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Gayle, Philip

Kansas State University

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Philip G. Gayle[*]

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Abstract

This study examines whether nonprofits (NP) engage in 'excessive' fundraising (EF) relative to what may be socially optimal. The investigation requires using a structural empirical model to approximate socially optimal fundraising levels. The analysis reveals evidence of EF of up to 31% in a year and identifies the "*donor-stealing*" attribute of fundraising across rival NPs as a key driver of EF. I show that if rival NPs cooperatively set fundraising levels, then this practice effectively eliminates EF since each NP internalizes the "*donor-stealing*" effect. The findings support united fund drives like those we see mobilized by the United Way.

Keywords: Nonprofit Organizations; Excessive Fundraising

JEL Classification Codes: L30; L13; L22

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[*]Kansas State University, Department of Economics, 322 Waters Hall, Manhattan, KS 66506; Voice: (785) 532-4581; Fax: (785) 532-6919 email: gaylep@ksu.edu.

1. Introduction

Rose-Akerman (1982) elegantly laid out a theoretical analysis predicting that, in the absence of policy intervention, competing nonprofit organizations (NP) will engage in “excessive fundraising” (EF). The analysis goes on to suggest that facilitating coordination among rival NPs with respect to their fundraising operations can mitigate the EF problem. Surprisingly, since this seminal work there has not been any formal empirical analysis that quantifies or show systematic evidence of EF relative to what may be socially optimal among NPs. Accordingly, the key objectives of this study are: (*i*) examine whether the evidence supports NPs engaging in EF; (*ii*) quantify the extent of EF among rival NPs; and (*iii*) consider the efficacy of specific policy interventions that may mitigate EF among rival NPs.

As pointed out in Meer (2017), the literature on charitable giving highlights the importance of solicitation [Andreoni et al., 2011; Meer and Rosen, 2011; DellaVigna et al., 2012]. The key result is that giving is rare without fundraising. Recent research has shown that fundraising plays a vital role in increasing both the propensity to give and the level of contributions. For example, using data drawn from tax returns of charitable organizations, Khanna, Posnett, and Sandler (1995); Okten and Weisbrod (2000); and Gayle and Harrison (2023) show that there is a positive relationship between NPs’ fundraising expenses and charitable contributions. A similar relationship is also found by Schervish and Havens (1997) and Yoruk (2009) using household level survey data.

NPs often seek to boost donations by providing various incentives for potential donors to give. These incentives include providing donors gifts [Falk, 2007; Alpizar et al., 2008; Eckel et al., 2015], recognition and prestige [Harbaugh, 1998], and, very commonly, matching grants [Eckel and Grossman, 2008; Karlan and List, 2007; Huck et al., 2015]. Implementing these fundraising tactics is costly. Krieg and Samek (2017) point out that the use of costly fundraising tactics has been criticized as inefficient as it may only lead to a shift in donor contributions between charities/NPs without raising new contributions, yet little consensus exists in the literature about the actual effect of such competition. This line of argument suggests that a determination of EF ought to crucially depend on the relative extent to which the costly fundraising activity shifts donor contributions between charities/NPs versus generate new donor contributions due to the additional expected surplus donors obtain from informative fundraising.

A formidable challenge in empirically examining the existence of EF is how to measure EF. The literature has not yet established a standard for measuring EF. Rose-Akerman (1982) approaches identifying excessive fundraising based on the proportion of donations a NP uses for covering fundraising expenses. This perspective is suggested in the following quote from the abstract of the paper:

"…competition for donations can push fundraising shares to high levels even when donors dislike charities that spend a large proportion of receipts on fundraising…" and further clarified by the next quote located at the bottom of page 199 in the paper: "If entry is costless, and if there is an adequate supply of potential charity entrepreneurs, charities will enter until the fundraising share of the marginal charity approaches one, subject to the breakeven condition in each charity." From this perspective, many will agree that fundraising expenses as a proportion of donations that is equal to 1, i.e., fundraising expenses that use up 100% of donations, constitutes EF since the NP will not have any monies left from donations received to fund its actual mission.

While it is likely easier to build a consensus that fundraising expenses as a proportion of donations that is equal to 1 constitutes EF, it is less clear whether a proportion equal to 50%, or 20%, or even 10% constitutes EF. Mungan and Yoruk (2012) point out that the US Internal Revenue Service (IRS) data on charitable organizations show that on average charities spend around 18% of total contributions in fundraising expenses, while Okten and Weisbrod (2000) report that the ratio between fundraising expenditures and private donations averages 15% for different types of charitable organizations. Andreonie and Payne (2011) point out that donors and charity watch-dog groups often perceive large fundraising expenses, rightly or wrongly, as indications of a low-quality charity. Charity Navigator, for instance, gives its lowest rating to a food bank or community foundation that raises fewer than $5 for every dollar spent on fundraising, i.e., a fundraising expense that is 20% or higher of donations. But is the 20% fundraising expense threshold appropriate for all types of NPs in determining EF? An important contribution of this study is that it sheds light on the reliability of using the ratio of a nonprofit's fundraising spending to the donations it receives as a predictor of the nonprofit's fundraising spending being excessive.

In measuring EF, this study takes a different approach than the proportion of donations approach suggested in the literature discussed above. Specifically, I first use the structural empirical framework laid out in Gayle and Harrison (2023) to approximate socially optimal levels of NP fundraising expenditure across various sectors. In determining socially optimal levels of fundraising, the model considers: (*i*) the marginal impact of fundraising on the expected surplus donors obtain from the available charity donation alternatives in the local market, which no doubt is influenced by donors' valuation of the informative attribute of fundraising; and (*ii*) the "*donor-stealing*" attribute of fundraising across rival NPs correctly deemed by Rose-Akerman (1982) and others as a source of inefficiency in fundraising. To determine EF, I compare actual fundraising expenditures to what the model predicts are socially optimal levels.

Specifically, a determination of EF is reached whenever actual fundraising expenditures exceed socially optimal levels.

As expected, the model estimates reveal that donors' positively value the informative attribute of fundraising, while the model's measure of the "*donor-stealing*" attribute of fundraising across rival NPs negatively impacts social welfare. Accordingly, the model illustrates that whether actual fundraising expenditure of a NP is 'excessive' or 'insufficient' relative to the socially optimal level of fundraising expenditure depends crucially on the relative sizes of the positively valued informative attribute of fundraising versus the countervailing "*donor-stealing*" attribute of fundraising across rival NPs.

Using a sample of 606 nonprofit US art organizations, Marudas and Jacobs (2007) empirically investigate whether each of these NP's fundraising expenditure is 'excessive', 'insufficient', or neither, relative to the level that maximizes their '*net*' donations. [1] It is important to note that Marudas and Jacobs determine whether actual fundraising expenditure is 'excessive' or not by comparing it to the level of fundraising expenditure that maximizes the net return (gross donations received minus fundraising expenses) of the NP's fundraising operations rather than comparing it to the socially optimal level of fundraising expenditure that accounts for donors' positive surplus generated by the informative attribute of fundraising.[2] Furthermore, the '*net*' donations approach used by Marudas and Jacobs (2007) does not consider the strategic interaction in NPs' fundraising decisions across rival NPs. Accordingly, the authors' approach of determining 'excessive' fundraising does not consider the "*donor-stealing*" aspect of fundraising across rival NPs, which is the key aspect of fundraising that is admonished by Rose-Akerman (1982), Krieg and Samek (2017) and much of the literature as the primary reason for socially inefficient and therefore 'excessive' fundraising.

Comparing nonprofits' actual fundraising spending to the model-predicted socially optimal fundraising spending reveals evidence of excessive fundraising spending by NPs. Specifically, in local donor markets where nonprofits compete for donations, I find that mean market-level actual solicitation spending exceeds the model-predicted mean socially optimal solicitation spending by an overall average

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[1] Marudas and Jacobs (2007) use their regression estimates to compute the elasticity of *net* donations with respect to fundraising expenditure for each NP, where *net* donation is defined as gross donations minus fundraising expenses. They use these computed elasticities to determine whether a NP's fundraising expenditure is 'excessive' or not. Specifically, if the computed elasticity is negative (positive) for a given NP, then the authors conclude that this NP's fundraising is 'excessive' ('insufficient') relative to the level of fundraising that would maximize its *net* donations. The reader is also referred to Jacobs and Marudas (2006) for a discussion and analysis of determining 'excessive' fundraising with respect to the "net" donation maximizing level of fundraising.

[2] For other studies that use the "net" donation maximizing level of fundraising to determine whether NPs engage in "excessive" fundraising, see Posnett and Sandler (1989); Khanna, Posnett, and Sandler (1995); and Khanna and Sandler (2000).

of 29%, with excess solicitation spending ranging from 27 to 31 percent of the actual solicitation spending each year over the 2008 through 2018 sample years considered in this study. Furthermore, I find evidence that the negative welfare impact of the "*donor-stealing*" attribute of fundraising across rival NPs often outweighs the positive welfare impact of the informative attribute of fundraising. Therefore, consistent with arguments first made in Rose-Akerman (1982), the model reveals that a key driver of excessive fundraising is the "*donor-stealing*" attribute of fundraising across rival NPs.

I also find that if rival NPs in a local market cooperatively set solicitation spending levels, then this practice is sufficient to effectively eliminate excessive solicitation spending. The reason is that cooperation allows each NP to internalize the adverse effect that its own fundraising activities have on its rivals' ability to secure donations, i.e., internalization of the "*donor-stealing*" aspect of fundraising across rival NPs, causing them to jointly choose lower levels of fundraising spending.

The policy-relevant takeaway message from the results is that implementing an industry structure in which rival NPs cooperatively set their solicitation spending levels can eliminate excessive solicitation spending. However, an independent institution may be needed to enforce cooperation due to an inherent incentive for each NP to renege on a cooperative agreement. Aldashev et al. (2014) carefully discusses the attributes of donor markets that are conducive for sustainable cooperative fundraising agreements between nonprofits.

The results of this study are supportive of united fund drives we often see mobilized by the United Way organization. United fund drives are typically done on behalf of multiple nonprofits in a coordinated fashion even though the nonprofits may have very different missions and therefore serve different nonprofit sectors, but they otherwise compete for slices from a common pie of donor dollars. Nonprofit organizations that partner with the United Way usually agree not to fundraise while the United Way campaigns are underway.[3]

The remainder of the paper is organized as follows. In the next section I describe the model and how it is used to capture key attributes of fundraising that are impactful on social welfare. Section 3 discusses the data used for the analysis. Section 4 presents results for the estimation of the donor demand aspect of the model. Section 5 describes how I use the estimated model to implement a counterfactual experiment designed to assess the extent and key source of excessive fundraising. In Section 6, I present and discuss the results from the counterfactual experiment. Concluding remarks are offered in Section 7.

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[3] See relevant information at the following URL: https://en.wikipedia.org/wiki/United_Way

2. A Model to Approximate Socially Optimal Solicitation Spending

2.1 Donor Demand

I begin by describing a donor demand model that follows Gayle and Harrison (2023). Let each donor i in local market m during period t choose to donate to one of the J_{mt} nonprofits in the market during period t, and these nonprofits are indexed by j, where $j = 1, \ldots, J_{mt}$. Donor i also has the option to not donate to any of the J_{mt} nonprofits, an outside option I designate as $j = 0$. Therefore, each donor's decision problem is effectively to maximize their own utility by choosing one among the $J_{mt} + 1$ donative alternatives in their local market, $j = 0,1, \ldots, J_{mt}$. Accordingly, each donor solves the following utility maximizing donation choice problem:

$$\max_{j \in \{0,1,\ldots,J_{mt}\}} \left\{ U_{ijmt} = \delta_{jmt} + \sigma\zeta_{ikmt} + (1-\sigma)\varepsilon_{ijmt} \right\} \tag{1}$$

where U_{ijmt} is the indirect utility donor i gets from donating to nonprofit j located in market m during period t. The indirect utility of donor i, U_{ijmt}, comprises three components, δ_{jmt}, $\sigma\zeta_{ikmt}$, and $(1-\sigma)\varepsilon_{ijmt}$. Component δ_{jmt} is the mean utility level across all donors who donate to nonprofit j.

I assume that NPs in a market are organized into K mutually exclusive groups indexed by k, where the groups correspond to sectors/industries. In this study each NP falls into one of seven (7) distinct sectors. The outside option is assumed to be the only member of group 0 ($k = 0$), yielding $K + 1$ mutually exclusive groups, $k = 0,1, \ldots, K$. For donor i, ζ_{ikmt} is a random component of utility that is common to all nonprofits in sector k, whereas ε_{ijmt} is a random preference component that is specific to NP j. Estimable parameter σ lies between 0 and 1, i.e., $0 \leq \sigma < 1$, and measures the correlation of the donors' utility across nonprofits belonging to the same sector. As σ approaches 1, the correlation of preferences for donating to nonprofits within the same sector increases. Conversely, if $\sigma = 0$, there is no correlation of donor preferences by sector, i.e., donors are equally likely to switch their donation across nonprofits in different sectors, compared to switching their donation across nonprofits within the same sector. In this case, the indirect donor utility specification becomes equivalent to the utility specification for a standard logit model in which nonprofits compete symmetrically for donations irrespective of their sector.

I specify that the mean utility, δ_{jmt}, is a function of various NP-level and market attributes as follows:

$$\delta_{jmt} = \gamma ln(f_{jmt}) + \beta x_{jmt} + \tau_j + \upsilon_t + \xi_{jmt} \tag{2}$$

where f_{jmt} represents solicitation intensity measured in dollars of spending for nonprofit j; and γ is an estimable parameter that measures the average change in donors' satisfaction induced by a change in the nonprofit's solicitation intensity. I expect $\gamma > 0$, implying that each nonprofit can influence the giving propensity of a donor through its choice of fundraising intensity. Specifically, $\gamma > 0$ implies that if NP j increases its fundraising, then this may: (*i*) encourage those who never gave to donate to NP j; and/or (*ii*) cause a donor simply to switch their giving from another charity to NP j. x_{jmt} is a vector of measured attributes of NP j; and β is the corresponding vector of estimable parameters that measure the marginal impacts of these respective attributes on donor satisfaction. τ_j and υ_t represent NP fixed effects and year fixed effects, respectively, to control for donation-influencing factors that vary by NP and by year that are unobserved to me the researcher. Last, ξ_{jmt} is a composite measure of residual donation-influencing factors that are unobserved to me the researchers but observed by donors and nonprofits in the relevant market.

With assumptions on the distribution of the unobserved components typically made for the nested logit model, optimal discrete donative choice behavior of donors described in equation (1) yields the following unconditional probability of donors in market m choosing to donate to nonprofit j:

$$s_{jmt}(\boldsymbol{f}_{mt};\theta) = \frac{exp\left(\frac{\delta_{jmt}}{1-\sigma}\right)}{D_{kmt}} \frac{D_{kmt}^{(1-\sigma)}}{1+\sum_{k=1}^{K} D_{kmt}^{(1-\sigma)}} \quad (3)$$

where $\theta = (\gamma, \beta, \sigma)$ is a vector of estimable parameters; $\boldsymbol{f}_{mt}$ is a vector of solicitation intensities measured in dollars of spending for the nonprofits in market m during period t, i.e., $f_{jmt} \in \boldsymbol{f}_{mt} \forall j \in J_{mt}$; and $D_{kmt} = \sum_{j\epsilon\Gamma_{kmt}} exp\left(\frac{\delta_{jmt}}{1-\sigma}\right)$, where Γ_{kmt} represents the set of NPs in sector k.

2.2 Building the Components of a Social Welfare Function

I approximate socially optimal solicitation spending by assuming a social planner chooses NP-level solicitation spendings to maximize a social welfare function. The social welfare function that I subsequently specify will comprise two key components: (*i*) the joint net revenue, or joint net return, to solicitation operations across the NPs in market m during period t; and (*ii*) the expected surplus measured in dollars that donors obtain from the available charity donation alternatives in the local market. I now describe these two components, respectively, before assembling them into a single social welfare function.

2.2.1 Nonprofits' Net Return to Solicitation Operations

The modeling framework used in this study for specifying NPs' net return from their solicitation operations is based on Gayle and Harrison (2023). The equilibrium fundraising model framework accounts for the crucial role of strategic interaction in fundraising decisions. In what follows I often omit the time subscript, t, only to avoid a clutter of notation. Therefore, each equation is still to be interpreted in a time-specific manner.

The expected donations, ED_{jm}, for nonprofit j in market m is specified as:

$$ED_{jm}\left(f_{jm}, \boldsymbol{f}_{-j,m}; \theta\right) = s_{jm}\left(f_{jm}, \boldsymbol{f}_{-j,m}; \theta\right) \times PD_m \tag{4}$$

where $s_{jm}\left(f_{jm}, \boldsymbol{f}_{-j,m}; \theta\right)$ is the model-predicted donation share of nonprofit j in market m, which is defined in equation (3) above as being equivalent to the unconditional probability a potential donor in the local market donates to nonprofit j; and PD_m is a measure of the aggregate potential money donations, i.e., the donative capacity of local market m. Based on the donor demand model laid out above, the reader is reminded that the model-predicted donation share of NP j is a function of its own solicitation intensity, f_{jm}, as well as the solicitation intensities, $\boldsymbol{f}_{-j,m}$, of nonprofits in market m that are rivals to NP j, i.e., $\boldsymbol{f}_{-j,m} = \boldsymbol{f}_m \backslash f_{jm}$. Accordingly, as revealed in equation (4), the expected donations of NP j is a function of its own solicitation intensity, f_{jm}, as well as the solicitation intensities, $\boldsymbol{f}_{-j,m}$, of nonprofits in market m that are rivals to NP j.

The cost nonprofit j incurs from its solicitation activities is specified as:

$$TC_{jm} = VC_{jm}\left(f_{jm}\right) + FC_{jm} \tag{5}$$

where $VC_{jm}\left(f_{jm}\right)$ measures the composite of implicit and explicit costs that change with solicitation intensity, f_{jm}; and FC_{jm} is the fixed cost nonprofit j incurs to facilitate solicitation activities, which do not vary with the amount of its solicitation activities. The implicit costs in $VC_{jm}(\cdot)$ stem from the opportunity costs of various resources the nonprofit uses for solicitation activities that could have been used for other activities, which include fulfilling the core mission of the nonprofit. These costs are incurred regardless of whether the person solicited contributes to the cause. Therefore, an increase in a nonprofit's solicitation activities involves an increase in its actual cash spending (explicit costs) on these activities, f_{jm}, as well as an increase in the opportunity cost (implicit costs) of implementing these activities due to the additional resources the nonprofit channels into these activities.

The net return to solicitation operations of nonprofit j in market m is
given by:

$$NR_{jm}(f_{jm}, \boldsymbol{f}_{-j,m}) = ED_{jm}(f_{jm}, \boldsymbol{f}_{-j,m}; \theta) - TC_{jm}$$
$$= s_{jm}(f_{jm}, \boldsymbol{f}_{-j,m}; \theta) \times PD_m - TC_{jm} \quad (6)$$

where the net return for nonprofit j, $NR_{jm}(f_{jm}, \boldsymbol{f}_{-j,m})$, is a function of its own solicitation intensity, f_{jm}, as well as the solicitation intensities, $\boldsymbol{f}_{-j,m}$, of nonprofits in market m that are rivals to nonprofit j. In a setting where there is no policy intervention, which I assume is the status quo, rival nonprofits independently and noncooperatively each choose their own level of solicitation spending to maximize the net revenue generated from their solicitation operations needed to maximize the nonprofit's service provision. Accordingly, in the status quo each nonprofit will solve the following optimization problem:

$$\max_{f_{jm}} NR_{jm}(f_{jm}, \boldsymbol{f}_{-j,m}) \quad (7)$$

which yields the following first-order conditions that must be simultaneously satisfied in a Nash equilibrium:

$$\frac{\partial s_{jm}(\boldsymbol{f}_m;\theta)}{\partial f_{jm}} \times PD_m - mc_{jm} = 0 \;\; \forall j \in J_m \quad (8)$$

where term $\frac{\partial s_{jm}(\boldsymbol{f}_m;\theta)}{\partial f_{jm}} \times PD_m$ in equation (8) measures the marginal change in donations received by nonprofit j in market m due to a marginal change in its solicitation spending; and $mc_{jm} = \frac{\partial vc_{jm}}{\partial f_{jm}}$ measures the marginal change in the composite of implicit and explicit costs incurred by the nonprofit due to a marginal change in its solicitation spending.

2.2.2 The Expected Surplus of Donors

Let $ES^{\$}(\boldsymbol{f}_m)$ represent the mean per capita expected surplus measured in dollars that donors obtain from the available charity donation alternatives in the local market. Based on using a nested logit framework for modeling donor demand, $ES^{\$}(\boldsymbol{f}_m)$ takes the following functional form:

$$ES^{\$} = exp(ES^{ln\$}) \quad (9)$$

where

$$ES^{ln\$} = \frac{1}{\gamma} ln\left[1 + \sum_{k=1}^{K} D_{km}^{(1-\sigma)}\right] \quad (10)$$

$ES^{ln\$}$ in equation (10) is the mean per capita expected surplus measured in the natural logarithm of dollars and as previously described, $D_{km} = \sum_{j\epsilon\Gamma_{km}} exp\left(\frac{\delta_{jm}}{1-\sigma}\right)$. As exemplified in equation (6) in Ivaldi and Verboven (2005), the right-hand-side of equation (10) above is the well-known functional form for expected surplus decision-makers obtain from the choice options when using a nested logit model to capture these individuals' discrete choice problem.

The mean per capita expected surplus measured in dollars and captured by equation (9) above simplifies to the following:

$$ES^{\$} = \left[1 + \sum_{k=1}^{K} D_{km}^{(1-\sigma)}\right]^{\frac{1}{\gamma}} \quad (11)$$

2.2.3 Assembling and Analyzing the Social Welfare Function

Based on the discussions above, I specify the following social welfare function for solicitation operations in a market:

$$SW(\boldsymbol{f}_m) = \sum_{j \in J_m} NR_{jm}(\boldsymbol{f}_m) + ES^{\$}(\boldsymbol{f}_m) \times Pop_m \quad (12)$$

where $\sum_{j \in J_m} NR_{jm}(\boldsymbol{f}_m)$ is the joint net revenue, or joint net return, to solicitation operations across the NPs in market m; Pop_m is the size of the population in the local market; and $ES^{\$}(\boldsymbol{f}_m) \times Pop_m$ the expected surplus measured in dollars that donors obtain from the available charity donation alternatives in the local market. Accordingly, the social planner solves the following problem:

$$\max_{f_{jm} \forall j \in J_m} SW(\boldsymbol{f}_m), \quad (13)$$

The first-order conditions for the optimization problem in (13) are the following:

$$\frac{\partial NR_{jmt}(f_{jm}, \boldsymbol{f}_{-j,m})}{\partial f_{jm}} + \sum_{r \neq j} \frac{\partial NR_{rmt}(f_{rm}, \boldsymbol{f}_{-r,m})}{\partial f_{jm}} + \frac{\partial ES^{\$}}{\partial f_{jm}} \times Pop_m = 0 \text{ for all } j = 1, \dots, J_m \quad (14)$$

Recall that $\frac{\partial NR_{jm}(f_{jm}, \boldsymbol{f}_{-j,m})}{\partial f_{jm}} = \frac{\partial s_{jm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m - mc_{jm}$ based on the previously specified net revenue function for a NP's solicitation operations. Therefore, the first-order condition expression in (14) can be re-written as:

$$\frac{\partial s_{jm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m - mc_{jm}$$
$$+ \frac{\partial ES^{\$}}{\partial f_{jm}} \times Pop_m + \sum_{r \neq j} \frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m = 0 \text{ for all } j = 1, \dots, J_m \quad (15)$$

Compared to the first-order conditions for the non-cooperative simultaneous-move Nash solicitation spending game between NPs captured in equation (8) above, the first-order condition expression in equation (15) has additional terms $\frac{\partial ES^{\$}}{\partial f_{jm}} \times Pop_m$ and $\sum_{r \neq j} \frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m$, respectively.

Based on the functional form for $ES^{\$}$ in equation (11) above, it can be shown that:

$$\frac{\partial ES^{\$}}{\partial f_{jm}} = \frac{1}{f_{jm}} \left[1 + \sum_{k=1}^{K} D_{km}^{(1-\sigma)}\right]^{\frac{1}{\gamma}} s_{jm} \quad \text{for all } j = 1, \dots, J_m \quad (16)$$

Therefore, from the right-hand-side expression in (16) it can be verified that $\frac{\partial ES^{\$}}{\partial f_{jm}} > 0$ when $\gamma > 0$ and $0 \leq \sigma < 1$, which are consistent with theoretical expectations. The partial derivative, $\frac{\partial ES^{\$}}{\partial f_{jm}}$, captures the marginal impact of fundraising on the expected surplus donors obtain from the available charity donation alternatives in the local market, which no doubt is influenced by donors' valuation of the informative attribute of fundraising. Second, the specified donor demand model yields $\frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} < 0$ for all rival pairs of NPs, implying that $\sum_{r \neq j} \frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m < 0$. I refer to $\frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} < 0$ as the "*donor-stealing*" effect since it captures the adverse effects that a NP's fundraising activities have on its rivals' ability to secure donations.

Since $\frac{\partial ES^{\$}}{\partial f_{jm}} \times Pop_m > 0$, $\sum_{r \neq j} \frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m < 0$, and as discussed in Gayle and Harrison (2023) that the net revenue function, $NR_{jm}(f_{jm}, \boldsymbol{f}_{-j,m})$, is increasing but concave in f_{jm}, then the socially optimal level of solicitation spendings that satisfy the first-order conditions in (15) may be higher or lower than the non-cooperative Nash equilibrium level of NPs' solicitation spendings, and the outcome of this comparison depends on the relative size of $\left| \frac{\partial ES^{\$}}{\partial f_{jm}} \times Pop_m \right|$ versus $\left| \sum_{r \neq j} \frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m \right|$. For example, if $\left| \sum_{r \neq j} \frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m \right| > \left| \frac{\partial ES^{\$}}{\partial f_{jm}} \times Pop_m \right|$, and given that a NP's net revenue function is concave in its own solicitation spending, then the socially optimal level of solicitation spendings that satisfy the first-order conditions in (15) will be *lower* than the non-cooperative Nash equilibrium level of NPs' solicitation spendings, yielding excessive solicitation spending from NPs that independently determine their optimal level of solicitation spending. Conversely, if $\left| \sum_{r \neq j} \frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} \times PD_m \right| < \left| \frac{\partial ES^{\$}}{\partial f_{jm}} \times Pop_m \right|$, i.e., donors' valuation of the informative attribute of fundraising dominates the "*donor-stealing*" effect of fundraising, then the socially optimal level of solicitation spendings that satisfy the first-order conditions in (15) will be *higher* than the non-cooperative Nash equilibrium level of NPs' solicitation spendings, yielding too little solicitation spending from NPs that independently determine their optimal level of solicitation spending.

The discussions above imply that implementing an industry structure to achieve cooperation among rival NPs in setting fundraising levels can mitigate an excessive fundraising problem. This policy recommendation is contrary to what we typically see suggested in for-profit industries. The reason why cooperation in the NP setting can solve an excessive fundraising problem is that cooperation allows each NP to internalize the adverse effects that its own fundraising activities have on its rivals' ability to secure donations, which is captured by $\frac{\partial s_{rm}(\boldsymbol{f}_m)}{\partial f_{jm}} < 0$, the "*donor-stealing*" effect in the model. Internalization of the "*donor-stealing*" aspect of fundraising across rival NPs will cause them to jointly choose lower levels of fundraising intensities.

3. Data

The donation and fundraising data, measured in dollars, are for 501(c)3 public organizations that filed tax returns over the period 2008 through 2018.[4] These annual frequency data 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 them to file a 990 tax return annually if their gross receipts are greater than $25,000.

The data also contain various measures of firm attributes. Specifically, I use the aggregate dollar value of a firm's assets at the beginning of the fiscal year as a measure of its size. Second, NPs receive revenues from mission-related services, which are called program service revenues. A reasonable conjecture is that NPs that generate higher program service revenues, all else equal, are less dependent on donations and therefore may engage in less fundraising. Accordingly, I use each NPs' program service revenue as a NP-attribute control in the donor demand model.

Like Gayle and Harrison (2023), I identify the sector/industry to which a NP belongs based on its primary mission as reported by the National Taxonomy of Exempt Entities (NTEE). The NTEE classification codes correspond to nonprofit services that are well-defined with a clear mission. In Table 1, I provide a few examples of nonprofits in the data sample organized by their NTEE classification (sectors). The table also reports, by sector, the mean annual NP count in the sample.

[4] All monetary variables are deflated with respect to year 2008 dollars using the consumer price index (CPI).

Table 1: Description of Nonprofits and Sectors in the Sample

Sector Number	Sector Name	Examples of Nonprofit Organizations	Mean Annual NP Count	Mean % of Sample NP Count
1	Arts	ABNOT ART MUSEUM; ACADEMY OF MUSIC OF PHILADELPHIA INC; ALLEY THEATRE; ATLANTA BALLET INC; AUSTIN CHILDREN'S MUSEUM; BOSTON SYMPHONY ORCHESTRA INC; CHICAGO SHAKESPEARE THEATER	431 - - -	10.62 - - -
2	Education	PERKINS SCHOOL FOR THE BLIND; PHOENIX COUNTRY DAY SCHOOL; PROVIDENCE CHRISTIAN ACADEMY INC; PUBLIC LIBRARY FOR UNION COUNTY; Philadelphia University; ROCKHURST UNIVERSITY	1,241 - - -	30.51 - - -
3	Environmental & Animal	ATLANTA BOTANICAL GARDEN INC; Cascade Forest Conservancy; ANIMAL RESCUE LEAGUE OF BOSTON; DELTA ANIMAL SHELTER; CHICAGO ZOOLOGICAL SOCIETY	176 - - -	4.31 - - -
4	Health	MEMORIAL HOSPITAL; MENDOTA COMMUNITY HOSPITAL; MENTAL HEALTH CENTER OF DENVER; METAMORA COMMUNITY NURSING HOME	906 - - -	22.45 - - -
5	Human & Social Services	LOWER EAST SIDE GIRLS CLUB; MERRIMACK VALLEY FOOD BANK INC; Madison Square Boys & Girls Club Inc; Morningstar Senior Living Inc; OZARKS REGIONAL YMCA	993 - - -	24.37 - - -
6	International	CHILDREN INTERNATIONAL; GLOBAL SOLUTIONS PITTSBURGH; Heifer Project International; VITAL VOICES GLOBAL PARTNERSHIP INC	52 - - -	1.27 - - -
7	Civil Rights & Advocacy	100 BLACK MEN OF ATLANTA; CENTER FOR AMERICAN PROGRESS; CENTER FOR POPULAR DEMOCRACY INC; CLEVELAND JOBS WITH JUSTICE; Los Angeles LGBT Center	265 - - -	6.45 - - -

Notes: This table describes the sector classifications for the data sample of nonprofits and provides a few examples of the nonprofits. The sample period spans 2008 through 2018.

Local geographic markets in this study are delineated by zip code area. To facilitate computing each nonprofit's donation share within a given local market for a given year, I first determine the donative capacity of each market, a variable denoted as PD_{mt} first defined above in equation (4). The donative capacity of a local market, PD_m, is computed as 2.5 times the maximum aggregate donations observed in the relevant zip code area in a given year over the sample years of the study. An advantage of using this method to measure the donative capacity of each market is that this method captures the variation across local markets of their populations' propensity to donate. For example, two local markets with the same number of individuals may have very different propensities to donate based on differences across the markets with respect to their populations' demographic characteristics such as income, etc. However, a caveat of the method is that the 2.5 multiplicative factor is an arbitrary number. Accordingly, it is prudent to assess the extent to which results are sensitive to the multiplicative factor used for approximating the donative capacities. To this end, I have re-estimated the demand model using multiplicative factors less than and greater than 2.5 and find that key qualitative results are largely robust to the resulting donative capacity changes. Estimation results based on the multiplicative factors 1.5 and 5, respectively, are reported in Table A2 in the Appendix.

I then compute each nonprofit's observed donation share within a given local market for a given year as, $S_{jmt} = Donations_{jmt}/PD_m$, where $Donations_{jmt}$ is the dollar amount of private donations received by nonprofit j located in market m during period/year t. Accordingly, the observed share of the outside option, S_{0mt}, i.e., the observed mean probability that potential donors choose not to donate to one of the nonprofits in the local market is computed as, $S_{0mt} = 1 - \sum_{j=1}^{J_{mt}} S_{jmt}$,[5] where as previously defined, J_{mt} is the number of nonprofit firms in the local market. Table 2 reports, by sector, summary statistics on nonprofit-level donation share within their local market as well as their donation share within the local market and sector. The table also reports summary statistics on nonprofit-level solicitation spending as a percentage of donations received by the nonprofit.

Organizations reporting negative contributions, program service revenues, or assets are deleted. Based on the primary focus of this study, I restrict the sample to NPs with strictly positive solicitation spending. This leaves 44,737 observations generated from 4,715 organizations across 28,533 market-year combinations. Table 3 reports summary statistics on the key variables used in the empirical analysis.

[5] It is well-known that estimation of the discrete choice demand model used in this study requires defining potential market sizes to be sufficiently large such that $S_{0mt} > 0$ for all markets in the sample.

Table 2: Summary Statistics on Nonprofits' Donation Shares and Solicitation Spending as a Percentage of Donations by Sector

Sector Number	Sector Name	Statistic	Nonprofits' Donation Share in Market	Nonprofits' Donation Share within Market and Sector	Nonprofit-level Solicitation Spending as a % of Donations
1	Arts	Mean	0.0943295	0.7419423	77.35524
		Std. Dev	0.110907	0.3653206	1774.752
		Min	7.31e-07	0.0000302	0.000107
		Max	0.4	1	95917.79
2	Education	Mean	0.1480946	0.8362252	88.2217
		Std. Dev	0.1256031	0.3151299	3168.004
		Min	1.03e-06	0.0000311	0.0000213
		Max	0.4	1	299462.50
3	Environmental & Animal	Mean	0.1439901	0.9624486	45.18683
		Std. Dev	0.1314399	0.1593914	802.0644
		Min	0.0000203	0.0066398	0.0071937
		Max	0.4	1	30845.82
4	Health	Mean	0.1272068	0.8421792	211.3168
		Std. Dev	0.1301592	0.3128314	6789.475
		Min	1.32e-07	1.94e-06	0.0008362
		Max	0.4	1	537530
5	Human & Social Services	Mean	0.1337784	0.8546187	90.61679
		Std. Dev	0.1350905	0.296005	3252.861
		Min	2.21e-08	0.0000375	0.0009689
		Max	0.4	1	327850
6	International	Mean	0.1297205	0.8382609	29.85087
		Std. Dev	0.1391915	0.3176007	340.1331
		Min	1.81e-06	0.0001377	0.0006603
		Max	0.4	1	7491.915
7	Civil Rights & Advocacy	Mean	0.1484979	0.9086242	170.0041
		Std. Dev	0.1346086	0.2468519	2709.841
		Min	3.40e-07	2.72e-06	0.0011617
		Max	0.4	1	120175

Table 3: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Market share of Donations	0.1338524	0.1295734	2.21e-08	0.4
Donations (000)	11259.84	52212.88	0.007717	2131589
Solicitation spending (000)	252.74	1242.69	0.0009242	48048.96
Program service revenue (000)	61431.73	299550.90	0	1.26e+07
Assets (000)	195055.10	1195494	0.0375102	6.75e+07
Number of nonprofits per local market	2.83	2.99	1	22
Number of observations (*N*)	44,737			

Notes: Source of the data: 2008-2018 990 Tax Returns. I calculate market shares of donations based on local market and year from nonprofit-level donations reported in the NCCS data. All monetary variables are deflated with respect to year 2008 dollars using the consumer price index (CPI).

4. Results from Donor Demand Estimation

Given the nested logit functional form of the donative share function in equation (3), the donor preference parameters in vector $\theta = (\gamma, \beta, \sigma)$ can be estimated using the following linear regression equation: [6]

$$ln(S_{jmt}) - ln(S_{0mt}) = \gamma ln(f_{jmt}) + \beta x_{jmt} + \sigma ln(S_{jmt|k}) + \tau_j + \upsilon_t + \xi_{jmt} \qquad (17)$$

where S_{jmt} is the observed market share of donations received by NP j in market m during period t; S_{0mt} is the observed proportion of the donative capacity of market m during period t that is not secured by the nonprofits in the market; and $S_{jmt|k}$ is the observed within sector donation share of NP j.

As discussed in Gayle and Harrison (2023), since both f_{jmt} and $S_{jmt|k}$ are endogenous variables in equation (17), instruments for these variables are needed to achieve consistent estimates of parameters γ and σ, respectively. Following Gayle and Harrison (2023), I construct and use well-known BLP-motivated type instruments for NPs' within sector donation share. Such BLP-motivated instruments include the means of asset value and program service revenue across a NP's rivals, which are also valid instruments for the solicitation intensity variable.

Additional instruments used for the solicitation intensity variable include: (*i*) number of competing nonprofits in the local market; and (*ii*) the number of competing nonprofits in the relevant nonprofit's own sector. The rationale for these instruments is that the number of competing nonprofits is a measure of the competitive intensity a given nonprofit faces to secure donations in a given market. The degree of competitive intensity a nonprofit face to secure donations should influence its optimal choice of solicitation intensity. Given that the number of competing nonprofits in a market during period t is determined by rival nonprofits' entry decisions in some previous period, then I do not expect the number of competing nonprofits in period t is correlated with ξ_{jmt}, making these valid instruments for f_{jmt}.

Table 4 reports parameter estimates of the donor demand model. In column (1) of the table I report parameter estimates when instruments are not used for endogenous variables f_{jmt} and $S_{jmt|k}$, while in column (2) instruments are used for the two endogenous variables. It is evident that the values of the parameter estimates associated with the endogenous variables are very different across columns (1) and (2), suggesting that instruments are needed to address the endogeneity challenges posed by variables f_{jmt}

[6] See Berry (1994) for a comprehensive discussion of the nested logit model and estimating it using firm-level or product-level market share data in for-profit industry settings.

and $S_{jmt|k}$. A formal statistical test reported in the table confirms the endogeneity of f_{jmt} and $S_{jmt|k}$. Accordingly, I use the estimates in column (2) for subsequent analysis.

As expected, the positive and statistically significant parameter estimate on fundraising intensity in the donor demand model, i.e., $\gamma > 0$, suggests that by increasing its fundraising intensity, a nonprofit firm can increase the donations it receives as well as its market share of donations, which is the estimation result of primary interest for the analysis in this study. Second, consistent with theory, the estimate of σ lies between 0 and 1. Furthermore, the estimate of σ is statistically different from zero, suggesting that donor preferences are correlated among nonprofit firms within the same sector.

Next, I use the estimated donor demand model jointly with the framework for determining optimal fundraising spending described in Section 2 to perform a counterfactual experiment designed to reveal whether NPs engage in excessive fundraising. I begin by describing how the counterfactual experiment is implemented.

Table 4: Donor Demand Model Estimates

	(1)	(2)
Variables	Ordinary Least Square Estimates	Two-stage Least Squares Estimates
Solicitation Spending (parameter: γ)	0.047*** (0.007)	0.755*** (0.224)
Within group donation share (parameter: σ)	0.363*** (0.008)	0.152*** (0.017)
Program service revenue	-0.010*** (0.004)	-0.014*** (0.005)
Assets	-0.078*** (0.017)	-0.178*** (0.037)
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
R-squared	0.162	-
Test of endogeneity: H0: Solicitation Spending & Within group donation share are exogenous variables	chi2 = 209.14 Prob > chi2 = 0.0000	
Number of observations	44,737	

Notes: *, **, *** p-value ≤ 10%, 5%, and 1%, respectively. Standard errors in parentheses.

5. Implementing the Counterfactual Experiment

The counterfactual experiment involves assuming the existence of a local market social planner who determines socially optimal solicitation spending levels across NPs in the market rather than the status quo in which NPs independently and noncooperatively determine their Nash equilibrium solicitation spending levels. To implement the counterfactual, it is convenient to represent in matrix notation the system of first-order conditions in (15).

Let Δ_m be a $J_m \times J_m$ matrix that captures the response of donation shares to changes in solicitation intensities, where J_m is the number of rival nonprofits in the relevant market. Specifically, matrix Δ_m contains first-order partial derivatives of donation shares with respect to solicitation intensities:

$$\Delta_m(\boldsymbol{f}_m;\theta) = \begin{bmatrix} \frac{\partial s_1}{\partial f_1} & \cdots & \frac{\partial s_1}{\partial f_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_J}{\partial f_1} & \cdots & \frac{\partial s_J}{\partial f_J} \end{bmatrix}$$

It is important to recognize that each first-order partial in the matrix above is a function of the variables and parameters in the donor demand function, i.e., $\Delta_m(\boldsymbol{f}_m;\theta)$.

Second, let Ω_m be a $J_m \times J_m$ matrix of zeroes and ones appropriately positioned to reflect the set of NPs for which solicitation intensities are cooperatively set. Specifically, let ω_{jr} represent an element in matrix Ω_m, where $\omega_{jr} = 1$ if $j = r$ and if solicitation intensities are cooperatively set among distinct NPs j and r, otherwise $\omega_{jr} = 0$. In the case where solicitation intensities are cooperatively set among all NPs in the local market, then Ω_m is a matrix of ones, i.e., $\omega_{jr} = 1$ for all pairs (j, r) and when $j = r$. Accordingly, the system of first-order conditions in (15) can now be represented in matrix notation as follows:

$$[(\Omega_m * \Delta_m) \times Ones(J_m, 1)] \times PD_m + \Delta \boldsymbol{ES}_m \times Pop_m - \boldsymbol{mc}_m = \boldsymbol{0} \qquad (18)$$

where $\Omega_m * \Delta_m$ is an element-by-element multiplication of the two matrices; $Ones(J_m, 1)$ is a $J_m \times 1$ vector of ones; PD_m is a scalar measure of the donative capacity of the local market; $\Delta \boldsymbol{ES}_m$ is a $J_m \times 1$ vector of first-order partial derivatives of mean expected surplus of donors with respect to solicitation intensities; Pop_m is the size of the population in the local market; and $\boldsymbol{mc}_m$ is a $J_m \times 1$ vector of marginal costs across the NPs in the local market.

Given the donor demand parameter estimates, $\hat{\theta} = (\hat{\gamma}, \hat{\beta}, \hat{\sigma})$, along with the non-cooperative Nash equilibrium game that I assume characterizes NPs' actual solicitation spending, I can recover each NP's marginal cost of solicitation using the following equation:

$$\left[\left(I * \Delta_m(\boldsymbol{f}_m;\hat{\theta})\right) \times Ones(J_m, 1)\right] \times PD_m = \widehat{\boldsymbol{mc}}_m \qquad (19)$$

where I in equation (19) is a $J_m \times J_m$ identity matrix. I assume the estimated marginal costs captured in vector, $\widehat{\boldsymbol{mc}}_m$, do not change with any cooperative/joint setting of solicitation spendings across NPs. Accordingly, with $\widehat{\boldsymbol{mc}}_m$ in hand, I use it in solving for the vector of socially optimal NP solicitation spendings, $\boldsymbol{f}_m^{so}$, that satisfy:

$$\left[\left(\Omega_m * \Delta_m\left(\boldsymbol{f}_m^{so};\hat{\theta}\right)\right) \times Ones(J_m,1)\right] \times PD_m + \Delta\boldsymbol{ES}_m\left(\boldsymbol{f}_m^{so};\hat{\theta}\right) \times Pop_m - \widehat{\boldsymbol{mc}}_m = \boldsymbol{0} \qquad (20)$$

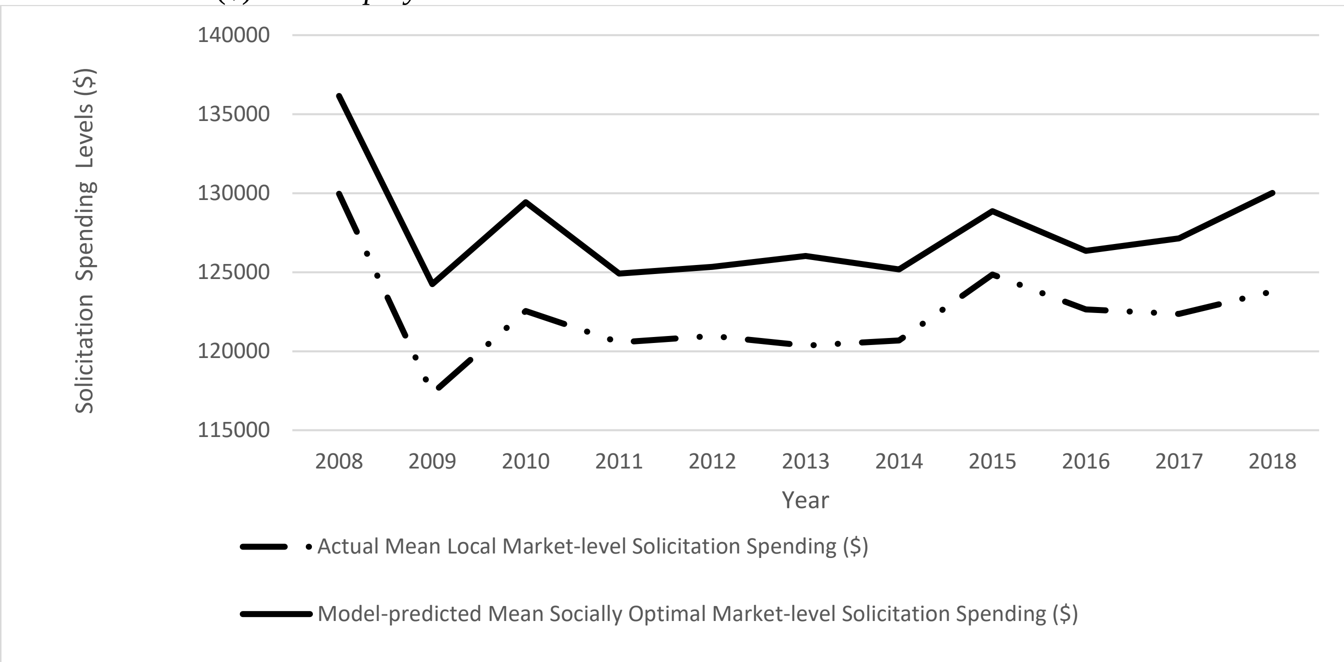
Last, I compare actual solicitation spendings, $\boldsymbol{f}_m$, with $\boldsymbol{f}_m^{so}$ to determine whether NPs engage in excessive fundraising.

6. Results from the Counterfactual Experiments

I begin by focusing on local zip code markets with a single nonprofit from my sample operating in the local market. I refer to these local markets as monopoly markets. Accordingly, there is no competition or strategic interaction with respect to fundraising and consequently no "*donor-stealing*" effects in the monopoly markets. However, there will be a distinction between the fundraising optimization problems solved by a social planner and the nonprofit, respectively. Specifically, unlike the nonprofit in determining its optimal level of solicitation spending, the social planner will consider the marginal impact of fundraising on the expected surplus donors obtain from the available charity donation alternatives in the local market, $\frac{\partial ES^{\$}}{\partial f_{jm}}$, which is influenced by donors' valuation of the informative attribute of fundraising.

Figure 1 shows time series plots of actual mean local market-level solicitation spending and model-predicted mean socially optimal market-level solicitation spending across the monopoly markets. The estimates used for creating the plots in Figure 1 are reported in columns (1) and (2) in Table A1 in the Appendix. The plots in the figure reveal evidence of insufficient solicitation spending by local monopoly nonprofits. Specifically, in each year actual solicitation spending falls short of the model-predicted socially optimal solicitation spending, a shortfall that ranges from 10 to 37 percent of the actual solicitation spending each year over the sample years with an overall mean shortfall of approximately 21%.

Figure 1: Actual and model-predicted socially optimal mean local market-level Solicitation Spending levels ($) in *monopoly* local markets.



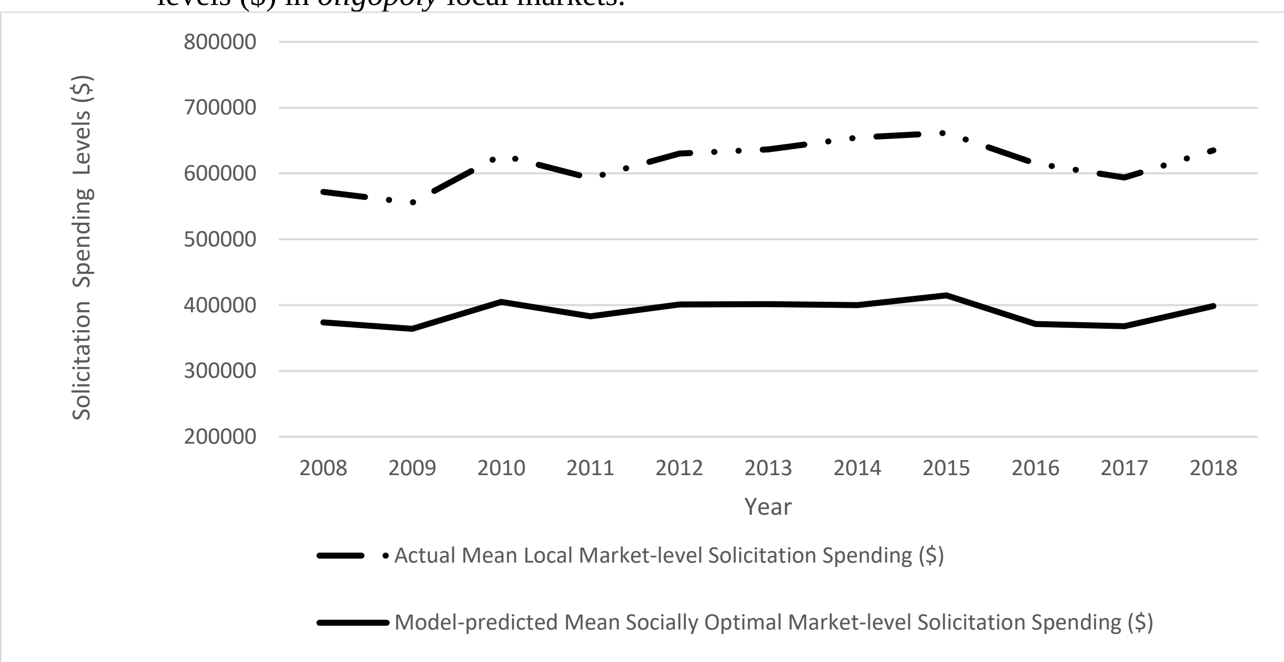
The model prediction that actual solicitation spending is insufficient in local monopoly markets is not surprising since: (*i*) there are no "*donor-stealing*" effects; and (*ii*) unlike a social planner, a nonprofit in determining its optimal solicitation spending does not consider the marginal impact of fundraising on the expected surplus donors obtain from the available charity donation alternatives in the local market. The monopoly nonprofit only considers the marginal impact of its solicitation intensity on its expected donations in comparison to the marginal cost of its solicitation intensity. Since the model estimates reveal that donors positively value the informative attribute of fundraising, which further implies a positive marginal impact of fundraising on the expected surplus of donors, then the nonprofit's omission of considering this positive marginal impact causes it to under spend on fundraising from a societal welfare perspective.

Next, I focus on local zip code markets with two or more nonprofits from my sample operating in the local market, i.e., oligopoly markets. Of course, in the oligopoly markets there exists competition and strategic interaction among nonprofits with respect to soliciting donations and consequently "*donor-stealing*" effects are present. Figure 2 shows time series plots of actual mean local market-level solicitation spending and model-predicted mean socially optimal market-level solicitation spending. The estimates used for creating the plots in Figure 2 are reported in columns (3) and (4) in Table A1 in the Appendix.

The plots in the figure reveal evidence of excessive solicitation spending by nonprofits across the oligopoly markets. Specifically, in each year mean market-level actual solicitation spending exceeds the model-predicted mean socially optimal solicitation spending, an excess in solicitation spending that ranges from 27 to 31 percent of the actual solicitation spending each year over the sample years with an overall mean excessive spending of 29%. These aggregated market-level results reveal that the negative welfare impact of the "*donor-stealing*" attribute of fundraising across rival NPs consistently outweighs the positive welfare impact of the informative attribute of fundraising.

In addition to examining how actual solicitation spending compares to my model-predicted socially optimal level of solicitation spending at the aggregated market-level shown in Figure 2, there is much to be learned from examining analogous metrics at the less aggregated nonprofit-level. Accordingly, Table 5 reports nonprofit-level model predictions on excessive fundraising. The summary statistics reported in the table are nonprofits' excessive fundraising spending as a percentage of their actual solicitation spending.

Figure 2: Actual and model-predicted socially optimal mean local market-level Solicitation Spending levels ($) in *oligopoly* local markets.



First, it is noticeable that, unlike what we observe in Figure 2 at the market level, in Table 5 it is evident from the negative minimum percentage values that at the nonprofit level there exist nonprofits with their actual solicitation spending being less than the level of fundraising spending they should be doing from a societal welfare perspective. Second, there is some variation across sectors in the mean levels of excess fundraising, ranging from the lowest mean level of 31.6% among nonprofits in the Civil Rights & Advocacy sector to 46.65% among nonprofits in the Arts sector.

Third, the mean percentage values of excess fundraising at the nonprofit level shown in Table 5 are larger in magnitude compared to analogous values at the market level revealed in Figure 2 and Table A1 in the appendix. This suggests that nonprofits with relatively lower levels of fundraising spending, with each accounting for relatively smaller proportion of aggregated market level fundraising spending, have larger percentage values of excessive fundraising compared to nonprofits with relatively higher levels of fundraising spending. A simple linear regression with the dependent variable being nonprofit-level percentage excessive fundraising and the right-hand side regressor being nonprofit-level actual solicitation spending, the result of which is $\%EF_{jm} = \underset{(std.err. = 0.23)}{43.28} - \underset{(std.err. = 0.0004)}{0.0023 * f_{jm}}$, confirms a negative and statistically significant correlation between these two variables.

Table 5: Nonprofit-level Results on Excessive Fundraising Spending measured by the Percentage of Actual Fundraising Spending that is in Excess of Model-predicted Socially Optimal Fundraising Spending in oligopoly markets.

Sector Number	Sector Name	Mean (%)	Std. Error of mean (%)	Min (%)	Max (%)
1	Arts	46.65	0.54	-64.87	100
2	Education	41.48	0.43	-35.61	100
3	Environmental & Animal	32.71	0.86	-26.05	99
4	Health	44.81	0.47	-32.50	100
5	Human & Social Services	45.58	0.43	-67.51	100
6	International	36.90	1.50	-1.73	98.50
7	Civil Rights & Advocacy	31.60	0.74	-51.44	100
Overall (across all sectors)		42.72	0.21	-67.51	100

In addition to examining the mean nonprofit-level estimates of excessive fundraising, there is still more to learn by examining the distribution of excessive fundraising across nonprofits. Table 6 reports frequency percentages of different percentage categories of excessive fundraising. The last column in the table reports these statistics for nonprofits across all sectors, while the preceding columns break down these statistics by sector. Beginning with the last column in the table, we observe that approximately 6% of the nonprofits in the sample have fundraising spending below the level of fundraising spending they should be doing from a societal welfare perspective. Second, the largest frequency percentage of nonprofits, 19.6%, is among nonprofits with excessive fundraising spending that is at most 10% of their actual fundraising spending. Third, approximately 9% of the nonprofits in the sample have excessive fundraising spending that is more than 90% of their actual fundraising spending.

Now turning to the predicted results in Table 6 that are broken down by sector, we see that all sectors have some nonprofits with fundraising spending that is less than the level of spending they should be doing from a societal welfare perspective. Second, in every sector the largest frequency percentage of nonprofits is among nonprofits with excessive fundraising spending that is at most 10% of their actual fundraising spending.

Table 6: Distribution of Nonprofit-level Results on Excessive Fundraising Spending measured by the Percentage of Actual Fundraising Spending in Excess of Model-predicted Socially Optimal Fundraising Spending in markets with two or more rival nonprofits (Oligopoly Markets).

	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	All Sectors
Excessive Fundraising Category	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %
< 0	3.50	7.16	4.49	5.87	6.56	5.80	5.62	5.97
> 0 but ≤ 10%	15.90	23.99	23.67	17.80	13.61	23.44	31.40	19.60
> 10% but ≤ 20%	8.51	7.38	12.14	8.05	8.14	9.60	9.46	8.26
> 20% but ≤ 30%	7.73	7.02	10.10	8.13	7.80	9.60	9.57	7.90
> 30% but ≤ 40%	7.27	6.17	12.24	7.17	8.18	7.59	8.77	7.48
> 40% but ≤ 50%	7.82	6.14	10.31	7.48	8.97	10.94	7.68	7.70
> 50% but ≤ 60%	8.22	5.95	9.18	7.23	8.81	5.80	5.79	7.33
> 60% but ≤ 70%	9.35	6.60	6.33	7.23	8.88	6.70	5.10	7.54
> 70% but ≤ 80%	12.51	8.08	4.59	8.66	9.51	5.80	6.13	8.85
> 80% but ≤ 90%	12.42	10.74	4.39	11.38	11.27	9.15	5.10	10.54
> 90%	6.75	10.76	2.55	11.01	8.27	5.58	5.39	8.82
Total	100	100	100	100	100	100	100	100

As I noted in the introduction section of this paper, donors and charity watch-dog groups often perceive large fundraising expenses as indications of a low-quality charity. For example, Charity Navigator gives its lowest rating to a food bank or community foundation that raises fewer than $5 for every dollar spent on fundraising, i.e., a fundraising expense that is 20% or higher of donations. This perspective then raises the following question: Is the ratio of a nonprofit's fundraising spending to the donations it receives a reliable predictor of the nonprofit's fundraising spending being excessive when compared to the level of fundraising spending it should be doing from a societal welfare perspective? I explore addressing this question in Table 7. Specifically, in Table 7 I focus on nonprofits in the sample that have fundraising spending that is at most only 10% of the donations they receive, which is well below the 20% threshold standard deemed by charity watch-dog groups as desirable. Among the nonprofits in the sample with fundraising spending that is excessive from a societal welfare perspective, most of them (approximately 73%) have satisfied the less than 10% fundraising spending to donations ratio.

The results in Table 7 reveal that even among nonprofits with fundraising spending that is at most only 10% of the donations they receive, their fundraising spending can be excessive when compared to the level of fundraising spending they ought to be doing from a societal welfare perspective. We can observe from the table that, considering these nonprofits across all sectors, the largest frequency percentage is 23% of them having fundraising spending that is excessive by at most 10% of their actual fundraising spending. Importantly, the results in the table reveal that, cumulatively, approximately 46% of these nonprofits have fundraising spending that is excessive by more than 40% of their actual fundraising spending.

Table 7: Distribution of Nonprofit-level Results on Excessive Fundraising Spending among nonprofits with fundraising spending that is less than 10% of their donations in markets with two or more rival nonprofits (Oligopoly Markets).

	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	All Sectors
Excessive Fundraising Category	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %	Frequency %
< 0	3.72	8.00	5.32	6.80	7.82	6.16	6.44	6.82
> 0 but ≤ 10%	17.65	27.25	24.08	22.98	15.59	25.62	35.60	23.04
> 10% but ≤ 20%	9.66	7.70	11.41	9.57	8.43	9.61	9.20	8.82
> 20% but ≤ 30%	8.15	7.34	9.89	8.75	8.01	9.61	9.34	8.19
> 30% but ≤ 40%	7.18	6.44	12.80	7.59	8.06	7.39	8.85	7.61
> 40% but ≤ 50%	7.72	6.29	10.39	6.74	8.99	11.08	7.08	7.53
> 50% but ≤ 60%	8.42	5.77	9.63	6.14	9.10	5.91	5.31	7.08
> 60% but ≤ 70%	9.62	6.18	5.96	6.80	8.81	5.67	4.88	7.24
> 70% but ≤ 80%	12.02	7.17	4.69	7.65	9.12	5.42	5.80	8.13
> 80% but ≤ 90%	10.67	8.50	3.42	8.59	9.18	8.13	3.89	8.37
> 90%	5.20	9.35	2.41	8.40	6.89	5.42	3.61	7.16
Total	100	100	100	100	100	100	100	100

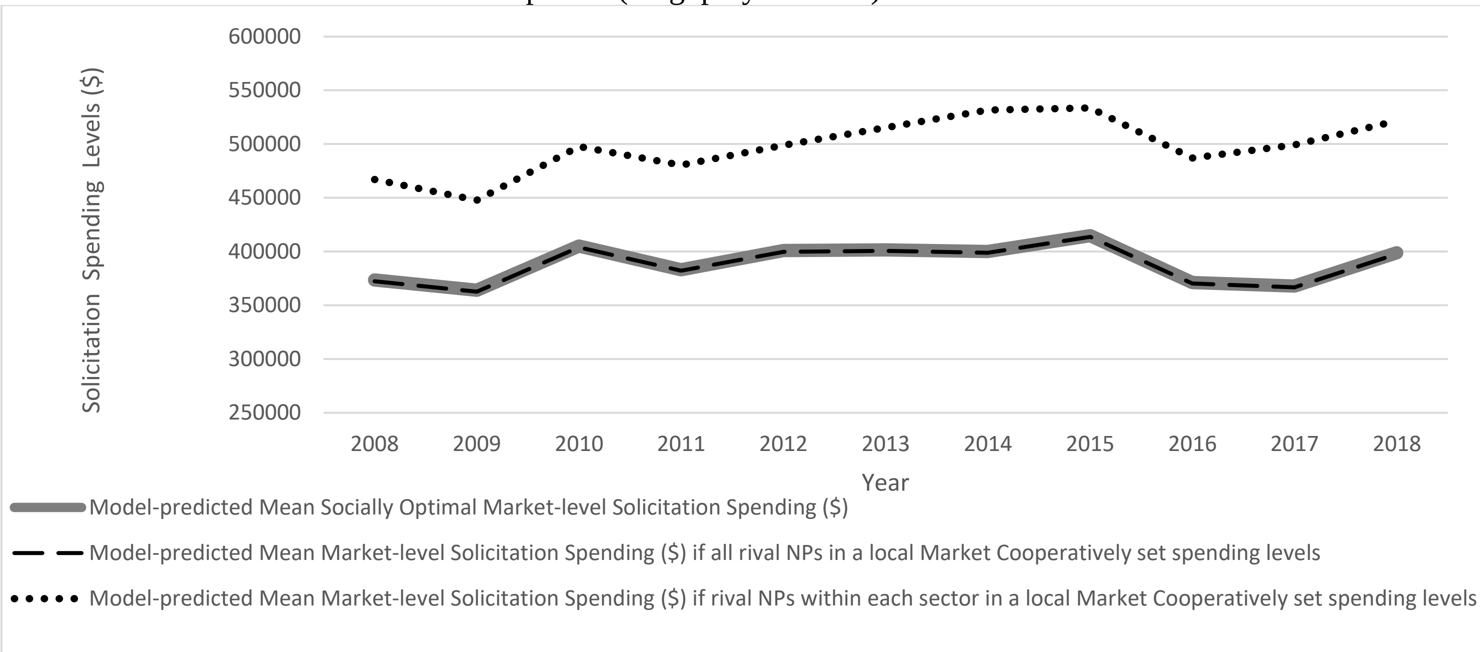
In summary, contrary to the approach and advice of charity watch-dog groups, the results in Table 7 suggest that the ratio of a nonprofit's fundraising spending to the donations it receives is not a reliable predictor of the nonprofit's fundraising spending being excessive when compared to the level of fundraising spending it should be doing from a societal welfare perspective. Rather than searching for a rule of thumb ratio, which is likely elusive since a single ratio will not be universally applicable across various NP sectors and local donor markets, to accurately identify and quantify excessive fundraising it is more fruitful to use a mechanism, like the framework in this study, that properly quantifies and trades off the positive welfare impact of the informative attribute of fundraising with the negative welfare impact of the "*donor-stealing*" attribute of fundraising. These attributes of fundraising with countervailing impacts on welfare will likely vary in magnitudes across NP sectors and local donor markets.

Analysis designed for exploring Policy Options to address Excessive Fundraising

Figure 3 has three time series plots: (*i*) Model-predicted mean socially optimal market-level solicitation spending; (*ii*) Model-predicted mean market-level solicitation spending if all rival NPs in a local market cooperatively set spending levels; and (*iii*) Model-predicted mean market-level solicitation spending if rival NPs within each sector in a local market cooperatively set spending levels. The estimates used for creating the plots in Figure 3 are reported in columns (4), (5), and (6), respectively, in Table A1 in the Appendix. First, it is important to note that the plots in the figure associated with (*i*) and (*ii*) effectively overlay each other, revealing that if rival NPs in a local market cooperatively set solicitation spending levels, then this practice is sufficient to eliminate excessive solicitation spending. Second, comparing the plots in the figure associated with (*iii*) and (*i*) above reveals that if cooperation in setting solicitation spending is limited to NPs within the same sector, then this level of cooperation will not be sufficiently extensive to eliminate excessive solicitation spending.

The policy-relevant takeaway message from the results is that implementing an industry structure in which rival NPs cooperatively set their solicitation spending or intensity levels can eliminate excessive fundraising, but such cooperation needs to extend across NP sectors. However, an independent institution may be needed to enforce cooperation due to an inherent incentive for each NP to renege on a cooperative agreement. Aldashev et al. (2014) provides a detailed discussion of the attributes of donor markets that are conducive for sustainable cooperative fundraising agreements among NPs.

Figure 3: Various Model-predicted mean local market-level Solicitation Spending levels ($) in markets with two or more rival nonprofits (Oligopoly Markets)



There exist examples where such cooperative fundraising behavior is being used in practice. One such example being united fund drives mobilized by the United Way organization. [7] United Way is an international network of over 1,800 local nonprofit fundraising affiliates. United Way organizations raise funds primarily via workplace campaigns, where employers solicit contributions that can be paid through automatic payroll deductions. After an administrative fee is deducted, money raised by local United Ways is distributed to local nonprofit agencies that would otherwise compete for the private donation dollars in their local donor markets. Major nonprofit organizations that have been recipients of monies from these united fund drives include the American Cancer Society, Big Brothers/Big Sisters, Catholic Charities, Girl Scouts, Boy Scouts, and The Salvation Army, all of which compete for slices from a common pie of donor dollars even though these NPs may have very different missions and therefore serve in different NP sectors. Nonprofit agencies that partner with United Way usually agree not to fundraise while the United Way campaigns are underway.

Based on the discussions above, the results of this study are supportive of united fund drives we often see mobilized by the United Way organization.

[7] See relevant information at the following URL: https://en.wikipedia.org/wiki/United_Way

7. Conclusion

This study is the first formal empirical analysis that quantifies and shows systematic evidence of excessive fundraising relative to what may be socially optimal among rival nonprofit organizations. Comparing market-level actual fundraising spending of nonprofits to the model-predicted socially optimal fundraising spending reveals evidence of excessive fundraising spending of up to 31% in a year. Second, I find that the negative welfare impact of the "*donor-stealing*" attribute of fundraising across rival NPs outweighs the positive welfare impact of the informative attribute of fundraising. Therefore, consistent with arguments first made in Rose-Akerman (1982), the analysis reveals that a key driver of excessive fundraising is the "*donor-stealing*" attribute of fundraising across rival NPs.

Third, contrary to the approach and advice of charity watch-dog groups, my results suggest that the ratio of a nonprofit's fundraising spending to the donations it receives is not a reliable predictor of the nonprofit's fundraising spending being excessive when compared to the level of fundraising spending it should be doing from a societal welfare perspective. Accordingly, instead of searching for a rule of thumb ratio, to accurately identify and quantify excessive fundraising this study proposes using a mechanism that properly quantifies and trades off the positive welfare impact of the informative attribute of fundraising with the negative welfare impact of the "*donor-stealing*" attribute of fundraising. These attributes of fundraising with countervailing impacts on welfare will likely vary in magnitudes across NP sectors and local donor markets.

Fourth, the results suggest that if rival NPs in a local market cooperatively set solicitation spending levels, then this practice is sufficient to effectively eliminate excessive solicitation spending. The reason is that cooperation allows each NP to internalize the adverse effect that its own fundraising activities have on its rivals' ability to secure donations, i.e., internalization of the "*donor-stealing*" aspect of fundraising across rival NPs, causing them to jointly choose lower levels of fundraising spending. Fifth, if cooperation in setting solicitation spending is limited to rival NPs within the same sector, then this level of cooperation will not be sufficiently extensive to eliminate excessive solicitation spending.

The policy-relevant takeaway message from the results is that implementing an industry structure in which rival NPs cooperatively set their solicitation spending levels can eliminate excessive solicitation spending, but such cooperation needs to extend across NP sectors. However, an independent institution may be needed to enforce cooperation due to an inherent incentive for each NP to renege on a cooperative agreement. The results and prescription of this study are supportive and exemplified, respectively, in united fund drives we often see mobilized by the United Way organization.

References

Aldashev, Gani, Marco Marini, Thierry Verdier (2014). "Brothers in alms? Coordination between nonprofits on markets for donations," *Journal of Public Economics*, Vol. 117, pp. 182-200.

Alpizar, F., F. Carlsson, and O. Johansson-Stenman (2008). "Anonymity, reciprocity, and conformity: evidence from voluntary contributions to a National Park in Costa Rica," *Journal of Public Economics*, Vol. 92, pp. 1047–1060.

Andreoni, James and A. Abigail Payne (2011). "Is crowding out due entirely to fundraising? Evidence from a panel of charities," *Journal of Public Economics*, Vol. 95, pp. 334-343.

Andreoni, J., J.M. Rao, and H. Trachtman (2011). "Avoiding the ask: a field experiment on altruism, empathy, and charitable giving," *NBER Working Paper* No. 17648.

Berry, S. (1994). "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, Vol. 25, No. 2 (Summer, 1994): 242-262.

DellaVigna, S., J.A. List and U. Malmendier (2012). "Testing for altruism and social pressure in charitable giving," *The Quarterly Journal of Economics*, 127 (1), 1–56.

Eckel, C.C., and P.J. Grossman (2008). "Subsidizing charitable contributions: a natural field experiment comparing matching and rebate subsidies," *Experimental Economics*, 11 (3), 234–252.

Eckel, C., D. Herberich and J. Meer (2015). "It's Not the Thought that Counts: A Field Experiment on Gift Exchange and Giving at a Public University," Working Paper.

Falk, A., 2007. "Gift exchange in the field," *Econometrica*, Vol. 75, pp. 1501–1511.

Gayle, Philip G. and Teresa D. Harrison (2023) "Competition and Strategic Responses to Fundraising in Donative Markets," Manuscript, *Kansas State University*. https://mpra.ub.uni-muenchen.de/120459/1/MPRA_paper_120459.pdf

Harbaugh, W., (1998). "What do donations buy? A model of philanthropy based on prestige and warm glow," *Journal of Public Economics*, 67 (2), 269–284 (February).

Huck, S., I. Rasul and A. Shepherd (2015). "Comparing charitable fundraising schemes: evidence from a natural field experiment and a structural model," *American Economic Journal: Economic Policy*, 7 (2), 326–369.

Ivaldi, Marc and Frank Verboven (2005). "Quantifying the effects from horizontal mergers in European competition policy," *International Journal of Industrial Organization*, Volume 23, Issues 9–10, December 2005, Pages 669–691.

Jacobs, Fred A. and Nicholas Marudas (2006). "Excessive, optimal, and insufficient fundraising among the Nonprofit Times 100," *International Journal of Nonprofit and Voluntary Sector Marketing*, Vol. 11, pp. 105–114.

Karlan, D. and J.A. List (2007). "Does price matter in charitable giving? Evidence from a largescale natural field experiment," *American Economic Review*, 97 (5), 1774–1793.

Krieg, Justin and Anya Samek (2017) "When charities compete: A laboratory experiment with simultaneous public goods," *Journal of Behavioral and Experimental Economics*, Vol. 66, pp. 40-57.

Khanna, J., J. Posnett, and T. Sandler (1995). "Charity donations in the UK: new evidence based on panel data," *Journal of Public Economics*, Vol. 56, pp. 257–272.

Khanna, J., and T. Sandler (2000). "Partners in giving: the crowding-in effects of UK government grants," *European Economic Review*, Vol. 44, pp. 1543–1556.

Marudas, Nicholas and Fred A. Jacobs (2007) "The extent of excessive or insufficient fundraising among US arts organizations and the effect of organizational efficiency on donations to US arts organizations," *International Journal of Nonprofit and Voluntary Sector Marketing*, Vol. 12, pp. 267–273.

Meer, Jonathan (2017) "Does fundraising create new giving?" *Journal of Public Economics*, Vol. 145, pp. 82-93.

Meer, J. and H.S. Rosen (2011). "The ABCs of charitable solicitation," *Journal of Public Economics*. 95 (5), 363–371.

Mungan, Murat C., and Baris K. Yoruk (2012) "Fundraising and Optimal Policy Rules," *Journal of Public Economic Theory*, 14 (4), 2012, pp. 625–652.

Okten, Cagla and Burton A. Weisbrod (2000) "Determinants of donations in private nonprofit markets," *Journal of Public Economics*, Vol. 75, pp. 255-272.

Posnett, J., and T. Sandler (1989). "Demand for charity donations in private non-profit markets: the case of the UK," *Journal of Public Economics*, Vol. 40, pp. 187–200.

Rose-Ackerman, Susan (1982). "Charitable Giving and "Excessive" Fundraising," *The Quarterly Journal of Economics*, Vol. 97, No. 2 (May 1982), pp. 193-212.

Schervish, P. G., and J. J. Havens (1997). "Social participation and charitable giving: A multivariate analysis," *Voluntas: International Journal of Voluntary and Nonprofit Organizations*, Vol. 8, pp. 235–260.

Yoruk, B. K. (2009). "How responsive are charitable donors to requests to give?" *Journal of Public Economics*, Vol. 93, pp. 1111–1117.

Appendix

Table A1: Actual and Model-predicted mean Local Market-level Solicitation Spending ($) by year

	Local markets each with a single nonprofit (Monopoly Markets)		Local markets each with two or more rival nonprofits (Oligopoly Markets)			
	(1)	(2)	(3)	(4)	(5)	(6)
Year	Actual Local Market-level Solicitation Spending ($)	Model-predicted Socially Optimal Market-level Solicitation Spending ($)	Actual Local Market-level Solicitation Spending ($)	Model-predicted Socially Optimal Market-level Solicitation Spending ($)	Model-predicted Market-level Solicitation Spending ($) if all rival NPs in a local Market Cooperatively set spending levels	Model-predicted Market-level Solicitation Spending ($) if rival NPs within each sector in a local Market Cooperatively set spending levels
2008	**129,963** (6,291)	**136,152** (6,469)	**571,795** (35,335)	**373,675** (19,620)	**372,458** (19,617)	**467,006** (25,967)
2009	**117,329** (5,646)	**124,244** (5,918)	**555,650** (32,991)	**364,047** (18,356)	**362,673** (18,352)	**447,777** (23,084)
2010	**122,543** (5,933)	**129,431** (6,294)	**628,137** (41,256)	**405,113** (21,548)	**404,083** (21,543)	**497,760** (27,136)
2011	**120,556** (5,542)	**124,902** (5,650)	**592,744** (35,093)	**383,115** (19,109)	**382,159** (19,101)	**480,322** (25,316)
2012	**120,968** (5,340)	**125,336** (5,457)	**630,092** (37,697)	**400,823** (20,128)	**399,903** (20,120)	**498,928** (26,086)
2013	**120,360** (5,378)	**126,019** (5,602)	**636,715** (37,193)	**401,612** (19,760)	**400,630** (19,748)	**515,391** (26,555)
2014	**120,678** (5,283)	**125,177** (5,387)	**654,711** (37,160)	**399,927** (18,341)	**398,984** (18,332)	**531,679** (26,355)
2015	**124,855** (5,513)	**128,855** (5,561)	**661,716** (38,901)	**414,819** (19,705)	**413,699** (19,691)	**533,649** (26,274)
2016	**122,654** (5,387)	**126,340** (5,438)	**615,335** (36,147)	**371,243** (16,315)	**370,270** (16,307)	**487,051** (22,830)
2017	**122,361** (5,394)	**127,148** (5,485)	**594,027** (30,988)	**367,841** (15,959)	**366,639** (15,945)	**499,355** (24,071)
2018	**123,778** (5,414)	**130,022** (5,616)	**635,115** (35,250)	**398,736** (17,890)	**397,626** (17,875)	**521,609** (24,997)

Notes: Numbers in parentheses are standard errors of the means, respectively. Estimates of means in the table are all statistically significant at conventional levels of statistical significance.

Table A2: Donor Demand Model Estimates based on alternate definitions of the donative capacity of local markets.

	(1)	(2)
Variables	Markets' donative capacity based on 1.5 times the maximum aggregate donations observed in the relevant zip code area in a given year over the sample periods.	Markets' donative capacity based on 5 times the maximum aggregate donations observed in the relevant zip code area in a given year over the sample periods.
Solicitation Spending (parameter: γ)	1.140*** (0.280)	0.592*** (0.202)
Within group donation share (parameter: σ)	0.065*** (0.021)	0.194*** (0.015)
Program service revenue	-0.016*** (0.006)	-0.013*** (0.004)
Assets	-0.252*** (0.046)	-0.146*** (0.033)
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Number of observations	44,737	

Notes: $*$, $**$, $***$ p-value ≤ 10%, 5%, and 1%, respectively. Standard errors in parentheses. Regressions are estimated using two-stage least squares.