the timing assumptions above, the innovation part η_{jt} is uncorrelated with k_{jt-1} and g_{jt}. Hence the moments for estimation are $E[\xi_{jt} + \eta_{jt}|k_{jt-1}] = 0$ and $E[\xi_{jt} + \eta_{jt}|g_{jt}] = 0$. 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

$$\min_{(\beta_k,\beta_g)} \sum_i \left[\frac{1}{J}\frac{1}{T}\sum_j \sum_t \left(\widehat{\xi_{jt} + \eta_{jt}}\right) Z_{j,it}\right]^2, \tag{10}$$

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. This algorithm is also known as a block-bootstrap procedure.

3.3. Alternative approaches

As we have seen above, one main challenge in the estimation of the donation function is the same endogeneity problem that is encountered in the estimation of any production function. The endogeneity problem arises from the contemporaneous correlation between fundraising productivity and other input variables, including fundraising expenditure and investments in managerial capacity (Griliches and Mairesse, 1998; Marschak and Andrews, 1944). In a setting with multivariate inputs, there exist different predictions on the signs of the biases of the OLS estimates.[20] We expect that the coefficient of fundraising expenditure, the variable input, is positively biased and that the coefficient on the managerial capacity is negatively biased. Intuitively, fundraising expenditures could be positively related to fundraising productivity because fundraising is more "profitable" in the case of high fundraising productivity or positive productivity shocks. Failing to control for the

[18] This modeling approach is also consistent with the findings in Straughan and Pollak (2008).

[19] 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.

[20] Previous empirical studies suggest that the estimates on variable inputs, such as labor, is positively biased and the estimates on invariable inputs, such as capital, are negatively biased (Griliches 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.

Table 5
Estimates from different estimation procedures and specifications.

Methodology/specification	Fundraising expenditure	Managerial capacity	Government grants	Lagged fundraising	Lagged grants
Base case	0.131 (0.036)	0.927 (0.396)	0.029 (0.019)		
Fixed effects	0.308 (0.067)	0.754 (0.128)	0.063 (0.017)		
OLS	0.305 (0.064)	0.556 (0.077)	0.025 (0.015)		
Dynamic panel	0.161 (0.074)	1.010 (0.128)	0.040 (0.020)		
Specification test 1	0.132 (0.037)	1.408 (0.368)	0.043 (0.019)	0.001 (0.003)	
Specification test 2	0.132 (0.032)	1.341 (0.422)	0.054 (0.017)		0.004 (0.003)

Note: standard errors are in parentheses; the sample is from land conservations after the standard screening.

endogeneity problem will result in the over-estimation of the impact from fundraising expenditure on donations.[21]

The donation function can also be estimated using a variety of other techniques. Dynamic panel data model (Blundell and Bond, 1998, 2000) is one prominent approach to deal with the problem of the unobserved dynamic heterogeneity in the empirical analysis.[22] 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(1) to capture the impact of productivity. To implement these estimators we use the GMM estimator proposed by Blundell and Bond (1998). 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 $E[(\varpi_{jt}-\rho\varpi_{jt-1})-(\varpi_{jt-1}-\rho\varpi_{jt-2})|\{k_{j\tau},e_{j\tau},g_{j\tau}\},\tau=1,\ldots,t-2]$.[23]

Instrumental variables are also employed to deal with the endogeneity problem. Andreoni and Payne (2003, 2011) 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. As additional specification checks we also implement these estimators as well.

4. Empirical results

4.1. Estimation of the donation function

Table 5 reports the estimates of the donation function. The OP procedure documented in Sections 3.2 is called base case. We also report estimates using OLS, fixed effects models, and dynamic panel data techniques. All estimations use the same benchmark sample of land conservation charities.[24] After controlling for fundraising productivity, the estimated impact of fundraising expenditure on donations is significantly reduced by 57%, from 0.305 to 0.131, comparing to the OLS estimate. An intuitive explanation is that the OLS estimate of the impact from fundraising expenditure actually incorporates the impact from the unobserved productivity is positively correlated with fund raising expenditures. A charity is more willing to increase its fundraising expenditure if its perceived fundraising productivity is higher.

Comparing OLS estimates to the base-case estimation, we find that the estimated impact from managerial capacity on donations is increased by 67%, from 0.556 to 0.927. The estimate of the coefficient measuring the impact of government grants, g_{jt}, decreases from 0.029 to 0.025.[25]

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 for 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. The estimates from the dynamic panel data model are close to the base-case estimates, as seen from the results in Table 5.

One methodological concern is whether there are important dynamic considerations related to fundraising expenditures or government grants that are not appropriately modeled. If fundraising expenditures have a dynamic impact on donations, the first stage estimator will not be consistent. Olley and Pakes (1996) propose a specification test which is based on the insight that ξ_{jt}, should be mean independent of e_{t-1} in the absence of dynamic spillovers. If there were an error in the first stage estimation of β_e, one would expect a significant coefficient for e_{t-1} in the following regression:

$$d_{jt}-\beta_e e_{jt}=\beta_k k_{jt}+\beta_g g_{jt}+\beta_e e_{jt-1}+E\left[\omega_{jt}\middle|\omega_{jt-1}\right]+\xi_{jt}+\eta_{jt}. \tag{11}$$

We implement this test and report the findings in Table 5 of the paper. We find that lagged fundraising expenditures do not have an impact on donations in later periods. This result suggests that dynamic impacts of fundraising are not likely to be important in this application.

Similarly, one can add lagged government grants, g_{t-1}, into the last step of the estimation. This allows us to test whether the index restriction in the bias term for the inversion is consistent with the data. Table 5 also reports this test. We find that the estimate of the coefficient of g_{t-1} is not significantly different from zero. We conclude that we do not find any evidence that supports dynamic spill-overs of government grants.

It is also useful to test the assumption that investment into managerial capacity is a monotonic function of productivity. We follow Levinsohn and Petrin (2003) and regress m_{jt} on the predicted fundraising productivity, ω_{jt}, controlling for g_{jt} and k_{jt-1}. The results of this test are summarized in Table 6. We report OLS and fixed effects estimates.

We find a significant positive relationship between m_{jt} and ω_{jt}. We conclude that these tests support the main identifying assumption of the control function approach.

We also implemented a variety of standard IV estimators along the lines suggested by Andreoni and Payne (2003) and Heutel (2009). The

[21] 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.

[22] See also Wooldridge (2005). Ackerberg, Caves and Frazer (2006) provide a comprehensive documentation of both approaches in the context of production function estimation.

[23] See Ackerberg, Caves and Frazer (2005) for a careful comparison of OP and DP techniques.

[24] We followed Andreoni and Payne (2003) to screen the data. 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. The main findings are not affected by different screening procedures, as shown in the robustness checks.

[25] Such positive impact supports the crowding-in hypothesis (Heutel, 2009).

Table 6
Managerial expenditure and fundraising productivity.

	OLS	Fixed effects
Fundraising productivity	0.418 (0.020)	0.529 (0.081)
Managerial capacity	1.063 (0.028)	0.878 (0.231)
Government grants	0.060 (0.008)	0.069 (0.013)
Intercept	−2.999 (0.341)	−0.725 (2.818)

Table 7
Estimation using instrumental variables from previous studies.

Variable	OLS	FE	FEIV (Instrument Fundraising)	2SLS (AP) (Instrument Grants)	2SLS (Heutel) (Instrument Grants)
Fundraising	0.329	0.314	0.626	0.382	0.333
Expenditure	(0.025)	(0.026)	(0.139)	(0.035)	(0.042)
Managerial	0.636	0.628	0.431	0.677	0.639
Capacity	(0.056)	(0.112)	(0.149)	(0.062)	(0.062)
Government	0.031	0.067	0.046	−0.095	0.023
Grants	(0.013)	(0.014)	(0.017)	(0.060)	(0.082)

Note: standard errors are in parentheses; samples are from land conservations with standard screening.

Table 8
Decomposition of the donation function in the log-linear form.

	Donation	Productivity	Fundraising ($\hat{\beta}_e \cdot e$)	Management ($\hat{\beta}_k \cdot k$)	Grant ($\hat{\beta}_g \cdot g$)
Mean	12.2	-.62	1.14	11.5	.203
s.d.	2.78	2.24	.441	1.57	.166

Table 9
Base case estimates using data from different screening procedure.

Data sample and/or screening procedure	Fundraising expenditure	Managerial capacity	Government grants
Use the standard screening procedure	0.131 (0.036)	0.927 (0.396)	0.029 (0.019)
Substitute zero fundraising expenditure	0.322 (0.074)	0.966 (0.431)	0.030 (0.020)
Delete zero government grants	0.131 (0.054)	0.955 (0.210)	0.291 (0.130)

Note: standard errors are in parentheses; samples come from the standard screening procedure if not specified.

results are shown in Table 7. We find that the estimates from the instrumental variable approach are not robust, especially the estimates of government grants on donations.

The estimated parameters of the donation function are elasticities. Hence, 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: $\hat{\beta}_e * (d/e)$, $\hat{\beta}_k * (d/k)$, and $\hat{\beta}_g * (d/g)$. 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.

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 8. Fundraising productivity is computed by $w_{jt} = d_{jt} - \hat{\beta}_e * e_{jt} - \hat{\beta}_k * k_{jt} - \hat{\beta}_g * g_{jt}$.[26] The decomposition shows that fundraising productivity is a key determinant of donations and its variance is much higher than other determinants.

4.2. Sample selection and measurement

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 many charities that never report fundraising expenditure but receive positive donations. This may be due to misreporting because charities facing pressure in reducing fundraising expenses. The observations are typically dropped from the sample. An alternative approach is to treat the observations with reported zero fundraising as missing data and use an imputation procedure. To evaluate the impact of these different procedures we estimate a model of the determination of fundraising spending, using the observed information such as managerial expenditure, total expenditure and total assets. We assume charities with similar size in expenditure and total assets should spend similar amounts in fundraising, after controlling fixed effects and other observed characteristics. We then use the estimates from the fixed effects model to impute the zero observations by the predicted value of fundraising expenditure. We report both sets of estimates in Table 9.

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 estimate of managerial capacity or government grants.

Next we consider the impact of deleting observations with zero government grants. The results in the third row of Table 9 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. But again the estimate of the coefficient of managerial capacity is unchanged.[27]

Finally, we evaluate the importance of heterogeneity among charities. Table 10 reports estimates for a variety of subsamples of green charities. We find that the relative importance of managerial capacity, fundraising efforts, and government grants varies across the samples. However, we also find that fundraising expenditures and managerial capacity are always significantly different from zero and positive.[28]

Note: Estimated standard errors are in the parenthesis. In column 4, other natural resource conservations and protection (C30) are environmental charities other than water and wetlands (C32), land (C34), energy (C35), and forest (C36).

[26] An alternative way to compute the fundraising productivity is using $W_{jt} = \exp\left(d_{jt} - \hat{\beta}_e * e_{jt}\right)$. 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.

[27] We also estimated the model for a variety of other samples that include other environmental charities such as water resources and wetlands conservation charities and other natural resource conservation charities. The results are qualitatively similar to the ones reported in this paper and available upon request from the authors.

[28] We expect that similar patterns exist among charities that focus on arts or social causes.

Table 10
Comparing estimates from different samples.

	Land conservations	Water and wetlands	Other conservation and protection	Environmental charities (All)
Fundraising	0.131	0.170	0.257	0.173
Expenditure	(0.036)	(0.050)	(0.033)	(0.020)
Managerial	0.927	0.947	0.544	0.700
Capacity	(0.396)	(0.386)	(0.103)	(0.351)
Government	0.029	−0.033	0.187	0.016
Grants	(0.019)	(0.035)	(0.011)	(0.011)

5. Policy analysis

The empirical results provide new estimates of the fundraising efficiency of the organizations in the sample. It is interesting to compare these estimates with the commonly used measures of fundraising efficiency. The most common measure is the ratio between donations and fundraising expenditure. The policy analysis is based on the following regression:

$$w_{jt} = \beta_j + \beta^{\mathrm{pe}} x_{jt}^{\mathrm{pe}} + \beta^{\mathrm{as}} x_{jt}^{\mathrm{as}} + \beta^{\mathrm{pr}} x_{jt}^{\mathrm{pr}} + \beta^{\mathrm{or}} x_{jt}^{\mathrm{or}} + \mu_{jt} \tag{12}$$

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.

We expect that fundraising efficiency is positively correlated with 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 11 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.

In the last column of Table 11, 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.

Finally, we use our approach to construct a quality ranking of charities and compare it to a popular method advocated by Charity Navigator. Charity Navigator analyzes a charity's financial performance in seven key areas, that assess its financial efficiency and financial capacity. After analyzing those performance metrics, they compare the charity's performance with the performances of similar charities. They then assign the charity a converted score ranging from zero to ten in all seven performance metrics, as well as a rating for its overall financial health. If the overall score of a charity is greater or equal to 60, Charity Navigator gives that charity four stars; if it is between 50 to 40, three stars; and so on. If the score is below 20, no stars. We can thus convert the Charity Navigator score into a rank score from 5 to 1. Our rank score is based on the estimated fundraising productivity. If the productivity of a charity is in the highest 20% quantile, the rank is set as 5; the lowest 20% are defined as 1. Note that one standard deviation in productivity translates into approximately one-fifth (0.2058) of a charity's total donation, i.e. on average 186,132 dollars for land conservation charities.

Charity Navigator evaluates only those charities that have public support larger than $500,000 and total revenues larger than $1,000,000 in the most recent fiscal year. Moreover, they do not review charities that receive most of their funding from government grants or from the fees they charge for their programs and services. They also exclude charities that report zero fundraising expenses since they are interested only in charities that actively solicit donations from the general public. As a consequence, we can only match a small number of charities in our sample with Charity Navigator scores. Table 12 reports the two different ranks for the small number of charities that we can match.

We find that the two ranks are similar, despite the different methodology and data used in the rankings. The rating score from the Charity Navigator are strongly positively correlated with our measure of fundraising productivity. Our quality measure is relatively simple to compute, requires only publicly available data and is fairly transparent. We thus conclude our measure is a good complement to the charity rating scores used by Charity Navigator.

6. Conclusions

This paper has shown how to incorporate managerial capacity into the analysis of donations to charitable organizations. The empirical

Table 11
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.

Table 12
Fundraising productivity measure vs rating score from CharityNavigator.

Name	Year	Navigator Rating	Fundraising Productivity	Rank by Rating	Rank by Productivity
Land trust alliance	2000	58.25	12.46	4	5
Land trust alliance	2001	58.23	12.81	4	5
Land trust alliance	2003	51.13	12.62	4	5
Battery conservancy	2001	56.87	11.38	4	4
Battery conservancy	2002	68.24	12.46	5	5
Battery conservancy	2003	58.95	12.51	4	5
Conservation foundation	2003	45.36	11.17	3	3
Western Penn. Conservancy	2000	68.21	12.56	5	5
Western Penn. Conservancy	2001	65.68	12.61	5	5
Western Penn. Conservancy	2002	61.40	12.19	5	5
Western Penn. Conservancy	2003	57.06	11.91	4	4
Regional trail corporation	2003	42.00	11.23	3	4
Land stewardship project	2001	55.74	11.31	4	4
Land stewardship project	2002	43.61	11.89	3	4
Land stewardship project	2003	55.57	11.87	4	4
Piedmont Env. Council	2001	58.79	12.98	4	5
Piedmont Env. Council	2002	61.08	12.67	5	5
Piedmont Env. Council	2003	61.51	12.62	5	5
Sonoran Institute	2002	57.12	12.12	4	4
Sonoran Institute	2003	60.05	12.06	5	4
Greenbelt alliance	2001	66.21	12.27	5	5
Greenbelt Alliance	2002	61.22	11.88	5	4
Greenbelt Alliance	2003	67.12	11.96	5	4
Correlation with		0.9129	0.4847	1	0.5072
Rank by rating (s. d.)		(0.0000)	(0.0191)	–	(0.0135)

findings suggest that managerial capacity is an important factor in determining charitable donations. This finding is robust among a number of different estimation strategies including Olley and Pakes (1996), dynamic panel data estimators, standard IV estimators and fixed effects estimators. In contrast, estimates of fund-raising expenditures and government are sensitive with respect to the different identification strategies, sample selection rules, and missing data imputation mechanisms. Charities' unobserved heterogeneity in fundraising productivity is a key factor in explaining the variation of donations.

The empirical findings of this paper have important policy implications. Matching grant policies may not be effective for charities with low fundraising productivity. A low fund raising productivity may arise from the fact that the mission of a new charity has not been recognized by society yet. Different policies are needed to support new and innovative charities that do not have an established and reliable donor base.

We view our results as providing ample scope for future research which should study differences in fundraising efficiency among other groups of charities, such as social service organizations and educational institutions. There is also a need to model the evolving market structure and analyze competition among charities. The analytical model can be extended to describe the dynamics of a charity market using dynamic game theoretical concepts. Modeling the strategic interaction among charities will also help us obtain a better understanding of the impacts from government policies.

With the emergence of the current economic crisis, charities have reduced their program services because of a decrease in private giving and government funding. Fundraising strategies that were effective in the pre-recession economy are likely to be more costly in the current economic environment. This makes it difficult for charitable organizations and non-for-profits to step in and fill the void in areas that are not served by the government.

Appendix A. Time series properties of managerial expenditures

Table 13 that reports the 25th, 50th, 75th and 90th quantile of managerial expenditures in our sample for each year. We find that the 25th percentile approximately is $1200, the median is $12933, and the 75th percentile is $44,443. We thus conclude that there a lot of heterogeneity in managerial expenditures within the sample. Managerial expenditures were growing at a faster rate at the lower end of the distribution than the higher end.

We also compute the correlation between current and lagged values of managerial expenses. The results are reported in Table 14. The correlation coefficients between current and lagged values of managerial expenditures range between 0.83 and 0.73. We, therefore, conclude that managerial expenditures are persistent over time. Donations are much less persistent than managerial expenditures since donations are affected by other of time-varying factors such as fundraising expenditures.

Table 13
Distribution of managerial expenditures over years.

Year	p25	p50	p75	p90
1998	707	10213	38062	100968
1999	775	10798	38153	105727
2000	1630	13348	42585	117750
2001	1393	13910	48112	127189
2002	1427	13848	48832	139826
2003	2177	15988	53291	139819
Total	1200	12933	44443	121280

Table 14
Correlation of Managerial Expenditures.

year	current	lag1	lag2	lag3	lag4	lag5
lag1	0.8190	1.0000				
lag2	0.8342	0.8014	1.0000			
lag3	0.7763	0.7838	0.7893	1.0000		
lag4	0.8152	0.8612	0.9706	0.8475	1.0000	
lag5	0.7391	0.7580	0.8486	0.9814	0.9408	1.0000

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