Competition and Strategic Responses to Fundraising in Donative Markets

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Abstract

Nonprofit (NP) organizations provide key social service goods but rely on donations, obtained in a competitive environment, for that provision. Yet most research focuses on competition in the output markets without considering inter- and intra-sector competition in the markets for donations. This paper develops and estimates a model of NPs' fundraising to secure donations. We highlight the strategic nature of the fundraising decision and show theoretically that rival NPs' fundraising responses can be either strategic complements or strategic substitutes but find empirically that responses are predominantly strategic substitutes. We find that donors are relatively inelastic to fundraising but also that NPs have nontrivial responses to rival's fundraising and these effects are stronger within than across sectors. However, in totality, the across sector impacts are important to consider. We find that counterfactually removing a NP from a market increases equilibrium NP-level fundraising but decreases total fundraising in the market.

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1 Introduction

The intensity and nature of competition amongst nonprofits and its corresponding influence on charities' and donor behavior have important implications for collective and social service goods. Nonprofit (NP) markets, while important in their own right, have unique economic properties: Because NP organizations engage private donor markets to provide goods and services that are often substitutes for government provision, the recipients of the goods are quite often not the individuals that provided the donations. Competition is therefore captured not in the output markets but in the donative markets. NPs in turn solicit or fundraise for these donations. Fundraising is also unique in that it functions similar to advertising but is a setting where the persuasive role (Bagwell, 2007; Andreoni et al., 2022) is more prominent: donors only give if solicited, commonly referred to as the "power of the ask" in the literature.[1] Yet we know very little about how rivalry in fundraising impacts the competitive market for donors. This paper seeks to fill that gap through two primary contributions.

First, our work demonstrates the importance of taking seriously the strategic fundraising response of charities/NPs. Rose-Ackerman (1982) recognizes in seminal work the interconnectedness of fundraising and competition amongst NPs but focuses on atomistic settings. The possibility of excessive fundraising, as highlighted in Rose-Ackerman (1982), can be magnified or dampened when one introduces strategic behavior. Similarly, a large literature highlights the role of the price of giving via matched donations or subsidies and changes to donor preferences in the presence of increased need for the public good (Karlan and List, 2007; Schmitz, 2021; Filiz-Ozbay and Uler, 2019), but has largely abstracted away from the setting where NPs are simultaneously choosing their fundraising efforts in the market. Indeed, as Gee and Meer (2020) highlight, endogeneity of the fundraising effort and the potential unobserved correlation between fundraising effort and donor/market level preferences, in addition to intertemporal substitution, are largely outstanding issues that would provide a more complete understanding of the donor's altruism budget.[2]

Precisely because of the inherent endogeneity issues, quantifying NP's strategic responses

[1] See Rose-Ackerman (1982); Andreoni and Payne (2003) as just a few examples.

[2] One notable exception to examining intertemporal shifts is Scharf et al. (2022). In addition to finding increased total donations in response to a natural disaster, they find evidence that donations increase for rival charities in the short term and then fall later for an approximate net zero effect.

proves difficult. First, one needs to observe own and rival fundraising levels which is not always possible, particularly in field or experimental settings. For example, Scharf et al. (2022) observe disaster relief charities' donation appeals and find evidence of increases to rival's donations in the short term but do not observe changes in fundraising appeals at these rival organizations. Second, one needs to be able to distinguish strategic responses from common-level market shocks that might also jointly change charity's responses. Indeed, Scharf et al. (2022), Meer (2017) and Deryugina and Marx (2021) employ identification strategies that specifically exploit an exogenous shock such as that induced by natural disasters.

As motivation for the importance of such analysis, Figure 1 illustrates how donations, fundraising expenditures, and the number of NPs has changed over our sample.[3] Consistent with well known trends highlighted in List (2011), we see that donations and fundraising expenditures per firm have been growing at a consistent pace over our sample and have a similar rate of increase. However, the number of NPs has also increased during this time period but at a faster rate than both donations and fundraising, resulting in declining market shares over time. Similar to advertising, these trends call into question the role of fundraising and the subsequent strategic responses of NPs to their competitive environment.

Central to our paper, we develop and estimate a structural model in which we incorporate fundraising intensity into the utility function of donors. Much like advertising models (e.g., Sinkinson and Starc (2019) and Shapiro et al. (2021)), our model captures the responsiveness of donors to fundraising and also the interplay between rival firm's fundraising decisions: firm i soliciting more donors (i.e., increasing the intensity of fundraising) may increase own-firm donations but can also impact rival charity's donations. This connection then implies a possible strategic response by firm j to change its own level of fundraising. To our knowledge, this is the first study to model and empirically estimate the role of strategic behavior in fundraising decisions. We find that donors are relatively inelastic to fundraising, a condition important to theoretical models of NP fundraising (Aldashev et al., 2014) but also that NPs have nontrivial responses to rival's fundraising.

Our empirical approach also provides our second contribution by allowing us to quantify the extent of competition across different types of NPs. Prior research has documented large growth in the number of NPs, stemming from remarkably low exit rates (Harrison and Laincz, 2008). Yet the size of the donor market has stayed constant over the last two decades

[3]We discuss the data details in Section 3.1.

with giving rates around 2% of GDP each year (List, 2011). These simultaneous trends have led to claims of more intense competition in the sector and have thus turned greater academic attention to measures of NP competition. Recent evidence suggests charities exhibit competitive behavior similar to for-profit firms. Lapointe et al. (2018) find a proportional relation analogous to for-profits between market size and firm count of charities but also find smaller magnitudes for this correlation, consistent with the presence of an NP motive. Using a different approach focused on the rate of change of market size to the number of firms, Gayle et al. (2017) show that a "relatively small number of nonprofits are needed to observe competition" with as little as four NPs in a market converging to a competitive equilibrium.

Yet much of the research, including that above and others (i.e., Thornton (2006); Seaman et al. (2014)) has specifically focused on competition *within* a given NP sector, driven by the assumption that competition is in the market for the provision of goods and services. While this approach aligns to most current industrial organization (IO) work in for-profit industries and also is most likely the correct market to consider for many research questions, competition in donor markets presents a different dimension of competition and consumer behavior that has received little attention thus far. Donative markets are a particular setting where the output market may be too narrow of a market definition.

Referring back to Figure 1, the declining market shares reinforces the motivation for our study in examining the degree of competition for donations within versus across NP sectors. To the extent that the number of NPs is rising faster outside a NP's sector, NPs within the sector would only be impacted if donors substitute giving away from that sector in response to more choices in the outside sector. Such across-sector competition for donations has not been investigated to date. Moreover, the variation in the market shares and fundraising intensities over time and across sectors are also a source of identification that our model will use to pin down own- and cross-NP fundraising elasticities.

We have little guidance on which charities should be considered as part of the same market as it relates to different sectors. Mayo (2021) finds spillovers to both donations and fundraising for charities within the same sector, with stronger effects for charities with more similar missions. Other work also leads us to suspect strategic fundraising plays an important role. Ribar and Wilhelm (2002) investigate how competition affects 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 choice of fundraising by NPs is intertwined and needs to be considered.

Our analysis captures across-firm competition for donations among charitable NPs, with particular emphasis on the NP's choice of fundraising effort to illicit donations. While conventional structural demand methodologies are powerful in this setting to estimate own- and cross-NP fundraising effects, the paper and its findings highlight that standard conclusions surrounding oligopolistic behavior do not directly port over to the NP setting. In particular, our focus on fundraising, while functioning similarly to prices in a standard demand model, are clearly not entering the models in the same fashion. We show, like Andreoni and Payne (2003) and Aldashev et al. (2014), that fundraising decisions can be strategic substitutes. However, we also show the strategic response can induce strategic complementarities, even when increased fundraising by a NP decreases donations for a rival NP.[4] Furthermore, our work highlights that even with strategic substitutes, incumbent NPs' equilibrium fundraising can either rise or fall with market entry of a new NP. The change in equilibrium fundraising hinges on the sign and magnitude of rivals' fundraising decisions and its impact on own-NP marginal productivity of fundraising, i.e., the second-order cross-partial of NPs' donation market share with respect to own- and cross-NP fundraising.

Using our demand estimates, we find that fundraising is predominantly a strategic substitute and that removing a NP from a market increases equilibrium NP-level fundraising. These effects are more pronounced within rather than across sectors. While the across sector impacts are small for each sector separately, they are significantly different from zero and in the aggregate explain 10-40% of the change in fundraising levels, lending support to the notion that competition for donations across industry boundaries should be taken into account.

In Section 2, we first develop our model, highlighting the distinction in strategic responses for NP fundraising as it compares to conventional for-profit settings. Section 3 describes the data for seven distinct NP industries for 1989-2003 and presents results from descriptive

[4] Aldashev et al. (2014)'s model allows fundraising to be strategic complements but the source of the complementarity originates from a direct positive demand spillover parameter whereby increased fundraising increases the overall awareness of the cause. In our model, any positive spillover from increased awareness (or other sources) is indirect in that it would not shift demand but increase the marginal productivity of fundraising.

linear regressions specified to examine the impacts of NP market structure in local markets on the fundraising expenditures of competing NPs. In Section 4, we lay out our empirical model based on competition between NPs for donations and describe how standard demand estimation techniques apply to this donative setting. Section 5 presents the estimation results, demonstrating both within and across sector sensitivity to own-firm fundraising choices. The last subsection of Section 5 provides a counterfactual analysis designed to better understand the equilibrium fundraising impacts of changes to NP market structure. Section 6 concludes and provides direction for future work.

2 A Model of Equilibrium Fundraising

We begin with our theoretical model of equilibrium fundraising that highlights the key role of strategic interaction in fundraising decisions. Section 4 will return to how we construct our empirical specification to quantify these relationships.

Consider a NP whose primary source of revenue is from donations. We do not explicitly model other revenue streams such as grants or earned revenue although both could be modelled in the same framework as the below. We abstract away from multiple revenue streams for two reasons. First, with multiple revenues, decisions regarding cross-subsidization and revenue diversification arise. While important, they are not the focus of this paper. Second, we assume that maximizing net revenue from donations allows the NP to maximize their NP service provision. Thus, our model allows us to highlight the fundraising-donation linkage[5]. We also subsume the cost of providing the charitable service into the fixed costs of fundraising.

Similar to Aldashev and Verdier (2010); Lapointe et al. (2018) and Gayle et al. (2017), the size of the donor market is key to our model and impacts the fundraising intensity choice of the NP. Our goal is to estimate the joint strategic fundraising choices within and across sectors. Therefore, let ED_{jm} represent expected donations for NP firm j in market m. We specify that,

$$ED_{jm}(f_{jm}, \mathbf{f}_{-j,m}; \theta) = s_{jm}(f_{jm}, \mathbf{f}_{-j,m}; \theta) \times PD_m \tag{1}$$

[5]In our view, our understanding of the implications of NP strategic behavior is still so nascent that we choose to begin with one choice variable in isolation and assume net revenue maximization. Optimal portfolio choices of revenues and further examination of NP conduct are indeed very important but are further down the evolution of scholarly work in this area

where $s_{jm}(f_{jm}, \mathbf{f}_{-j,m}; \theta)$ is the model-predicted donation share of NP j in market m, which is equivalent to the probability a potential donor in the local market donates to NP j. The donation share of NP j is a function of its own solicitation intensity, f_{jm}, measured in dollars of spending, as well as the solicitation intensities of rivals to NP j, $\mathbf{f}_{-j,m}$, i.e., $\mathbf{f}_{-j,m} = \mathbf{f}_m \setminus f_{jm}$, where $\mathbf{f}_m$ is a vector of solicitation intensities for the NPs in market m. The estimable parameters in parameter vector θ will be further detailed in Section 4 when we discuss how we take this model to the data. PD_m is the aggregate potential money donations, i.e., the donative capacity of local market m.

Let the cost NP j incurs from solicitation activities be specified as:

$$TC_{jm} = VC_{jm}(f_{jm}) + FC_{jm} \tag{2}$$

where $VC_{jm}(f_{jm})$ measures the composite of implicit and explicit costs that change with solicitation intensity, f_{jm}; and FC_{jm} is the fixed cost NP j incurs to facilitate solicitation activities, which do not vary with the amount of its solicitation activities. The implicit costs in $VC_{jm}(f_{jm})$ stem from the opportunity costs of various resources the NP uses for solicitation activities that could have been used for other activities, which include fulfilling the core mission of the NP. These costs are incurred regardless of whether the person solicited actually contributes to the cause. So, an increase in a NP'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 NP channels into these activities.

The net revenue or net return to solicitation operations of NP firm j in market m is given by:

$$NR_{jm}(f_{jm}, \mathbf{f}_{-j,m}) = ED_{jm}(f_{jm}, \mathbf{f}_{-j,m}; \theta) - TC_{jm} = s_{jm}(\mathbf{f}_m; \theta) \times PD_m - TC_{jm} \tag{3}$$

Note that the net return for NP firm j is a function of its own solicitation intensity, f_{jm}, as well as the solicitation intensities of rival NP firms, $\mathbf{f}_{-j,m}$. We assume that NP firms noncooperatively and independently choose their own solicitation intensity to maximize net return of their solicitation operation. Accordingly, each NP firm solves the following optimization problem:

$$max_{f_{jm}} NR_{jm}(f_{jm}, \mathbf{f}_{-j,m}) \tag{4}$$

The optimization problem in (4) implies that a Nash equilibrium in solicitation intensities must satisfy the following first-order conditions:

$$\frac{\partial s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}} \times PD_m - mc_{jm} = 0 \quad \forall j \in J_m \tag{5}$$

where term $\frac{\partial s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}} \times PD_m$ in equation (5) measures the marginal change in donations received by NP firm 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 NP due to a marginal change in its solicitation spending.

2.1 Equilibrium Fundraising

The features of our model emphasize the importance of considering the strategic interaction and competitive equilibrium of fundraising intensity. Accordingly, we characterize the strategic fundraising decisions using reaction functions adapted to our setting. A positively sloped reaction function prescribes that a NP's best response is to increase its solicitation spending whenever rival NPs increase their solicitation spending, and vice versa. Conversely, a negatively sloped reaction function prescribes that a NP's best response is to decrease its solicitation spending whenever rival NPs increase their solicitation spending, and vice versa. When these reaction functions are positively sloped, this means that rival NPs' solicitation spending responses to each other are strategic complements, while negatively sloped reaction functions implies strategic substitutes. [6]

Figures 2a and 2b below illustrate reaction functions when solicitation spending between competing NP pair j and r are strategic complements and strategic substitutes respectively. Let f_j represent the solicitation spending for NP j; f_r represents the solicitation spending for NP r; and $\mathbf{f}_{-jr}$ represent a vector of solicitation spending for NPs other than NP j and NP r. In each figure, $f_j = R_j(f_r, \mathbf{f}_{-jr})$ represents the reaction function for NP j, which determines the optimal solicitation spending level for NP j conditional on the solicitation spending levels of competing NPs. Analogously, $f_r = R_r(f_j, \mathbf{f}_{-jr})$ represents the reaction function for NP r, which determines the optimal solicitation spending level for NP r conditional on the solicitation spending levels of competing NPs. The Nash equilibrium solicitation spending

[6] For formal definitions and treatment of the concepts of strategic complements and strategic substitutes, the reader is referred to pages 207 through 208 in Tirole (1988) as well as Bulow et al. (1985).

across NP pair j and r occurs as is typical, at the intersection of the reaction functions and is denoted in each figure by (f_j^0, f_r^0).

2.1.1 Analyzing the Slope of Reaction Functions for Solicitation Spending

NP j's solicitation spending reaction function, $R_j(\mathbf{f}_m;\theta)$, is obtained by using first-order conditions in equation (5) to express f_{jm} as a function of rival NPs' solicitation spending such that:

$$f_{jm} = R_j(\mathbf{f}_m;\theta) \tag{6}$$

Totally differentiating the first-order conditions in equation (5) for an arbitrary pair of NPs yields[7]:

$$\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}^2} PD_m df_{jm} - \frac{\partial mc_{jm}}{\partial f_{jm}} df_{jm} + \frac{\partial^2 s_{jm}(f_m;\theta))}{\partial f_{jm}\partial f_{rm}} PD_m df_{rm} = 0 \tag{7}$$

$$\frac{df_{jm}}{df_{rm}} = \frac{\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}} PD_m}{-[\frac{\partial^2 s_j m(f_m;\theta)}{\partial f_{jm}^2} PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}]} \tag{8}$$

where $\frac{df_{jm}}{df_{rm}} = R_j'(f_{rm})$ is the slope of NP j's solicitation spending reaction function with respect to the solicitation spending of NP r.

First, if each NP's expected donation function, $ED_{jm} = s_{jm}(\mathbf{f}_m;\theta)PD_m$, is concave with respect to its solicitation spending, then $\frac{\partial^2 s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}^2} < 0$.[8] Therefore, donations generated by soliciting more potential donors generates additional revenue, but each additional donor has a lower expected donation. With $\frac{\partial^2 s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}^2} < 0$, then a sufficient condition for $-[\frac{\partial^2 s_j m(f_m;\theta)}{\partial f_{jm}^2} PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}] > 0$ is for the NP's marginal cost to be non-decreasing in its solicitation activities, i.e., $\frac{\partial mc_{jm}}{\partial f_{jm}} \geq 0$. Note that $-[\frac{\partial^2 s_j m(f_m;\theta)}{\partial f_{jm}^2} PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}] > 0$ also implies that the net revenue function of the NP is concave in its solicitation spending.[9] Therefore, the sign of $\frac{df_{jm}}{df_{rm}}$ depends on the sign of the second-order cross partial, $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}}$, in the numerator of equation (8).

[7]We note that while these comparative statics hold market size fixed, our empirical estimation allows for potential growth in the market size over time.

[8]We verify that this condition holds for all observations in our data at the estimated values of the donor demand parameters.

[9]Again, we verify that this condition holds for all observations in our data at the estimated values of the demand and marginal cost parameters.

Formally, the second-order cross partial, $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}}$, measures how $\frac{\partial s_j}{\partial f_j}$ changes due to a marginal change in f_r. The first-order partial, $\frac{\partial s_j}{\partial f_j}$, measures the effectiveness or efficiency of NP j's solicitation activities in securing donations for fulfilling its mission. Accordingly, $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}}$ measures how the solicitation activities of competing NP r influences the efficiency of NP j's solicitation activities in securing donations for fulfilling NP j's mission. We may interpret $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}} > 0$ as revealing that the solicitation activities of competing NP r positively impacts the efficiency of NP j's solicitation activities in securing donations for fulfilling NP j's mission; conversely, $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}} < 0$ reveals that the solicitation activities of competing NP r negatively impacts the efficiency of NP j's solicitation activities in securing donations for fulfilling NP j's mission.

If the solicitation activities of competing NP r positively impacts the efficiency of NP j's solicitation activities in securing donations for fulfilling NP j's mission, then we should expect that NP j's best response on the margin is to increase its solicitation spending whenever rival NP r increases its solicitation spending, producing a positively sloped solicitation spending reaction function and strategic complements. Conversely, if the solicitation activities of competing NP r negatively impacts the efficiency of NP j's solicitation activities in securing donations for fulfilling NP j's mission, then we should expect that NP j's best response on the margin is to decrease its solicitation spending whenever rival NP r increases its solicitation spending, giving a negatively sloped solicitation spending reaction function and strategic substitutes.

What would explain strategic complementarities in solicitation intensities? We envision a setting whereby a NP increases its solicitation activities, potential donors are more aware of a deserving unfulfilled need and therefore more pre-disposed to support any NP with the mission of fulfilling this need. In this case, rival NPs' solicitation activities may become more efficient/effective in securing donations given that potential donors have been "primed" to support fulfilling the need owing to them being solicited by one of the NPs. This salience argument has been highlighted in prior work Scharf et al. (2022); Aldashev et al. (2014) but the channel of increasing giving is linked more directly to the "power of the ask." The potential increased salience does not shift the demand curve directly; NPs must choose to solicit the donor and, conditioned on that solicitation, fundraising will be more efficient. For strategic substitutes, we instead envision a setting whereby increased solicitations increases donor fatigue for subsequent solicitations, thereby decreasing the efficiency of the rival's fundraising efforts. Since in principle either strategic fundraising relationship may occur across rival NPs, it is an empirical question which of the two relationships most often occurs in real-world donor markets, a question we subsequently answer using a sample of diverse NP organizations across local donor markets in the United States.

To better solidify the intuition of the model and the potential differences in this NP setting, Appendix A.1 pares down this more general model into a simple two-firm model with simplified downward sloping linear donor demand functions and constant marginal cost of solicitation. In this specific case, we see that the cross-partial is indeed negative and it is straightforward to derive that rival fundraising will be strategic substitutes. We again note that clearly this particular functional form does not allow for strategic complements. Our more general and flexible empirical model will allow us to empirically analyze whether strategic substitutes or strategic complements dominate in this setting.

2.1.2 Illustrative Equilibrium Analysis using Reaction Functions for Solicitation Spending

In the case of strategic complements, suppose a third NP, say NP g, has solicitation spending that is also a strategic complement to solicitation spending of NP j and r, respectively, then $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm} \partial f_{gm}} > 0$ and $\frac{\partial^2 s_{rm}(f_m;\theta)}{\partial f_{rm} \partial f_{gm}} > 0$, which implies that an increase in f_g will simultaneously shift the reaction functions of NP j and r when these are plotted in (f_j, f_r) space. The reaction function for NP j will shift to the right, while the reaction function for NP r will shift to the left. The shifts in reaction functions stimulated by an increase in f_g are illustrated in Figure 3 below.

Panel (a) in Figure 3 illustrates that when solicitation spending across competing NPs are strategic complements, then an increase in the solicitation spending of one will stimulate an increase in Nash equilibrium solicitation spending of all competing NPs, captured by the move from initial Nash equilibrium, (f_j^0, f_r^0), to the new Nash equilibrium, (f_j^*, f_r^*). The increase in solicitation spending of NP g can be interpreted from the perspective of the extensive margin in which Figure 3 illustrates the impact on equilibrium solicitation spending of incumbent NP j and r when NP g enters the market with positive solicitation spending.

Now, consider the case where solicitation spending across NP j and r are strategic substitutes. Suppose a third NP, say NP g, has solicitation spending that is a strategic substitute to solicitation spending of NP j and r, respectively, then $\frac{\partial^2 s_{jm}(f_m;\theta))}{\partial f_{jm}\partial f_{gm}} < 0$ and $\frac{\partial^2 s_{rm}(f_m;\theta))}{\partial f_{rm}\partial f_{gm}} < 0$, which implies that an increase in f_g will simultaneously shift the reaction functions of NP j and r when these are plotted in (f_j, f_r) space. The reaction functions for both NP j and r will shift to the left as illustrated in panel (b) of Figure 3 below.

When solicitation spending across competing NPs are strategic substitutes, then an increase in the solicitation spending of one can stimulate either an increase or decrease in Nash equilibrium solicitation spending of other competing NPs. The initial Nash equilibrium in solicitation spending is (f_j^0, f_r^0), and the final Nash equilibrium can either be (f_j^*, f_r^*), (f_j^{**}, f_r^{**}), or (f_j^{***}, f_r^{***}), depending on the relative sizes of the shifts of the reaction functions for NP j and r, respectively. Relative to the initial Nash equilibrium in solicitation spending (f_j^0, f_r^0), the new Nash equilibrium (f_j^*, f_r^*) corresponds to an increase in solicitation spending of NP j, but a decrease in solicitation spending of NP r; (f_j^{***}, f_r^{***}) corresponds to a decrease in solicitation spending of NP j, but an increase in solicitation spending of NP r; while (f_j^{**}, f_r^{**}) corresponds to a decrease in solicitation spending of both NP j and NP r. The increase in solicitation spending of NP g can be interpreted from the perspective of the extensive margin in which Figure 3 illustrates the impact on equilibrium solicitation spending of incumbent NP j and r when NP g enters the market with positive solicitation spending.[10]

As a preview to our main results, considering all the competing pairs of NPs in our data sample, there exist pairs for which $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{gm}} > 0$ and pairs for which $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{gm}} < 0$; but for the vast majority of the pairs, $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{gm}} < 0$. In other words, in the vast majority of cases the solicitation activities of competing NP r negatively impacts the effectiveness/efficiency of NP j's solicitation activities in securing donations for fulfilling NP j's mission, making optimal solicitation activities across NPs predominantly strategic substitutes. Accordingly, compared to panel (a) in Figure 3, panel (b) in the figure better characterizes strategic interaction between NPs with respect to their use of solicitation activities to secure donations to fulfill their mission.

[10] We do not model endogenous entry in this paper. We begin with static models given the lack of development and understanding of NP competitive behavior and encourage continued work in this area.

2.1.3 Relating to Marginal Revenue and Marginal Cost

As another way of previewing our main results and our finding that NP fundraising decisions are predominantly strategic substitutes, we now turn to the corresponding impact on a net-revenue maximizing NP. First, as mentioned above, it is verified for all observations in our data at the estimated values of the donor demand parameters that each NP's expected donation function, $ED_{jm}(f_{jm}, \mathbf{f}_{-j,m}; \theta)$, is concave with respect to its solicitation spending. Accordingly, each NP's marginal revenue, $mr_{jm}(f_{jm}, \mathbf{f}_{-j,m}; \theta)$, is a decreasing function of its solicitation spending, i.e., $\frac{\partial mr_{jm}(f_{jm}, \mathbf{f}_{-j,m})}{\partial f_{jm}} < 0$. Donations generated by soliciting more potential donors generates additional revenue but each additional donor has a lower expected donation.[11]

Second, assume increasing marginal costs as embodied in solicitation activities as plotted in Figure 4. We denote firm j's initial optimal choice of solicitation spending as f_j^0. Now suppose there is a change to demand (this could be a change to preferences but we will consider a counterfactual that a competitor is removed from the market) such that marginal revenue shifts to the right. The rightward shift in each firm's marginal revenue, represented by the shift from $mr_j^0(f_j, \mathbf{f}_{-j})$ to $mr_j^1(f_j, \mathbf{f}_{-j})$ will incentivize each NP to increase its solicitation spending from f_j^0. However, as Figure 4 highlights, assuming strategic substitutes, when firm j's rivals increase their solicitation spending, the strategic response will shift firm j's marginal revenue curve to the left. The leftward shift in firm j's marginal revenue could be from $mr_j^1(f_j, \mathbf{f}_{-j})$ to $mr_j^{2A}(f_j, \mathbf{f}_{-j})$ or from $mr_j^1(f_j, \mathbf{f}_{-j})$ to $mr_j^{2B}(f_j, \mathbf{f}_{-j})$. If the leftward shift in firm j's marginal revenue curve is to $mr_j^{2A}(f_j, \mathbf{f}_{-j})$, then its new equilibrium solicitation spending, f_j^*, will be higher than its initial level of f_j^0, but if the leftward shift is to $mr_j^{2B}(f_j, \mathbf{f}_{-j})$, then its new equilibrium solicitation spending, f_j^*, will be lower than its initial level of f_j^0. Therefore, due to the strategic interdependent responses of the remaining NP firms, the elimination of one NP firm from the market can result in either an increase or a decrease in the optimal solicitation spending of a given remaining firm.

[11] See Gayle et al. (2017) for a proof of this downward sloping expected donation function

3 Initial Trends and Data

3.1 Data

The donation and fundraising data are for 501(c)3 public organizations who filed a tax return from 1989-2003 National Center for Charitable Statistics (1989-2003).[12] These data are obtained from the National Center on Charitable Statistics (NCCS) at The Urban Institute. Although most NPs 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.

The data also contain other financial characteristics. Firm size is correlated with fundraising levels and is therefore proxied using assets at the beginning of the fiscal year. In addition, firms receive revenues not only from donations and government grants but also from mission-related services, called program service revenues. 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 NP industries used in the empirical analysis. NPs 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 NP firms. More importantly, our methodology uses NPs' 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 relatively little for-profit competition. We also focus on NPs who primarily compete locally for donors; that is, most of the donors reside in the market area where the service is provided.[13] Finally, we define NPs based on their primary missions as reported by the National Taxonomy of Exempt Entities, similar to the NAICS codes.[14] Some industries could be classified in multiple sectors given the subjective nature of the classification.[15] Although we cannot ensure completely that we capture all of the NPs in a

[12]We intentionally stop our analysis at 2003 due to the mounting evidence of strategic behavior regarding fundraising reporting once monitoring and rating of such expenses was introduced (Mayo, 2022).

[13]We construct markets using Census places following Harrison and Seim (2019); Gayle et al. (2017). We do not impose a size constraint on the selection of the markets nor do we restrict the analysis to isolated markets given the richness of our donation data and our empirical model (i.e., inclusion of firm, time fixed effects and local market-specific time trends). We intentionally chose larger markets but note that Gayle et al. (2017) find little sensitivity to smaller markets in work that has a similar channel for the role of the size of the market.

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

[15]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

particular sector, choosing services that are well-defined with a clear mission decreases the measurement error of identifying all competitors.

Table 1 lists the number of organizations by NTEE code and our broad seven industry types included in the estimation.[16] The table also reports, by sector, summary statistics on firm-level donation share within their local market as well as their donation share within sector and local market. We note that the summary statistics on firm-level donation shares in Table 1 reveal that the mean shares do not vary much across sectors but there is quite a bit of variation across firms within a given sector. This finding will be important when we calculate own- and cross-fundraising elasticities in Section 5.2.

Measurement error in the financial information exists, particularly given that most of the tax forms are not audited (Tinkelman, 2004)[17]. 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 and also delete any charities reporting negative and zero fundraising expenses. This leaves 242,350 observations from 47,889 organizations across approximately 10,500 markets . Table 2 provides descriptive statistics by organization (Panel A) and markets (Panel B). Similar to Table 1, we again note the variation in market shares across firms and that it is larger across NPs than across the markets. Similar NP level variation exists in the extent of program service revenues and size of the organization. This highlights the importance of the inclusion of firm-fixed effects in our model. As shown in the table, we identify national level players as about 10% of our sample but note that this will be absorbed by the fixed-effects in our specification. Future work may want to investigate the role of national fundraising, analogous to franchise and chain-level attributes but that is not the focus of our study.

organizations are filed under G30 while others are in H11.

[16] Given that no prior estimates of across-sector donative competitive effects exist to our knowledge, we begin with this seven industry analysis. We leave for future work to investigate the extent to which more granular sector definitions are warranted.

[17] We are particularly concerned about the possibility of under or over-reporting on donations and fundraising expenses to meet particular best practice criteria (Mayo, 2022) and its potential subsequent impact on our within group share estimation. Our panel structure mitigates these biases through the use of time and firm fixed effects (e.g., firms that systematically over/under-report financial values should be captured in the firm fixed effects). This is also another reason why we estimate a coefficient on the marginal cost of fundraising in equation (18).

3.2 Evidence from Descriptive Linear Regressions

Following a first-step approach used in several studies in the empirical industrial organization literature [e.g. see Goldberg and Verboven (2001); Thomadsen (2005); Bonnet et al. (2013); and Gayle and Xie (2019)], as a first step to our analysis we specify and estimate NP-level descriptive linear solicitation spending regressions to examine basic patterns in the data. We focus on the associations between fundraising intensity and the number of competitors in the market with the following:

$$ln(f_{jmt}) = \pi_1 NumNP_{mt} + X_{jmt}\phi + \tau_j + \nu_t + \Sigma_{m=1}^{M}\theta_m(L_m \times T_t) + \eta_{jmt} \tag{9}$$

where f_{jmt} represents solicitation intensity measured in dollars of spending for NP firm j in market m at time t; $NumNP_{mt}$ counts the number of NPs in market m during period t and the key parameter of interest, π_1, measures the marginal impacts on solicitation spending of market concentration; X_{jmt} is a matrix of control variables and ϕ the associated vector of parameters. The firm-level fixed effects (τ_j) in our empirical analysis account for both market and firm-specific, time invariant factors that affect the demand for NP services, while year fixed effects (ν_t) control for time-varying factors that may influence donor and NP behaviors over time. $L_m \times T_t$ is an interaction between a zero-one local market dummy, L_m, and a time trend variable, T_t, that controls for the impacts of local market-specific trends. Last, η_{jmt} is a mean zero random error term that is assumed independently and identically distributed across firms, markets and time.

There are flaws with such linear regression analysis analogous to the criticisms of the classic Structure-Conduct-Performance (SCP) paradigm approach (Schmalensee, 1989), (Bresnahan, 1989).[18] For example, the number of NPs in the market is clearly endogenous – idiosyncratic variations in fundraising captured by η_{jmt} are most likely correlated with the number of NPs in the market, even after inclusion of market-specific fixed effects. Consider the following mechanism: markets that attract more NPs may inherently have a preference for a greater number of NPs which will impact fundraising productivity. Such a demand-side, preference-driven mechanism would create positive bias on π_1 in a naive regression.

[18] The SCP paradigm would regress market equilibrium outcome variables such as price on various measures of market structure such as number of rival firms, their spendings on research and development, their spendings on advertising, etc. The main criticism of the SCP approach is that price along with the measures of market structure such as number of rival firms are determined simultaneously by market exogenous factors as well as choice behavior/conduct of the firms, and thus generates biased estimates.

Second and of particular interest in our study, the number of NPs is an equilibrium determined by strategic fundraising behavior of all NPs in the market. The NP's fundraising spending and the number of rival NPs variables in equation (9) are jointly determined by the market's "basic conditions" (exogenous factors) as well as the choice behavior/conduct of NPs, but equation (9) makes no attempt to account for the conduct of NPs. For example, if fundraising efforts are strategic complements, then increases in the number of NPs would illicit both a direct and indirect effect of increasing fundraising levels for each NP. If instead fundraising efforts are strategic substitutes, then the direct negative effect of decreasing fundraising in response to a leftward shift in the marginal donative revenue curve would be confounded by the indirect positive effect of increasing fundraising in response to competitors' decreases in fundraising levels. Thus, both scenarios would lead to bias in π_1 since we do not explicitly control for the strategic interaction between firms and that bias is ambiguous as it depends on the nature of the strategic behavior.

With the endogeneity challenges described above in mind, we present estimates of the linear regression equation in (9) on the full sample of markets. Column (1) of Table 3 presents our naive model without our interacted time trend controls. As we anticipated, the coefficient on Number of NPs is positive albeit insignificant. Like prior work, Dai et al. (2014), we find evidence of potential nonlinearities in the effect of competition as measured by Number of NPs and (Number of NPs)^2 in Column (2), and now a positive and significant first-order effect. Column (3) now includes the market specific time trends discussed above and as anticipated, such controls appear to mitigate the positive bias stemming from market-level related correlations.

However, such fixed effects still do not account for the strategic nature of NP entry. We therefore instrument for Number of NPs in columns (4) and (5) using a demand side shifter of the expected size of the market – the market population. We reject exogeneity of Number of NPs but admittedly note that the instrument choice is not as strong as desired. Since our goal is not to place a causal interpretation on these estimates, we are less concerned about the latter although we recognize that we should still exercise caution in interpreting the results. However, as anticipated, once we instrument, the coefficient on Number of NPs is negative and significant in column (4). We find evidence again of nonlinearities in the competitive effect in column (5) but have less precision on those estimates.

Again, our goal with this descriptive linear regression analysis is not to identify causality but to demonstrate initial relationships in the data and the benefits of a structural model going forward. Our empirical model presented below will account for the strategic interactions between NPs and also the possible nonlinearities in the impact of NP competition.

4 Empirical Model

We now turn to discussing the specification and estimation of our structural model. The section begins with specifying the donor demand aspect of the model, and then moves on to specify NP firms' solicitation cost function. We close the section with a discussion of estimation details.

4.1 Donors' Decision Problem

Let each donor i in local market m choose to donate to one of the J_m NP firms in the market, and these firms are indexed by j, where $j = 1, \ldots, J_m$. Donor i also has the option to not donate to any of the J_m NP firms, an outside option we designate as $j = 0$. Therefore, each donor's decision problem is effectively to maximize their own utility by choosing one among the $J_m + 1$ donative alternatives in their local market, $j = 0, 1, \ldots, J_m$. [19]

NP firms in a market are organized into K mutually exclusive groups indexed by k, where the groups correspond to sectors/industries. For example, in our application each NP firm falls into one of seven (7) distinct sectors. The outside option, $j = 0$, is assumed to be the only member of group 0 ($k = 0$). As such, there are $K + 1$ mutually exclusive groups, $k = 0, 1, \ldots, K$.

Let the indirect utility donor i gets from donating to NP firm j located in market m at time t be specified as:

$$u_{ijmt} = \delta_{jmt} + \sigma\zeta_{ikmt} + (1 - \sigma)\varepsilon_{ijmt} \tag{10}$$

where δ_{jmt} is the mean utility level across all donors who donate to firm j. For donor i, ζ_{ikmt} is a random component of utility that is common to all NP firms in sector k, whereas the random term ε_{ijmt} is specific to firm j. Estimable parameter σ lies between 0 and 1, i.e.,

[19] Our preferred specification includes in the outside option giving to religious or undefined sectors or not giving to any charity. We could also define the outside option as exclusively not giving to any charity. However, this specification would require additional flexibility in the substitution patterns between NP industries and introduces bias given the known sample selection of nonreporting by religious organizations.

$0 \leq \sigma < 1$, and measures the correlation of the donors' utility across NP firms belonging to the same sector. As σ approaches 1, the correlation of preferences for donating to NP firms 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 NP firms in different sectors, compared to switching their donation across NP firms 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 NP firms compete symmetrically for donations irrespective of their sector.

NP firms can influence the giving propensity of a donor through its choice of fundraising which will also be reflected in its marginal costs as discussed below. By increasing its fundraising intensity, NP j that belongs to sector k may encourage: (i) potential donors who never gave to donate to NP j; and/or (ii) some donors to other rival charities within sector k simply to switch their giving to NP j; and/or (iii) some donors to rival charities in sectors other than k to switch their giving to NP j. In other words, we seek to understand how changes to the fundraising intensity influences giving within and across sectors. The mean utility level, δ_{jmt}, is therefore parameterized as:

$$\delta_{jmt} = \gamma ln(f_{jmt}) + x_{jmt}\beta + \tau_j + \nu_t + \Sigma_{m=1}^{M}\phi_m(L_m \times T_t) + \xi_{jmt} \quad (11)$$

where f_{jmt} represents solicitation intensity measured in dollars of spending for NP firm j in market m at time t; and γ is an estimable parameter that measures the average change in donors' satisfaction induced by a change in the NP's solicitation intensity. Therefore, through its solicitation activities, NP firm j has the ability to influence the propensity that donors give to firm j. x_{jmt} is a vector of observed characteristics of NP firm j; and β is the corresponding vector of estimable parameters that measure the marginal impacts of these respective characteristics on donor satisfaction. We again include firm-, and year-fixed effects and also include $\Sigma_{m=1}^{M}\phi_m(L_m \times T_t)$ for the local market-specific trends which were shown to be important in the descriptive linear regression estimation. ξ_{jmt} is a composite measure of residual characteristics that are unobserved to us the researchers, but observed by donors and NP firms in the relevant market.

Contrary to a typical for-profit setting, our main coefficient of interest is γ as opposed to the conventional price coefficient. As discussed earlier, we seek to understand how changes to fundraising influence giving patterns across charities.[20] Donors will give to the charity that maximizes their utility. In market m, let there be Γ_{km} NP firms that belong to sector k. If NP firm j is in sector k, the well-known nested logit formula for the model-predicted donation share of NP firm j relative to the donation share of sector k is:

$$s_{jm/k} = \frac{exp(\frac{\delta_{jm}}{1-\sigma})}{D_{km}} \tag{12}$$

where

$$D_{km} = \Sigma_{j \in \Gamma_{km}} exp(\frac{\delta_{jm}}{1-\sigma}) \tag{13}$$

This expresses the model-predicted within sector donation share of NP firm j. The model-predicted probability of donors choosing a firm in sector k is then given by:

$$s_{km} = \frac{D_{km}^{(1-\sigma)}}{1 + \Sigma_{k=1}^{K} D_{km}^{(1-\sigma)}} \tag{14}$$

Last, the unconditional probability of donors in market m choosing NP firm j is:

$$s_{jm}(f_{jm}, \mathbf{f}_{-j,m}; \theta) = s_{jm}(\mathbf{f}_m; \theta) = s_{jm/k} * s_{km} \tag{15}$$

$$= \frac{exp(\frac{\delta_{jm}}{1-\sigma})}{D_{km}} \frac{D_{km}^{(1-\sigma)}}{1 + \Sigma_{k=1}^{K} D_{km}^{(1-\sigma)}} \tag{16}$$

where $\theta = (\gamma, \beta, \sigma)$ is the vector of estimable parameters in the donation share function; and $\mathbf{f_m}$ is a vector of solicitation intensities measured in dollars of spending for the NP firms in market m.

Given the nested logit functional form of the donative share function in equation (16), the parameters in vector θ can be estimated using the following linear regression equation:

$$ln(S_{jmt}) - ln(S_{0mt}) = \gamma ln(f_{jmt}) + x_{jmt}\beta + \sigma ln(S_{jmt/k}) + \tau_j + \nu_t + \Sigma_{m=1}^{M} \phi_m (L_m \times T_t) + \xi_{jmt} \tag{17}$$

where S_{jmt} is the observed market share of donations received by firm j in market m at time t; S_{0mt} is the observed proportion of the donative capacity of market m at time t that is not secured by the NP firms in the market; and $S_{jmt/k}$ is the observed within sector donation

[20] As noted in the literature (Okten and Weisbrod, 2000), one can think of the price of the donation as a function of the intensity of fundraising by the NP relative to the returns from fundraising. As a NP 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. We have run specifications with and without such a price variable included with little change to our coefficient of interest and note that excluding the price coefficient facilitates estimation of the forthcoming supply side.

share of NP firm j. It is worth pointing out that, similar to other discrete choice demand models, the nested logit structure assumes donors perceive rival NPs as substitutes for where to channel their donations but that does not imply that fundraising spending/efforts across NPs are strategic substitutes in equilibrium. This is precisely why our structural model estimates and analysis will investigate this empirical question.

The error term in equation (17) is ξ_{jmt}, which is a composite measure of residual firm and market characteristics that are unobserved to us the researchers but observed by donors and NP firms in the relevant market. Optimizing behavior of donors and NPs imply that in equilibrium solicitation intensities, f_{jmt}, as well as within sector donation share of NP firms, $S_{jmt/k}$, will be correlated with ξ_{jmt}. We will therefore instrument for f_{jmt} and $S_{jmt/k}$ in regression equation (17) and discuss these instruments and identification in subsection 4.3.

4.2 Nonprofits' Solicitation Costs

Recalling our model for total costs from equation (2) and the subsequent discussion, we now define our specifications. We assume the following functional form for marginal cost:

$$mc_{jm} = exp(\rho_f f_{jm} + c_{jm}) \tag{18}$$

where estimable parameter ρ_f reflects the cost technology embodied in NPs' solicitation activities; and c_{jm} is a composite of other cost components.

Our model incorporates the possibility of implicit solicitation costs in addition to the explicit expenses/intensities (f_{jm}) we observe. If we find that $\rho_f = 0$, then each NP's marginal cost of solicitation is invariant to the level of its solicitation intensity. With $\rho_f > 0$, each NP's marginal cost of solicitation is an increasing convex function of its solicitation intensity, i.e., $\frac{\partial mc_{jm}}{\partial f_{jm}} = \rho_f exp(\rho_f f_{jm} + c_{jm}) > 0$, and $\frac{\partial^2 mc_{jm}}{\partial f_{jm}^2} = \rho_f^2 exp(\rho_f f_{jm} + c_{jm}) > 0$. The cost technology embodied in a NP's solicitation activities depends on the extent to which the opportunity cost of the extra resources channeled to these activities differs from the opportunity cost of the resources that have been used in these activities prior to the NP's increase in its solicitation activities. For example, to the extent that increasing fundraising efforts involves greater sophistication in solicitation programs such as investment in social media technology, greater expertise in institutional advancement etc., increasing marginal costs may exist in that additional costs not accounted for in the explicit fundraising expenses are also needed and allocated to fundraising efforts. We do not constrain ρ_f to be positive; $\rho_f < 0$ would imply that increasing variable inputs (i.e., workers) devoted to fundraising activities decreases the implicit costs associated with the activities.[21]

We highlight that in addition to being a salient piece of modelling NP's fundraising decision, our model provides insight into the NP fundraising production process, an area understudied in the economics of NPs. While a large literature exists focused on crowd-out and returns to fundraising in regards to donation, much less attention has focused on the cost side of fundraising. This is particularly important in this setting given that the "output" of fundraising is measured in donation dollars. Analogous to production function settings that use total revenue for outputs (Syverson, 2004), this dollar-based measure confounds the monetary costs with the choice of inputs. Our model explicitly acknowledges this shortcoming and allows for greater flexibility in the role that fundraising plays in NP costs.

The composite of cost components, c_{jm}, is specified as follows:

$$c_{jm} = \rho_0 + \rho_1 w_{jm} + \tau_j^c + \nu_t^c + \Sigma_{m=1}^M \phi_m^c (L_m \times T_t) + \epsilon_{jm}^c \tag{19}$$

where w_{jm} is a vector of cost-shifting variables, ρ_1 a vector of associated parameters and ϵ_{jm}^c represents random shocks to costs. Analogous to our demand estimation, we include firm-, and year-fixed effects and also include local market-specific trends to capture local cost shifters.

Let term $\frac{\partial s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}} \times PD_m$ in equation (5) be denoted by mr_{jm}, i.e.,

$$mr_{jm} = \frac{\partial s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}} \times PD_m \tag{20}$$

where the right-hand-side of equation (20) is a function of variables and parameter estimates in the donation share function, i.e., $mr_{jm}(\mathbf{f}_m, \mathbf{x}_m; \theta)$. As such, with vector of variables $\mathbf{f}_m$ and $\mathbf{x}_m$ along with parameter estimates $\hat{\theta}$, we can use equation (20) to obtain estimates, $\widehat{mr}_{jm}(\mathbf{f}_m, \mathbf{x}_m; \hat{\theta})$. The first-order condition in equation (5) along with equations (18) and (20) imply:

$$\widehat{mr}_{jm} = exp(\rho_f f_{jm} + c_{jm}) \tag{21}$$

[21] One can show that this also would imply an increasing returns to scale technology in our model. However, given that we do not estimate fixed costs, such an implication is likely biased so we refrain from such conclusions.

Taking the logarithm of both sides of equation (21), and using equation (19) to substitute for c_{jm}, yields the following regression equation:

$$ln(\widehat{mr}_{jm}) = \rho_0 + \rho_f f_{jm} + \rho_1 w_{jm} + \tau_j^c + \nu_t^c + \Sigma_{m=1}^{M} \phi_m^c (L_m \times T_t) + \epsilon_{jm}^c \qquad (22)$$

Equation (22) is used to obtain estimates of the parameters in vector $\rho = (\rho_0, \rho_f, \rho_1)$, where the estimate of ρ_f will reveal important attributes of the marginal cost technology embodied in NPs' solicitation activities.

4.3 Estimation & Instruments

The error term in equation (11) is ξ_{jmt}, which as described above is a composite residual measure of firm and market characteristics that are unobserved to us the researchers but observed by donors and NP firms in the relevant market. Optimizing behavior of donors and NPs imply that in equilibrium solicitation intensities, f_{jmt}, as well as the within sector donation share of NP firms, $S_{jmt/k}$, will be correlated with ξ_{jmt}. Therefore, we need to instrument for f_{jmt} and $S_{jmt/k}$ in regression equation (11).

We construct and use well-known BLP-motivated type instruments for firms' within sector donation share.[22] Such BLP-motivated instruments include the means of asset values and program service revenues across a firm's rivals within the sector. These are also valid instruments for the solicitation intensity variable.

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

[22] For discussions on BLP-motivated type instruments the reader is referred to Berry et al. (1995). We note that use of such instruments is distinct from adopting a random coefficients framework. We begin with a nested logit estimation given the paucity of understanding of donation substitution across sectors but indeed recognize that adopting a BLP type estimation is warranted in future research to allow for more flexible substitution patterns.

On the supply side, equilibrium solicitation intensity, f_{jmt}, will be correlated with unobserved cost shocks captured by ϵ^c_{jm}. As instruments for f_{jmt} in the marginal cost regression we use our measure of markets' donative capacities interacted with the full set of sector-specific dummy variables. The rationale is that a market's donative capacity will influence NPs' expected donations, and therefore NPs' optimal choice of solicitation intensities. The rationale for interacting a market's donative capacity with sector-specific dummy variables is that a marginal increase in a market's donative capacity is likely to impact NPs' solicitation intensity responses differentially across sectors. Furthermore, a market's donative capacity is likely uncorrelated with cost shocks captured by ϵ^c_{jm}.

5 Results

5.1 Donor Demand and Solicitation Cost Estimates

Table 4 provides several specifications of the nested logit empirical demand estimates. We provide estimates employing different instrument sets.[23] Column (1) uses the number of firms (N), and N squared. Column (2) also interacts N and N^2 with year dummies to allow for additional richness in how local market-level trends are associated with local competition. Our instrument validity checks suggest valid instruments as it relates to weak instruments (Anderson-Rubin test) and also exogeneity of the instruments. Because the year dummies are both in the structural and 1st stage regressions, column (1) gives the valid overidentification test and supports our exclusion restriction assumptions. It is the declining impact of competition that our exclusion restrictions capture. Given that and concern over adding too many instruments, Column (3) excludes N interacted with years. Column (4) incorporates classic BLP type instruments and it will be our preferred specification moving forward.

As expected, increasing fundraising efforts increase a charities' market share. Our point estimates range from 0.38-1.0. Our within-group share estimate (σ) is quite consistent across all of the specifications with estimates that are significant between 0.138 and 0.31. We therefore find a moderate level of substitution between charities within the same sector and thus support for our nesting structure. Our cross-fundraising elasticities will allow us to

[23]Prior versions of the paper used other normalized measures of fundraising intensity and varied instruments with similar demand estimates. We also note that we estimated the demand model on sector-level sub-samples of the data producing parameter estimates qualitatively similar to the full sample estimation.

investigate the substitution patterns *across* sectors which we turn to in the next section. Size as measured by assets is not significant once we account for our market specific time trends. However, increased earned revenues tends to decrease donative market shares which is strongly consistent with a shift in revenue portfolio from donations to a more fee-for-service funding model. This finding is also consistent with the diversified revenue NP literature.

Table 5 provides the cost estimation. We use the age and size of the organization (measured by assets) and their respective interactions as cost shifters. We present three alternatives instrument sets.[24] The first employs our donative capacity measure interacted with sector fixed effects. The second also includes donative capacity interacted with year fixed effects while the third includes our local market specific time trends. The results are robust across all the specifications. Our estimates support our prior of increasing marginal costs as the coefficient on fundraising intensity is positive and significant. In addition, younger and larger firms have lower marginal costs with size attenuating the effect of age.

5.2 Fundraising Elasticities

We now turn to the calculation of the own-NP and cross-NP fundraising elasticities. Based on the specification of our donation share function in equation (16) and our mean donor utility function in equation (11), the formula for computing own-NP fundraising elasticity for NP j is:

$$e_{jmt} = \frac{\partial s_{jmt}}{\partial f_{jmt}} \frac{f_{jmt}}{s_{jmt}} = \frac{\gamma}{1-\sigma}[1 - \sigma S_{jmt/k} - (1-\sigma) S_{jmt}]. \tag{23}$$

In the case where NP j and NP r belong to the same sector k, the cross-NP fundraising elasticity formula is:

$$e_{rjmt} = \frac{\partial s_{jmt}}{\partial f_{rmt}} \frac{f_{rmt}}{s_{jmt}} = -\frac{\gamma}{1-\sigma} \frac{S_{rmt}}{S_{jmt}}[\sigma S_{jmt/k} + (1-\sigma) S_{jmt}]. \tag{24}$$

However, if NP j and NP r are from different sectors, the cross-NP fundraising elasticity formula is:

$$e_{rjmt} = \frac{\partial s_{jmt}}{\partial f_{rmt}} \frac{f_{rmt}}{s_{jmt}} = -\gamma S_{rmt}. \tag{25}$$

[24] Since age increments on a yearly basis, we also run specifications excluding age and age*assets with very similar results. We also note that we have a similar issue regarding the overidentification tests as discussed above (i.e., year dummies are both in the structural and 1st stage regressions) and the model is exactly identified when we exclude the interaction effects. We therefore do not report overidentification statistics for the cost table.

Table 6 reports mean own-NP elasticities using our preferred demand specification from column (4). Our own-NP fundraising elasticities are reported by sector. All elasticities are significantly different from and less than one and thus suggesting inelastic demand. The elasticities range are closely grouped around 0.83. While inelastic demand may at first glance seem counterintuititve, as suggested by our discussion of strategic decisions, we should not anticipate fundraising demand functions to follow conventional demand functions (i.e., where the focus is on prices). The lack of variation in the elasticities may also seem initially surprising. However, as shown in equation (23), the variation in elasticities stems from the share variables which are quite similar (at the mean) across sectors as shown in Table 1.

Figure 5 provides the cross-NP fundraising elasticities.[25] Consistently for all sectors, we find greater sensitivity within than across sectors. While the within sector cross-NP fundraising elasticities are larger than across sectors, they are considerably smaller in absolute magnitudes than the own-NP fundraising elasticities indicating that individual charity changes to fundraising impact its donation market shares much stronger than other charities in the sector. Interestingly, we find that environmental and animal-related charities appear to face the most fierce cross-NP fundraising sensitivity with other charities of similar missions. This may be due to the relatively early life-cycle stage of these sectors relative to those such as arts or health. While it is not the main goal of the paper, it highlights why measuring the changes in the donation market shares over time provides an additional source of identification for our study.

The across sector elasticities are, in general, two orders of magnitude smaller than the within-sector cross-NP fundraising elasticities. While these within and across sector elasticities are relatively small we do note they are all highly statistically significant, indicating additional consideration of donative market definitions. On the other hand, even though they are statistically significant, they are economically quite small relative to the own-NP fundraising response. We further examine the across vs. within substitution magnitudes in the next subsection.

[25] A numerical table for the cross-firm fundraising elasticities is in the Appendix, Table A4.

5.3 Diversion Ratios

To get a more thorough understanding of donor substitution behavior across competing NPs, we also compute diversion ratios. It has been shown above that own-NP fundraising elasticities are positive, while cross-NP fundraising elasticities are negative, implying that by marginally increasing fundraising expenditure a NP can increase the donations it receives; and a subset of the increased donations received will come from donations that rival NPs would have received otherwise, *ceteris paribus*. Accordingly, the diversion ratio from NP r to NP j, D_{jr}, answers the following question: If NP j marginally increases its fundraising spending, what fraction of the increased donations it receives comes from donors who switched their donations from NP r to NP j? For the discrete choice demand model we use, the diversion ratio from NP r to NP j is obtained by $D_{jr} = \frac{\partial s_r/\partial f_j}{|\partial s_j/\partial f_j|}$.[26]

Table 7 summarizes our estimates of diversion ratios. The table shows that for most of the NP sectors we consider, on average, between 73 to 81% of the increased donations NP j receives from marginally increasing its fundraising spending comes from the outside option rather than from rival NPs, i.e., most of the increased donations comes from new donative sources.[27] In tandem, 13-16% of the increased donations received by NP j comes from moneys that rival NPs in the same sector as NP j would have received otherwise, *ceteris paribus*. Consequently, between 5-13% of the increased donation received by NP j comes from moneys that rival NPs in a different sector than NP j would have received otherwise.[28]

This latter diversion across sectors is important to note; the diversion from any one sector is fairly small (generally 1% or less) but when we take the totality of the diversion across all of the sectors, analogous to aggregate diversion ratios (Katz and Shapiro, 2002), we see across-sector diversions that are between 35% to 90% of the within-sector diversions. In summary, the diversion ratio estimates reveal two key takeaway messages: (*i*) most of the increased donation to a given NP as a result of increased fundraising activities comes from new donative sources; and (*ii*) competition between NPs for donative dollars is stronger within sector than across sectors but the aggregate impact across the sectors is not trivial and justifies consideration of the competitive fundraising impacts outside a particular charity's

[26]For discussions of diversion ratios in the context of product market competition see Shapiro (2010). For a comprehensive discussion of diversion ratios in the context of discrete choice demand models see Conlon and Mortimer (2021).

[27]Appendix A.2 presents robust results with different scales for the donative capacity.

[28]Note that because diversion ratios aggregated over all markets do not sum exactly to 100%, we have normalized the percentages so they sum to 100%.

sector.

5.4 Fundraising Effectiveness

Recall from subsection 2.1.1, that an important metric for our analysis is how the sensitivity of donations with respect to fundraising or fundraising effectiveness for a NP changes as a competing NP increases its fundraising efforts. We therefore provide further evidence on this sensitivity. Let FRE_j denote a metric of fundraising effectiveness for NP j. We use our estimated model to measure a NP's fundraising effectiveness by computing the first-order partial, $\partial s_j/\partial f_j$, that measures the marginal change in NP j's donations resulting from a marginal change in its own solicitation spending. Accordingly, we can think of $\partial s_j/\partial f_j$ as simply an index of own-NP fundraising effectiveness, i.e., $FRE_j = \partial s_j/\partial f_j$.

Table 8 reports summary statistics on FRE for NPs by sector.[29] Based on the results in the table, human service NPs on average have the most effective fundraising campaigns relative to NPs in the other sectors of our study. All the mean measures of the fundraising effectiveness index reported in the table are positive and statistically different from zero at conventional levels of statistical significance.

We now consider how a NP's fundraising effectiveness is influenced by the solicitation spending of rival NPs, which is captured by the metric, $\frac{\partial(\frac{\partial s_j}{\partial f_j})}{\partial f_r} = \frac{\partial^2 s_j}{\partial f_j \partial f_r}$ – what we refer to as the second-order cross-partial in subsection 2.1.1. For the purpose of interpretation, we examine the elasticity of how a marginal change in a rival firm's solicitation spending influences the marginal effectiveness of NP j's own solicitation spending in securing donations, such that

$$\Delta FRE_{jr} = \frac{\partial(\frac{\partial s_j}{\partial f_j})}{\partial f_r} \frac{f_r}{(\frac{\partial s_j}{\partial f_j})} \tag{26}$$

Therefore, metric ΔFRE_{jr} is NP j's elasticity of fundraising effectiveness with respect to the solicitation spending of rival NP r.

Panel B reports summary statistics on ΔFRE_{jr} among rival NP pairs within the same sector versus rival NP pairs across different sectors. First, while ΔFRE_{jr} is negative for almost all NP pairs, there exists a small set of within sector NP pairs, less than 1% among

[29] While not the primary focus of this paper, we note that the variation in FRE is larger than the own-firm elasticities and is driven by a long right-tail. Harrison et al. (2023) discuss this large variation in the marginal productivity of fundraising across firms. This is why all elasticities and diversion ratios are calculated at the firm level and then averaged for each sector. Such large skewness is not present in the counterfactuals as they rely more on the elasticity estimates.

within sector pairs, for which ΔFRE_{jr} is positive. The mean of ΔFRE_{jr} is 0.0044 among within sector pairs for which ΔFRE_{jr} is positive, suggesting that on average a 10% increase in the solicitation spending of a rival NP r increases the fundraising effectiveness of NP j by 0.0044%.

Second, the scaled mean of ΔFRE_{jr} is -11.3 among within sector pairs for which this elasticity metric is negative, suggesting that on average a 10% increase in the solicitation spending of a rival NP r decreases the fundraising effectiveness of NP j by 11.3%. Third, the scaled metric ΔFRE_{jr} is negative for all cross-sector rival pairs of NPs and is equal to a mean of -2.27. Therefore, on average a 10% increase in the solicitation spending of a rival NP r decreases the fundraising effectiveness of NP j by 2.27% when NPs r and j are in different sectors. These estimates reveal an intuitively appealing result that a NP's fundraising effectiveness is decreased more by a rival NP's solicitation spending if the rival belongs to the same sector versus if the rival belongs to a different sector.

In summary, consistent with the strategic interaction framework laid out in subsection 2.1.1 above, the summary evidence on the metric ΔFRE_{jr} reveals that optimal solicitation spending levels across rival NPs are most often strategic substitutes rather than strategic complements. The reason is that a NP's fundraising effectiveness is decreased by the increased solicitation spending of rival NPs, causing the NP to optimally respond on the margin by decreasing its solicitation spending.

5.5 Implementing Counterfactuals

The demand and supply-side framework above can be used to perform various counterfactual experiments of interest. We focus on investigation of the impact on NPs' optimal choice of their solicitation efforts due to elimination of one NP firm from the same sector in each market. To discuss implementation of this counterfactual, let Δ be a $J \times J$ matrix that captures the response of donation shares to changes in solicitation intensities. Market subscripts are dropped in much of what follows only to avoid a clutter of notation. However, equations should still be interpreted as being market-specific. Specifically, matrix Δ contains first-order partial derivatives of donation shares with respect to all solicitation intensities:

$$\Delta = \begin{pmatrix} \frac{\partial s_1}{\partial f_1} & \vdots & \frac{\partial s_1}{\partial f_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_J}{\partial f_1} & \vdots & \frac{\partial s_J}{\partial f_J} \end{pmatrix} \tag{27}$$

In matrix notation, the system of first-order conditions in equation (5) can conveniently be expressed as:

$$[(I * \Delta) \times Ones(J,1)] \times PD - \mathbf{mc} = 0 \tag{28}$$

where I is a $J \times J$ identity matrix; $I * \Delta$ represents element-by-element multiplication of the two $J \times J$ matrices; $Ones(J,1)$ is a $J \times 1$ vector of ones; PD is a scalar measure of the donative capacity of the local market; and $\mathbf{mc}$ is a $J \times 1$ vector of marginal costs across the NP firms in the local market.

Let term $[(I * \Delta) \times Ones(J,1)] \times PD$ in equation (28) be denoted by vector $\mathbf{mr}$, i.e.,

$$\mathbf{mr} = [(I * \Delta) \times Ones(J,1)] \times PD. \tag{29}$$

A given element in vector $\mathbf{mr}$ measures the marginal change in donations received by the relevant NP firm due to a marginal change in its solicitation intensity. As previously discussed, $\mathbf{mr}$ is a function of variables and parameter estimates in the donation share function, i.e., $\mathbf{mr}(\mathbf{f}, \mathbf{x}; \theta)$. As such, with vector of variables $\mathbf{f}$ and $\mathbf{x}$ along with parameter estimates $\hat{\theta}$, we can use equation (29) to obtain estimates, $\widehat{\mathbf{mr}}(\mathbf{f}, \mathbf{x}; \hat{\theta})$. Furthermore, the first-order conditions in (28) imply that $\widehat{\mathbf{mr}}(\mathbf{f}, \mathbf{x}; \hat{\theta}) = \widehat{\mathbf{mc}}$, which effectively allows us to recover estimates of marginal costs at the actual levels of solicitation intensities in the data.

With estimates of $\widehat{\mathbf{mc}}$ in hand, the functional form for marginal cost in equation (18) implies:

$$\widehat{\mathbf{mc}} = exp(\hat{\rho}_f \mathbf{f} + \mathbf{c}) \tag{30}$$

Using equation (30), we can recover estimates of the composite of other cost components, $\hat{\mathbf{c}}$, at the actual levels of solicitation intensities in the data as follows:

$$\hat{\mathbf{c}} = ln(\widehat{\mathbf{mc}}) - \hat{\rho}_f \mathbf{f} \tag{31}$$

where $\hat{\rho}_f$ is an estimate of the parameter that reveals the marginal cost technology embodied in NPs' solicitation activities.

In implementing the counterfactual experiment, we assume that recovered composite cost component estimates, $\hat{\mathbf{c}}$, and variables in $\mathbf{x}$ for remaining NPs are unchanged with the counterfactual elimination of a NP firm from the relevant market. Once one NP firm from the same sector in each market is eliminated, we then solve for the new Nash equilibrium levels of solicitation intensities, $\hat{\mathbf{f}}^*$, that satisfy the following system of equations:

$$\mathbf{mr}(\mathbf{f}^*, \mathbf{x}; \hat{\theta}) - exp(\hat{\rho}_f \mathbf{f}^* + \hat{\mathbf{c}}) \;\; = \;\; \mathbf{0} \qquad (32)$$

We then compare $\mathbf{f}$ with $\mathbf{f}^*$ to see how eliminating a NP firm from the same sector in each market affects solicitation intensities.

5.5.1 Counterfactual Predictions

Per our discussion in Section 2.1.3, with strategic substitutes, panel (b) in Figure 3 reveals that it becomes an empirical question of how NPs alter their equilibrium solicitation spending after elimination of another NP (selected at random) within and across NP industries. First, we examine the predicted effects due to the counterfactual elimination of one NP firm from each market among the remaining firms within the sector from which the eliminated NP firm belonged. For example, results in Figure 6a reveal that if a NP from the Education sector is eliminated, equilibrium solicitation spending among the remaining Education NPs is predicted to increase by approximately 13% on average.[30] The Environmental and International sectors show the largest within industry fundraising changes to an elimination of a NP within the sector. The within-sector predicted percent changes are all positive and statistically different from zero at conventional levels of statistical significance.

Figure 6b shows the across sector impacts of a NP elimination, and similar to 6a, we find statistically significant increases in fundraising across all sectors. However, all of the estimates are around one order of magnitude smaller than the within sector estimates in panel a of the figure. For example, eliminating an Environmental NP in the top right panel increases fundraising in other sectors between .08 and .13%, with the impacts on the Advocacy sector being the largest. Overall, eliminating Education NPs have the largest positive fundraising impacts in other sectors. While the individual across sector point estimates are smaller, similar to the diversion ratios shown in Table A1, the totality of the fundraising changes are non-trivial. Back of the envelope calculations based on these estimates suggest that an

[30] The table with estimates and standard errors is provided in Appendix Table A5.

average of 21% of the increase in fundraising stems from outside the eliminated firms' own sector. Thus, our findings support greater consideration for across sector competition when considering changes to market structure.

Our counterfactuals also allow us to examine how the nature of competition changes with the number of firms in a market. Table 9 therefore decomposes the within sector predicted changes based on the number of NPs in the market. The results in the table reveal that, irrespective of the number of competing firms in a sector, the remaining firms in the sector are predicted to increase their solicitation spending on average when one firm is counterfactually eliminated from the sector. However, consistent with a model akin to Bresnahan and Reiss (1991) Bresnahan and Reiss (1990) and modified for NPs by Gayle et al. (2017), the impact on rivals' solicitation spending caused by the eliminated firm declines as the number of NPs in the market increases. Conversely, we can infer from these counterfactual predictions that entry of a NP in a local market causes rival NPs to reduce their fundraising on average, with the magnitude of the reductions attenuating in markets with more rival incumbent NPs. These results are consistent with declining variable profits/net-revenue from NPs' fundraising operations as competition for donations in a donor market increases (Gayle et al., 2017).

Our prior discussions highlighted that NPs may optimally choose to either increase or decrease their solicitation spending in response to the elimination of a competing NP. However, Table 10 shows that the vast majority of remaining NPs optimally choose to increase their solicitation spending in response to the elimination of a competing NP. For example, column (2) shows that when an Education NP is eliminated, approximately 84% of the remaining NPs in this sector are predicted to respond by increasing their solicitation spending.[31] We find similar patterns for all sectors. Our counterfactual results therefore suggest that elimination of a NP in the relevant market will cause most competing NPs to increase their solicitation spending. In the reverse, these results also imply that entry of a new NP will result in decreased fundraising for the vast majority of incumbent NPs in the same and other sectors.

Relating these results back to our introductory discussion of Rose-Ackerman (1982)'s result that entry can create excessive fundraising, we find in the aggregate, that elimination of a NP decreases *total* fundraising in the sector. Column (3) and (5) of Table 10 show the average total dollar change and percentage change respectively over all market-years. In

[31] Percentages disaggregated by sector are shown in the Appendix, Table A5.

Column (4), we give some sense of the average fundraising spending for the eliminated NP. We therefore see that the average increase in solicitation spending of the remaining NPs is not sufficient to offset the fundraising spending lost from the market with the elimination of the NP, yielding an aggregate reduction in solicitation spending. The corollary then suggests that new entry of a firm, while decreasing individual incumbent NP fundraising spending, will increase total market-level fundraising spending. Our results therefore provide what we believe is the first empirical evidence that new NP entry may lead to increased overall fundraising efforts after accounting for strategic responses in the fundraising efforts of incumbent NPs. While we want to emphasize caution that these implications for NP-level and total market-level fundraising and the relation to market structure stop short of inferring overall welfare, our analysis suggests a path for additional work that can build on our framework to investigate optimal fundraising levels and market structure.

6 Discussion & Conclusion

Our paper provides a framework to gain additional insight into competition in donative markets. We provide a new lens on important questions about the intensity of competition within and across NP sectors. It also begins to link more clearly the strategic fundraising decisions of NPs to empirics, and structurally investigates those relations. We establish what we believe are the first estimates of own- and cross-fundraising elasticities as they impact donations. Our estimates suggest that donors are relatively inelastic to the level of own-fundraising and establishes negative cross-firm elasticities that are stronger within a sector than across sectors.

However, calculations of the diversion ratios as well as our counterfactual predictions demonstrate that impacts outside a NP's own sector are nontrivial. Depending on the particular research question and/or policy analysis, our results imply that one may need to evaluate competitive effects for other NPs not only for a NP's own sector but for other NPs outside the sector of interest. Our findings suggest that 30-40% of changes in fundraising and donative market shares can stem from competing NPs outside the sector. Our model of equilibrium fundraising also demonstrates the unique nature of competition in the NP donative setting. Fundraising can in theory be strategic substitutes or strategic complements and we find evidence that they are most often strategic substitutes. This is different than what we typically assume in an oligopoly for-profit setting where prices enter as strategic complements. Taken together, these findings therefore have implications for important questions in the donative space such as decisions regarding large fundraising campaigns (i.e., capital campaigns), the effectiveness of matched grants, and the potential impact of mergers between NPs if they rely heavily on donations as a source of income. For example, in Aldashev et al. (2014), inelastic fundraising and strategic substitutes are necessary conditions for the successful formation of coordinated fundraising amongst NPs. Similarly, our results suggest that strategic fundraising responses outside a particular industry are nontrivial and thus any potential consolidations in one sector, for example the increased merger activity in universities that is currently transpiring, may impact other NP organizations more heavily than the setting we typically consider when competitive forces are concentrated in output markets rather than in input markets.

Our study documents what we believe are important strategic considerations in NP markets that have gone largely understudied. While our paper focuses specifically and intensely on strategic fundraising responses and the ensuing rivalry, one desired goal of this paper is to highlight the broader importance of such strategic interactions and encourage additional research in this area. There are many avenues that warrant serious consideration. Within the specifics of NP markets, our model can be used to examine to what extent this strategic fundraising rivalry is wasteful and simply reallocates donations amongst NPs. Indeed, our work draws analogs between fundraising and advertising such as whether fundraising is combative or does it expand the market; but of specific interest for advertising scholars is some unique characteristics in NP fundraising that may allow better distinctions between the persuasive, informative, and complementary roles for advertising (Bagwell, 2007). This paper is one step in what we hope becomes a broader research area into quantifying the impacts of NP strategic behavior and its potential broader applicability for our understanding of other markets.

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Figures

Figure 1: Trends in Donations and Fundraising

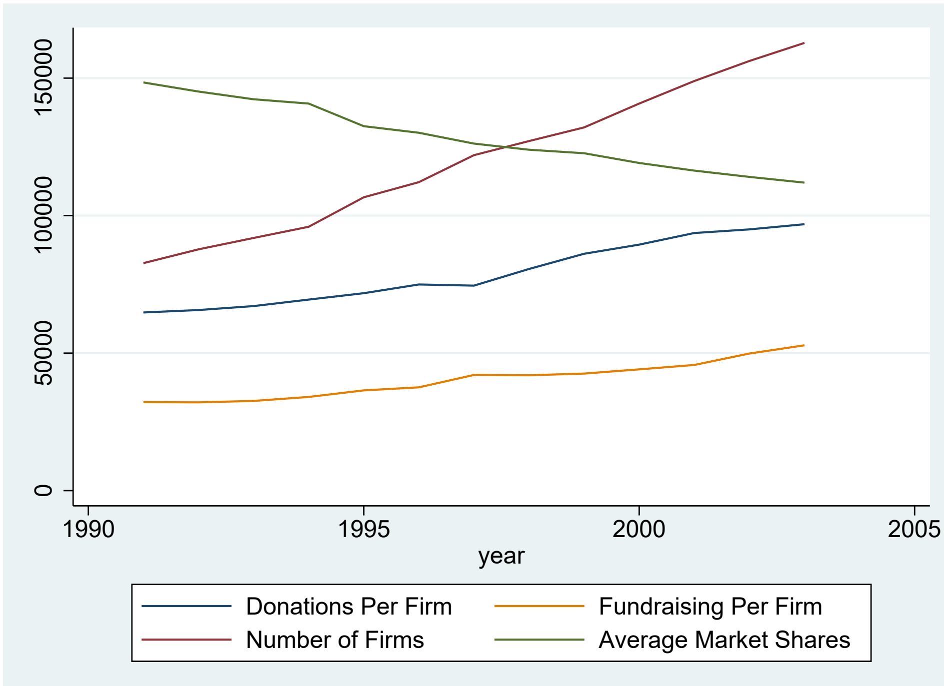
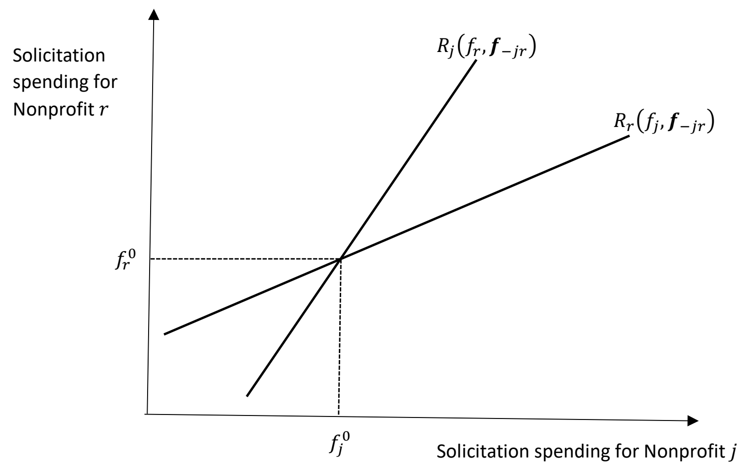


Figure 2: Reaction functions for solicitation spending

(a) Strategic complements



(b) Strategic substitutes

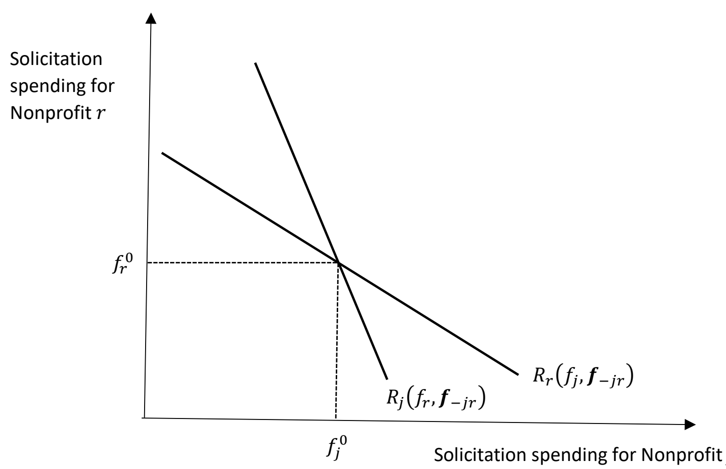
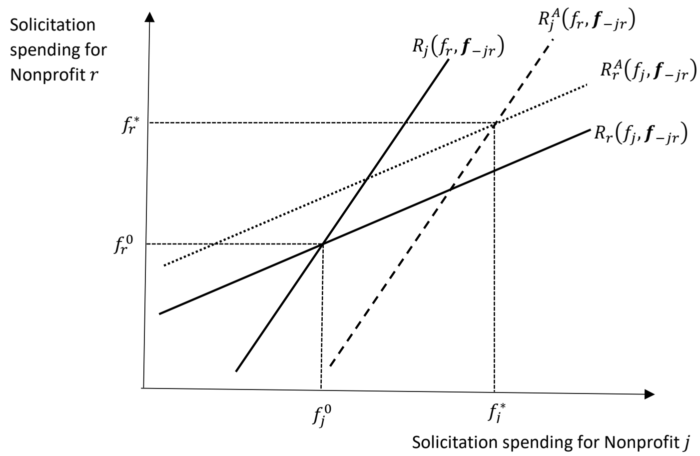


Figure 3: Shifts in reaction functions for nonprofits j and r stimulated by increased solicitation spending of a third nonprofit

(a) Strategic complements



(b) Strategic substitutes

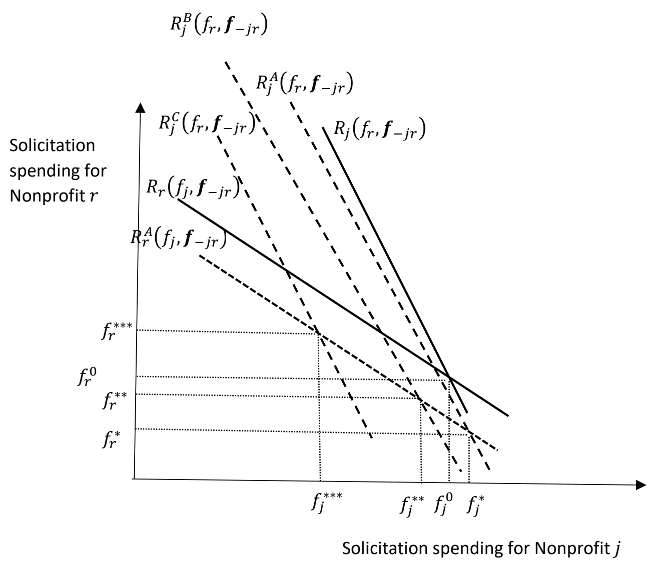


Figure 4: Strategic Fundraising Equilibria

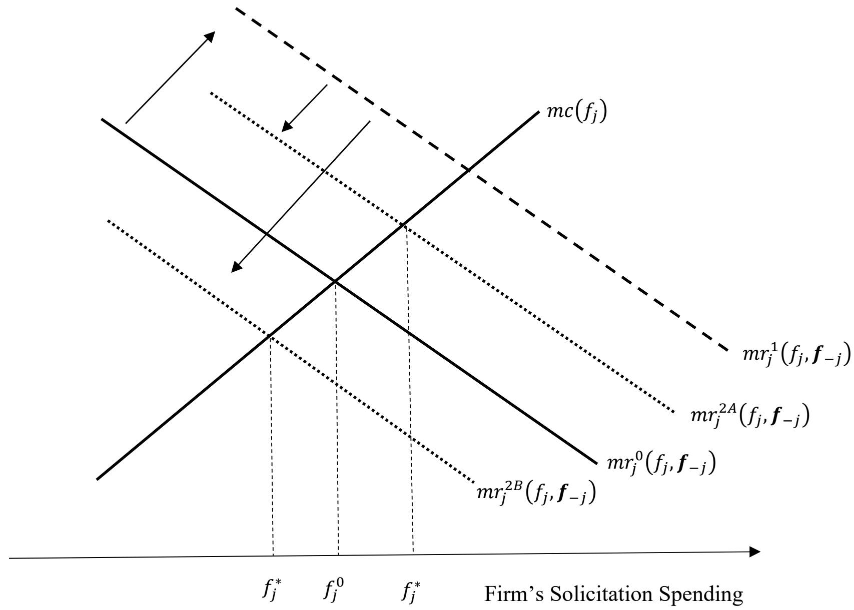
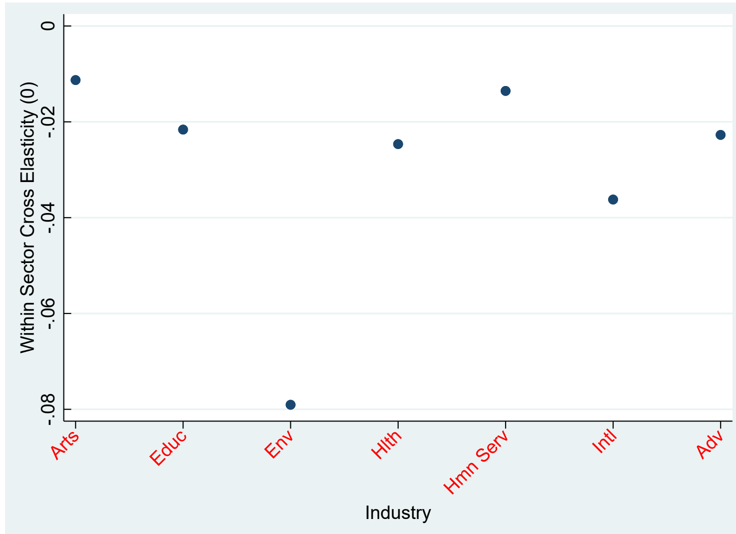
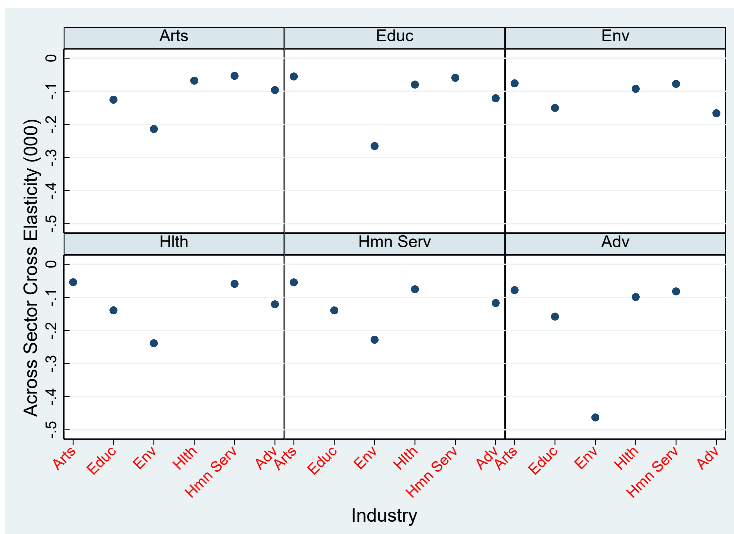


Figure 5: Cross-firm Fundraising Elasticities

(a) Within sector



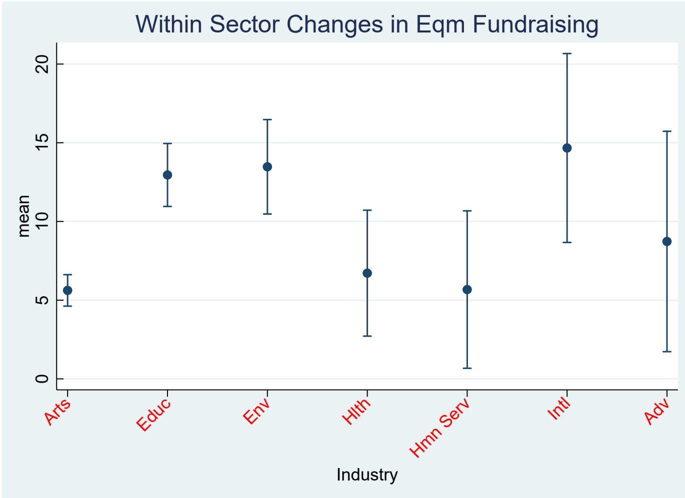
(b) Across sector



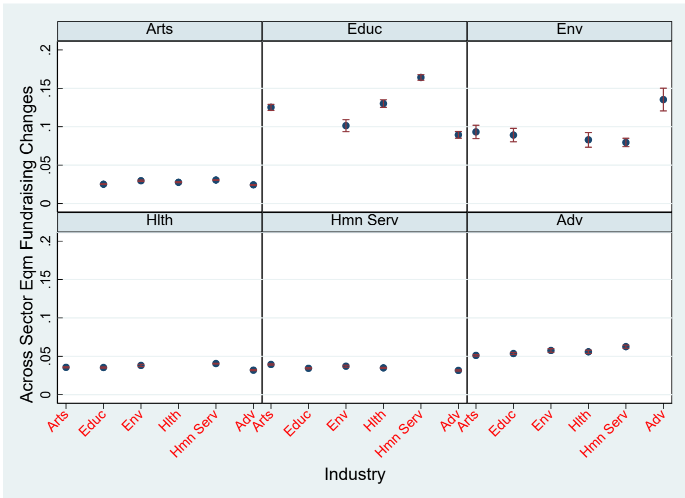
Note: We provide cross-fundraising elasticities by NP sector discussed in Section 5.2 and calculated as in equation 25.

Figure 6: Counterfactual % Changes in fundraising when NP eliminated

(a) Within sector



(b) Across sector



Note: Counterfactual estimates are calculated by NP sector as discussed in Section 5.5.

Tables

Table 1: Market Shares by Sector

Sector Number	Sector Name	Statistic	Firm Donation Share in Mkt	Firm Donation Share within Sector and Mkt	Firm Count	% of Sample
1	Arts	Mean	0.00019	0.097	7,992	16.69
		Std. Dev.	0.0014	0.195	-	-
		Min.	1.07e-09	1.07e-07	-	-
		Max.	0.0945	0.999	-	-
2	Education	Mean	0.00076	0.114	7,504	15.67
		Std. Dev.	0.0046	0.235	-	-
		Min.	7.20e-10	2.12e-07	-	-
		Max.	0.337	0.999	-	-
3	Environmental & Animal	Mean	0.0005	0.184	1,906	3.98
		Std. Dev.	0.0056	0.256	-	-
		Min.	2.40e-08	1.59e-06	-	-
		Max.	0.203	0.999	-	-
4	Health	Mean	0.0002	0.102	7,324	15.29
		Std. Dev.	0.0010	0.198	-	-
		Min.	2.44e-09	9.17e-07	-	-
		Max.	0.047	0.999	-	-
5	Human & Social Services	Mean	0.00025	0.092	18,218	38.04
		Std. Dev.	0.0011	0.187	-	-
		Min.	1.88e-10	9.12e-08	-	-
		Max.	0.093	0.999	-	-
6	International	Mean	0.00026	0.136	477	1.00
		Std. Dev.	0.001	0.255	-	-
		Min.	1.53e-08	7.03e-06	-	-
		Max.	0.024	0.999	-	-
7	Civil Rights & Advocacy	Mean	0.0003	0.098	4,468	9.33
		Std. Dev.	0.001	0.216	-	-
		Min.	6.14e-09	5.07e-07	-	-
		Max.	0.094	0.999	-	-

Note: This table gives the industry classifications and their respective markets for our sample of nonprofits. Our panel is from 1989-2003.

‘

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: By Firm				
Donation share in Mkt (%)	0.033	0.24	1.88×10^{-8}	33.70
Donation share in Sector (%)	10.2	20.5	9.12×10^{-06}	99.9
Donations (000)	2,057.60	14,447.44	0.02	1,221,300.11
Solicit (000)	169.55	1,101.22	0.001	139,710.74
Program service revenue (000)	4,826.83	40,473.88	0.001	2,228,846.97
Assets (000)	13,176.95	122,022.26	0.001	13,649,708.70
National organization	0.103	0.304	0	1
N	242,350			
Panel B: By Market-Year				
Donation share in Mkt (%)	0.104	0.391	3.83×10^{-05}	17.58
Donation share in Sector (%)	34.8	15.1	0.40	50.0
Donations (000)	1,015.87	2,177.57	1.64	88,989.23
Solicit (000)	89.57	165.28	0.050	2,330.72
Program service revenue (000)	3,069.99	8,078.81	0.250	198,286.77
Assets (000)	7,891.15	17,730.63	3.591	324,298.84
National organization	0.089	0.156	0	1
# of Firms	23.16	81.93	2	1,737
N	10,464			

Note: Source of the data: 1989-2003 990 Tax Returns. We calculate market shares of donations based on dollar value donations in our local markets by industry and year. Panel A calculates averages for each firm while Panel B averages the variables within a market and year and then averages across markets. Donations, Solicit, Program Service Revenue, and Assets are total donations, fundraising expenses, earned revenues and assets received in a year. National Organization statistics: author-calculated.

Table 3: Descriptive Linear Regression Results

Variables	(1)	(2)	(3)	(4)	(5)
Number of NPs (000)	0.0416	0.5903***	0.0342	−0.1198**	−0.2012
	(0.0286)	(0.0627)	(0.1049)	(0.0396)	(0.2011)
Number of NPs^2(000)		−0.2698***	−0.0085		0.0363
		(0.0274)	(0.0448)		(0.0880)
Log Prog Serv Rev	0.0919***	0.0917***	0.0896***	0.0918***	0.0918***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Log Assets	0.1800***	0.1793***	0.1756***	0.1804***	0.1805***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Local Mkt Time Trends	No	No	Yes	Yes	Yes
Instrument	No	No	No	Yes	Yes
Anderson Rubin				9.3496	9.3496
Anderson Rubin P-value				0.0093	0.0093
Exog				34.8149	26.5175
Exog P-value				0.0000	0.0000
Overid				0.1706	–
Overid P-value				0.6796	–

Note: *, **, *** p-value $\leq$ 10%, 5%, and 1%, respectively. Standard errors in parentheses. Specifications are discussed in Section 3.2 and equation 9. We report the Anderson-Rubin underidentification test as well as tests for exogeneity and overidentification of our instruments.

Table 4: Nested Logit Demand Estimates

Variables	(1)	(2)	(3)	(4)
Solicit	0.383*	1.003***	0.862***	0.726***
	(0.165)	(0.081)	(0.079)	(0.129)
Within group	0.162***	0.310***	0.246***	0.138***
	(0.032)	(0.014)	(0.018)	(0.0097)
Program service revenue	-0.056***	-0.109***	-0.098***	-0.085***
	(0.015)	(0.008)	(0.007)	(0.012)
Assets	0.064	-0.069***	-0.035*	0.0048
	(0.034)	(0.016)	(0.016)	(0.023)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Local Market-specific Time Trends	No	No	No	Yes
Instruments	N	N*year		
	N^2	N^2*year	N^2*year	N^2*year
	-	-	-	BLP-type
AndersonRubin	63.0277	1231.8911	438.3060	790.0363
Anderson Rubin P-value	0.0000	0.0000	0.0000	0.0000
Exog	5645.4470	8402.6723	6113.3897	13977.5508
Exog P-value	0.0000	0.0000	0.0000	0.0000
Overid	0.9847	-	-	-
Overid P-value	0.6112	-	-	-
Observations	242350	242350	242350	242350
Number of ein	47,887	47,887	47,887	47,887

Note: *, **, *** p-value $\leq$ 10%, 5%, and 1%, respectively. Standard errors in parentheses. Specifications are discussed in Section 4.1 and equation 17. We report the Anderson-Rubin underidentification test as well as tests for exogeneity and overidentification of our instruments.

Table 5: Marginal Cost Function Estimates

Variables	(1)	(2)	(3)
Solicit	0.000**	0.000**	3.41e-08***
	(0.000)	(0.000)	(1.13e-08)
Age	0.017**	0.014**	0.018***
	(0.005)	(0.005)	(0.006)
Assets	-0.037***	-0.039***	-0.035***
	(0.006)	(0.006)	(0.006)
Assets*Age	-0.001**	-0.001**	-0.001***
	(0.000)	(0.000)	(0.0003)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Local Market-specific Time Trends	No	No	Yes
Instruments	Nestid*Donative Cap	Nestid*Donative Cap; Year*Donative Cap	Nestid*Donative Cap;
AndersonRubin	24.6926	36.4421	33.2873
Anderson Rubin P-value	0.0009	0.0137	0.0000
Exog	17.9038	19.4098	17.0490
Exog P-value	0.0000	0.0000	0.0000
Observations	242350	242350	242350

Note: *, **, *** p-value $\leq$ 10%, 5%, and 1%, respectively. Standard errors in parentheses. Specifications are discussed in Section 4.2 and equation 22. We report the Anderson-Rubin underidentification test as well as tests for exogeneity of our instruments.

Table 6: Own-firm Fundraising Elasticities

Sector	Mean	Std. Error	25th Perc	75th Perc
Arts	0.8311	0.0001	0.8329	0.8424
Education	0.8287	0.0001	0.8338	0.8424
Environment/Animal	0.8207	0.0003	0.8120	0.8414
Health	0.8305	0.0001	0.8322	0.8422
Human Services	0.8316	0.0001	0.8340	0.8423
International	0.8265	0.0006	0.8283	0.8421
Civil Rights/Advocacy	0.8309	0.0002	0.8363	0.8423

Note: We provide descriptive statistics for fundraising elasticities by NP sector discussed in Section 5.2 and calculated as in equation 23.

Table 7: Diversion Ratios

Sector	Outside Good Diversion	Own Sector Diversion	Across Sector Diversion	% of across vs within sector diversion
1–Arts	80.74%	14.09%	5.17%	36.67%
2–Education	80.51%	14.22%	5.27%	37.10%
3–Env & Animals	79.52%	13.26%	7.21%	54.37%
4–Health	80.84%	13.58%	5.58%	41.06%
5–Human Serv	80.92%	13.98%	5.10%	36.50%
6–International	73.21%	14.07%	12.72%	90.37%
7–Civil Rights	76.82%	15.99%	7.19%	44.97%

Note: We provide descriptive statistics for diversion ratios by NP sector discussed in Section 5.3 and calculated as $D_{jr} = \frac{\partial s_r/\partial f_j}{|\partial s_j/\partial f_j|}$.

Table 8: Nonprofits' Fundraising Effectiveness Index

Panel A: Own-NP FRE				
Sector	Mean	Std. Error	25th Perc	75th Perc
Arts	19.9319	2.8953	0.1934	2.8535
Education	18.0288	1.5474	0.1975	3.1663
Environment/Animal	19.4069	3.0179	0.2554	3.2215
Health	33.5685	5.3686	0.2562	3.5418
Hmn Serv	94.2188	30.1601	0.4023	7.6040
International	16.5750	9.0208	0.1441	2.0492
Civil Rights/Advocacy	22.5435	4.6628	0.2528	2.9374
Panel B: Among rival nonprofit pairs within the same sector				
Percent w negative FRE elasticities	99.97			
Positive FRE elasticities for 10% increase	0.0044	0.0007	0.0000	0.0005
Negative FRE elasticities for 10% increase	-11.3445	0.6751	-0.0306	-0.0001
Panel C: Among rival nonprofit pairs across sectors				
Percent w negative FRE elasticities	100			
Negative FRE elasticities for 10% increase	-2.2670	0.1339	-0.0016	-0.0000

Note: We provide descriptive statistics for FRE in Panel A and the ΔFRE_{jr} in Panel B by NP sector discussed in Section 5.4 and calculated as in equation 26. Panel A is scaled by 10,000,000,000 while Panel B and C elasticities are multiplied by 10.

Table 9: Model-predicted mean percent Changes in firm-level Solicitation Spending by Number of Remaining Competing Firms

Sector	$N \leq 5$	$N \leq 10$	$N \leq 20$	$N \leq 30$	$N \leq 50$	$N \geq 50$
Arts	31.19	10.56	4.97	3.04	1.54	0.47
	(1.22)	(0.31)	(0.14)	(0.11)	(0.10)	(0.01)
Education	71.73	12.76	7.2	2.17	6.77	0.757
	(3.47)	(0.54)	(0.50)	(0.12)	(0.69)	(0.04)
Environment/Animal	36.93	10.29	6.05	2.7	3.06	4.31
	(2.73)	(0.55)	(0.57)	(0.18)	(0.29)	(0.41)
Health	37.33	12.52	4.45	2.48	1.36	0.536
	(1.65)	(0.44)	(0.13)	(0.10)	(0.05)	(0.01)
Human Services	33.61	11.74	4.35	2.27	1.32	0.503
	(1.00)	(0.26)	(0.09)	(0.05)	(0.01)	(0.01)
International	62.97	16.61	0.368	–	0.558	2.15
	(13.96)	(2.84)	(0.07)	–	(0.05)	(0.16)
Civil Rights/Advocacy	47.82	15.24	10.19	4.26	0.918	0.61
	(2.88)	(0.84)	(0.63)	(0.32)	(0.05)	(0.03)

Note: We provide our counterfactual estimates grouped by the number of NPs in each sector and market. Standard error of mean is in parentheses.

Table 10: Model-predicted percent Changes in Market-level Solicitation Spending

Sector from which NP is Eliminated	(1) Avg Perc Δ in NP f	(2) Perc NP with $\Delta f \geq 0$	(3) Avg Δ in Total f	(4) Avg f for Elim NP	(5) Avg Perc Δ in Total f
Arts	1.068	82.30	-107,080.85	64,773.20	-1.346
Education	2.196	83.80	-272,868.44	309,054.44	-3.169
Environment/Animal	0.654	79.90	-328,329.31	136,038.51	-0.736
Health	1.094	82.90	-99,253.69	82,024.39	-1.243
Human Services	2.105	85.80	-37,896.50	42,099.36	-1.985
International	0.348	72.60	-162,833.00	222,161.23	-0.214
Civil Rights/Advocacy	0.842	79.20	-94,259.19	122,652.10	-0.858

Note: We provide our counterfactual estimates of changes in fundraising (f) for each market-year pair and averaged over all sectors in which a firm in the representative sector was eliminated. Column (1)=Average percentage change in each NPs fundraising. Column (2)=Average percentage of NPs in each market-year that has positive change in f. Column (3)=Avg \$ change in total fundraising for each market-year. Column (4)=Avg \$ of fundraising for the NP eliminated in each market-year. Column (5)=Avg percentage change in total fundraising for each market-year.

A Appendix

A.1 Simple model of equilibrium fundraising with linear donor demand and constant marginal cost of solicitation

We construct a simple 2-nonprofit model to better solidify the underpinnings of our more general model in Section 2. Let d_i and f_i represent average donations per donor and fundraising effort, respectively, for nonprofit i for $i = 1, 2$ and let $d_i = A - bf_i - af_j$ with parameters $A > 0$, $b > 0$ and $a > 0$. This donor demand specification yields $\frac{\partial d_i}{\partial f_i} < 0$ and $\frac{\partial d_i}{\partial f_j} < 0$. The first-order effects follow Gayle et al. (2017) in interpretation–under the assumptions in that model where a nonprofit solicits the highest value donors first, additional fundraising efforts decrease the average donation per donor. Given our results in Section 2, this would imply that fundraising efforts across rival nonprofits are strategic substitutes which we will demonstrate below.

Let the total number of possible donors solicited be a function of the fundraising effort such that $N_i = \gamma_i f_i$. Even with this simple toy model, it makes clear the tension nonprofits face in increasing their fundraising efforts. Additional fundraising increases the total number of donors solicited but given that average donations per donor falls, total donations will rise but at a decreasing rate with additional fundraising.

Finally, for this simple toy model we assume marginal cost of fundraising is constant per donor solicited and equal to c. As we often assume, variable costs will rise with each additional donor solicited. With that we can define net revenue from nonprofit $i's$ solicitation operations as:

$$\begin{aligned} NR_i &= d_i \gamma_i f_i - c\gamma_i f_i \qquad (1) \\ &= (A - bf_i - af_j)\gamma_i f_i - c\gamma_i f_i \end{aligned}$$

(2)

Differentiating w.r.t f_i gives:

$$\frac{\partial NR_i}{\partial f_i} = (A - bf_i - af_j)\gamma_i - \gamma_i f_i b - c\gamma_i \qquad (3)$$

Setting equal to 0 and solving for f_i gives:

$$f_i = \frac{A - af_j - c}{2b} \qquad (4)$$

Under such a model, fundraising will be strategic substitutes such that $\frac{\partial f_i}{\partial f_j} < 0$. It also makes very clear that standard oligopoly models can't be naively applied to our setting; the differences of how fundraising enters the model as opposed to prices is key to understanding the intricacies of the model.

A.2 Sensitivity Analysis for Diversion Ratios

We implement a sensitivity analysis for the purpose of assessing the extent to which the diversion ratio estimates vary with changes in our definition of the donative capacity of local markets. For the main demand estimation, we define the donative capacity of a local market as the national per capita money donation rate multiplied by the size of the population in the relevant zip code area (local market). To implement the sensitivity analysis, we consider the following two distinct changes in the donative capacity of local markets: (*i*) A donative capacity that is 30% less than the donative capacity used in the main analysis; and (*ii*) A donative capacity that is 50% greater than the donative capacity used in the main analysis. One way to think of these donative capacity changes is to imagine that either the local market's population size, the per capita propensity to donate, or both, change in a manner that yield a 30% fall, or alternatively a 50% rise, in the donative capacity of the local market. We first re-estimate the donor demand model under each of these two donative capacities, and re-compute their implied diversion ratios, respectively.

As shown in Table A2 and Table A3, respectively, in the case where a market's donative capacity is 30% less (50% greater) than the donative capacity used in the main analysis, the associated diversion ratio estimates suggest that for most of the nonprofit sectors we consider, on average, approximately 83% (85%) of the increased donations nonprofit j receives from marginally increasing its fundraising spending comes from the outside option rather than from rival nonprofits. Furthermore, approximately 14% (15%) of the increased donations received by nonprofit j comes from moneys that rival nonprofits in the same sector as nonprofit j would have received otherwise, *ceteris paribus*. Accordingly, diversion ratio estimates under the distinct donative capacities considered are similar to the main results.

A.3 Diversion Ratio Main Estimate Details

Table A1: Diversion Ratios–Main Estimates

Sector	Title	Outside Option	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7
		Proportion of the increased donations diverted to							
1	Mean	83.90	14.64	1.42	0.62	0.67	0.96	0.45	1.25
1	SE	0.0327	0.0005	0.0008	0.0022	0.0004	0.0004	0.0011	0.0020
2	Mean	84.29	0.84	14.88	0.77	0.66	0.98	0.64	1.64
2	SE	0.0397	0.0006	0.0012	0.0032	0.0006	0.0006	0.0020	0.0030
3	Mean	84.33	0.96	1.40	14.07	0.73	1.18	0.91	2.47
3	SE	0.0968	0.0016	0.0023	0.0091	0.0014	0.0016	0.0043	0.0073
4	Mean	84.40	0.79	1.23	0.70	14.18	0.93	0.61	1.57
4	SE	0.0360	0.0006	0.0010	0.0031	0.0009	0.0006	0.0019	0.0030
5	Mean	84.69	0.79	1.21	0.66	0.60	14.63	0.60	1.48
5	SE	0.0212	0.0004	0.0007	0.0020	0.0004	0.0005	0.0014	0.0020
6	Mean	75.96	1.20	2.24	2.12	1.11	1.90	14.60	4.62
6	SE	0.3106	0.0018	0.0038	0.0109	0.0020	0.0033	0.0067	0.0103
7	Mean	81.10	1.07	1.66	1.53	0.86	1.42	1.05	16.88
7	SE	0.0828	0.0010	0.0015	0.0050	0.0009	0.0011	0.0023	0.0048

Diversion Ratio Robustness Checks–Estimates for Different Donative Capacities

Table A2: Diversion Ratios–30% less Donative Capacity

Sector	Title	Outside Option	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7
		Proportion of the increased donations diverted to							
1	Mean	-82.97	-14.40	-2.04	-0.90	-0.96	-1.39	-0.65	-1.80
1	SE	0.0441	0.0007	0.0011	0.0032	0.0006	0.0006	0.0016	0.0029
2	Mean	-83.40	-1.21	-14.80	-1.11	-0.95	-1.41	-0.92	-2.36
2	SE	0.0530	0.0009	0.0016	0.0046	0.0009	0.0009	0.0028	0.0044
3	Mean	-83.03	-1.38	-2.02	-13.91	-1.04	-1.70	-1.31	-3.55
3	SE	0.1309	0.0023	0.0033	0.0120	0.0020	0.0023	0.0063	0.0105
4	Mean	-83.65	-1.13	-1.77	-1.00	-13.80	-1.34	-0.88	-2.25
4	SE	0.0487	0.0009	0.0014	0.0044	0.0011	0.0009	0.0028	0.0044
5	Mean	-84.13	-1.14	-1.75	-0.95	-0.86	-14.39	-0.87	-2.13
5	SE	0.0286	0.0006	0.0010	0.0029	0.0005	0.0006	0.0020	0.0029
6	Mean	-71.27	-1.73	-3.22	-3.06	-1.60	-2.73	-14.46	-6.65
6	SE	0.4314	0.0026	0.0055	0.0157	0.0029	0.0047	0.0080	0.0148
7	Mean	-78.91	-1.55	-2.39	-2.21	-1.23	-2.04	-1.51	-17.68
7	SE	0.1151	0.0014	0.0022	0.0071	0.0014	0.0016	0.0033	0.0067

Table A3: Diversion Ratios–50% greater Donative Capacity

Sector	Title	Outside Option	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7
		Proportion of the increased donations diverted to							
1	Mean	-84.81	-14.63	-0.94	-0.41	-0.44	-0.64	-0.30	-0.83
1	SE	0.0244	0.0004	0.0005	0.0015	0.0003	0.0003	0.0008	0.0013
2	Mean	-85.15	-0.56	-14.75	-0.51	-0.44	-0.65	-0.42	-1.09
2	SE	0.0300	0.0004	0.0010	0.0021	0.0004	0.0004	0.0013	0.0020
3	Mean	-85.50	-0.64	-0.93	-14.00	-0.48	-0.78	-0.60	-1.64
3	SE	0.0720	0.0011	0.0015	0.0070	0.0009	0.0010	0.0029	0.0049
4	Mean	-85.16	-0.52	-0.82	-0.46	-14.27	-0.62	-0.41	-1.04
4	SE	0.0268	0.0004	0.0007	0.0021	0.0008	0.0004	0.0013	0.0020
5	Mean	-85.31	-0.53	-0.81	-0.44	-0.40	-14.61	-0.40	-0.98
5	SE	0.0158	0.0003	0.0005	0.0014	0.0002	0.0003	0.0009	0.0013
6	Mean	-79.72	-0.80	-1.49	-1.41	-0.74	-1.26	-14.51	-3.07
6	SE	0.2199	0.0012	0.0025	0.0072	0.0014	0.0022	0.0060	0.0068
7	Mean	-82.96	-0.71	-1.11	-1.02	-0.57	-0.94	-0.70	-16.08
7	SE	0.0586	0.0006	0.0010	0.0033	0.0006	0.0008	0.0015	0.0033

Counterfactual Table Corresponding to Figures 5 & 6

Table A4: Cross-firm Fundraising Elasticities

Cross-firm Fundraising Elasticity Estimates

Sector		1	2	3	4	5	6	7
1	Mean Estimates	**-0.0011**	-0.00013	-0.000214	-0.000068	-0.000054	-0.000106	-0.000096
	Std. Error of mean	0.0000025	0.0000006	0.0000033	0.0000003	0.0000001	0.000001	0.0000004
	T - Ratio	-456.76	-205.40	-64.85	-220.45	-379.43	-133.67	-270.03
2	Mean Estimates	-0.000055	**-0.0022**	-0.000265	-0.000080	-0.000059	-0.000132	-0.000121
	Std. Error of mean	0.0000005	0.000007	0.000005	0.0000005	0.0000002	0.000001	0.0000005
	T - Ratio	-120.22	-329.10	-55.29	-171.77	-306.19	-119.73	-239.13
3	Mean Estimates	-0.000076	-0.000150	**-0.0079**	-0.000093	-0.00008	-0.000177	-0.000166
	Std. Error of mean	0.000001	0.000002	0.00005	0.000001	0.0000005	0.000002	0.000001
	T - Ratio	-63.87	-93.29	-157.78	-91.78	-161.12	-72.62	-138.50
4	Mean Estimates	-0.000054	-0.000139	-0.000239	**-0.0025**	-0.00006	-0.000128	-0.000121
	Std. Error of mean	0.0000004	0.000001	0.000004	0.000006	0.0000002	0.000001	0.0000005
	T - Ratio	-121.21	-169.43	-53.96	-402.07	-310.47	-111.84	-228.73
5	Mean Estimates	-0.000055	-0.000139	-0.000228	-0.00008	**-0.0014**	-0.000130	-0.000117
	Std. Error of mean	0.0000003	0.0000006	0.000003	0.0000003	0.000002	0.000001	0.0000004
	T - Ratio	-183.56	-243.53	-76.77	-261.59	-713.11	-155.70	-322.59
6	Mean Estimates	-0.000069	-0.000177	-0.000516	-0.000105	-0.00010	**-0.0036**	-0.000246
	Std. Error of mean	0.000001	0.000002	0.000011	0.000001	0.0000007	0.00004	0.000002
	T - Ratio	-62.73	-89.95	-47.74	-106.31	-138.16	-82.69	-135.11
7	Mean Estimates	-0.000078	-0.0002	-0.000463	-0.000099	-0.000082	-0.000183	**-0.0023**
	Std. Error of mean	0.000001	0.000001	0.000007	0.0000007	0.0000003	0.000001	0.000009
	T - Ratio	-107.59	-171.00	-67.14	-151.22	-263.67	-149.02	-262.11

Table A5: Model-predicted percent Changes in firm-level Solicitation Spending

		Model-predicted percent Changes in firm-level solicitation spending of the remaining competing incumbent nonprofits after one nonprofit is counterfactually eliminated						
Sector		A Firm in sector 1 eliminated in each market	A Firm in sector 2 eliminated in each market	A Firm in sector 3 eliminated in each market	A Firm in sector 4 eliminated in each market	A Firm in sector 5 eliminated in each market	A Firm in sector 6 eliminated in each market	A Firm in sector 7 eliminated in each market
1	Mean	**5.62**	0.125	0.093	0.036	0.039	0.104	0.051
	Std. Error of mean	0.141	0.004	0.009	0.001	0.001	0.004	0.001
	T - Ratio	39.73	32.10	10.70	51.98	50.05	29.58	55.41
	Min.	-0.509	-0.176	-0.174	-0.170	-0.203	-0.174	-0.203
	No. of Cases	39711	39669	34634	39473	42324	21566	35921
	% of Cases > 0	94.14	79.86	78.35	78.97	78.98	71.10	76.52
2	Mean	0.025	**12.95**	0.089	0.035	0.034	0.077	0.054
	Std. Error of mean	0.0005	0.476	0.009	0.001	0.001	0.003	0.001
	T - Ratio	54.10	27.20	10.09	46.08	45.15	24.80	39.99
	Min.	-0.374	-0.508	-0.390	-0.374	-0.325	-0.211	-0.207
	No. of Cases	33873	33978	29022	33601	36311	16926	29801
	% of Cases > 0	71.95	89.50	73.01	73.21	73.51	66.35	69.82
3	Mean	0.030	0.101	**13.47**	0.038	0.037	0.109	0.058
	Std. Error of mean	0.001	0.008	0.708	0.002	0.001	0.007	0.002
	T - Ratio	33.80	13.00	19.03	24.05	27.49	15.94	25.82
	Min.	-0.168	-0.184	-0.500	-0.275	-0.196	-0.165	-0.165
	No. of Cases	8679	8585	7595	8472	8989	4295	7810
	% of Cases > 0	82.22	83.67	96.23	85.95	85.76	78.04	81.28
4	Mean	0.028	0.130	0.083	**6.71**	0.035	0.067	0.056
	Std. Error of mean	0.001	0.005	0.010	0.191	0.001	0.003	0.002
	T - Ratio	38.72	26.68	8.66	35.24	44.97	20.36	25.79
	Min.	-0.399	-0.177	-0.187	-0.497	-0.195	-0.146	-0.196
	No. of Cases	34094	33653	28430	33496	36294	15929	30056
	% of Cases > 0	81.96	84.28	81.99	95.09	82.87	75.30	80.91
5	Mean	0.031	0.164	0.080	0.041	**5.67**	0.076	0.063
	Std. Error of mean	0.0004	0.004	0.006	0.0005	0.108	0.002	0.002
	T - Ratio	84.28	45.05	14.41	81.17	52.61	31.73	30.75
	Min.	-0.403	-0.403	-0.218	-0.289	-0.504	-0.149	-0.177
	No. of Cases	76713	75385	61717	76209	83927	33554	64520
	% of Cases > 0	81.02	83.50	80.40	84.01	96.06	72.29	79.96
6	Mean	0.012	0.027	0.083	0.025	0.019	**14.67**	0.040
	Std. Error of mean	0.001	0.002	0.028	0.002	0.001	2.659	0.002
	T - Ratio	15.01	13.11	2.94	13.22	15.46	5.52	17.99
	Min.	-0.145	-0.147	-0.147	-0.147	-0.141	-0.506	-0.147
	No. of Cases	2203	2201	2166	2211	2209	1912	2189
	% of Cases > 0	73.26	68.61	79.55	76.66	77.23	93.62	72.36
7	Mean	0.024	0.089	0.135	0.032	0.032	0.091	**8.73**
	Std. Error of mean	0.001	0.004	0.015	0.001	0.001	0.004	0.327
	T - Ratio	45.71	20.29	9.13	43.13	40.43	22.31	26.65
	Min.	-0.210	-0.348	-0.328	-0.230	-0.258	-0.138	-0.505
	No. of Cases	18207	18057	16642	18114	18618	11333	16967
	% of Cases > 0	78.82	80.61	80.24	77.50	78.78	75.63	93.00