Nonprofit Entry, Competition, and Fundraising

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January 26, 2020

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1 Introduction

Recent work has documented the large growth in the nonprofit sector relative to the for-profit and government sector and also relative to the nonprofit sector's trend over time (Harrison and Laincz, 2008). This trend spurs questions about why such dynamics have occurred and also whether such growth is optimal from a social perspective. In order to estimate social welfare, we need to be able to measure the value of the good being provided and also the costs of providing that good. Nonprofits (NPs) pose unique challenges to this estimation due to the public goods nature of the service provision. Valuing the service is difficult because there may not be an observed price for the good–many NPs rely on donations to fund a large portion of their expenditures. Moreover, often times donors who "pay" for the service are not the individuals who actually receive the service.

In this paper, we focus on the fact that nonprofits compete for donations in order to infer the value of a particular charity's services. Individuals choose to which nonprofits to donate, leaving nonprofits to compete for this limited resource. Charities with more donations relative to their competitors (all else constant) are assumed to be provide greater value to donors and therefore to society. Because we can observe the total amount of donations that are received by one nonprofit relative to its competitors, we can therefore calculate the market share of donations and use discrete choice demand models to estimate how these market shares vary with firm and other market characteristics.

One of the critical choices for the nonprofit is how much to spend on fundraising. Soliciting more donors or increasing the intensity of fundraising to existing donors may increase donations but also increases expenses. In order to maximize net revenues, nonprofits should fundraise until a dollar increase in fundraising produces one additional dollar in donations. Much of the prior work on nonprofit donative behavior has focused on the potential crowd-out between donations and government grants. In investigating this relation, studies have shown that one dollar increase in fundraising expenditures produces well above one additional dollar in donations (Harrison and Laincz, 2010, Khanna and Sandler, 1995, 2000). Although this estimate suggests that the fundraising efforts are effective in raising donations, it also implies that the NP is not maximizing net income. In other words, if their goal is to increase net income in order to offer more services, NPs are not spending enough resources on fundraising.

In contrast to these findings, anecdotal evidence and public sentiment often suggest that NPs allocate too much time and energy towards fundraising. The resolution of this contradiction may lie in the extent to which NPs adopt strategic behavior in order to compete with other NPs for donors. Ribar and Wilhelm (2002) investigate how competition effects crowding-out and find that markets with a large number of donors will experience less crowding-out than markets with a small number of donors. Thornton (2006) showed empirically that NPs facing less competition within their own industry have higher fundraising expenditures. However, the endogeneity of competition was not explicitly considered. Since more NPs in a market most likely implies increased competition and in turn potentially decreased fundraising, the entry and fundraising decisions of NPs are intertwined and need to be jointly modelled.

The paper therefore explores the relation between NP fundraising and competition and the role of donor generosity in that relationship. I develop a model of nonprofit's simultaneous decisions of entry and efforts allocated toward fundraising. The model will draw from prior work on the entry decisions of for-profits (Bresnahan and Reiss, 1990, Berry and Waldfogel, 1999). Using tax return data for nonprofits, I can compute the percentage of donations that a firm earns relative to total donations received in that industry (i.e., market share of donations). These market shares are a function of the number of other NPs competing in that industry, demographic characteristics of prospective donors, and other market characteristics. The intensity of fundraising also impacts the level of philanthropic activity. In fact, some economic models assume that donors will only give if solicited (Rose-Ackerman, 1982, Andreoni and Payne, 2003). Moreover, donors take into account the "price" of a donation, as measured by the amount of donations used to fund administrative and fundraising expenses (Okten and Weisbrod, 2000). We can therefore incorporate this price and fundraising intensity into the utility function of donors and estimate the donors demand for nonprofit services.

The market share estimation provides insight into the donor decision, but also allows me to predict how, for example, changes in income affect the propensity to donate and subsequently, market shares and potentially community welfare. Based on these market shares, NPs decide whether it is desirable to enter a particular market. If they choose to enter the market, they would then choose their fundraising expenditures to maximize net revenues. Note the circular or feedback effect from the model. The fundraising decisions affect the level of donations, which in turn affect the anticipated market shares and the total number of firms in the market. These types of effects can only be captured in a structural model that estimates the demand and supply side simultaneously.

Philanthropy, although perhaps inherently present through cultural and societal norms, is no doubt influenced by nonprofit's fundraising abilities. This paper therefore provides insight into how fundraising changes the propensity for individuals to actively express their generosity. The number of other nonprofits competing for donors, as discussed above can impact the level of fundraising and, perhaps more importantly, the effectiveness of the fundraising efforts. The potential competitive interactions have implications for the level of service provision and therefore overall societal welfare. Fundraising might increase donations for a particular firm. But if the entry of that particular firm cannibalized existing donations then the increased fundraising might not be welfare improving. In the situation above, we would conclude that donor's generosity is allocated over too many nonprofits. That is, increasing the number of firms did not increase total giving, but simply decreased the amount of giving per firm. Using the methodology above, I therefore estimate the optimal number of firms, taking into account the donor's willingness to give.

The next section details more explicitly the model of donor and nonprofit behavior. Section 3 describes the data and Section 4 presents the estimates of the model. The final section discusses potential biases in the current estimation and the next steps forward.

2 Empirical Model

2.1 Donor Utility

We envision a market m with market size M, representing the total donations given by donors. Each donor i can give to charity j which is in subsector b in industry k. Each donor also has the outside option to give to another nonprofit in industry k.[1] Nonprofit firms can influence the giving propensity of a donor through its choice of fundraising. Increasing fundraising or awareness of the nonprofit may encourage those who never gave to donate to a firm in subsector b or it may cause a donor simply to transfer their giving to another charity within the same subsector. In other words, we seek to understand whether increased fundraising primarily results in business stealing from another firm in subsector b or increases total giving to subsector b. We therefore follow Berry and Waldfogel (1999) where the utility of the donor is given by

$$u_{ij} = \delta_j + v_j(\sigma) + (1-\sigma)\varepsilon_{ij} \tag{1}$$

[1] We could also define the outside option to be not giving to any charity. However, this specification would require additional flexibility in the substitution patterns between nonprofit industries since we would be investigating multiple nonprofit services. Preliminary analysis suggests that our demand estimates are robust to variations in the outside option but additional analysis is needed.

The parameter δ_j gives the mean utility of donating to charity j while σ captures the business stealing effect, and ε_{ij} captures the idiosyncratic variation and has an expected value of zero. As σ goes to one, the idiosyncratic variation between charities within the subsector is eliminated and all charities are identical. In this scenario, business stealing is the only effect and increases in fundraising simply shift donors from one charity to another.

The mean utility is parameterized as:

$$\delta_{jm} = \alpha(y_i + p_{jm}) + x_{jm}\beta + f_{jm}\gamma + \xi_{jm} \tag{2}$$

where y_i represents the income of donor i, x_{jm} and ξ_{jm} are respectively the observed and unobserved product and market characteristics, f_{jm} is the fundraising intensity of charity j. The price of the donation is a function of the intensity of fundraising by the nonprofit relative to the returns from the fundraising. We assume that donors give to the nonprofit to support the charitable services. As a nonprofit spends a larger fraction of its donations on fundraising expenses, the price to the donor of giving increases because less of the donations are allocated to provision of the services (Okten and Weisbrod, 2000). Price is therefore given by $\frac{F_j}{(F_j - f_j)}$ where F represents the total amount of donations received by nonprofit j.

Donors will give to the charity that maximizes their utility. We assume that ε_{ij} is an i.i.d. Type I extreme value distribution. Berry and Waldfogel (1999) show that the market share of donations for charity j are:

$$s_j = \frac{exp(\frac{\delta_j}{1-\sigma})}{D} \frac{D^{1-\sigma}}{1 + D^{1-\sigma}} \tag{3}$$

where

$$D = \sum_j exp(\frac{\delta_j}{1-\sigma}) \tag{4}$$

Given this nested logit demand, we can invert the market shares to provide a linear model such that:

$$ln(s_{jm}) - ln(s_{om}) = \alpha p_{jm} + x_{jm}\beta + f_{jm}\gamma + \sigma ln(s_{jk_b}) + \xi_{jm} \tag{5}$$

where s_{jm} gives the donations to charity j relative to all donations received by industry k and s_{jk_b} provides the percentage of donations received by charity j relative to all other charities in subsector b in industry k. Notice the tension here on donor demand as fundraising intensity increases. As fundraising rises, the direct effect is measured by γ which we predict will be positive–more solicitation results in a higher probability that a particular donor is solicited and therefore gives to the charity. However, the price to the donor may also increase if fundraising expenditures are rising faster than donations. As the price of giving to firm j increases, this indirect effect will work to decrease giving to firm j.

2.2 Charity's Net Revenues from Donations

We focus on the net income generated by a nonprofit from its fundraising activities. Although nonprofits no doubt have other revenue streams which enter into the total function, we assume that those revenues are additively separable and therefore maximization of net income from donations (NID), holding all else constant, will maximize the total resources available to provide the nonprofit services. We therefore specify the following:

$$NID = M * s_{jm} - f_j - FC \tag{6}$$

This specification needs some explanation. In the data section discussed below we do not observe the number of people solicited nor the number of actual donors. This stands in contrast to traditional for-profit settings where quantity is known. We instead observe the total amount of fundraising activity and total donations received. We therefore envision a scenario where a nonprofit is choosing the amount of fundraising activity it wants to engage in in order to maximize

NID. Because each donor can give \$1 based on the donor model above, we conceptualize an increase in f_j to represent an increase in the probability that more potential donors are solicited. The market share given by s provides the probability that a donor will give conditional on being solicited. Multiplying that probability by the total market size therefore provides the total donations received by firm j. Notice though that the second term is not multiplied by s. This is because the nonprofit incurs the cost of soliciting an additional person regardless of whether they give to the charity.

Take the derivative w.r.t f_j to get:

$$M * \partial s_j / \partial f - 1 = 0 \tag{7}$$

In other words, the optimal fundraising level is one that produces exactly one additional dollar in donation revenue, given that we increased fundraising by one additional dollar. Once again, we see the tension between increasing fundraising. To see this, note that $\partial s_j/\partial f = s_j * (1 - s_j)(\gamma + \alpha * \partial p/\partial f)$ where $\partial p/\partial f = (F - F'(f))/(F - f)^2$. We anticipate γ to be positive and α to be negative. However, the sign of $\partial p/\partial f$ depends on the level of donations relative to the marginal return of fundraising. If the elasticity of fundraising is > 1 then $\partial p/\partial f$ will be negative and is positive otherwise. When it is negative, it cancels out the negative sign on α and $\partial s_j/\partial f$ will be unambiguously positive. When it is positive, the sign of $\partial s_j/\partial f$ depends on the relative magnitude of the first order and second order fundraising effects. In this case, there is a point at which the marginal returns of fundraising are low enough that increased fundraising will decrease the nonprofit's market share.

Given the optimal fundraising level, we assume that a nonprofit will enter the market if NID is non-negative and will not enter otherwise. Like Berry and Waldfogel (1999), this provides bounds for fixed costs which are assumed to be log-normally distributed such that:

$$ln(FC_j) = z_j * \mu + \lambda * v \tag{8}$$

In this case, if a nonprofit enters then we know that:

$$\frac{NID_{N+1} - z_j * \mu}{\lambda} < v < \frac{NID_N - z_j * \mu}{\lambda} \tag{9}$$

The log-likelihood is then:

$$LLF = \Phi(\frac{NID_N - z_j * \mu}{\lambda}) - \Phi(\frac{NID_{N+1} - z_j * \mu}{\lambda}) \tag{10}$$

2.3 Estimation Procedure

The order of estimation is as follows. Using market shares, firm, and market characteristics, we estimate the discrete logit demand function given in (1) using 2SLS. Instrumental techniques are needed because the within-group market shares are correlated with the error. Population and income are used as our excluded instruments. These estimates then allow us to estimate market shares for different market structures. In particular, we estimate the market shares for N+1 number of firms. Using the FOC given in (7), we also predict the optimal level of fundraising for a given number of firms and the implied market shares. We then form the log-likelihood using the predicted market shares and predicted fundraising levels and estimate the parameters μ and λ. Although we allow for product differentiation in the demand estimation, we do assume symmetry for the entry model for tractability.

Based on these estimates, we now have bounds for v and then take draws from v in order to calculate the socially optimal number of firms. We assume that a social planner will choose N in order to maximize:

$$M \int_0^{Ns(N)} dx - N * FC \tag{11}$$

3 Data

The data for nonprofit firms are obtained from the National Center on Charitable Statistics (NCCS) at The Urban Institute. Although most nonprofits are exempt from federal income taxation, the IRS requires they file a 990 tax return annually if their gross receipts are greater than $25,000. Our data contain all 501(c)3 public organizations who filed a tax return in 2002. Future versions of the paper will expand the analysis to include a panel. From the data, we obtain all of our financial information including funds raised/total donations (F), and fundraising expenditures (f).

We also control for other financial characteristics. Firm size is correlated with fundraising levels and is therefore proxied using assets at the beginning of the fiscal year (ASSETS). In addition, firms receive revenues not only from donations and government grants but also from mission-related services, called program service revenues (PSREV). Firms with more of these revenues, all else equal, are less dependent on donations. Since less dependence on donations implies less need for fundraising, we include this variable in the demand regression.

We need to define our criteria for selecting the nonprofit industries of analysis. Nonprofits are widely varied in their delivery of services, their donor base, and also the degree of for-profit competition within the industry. Our data only provide information on nonprofit firms. More importantly, our methodology uses the market share of donations to infer preferences about the value of the delivery of services. For these two reasons, we limit our analysis to industries with little for-profit competition. We also desire nonprofits who primarily compete locally for donors; that is, most of the donors reside in the market area where the service is provided. Local giving is positively correlated with local provision of the nonprofit services. Finally, we require nonprofits whose services, while potentially multi-faceted, are directed at one particular mission that is well defined. This criteria is important because the National Taxonomy of Exempt Entities, similar to the NAICS codes, classifies nonprofits based on their primary mission.[2] Some industries could be classified in multiple sectors given the subjective nature of the classification.[3] Although we cannot ensure completely that we capture all of the nonprofits in a particular sector, choosing services that are well-defined with a clear mission decreases the measurement error of identifying all competitors. Based on these criteria, we initially chose museums and zoos. Unfortunately, zoos did not provide enough variation across markets in the number of firms so we eliminated this industry. Future versions of the paper will examine other sectors.

In order to estimate the model above, we need information on the number of nonprofit firms in selected markets and demand and demographic characteristics of the market. We define a market as a Census place or set of Census places. We identified Census places that fall into the same market area as follows. We overlaid the universe of Census places with zip codes and Census tracts using the online geographic correspondence engine MABLE/Geocorr. We grouped Census places together that shared either zip codes or Census tracts. Currently, we do not impose a size constraint on the selection of the markets nor do we restrict the analysis to isolated markets. This is because the richness of the donation information allows us to better identify the competitive effects. We are currently exploring whether allowing adjacent markets into the analysis seems to create any bias and may modify the selection criteria in subsequent revisions.

We also account for factors that affect the demand for nonprofit services. We control for demographic and economic characteristics using zip code-level Census data on income per capita and population. We also ran specifications including percent of the population that is black or hispanic, median age, percent of population between 18 and 65, percent of population with

[2]For more information on the NTEE classification system, please see www.nccs.urban.org.

[3]For example, the American Cancer Society (ACS) promotes awareness and raises funds to support cancer research but also performs cancer research. Indeed a quick glance at the filings shows that some ACS organizations are filed under G30 while others are in H11.

at least a bachelor's degree, and percent of population that is single with little change in the results. Zip code population is aggregated up to the market level. We then use the zip codes population as a percentage of the total market population to create a weighted average of all other demographics. For the discrete logit demand model, we found it important to include market-level fixed effects in the second stage estimation. Since these effects are perfectly collinear with the demographic characteristics, we only present estimates with the fixed effects.

Measurement error in the financial information exists, particularly given that most of the tax forms are not audited (Tinkelman, 2004). We therefore take care to delete observations with implausible or missing information from the sample. Organizations reporting negative contributions, program service revenues, or assets are deleted. We also remove any firms where the ratio of fundraising expenses to total contributions is greater than one. This leaves 2,055 museums in 2002 located in 839 markets for the demand and fundraising estimation. For the entry model, given the form of our profit function and because we assume symmetry in post-entry profits, we restrict our attention to 411 markets where the average amount of fundraising expenses is positive.

Table 1 provides descriptive statistics for our museums (Panel A) and markets (Panel B). The average museum garners about 19 percent of the donations relative to all nonprofit arts organizations. Average donations to museums in levels is approximately one million dollars, with fundraising expenses accounting for about 10% of those revenues. Each market has approximately 4 museums with a large dispersion between markets. We can also see from Figure 1 a positive relationship between total giving to museums and the number of museums, suggesting that business stealing may not be complete.

4 Results

Table 2 provides the empirical estimates for the logit demand, the total fundraising function, and the entry model. We can see from column (1) that, as expected, increasing the intensity of fundraising increases the market share for a museum relative to other museums in that market. The coefficient is significant although the effect is relatively small. A $1,000 rise in solicitation expenses increases market share by .0019 percentage points. The indirect effect of increasing fundraising on the price of donating does not seem to play a large role for museums. Holding the amount of total donations raised constant, larger fundraising expenses decreases the total amount of net revenue available for service provision. This decreased ability for service provision (i.e., increase in the price of donating) does decrease a donor's sensitivity to giving but the effect is not significant. Resources available from different sources negatively impacts a museum's donation market share. Museums with more assets and also more fee-for-service based revenue have lower market share within their market. Our estimate of $\sigma = .787$ suggests a moderately high level of substitution between museums rather than between museums and other arts organizations.

The fundraising production function is generally consistent with our discrete logit demand estimates but allows us to calculate the effect in dollars rather than in market shares. The one exception is the effect of assets. A museum with a larger asset base generates a higher level of donations in column (2). However, in conjunction with the estimates in column (1), we can conclude that the increase in donations is less than similar competitors with fewer assets. As discussed in the model section, the main reason to estimate this specification is to derive an estimate for $\frac{\partial F}{\partial f}$. A one dollar increase in fundraising expenses increases donations by seven dollars. This effect suggests that, on average, fundraising levels are not at an optimum level and should be increased. Calculated at the mean, the price effect from increased solicitations is slightly negative although there is a wide dispersion between museums with the median positive. Combining these effects, we find that the average nonprofit is spending on fundraising such that increases in fundraising still imply increased market share (i.e., $\partial s_j/\partial f > 0$).

Our entry model has the expected signs. Markets with a larger population and more affluent areas have larger fixed costs. The estimates also suggest that income has a slightly larger effect, perhaps due to a correlation with the price of land and buildings.

4.1 Predicting the socially optimal number of firms

Using all of these estimates, we calculate the average optimal number of museums in a market to be 3.97. This value is remarkably close to the observed density of 3.8 suggesting, at least initially, that free entry of museums seems efficient. Given that one would assume museums to have relatively high fixed costs, this result is a little surprising. However, given the preliminary nature of the estimates, we are cautious in drawing strong conclusions yet. The next section lays out the next steps and concerns over the current estimation.

5 Remaining work

There a few issues yet to be addressed in the current estimates. First, as we discussed in the modelling section, the first-order condition on NID allows us to estimate the optimal fundraising for a given market share. However, this function is highly nonlinear and does not have an analytic solution. We have attempted to solve for the optimal f associated with N+1 firms and also when predicting the optimal number of firms but they have not produced reasonable results. Future work will develop a tractable estimation strategy for the fundraising equation. As for now, all of the estimates above use the observed fundraising level to predict NID and therefore the optimal number of firms. It is unclear the direction of the bias associated with this methodology. The changes in the optimal fundraising level depend on the current market share and the sensitivity of donors to increases in the price of donating due to increases in fundraising. This is why estimation itself is so difficult. As the number of firms increases, market shares will fall, all else constant. A nonprofit might increase fundraising in order to target a given level of donations but that incentive depends on the expected reaction of donors to the increase in fundraising. If all firms increased fundraising, then we would expect no change in market shares and thus extra spending on fundraising is inefficient. However, it is unreasonable to expect a uniform reaction to fundraising; some firms will increase and some decrease. The overall effect on the optimal number of firms therefore depends on the proportion of firms adopting each strategy.

Currently, we simply look at museums for reasons defined in the data section. We would like to expand the analysis to other nonprofit sectors. In particular, museums clearly provide a good with at least some public good attributes. Although some large donors clearly subsidize the enjoyment of the arts for others, the connection between the value of donating and the value of the service is more clear. We therefore also intend to target industries with a more distinct separation between the payer and the consumer of the service. Possible candidates are foodbanks or homeless shelters. These charities also rely heavily on donations but likely have much lower fixed costs. We might therefore predict the socially optimal number of firms to be higher than that observed. We also recognize that our current definition of the outside good may need to be expanded. Nonprofits compete across industry lines for donors. We will need to specify a richer demand model however in order to be able to control for variations in the size of sectors, the degree of for-profit competition, and variations in economies of scale in production and in fundraising.

Finally, we would like to build additional complexity into the nonprofit objective function.

Nonprofits are generally exempt from income and property taxes. This clearly decreases both their fixed and variable costs and therefore impacts our predictions of the optimal number of firms. The decline in fixed costs would most likely imply that our estimate of the socially optimal number of firms is biased downward. The social planner would likely value more nonprofits in that scenario. However, this current model of the social planner also does not take into account the lost tax revenues associated with the tax exemption. From that perspective, the social planner might prefer fewer nonprofits, particularly if large economies of scale exist. Moreover, including objectives other than profit maximization can alter the predicted outcome from such models. For example, Lakdawalla and Philipson (2006) show theoretically that if nonprofits are explicitly motivated by serving individuals, they will act as if they have lower costs. Indeed, Gaynor and Vogt (2003) find empirical evidence of lower effective costs for nonprofit hospitals. Similar to the case with taxes, these lower costs will be attractive to a social planner and would likely increase the socially optimal number of firms. The degree of this effect though ultimately lies in the estimates and once again in the value of the services provided by the nonprofit.

Nonetheless, our paper provides a methodology to infer the value of a privately provided public good. Moreover, it provides insight into the strategic fundraising decisions of nonprofits, and structurally investigates those relations. Our current estimates suggest that donors are responsive to the level of fundraising but not to the price of donating associated with increased fundraising. The entry of nonprofits also seems to be consistent with our current notion of social welfare maximization. We hope that continued progress to this paper provides additional insight into the social value of nonprofits.

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Table 1

Descriptive Statistics

	Mean	Sd	Min	Max
Panel A: Firm level				
Museum market share	.1969385	.32019	7.07e-08	1
Market share for all other Arts orgs	.6230057	.2949851	0	.99997
Fundraising expenditures	106700.7	465923.6	0	8655505
Price	1.191544	1.640312	1	63.48898
Total donations to museums	1161081	5812829	25	1.23e+08
Program service revenues	310059.9	2117728	0	7.29e+07
Assets	9454610	6.92e+07	0	2.31e+09
N	2055			
Panel B: Market level				
Market population	389670.9	1069688	555	1.21e+07
Market income	20672.01	5347.437	6975	51490.46
Total market share for museums	.4314381	.3215015	.0030714	1
Total donations for all Arts orgs	2.45e+07	1.15e+08	2711	1.74e+09
Total number of Museums	3.793187	7.85469	1	107
N	411			

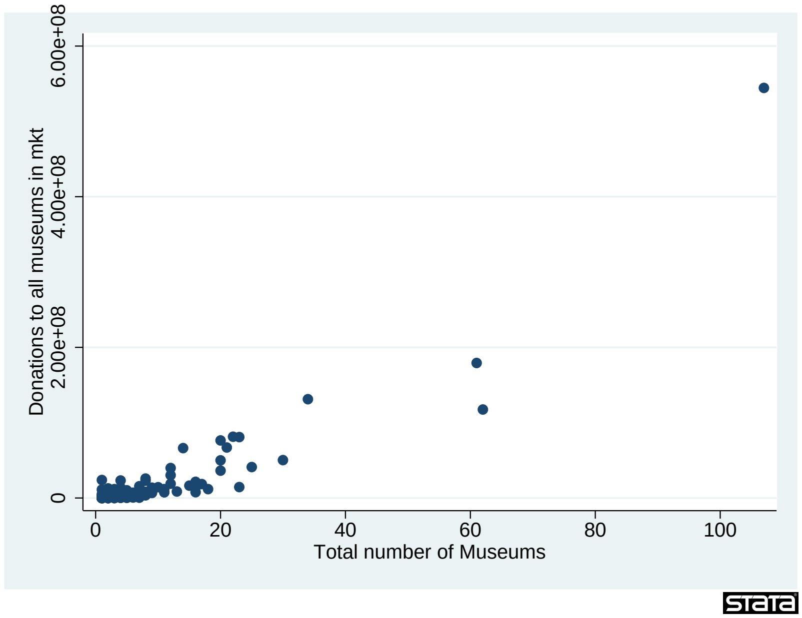

Figure 1: Correlation between Donations and Number of Museums

Table 2

Empirical Estimates of Demand and Entry Model

Variable	Demand	Fundraising	Entry
Fundraising expenses	1.9e-06***	7.1e+00***	
	(1.3e-07)	(2.0e-01)	
Price	-0.0254		
	(0.0218)		
Program service revenue	-4.0e-08*	-3.5e-01***	
	(2.4e-08)	(3.8e-02)	
Assets	-1.8e-09**	4.1e-02***	
	(8.0e-10)	(1.3e-03)	
Market population		2.1e-02	0.6168***
		(1.8e-02)	(7.73e-02)
Market income		-1.3e+00	0.8367*
		(1.2e+01)	(5.24e-01)
σ	.787		
	(.01)		
λ			2.2920***
			(8.06e-02)
N	2055	2055	411
R^2	0.0000	0.8096	

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$