Competition and Nonprofit's Strategic Responses: Evidence from Fundraising in Donative Markets

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February 4, 2026

Forthcoming in *Review of Economics and Statistics*

Abstract

Nonprofit (NP) organizations rely on donations, obtained in a large competitive marketplace, to provide key social service goods. Yet most research focuses on competition in the output markets without considering inter- and intra-sector competition in the philanthropic markets where nonprofits make decisions about how much effort to put into fundraising. This paper develops and estimates a model of NP's fundraising to secure donations. We highlight the strategic nature of the fundraising decision, show theoretically that rival NP's fundraising responses can be either strategic complements or strategic substitutes and find empirically that responses are predominantly strategic substitutes. While donors are relatively inelastic to fundraising over our sample, NPs demonstrate nontrivial strategic responses to rival's fundraising. These effects are stronger within than across sectors but, in totality, the across sector impacts are important to consider. We conduct several counterfactual exercises showing that a reduction in competition increases equilibrium NP-level fundraising but decreases total fundraising in the market. NP cooperation in fundraising also decreases equilibrium fundraising levels.

JEL classification codes: L30; L13; L22

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1 Introduction

Charitable organizations in the United States, often called nonprofits, were reported to have earned $551 billion in contributions, gifts, and grants in tax year 2019, amounting to about 2.5% of US GDP (Internal Revenue Service, Statistics of Income Division, 2023). To put the size of the philanthropic market into perspective, the US airline industry reported revenues of about $248 billion (U.S. Department of Transportation, Bureau of Transportation Statistics, 2020). Charitable giving would rank 32nd based on gross receipts relative to other 3-digit NAICS code industries (U.S. Census Bureau, 2024). While donor's preferences for giving have received considerable attention, less studied is the competition that ensues between nonprofits to capture those donations. This paper focuses on that competition and highlights that 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, also have unique economic properties that aid our understanding of markets with collective goods. 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 generally 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 contributes to the line of work that highlights how nonprofits behave optimally to their funding environment by demonstrating 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

[1]See Rose-Ackerman (1982); Andreoni and Payne (2003a) as just a few examples. There are exceptions like Ekström (2018) that document donors giving without direct solicitation.

(1982), can be magnified or dampened when one introduces strategic behavior. Andreoni and Payne (2003a)'s well-known paper demonstrates theoretically and empirically how non-profits optimally shift their fundraising efforts in response to changes in government grants.[2] Aldashev and Verdier (2010) develop a model of fundraising competition highlighting the decision to spend effort on fundraising versus time on a mission-related project and allow for endogenous entry of NPs within a monopolistically competitive framework. Our work demonstrates another dimension of optimal decision making on the part of the NP by focusing specifically on the extent to which a NP can and does change its own fundraising levels in response to similar fundraising decisions made by competing NPs.

This series of actions and reactions is what we mean by strategic fundraising behavior and in general, quantifying the extent of strategic behavior by NPs has been overlooked in the literature. For example, 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 making their fundraising choices in the market. Indeed, as Gee and Meer (2020) highlight, endogeneity of fundraising choices 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.[3]

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

[2] As we discuss further below, Andreoni and Payne (2003a) show theoretically that fundraising between rival charities can be strategic substitutes but their propositions and subsequent empirical work focuses on the own-firm optimal changes to fundraising in response to changes in government grants.

[3] 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.

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.[4] 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 donor demand model in which we incorporate fundraising intensity into the utility function of donors. Building on the discrete choice demand literature (e.g., Berry (1994); Nevo (2000); Miller and Weinberg (2017)) and much like advertising models (e.g., Sinkinson and Starc (2019); 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 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

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

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); Mayo (2021, 2025)) 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 other sector.[5] 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.

Empirically there is little work that assesses or quantifies explicitly the degree of strategic interaction between nonprofits or gives 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 but focuses on spillovers within the market leaving open whether there are spillovers across markets. Xu (2024) finds evidence that a negative reputational shock to a NP increases donations to other NPs with similar missions.[6] Other

[5]Our model is static as we believe this is an important starting point for understanding nonprofit strategic behavior. As we discuss in the conclusion, our goal is to build a baseline model and set of analysis that can serve as a building block for future work that can incorporate other complexities such as endogenous entry and exit.

[6]Unlike other work discussed earlier, Xu (2024) observe fundraising effort and find little evidence that fundraising changes drive the spillovers to donations but their empirical framework does not directly test for

work also leads us to suspect strategic fundraising plays an important role. Ribar and Wilhelm (2002) investigate how the size of the donor market 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. While Ribar and Wilhelm (2002) does not consider the inter-firm interactions, the size of the donor market is likely to impact entry of nonprofits (Gayle et al., 2017) and thus the degree of strategic interaction between charities. 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 elicit donations. Conventional structural demand methodologies are powerful in this setting to estimate own- and cross-NP fundraising effects. The empirical model and estimation also highlights two of our key contributions: we quantify (*i*) the degree that donors view NPs across sectors as substitutes; and (*ii*) the direction and magnitude that NPs change their fundraising efforts in response to changes in other NPs fundraising efforts. We stress here that while related, quantifying these two effects are distinct. Our model demonstrates that fundraising efforts between NPs can be strategic substitutes or strategic complements which is distinct from donors viewing two NPs as substitutes. Strategic substitutes (complements) in fundraising refers to a NP decreasing (increasing) its fundraising effort in response to another competing NP increasing its fundraising levels. The paper and its findings highlight that standard conclusions surrounding oligopolistic behavior do not directly port over to the NP setting.

In particular, while fundraising functions in some respects similarly to prices in a standard demand model, it does not convey the same implications for firm behavior. In a standard Bertrand pricing model, the well-known result is that prices between competing firms are most often strategic complements such that a increase in price for one firm induces an increase in prices at rival firms (Bulow et al., 1985). We show, like Andreoni and Payne (2003a) and Aldashev et al. (2014), that fundraising decisions can be strategic substitutes. However, we also show the strategic response can induce strategic complementarities, even

strategic interaction.

when increased fundraising by a NP decreases donations for a rival NP. Our model focuses on a mechanism by which changes in fundraising by a competing firm alters the marginal productivity of own-firm fundraising efforts. In this framework, strategic complementarities can exist due to donor's increased salience (Scharf et al., 2022; Aldashev et al., 2014),[7] while strategic substitutes may instead exist due to increased donor fatigue. After establishing that strategic substitutes or complements can occur, we also highlight 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 NP's 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, in one of our counterfactuals, removing a NP from a market increases equilibrium fundraising at the firm level but decreases total fundraising at the market level. We show in our other counterfactual that fundraising levels at the market level also decrease when NPs coordinate their fundraising levels. We believe this is some of the first empirical evidence documenting the potential benefits to consolidation or coordinated fundraising campaigns that takes seriously the strategic nature of the choice in a competitive environment.

Our results also speak to our understanding of considering the extent to which NPs compete for donations across industry sector. The strategic effects we identify in our analysis 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 when considering the overall size of NP donative markets.

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 our data for seven distinct NP industries and presents results from descriptive linear regressions specified to examine the impacts of NP market structure in local markets on the fundrais-

[7] 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.

ing 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 private donations. In the model presented here, we do not explicitly model other revenue streams such as grants and earned revenue but make a few related points. To fully model more than one revenue stream, one needs to consider the choice of the level of effort to expend to acquire each revenue stream. This would entail comparing the marginal return from each revenue source. Thus, with multiple sources of revenues, decisions regarding optimal portfolio mix, cross-subsidization, and revenue diversification arise. While clearly important, they are not the focus of this paper.[8] Our model therefore focuses on choosing efforts and the corresponding strategic interactions for one revenue source at a time, holding efforts for other revenue sources constant. While we focus on fundraising and donations, the model can be used to consider, for example, strategic interactions between NPs choosing level of effort in acquiring an earned revenue stream (e.g., running a gift shop for example). Again, while we think highlighting and quantifying the degree of strategic interactions in the NP sector across other choice dimensions is quite important, we begin with the fundraising side given prior work that demonstrates the potential inefficiencies in and distaste for fundraising (Rose-Ackerman, 1982; Andreoni and Payne, 2003a). We also note here that, consistent with our data, government grants

[8] In our view, our understanding of the implications of NPs' strategic solicitation behavior of private donations 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.

are included both in the revenue (i.e., donations) and in the efforts for generating such revenue (i.e., what we denote as fundraising efforts). This modeling choice does not diminish our theme of highlighting the importance of strategic interaction and competition between nonprofit organizations,[9] but it does mean that our paper cannot speak to any substitution between efforts to raise donations versus government grants.[10] We also subsume the cost of providing the charitable service into the fixed costs of fundraising.

Our goal is to estimate the joint strategic fundraising choices within and across sectors. Therefore, let ED_{jm} represent expected private donations for NP firm j in market m. We specify that,

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

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. Equation (1) recognizes that NP $j's$ share of private donations, s_{jm}, is also a function of other revenues, OR_{jm}, it receives, i.e., revenues from sources other than private donations (e.g., government grants), as well as other revenues received by rivals to NP j, $\mathbf{OR}_{-j,m}$, i.e., $\mathbf{OR}_{-j,m} = \mathbf{OR}_m \setminus OR_{jm}$, where $\mathbf{OR}_m$ is a vector of other sources of revenues secured by the NPs in market m. In the case where these other revenues are government grants, a rationale why private donations to NPs might be affected by the government grants received by them is that private donors may perceive government grants to a NP as a substitute, or complement, to their own private donation (Andreoni and Payne, 2003a) and therefore may accordingly change the level of their private donations in response to government grants received by the relevant NP. As suggested above, we treat these other sources of revenues, $\mathbf{OR}_m$, as exogenous and fixed in our model for the purpose of focusing on NPs' strategic

[9] Indeed, Aldashev et al. (2014) demonstrate that the introduction of government grants (absent endogenizing effort spent to acquire government grants) does not change the result of whether fundraising is a strategic substitute/complement.

[10] This also means that our preferred model presented here cannot distinguish between indirect crowd-out and strategic interactions. We return to discuss this limitation in the data section. However, the model outlined in equation 1 allows for exogenous shifts in government grants. The shifts in marginal revenue discussed in Section 2.1.3 also show a result analogous to Andreoni and Payne (2003a) i.e., such a shift would decrease own-fundraising effort.

solicitation of private donations. Accordingly, for simplicity we suppress the notation of ED_{jm} being a function of OR_{jm} and $\mathbf{OR}_{-j,m}$ in subsequent equations.

PD_m is the aggregate potential money donations, i.e., the donative capacity of local market m. The estimable parameters in parameter vector θ capture donor's preferences for donating to the nonprofit and will be further detailed in Section 4 when we discuss how we take this model to the data. We also note here that PD_m is our nonprofit analog to the conventional market size parameter for such models.

Let the cost NP j incurs from soliciting private donations 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 NP $j's$ operations for soliciting private donations 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, $\mathbf{f}_{-j,m}$. Our model is specified to explain "short-run" strategic interactions between NPs with respect to their choice of fundraising to secure private donations. Therefore, our model envisions a "short-run" planning horizon for each NP in determining their optimal fundraising decisions conditional on other predetermined firm-level and market-level attributes. 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:

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

Thus the nonprofit chooses fundraising to maximize their net-revenue. Note that, as discussed in the introduction, this provides flexibility in how fundraising influences total donations.[11]

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, i.e., the "short-run" marginal revenue obtained by the relevant nonprofit due to a marginal change in the intensity of its solicitation activities; 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, i.e., the "short-run" marginal cost incurred by the relevant nonprofit due to a marginal change in the intensity of its solicitation activities.

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, what we refer to as strategic complements, 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, defined as strategic substitutes, prescribes that a NP's best response is to decrease its solicitation spending whenever rival NPs increase their solicitation spending, and vice versa.[12]

[11] As an example, fundraising can have an advertising function to promote or differentiate the nonprofit. In our model, such a mechanism would still potentially impact donations. However, we do note that the impact to donations is assumed to occur in the current period since our model is static. But as discussed in other areas, given the lack of work in this area, we begin with a static model with the goal that future research can build additional complexities such as dynamic concerns.

[12] The concept of strategic substitutes and complements is most familiar in Bertrand and Cournot oligopoly models. Our concepts are similar but as emphasized earlier, our framework demonstrates why we need more explicit consideration to the NP setting as fundraising does not enter in the same manner as prices. For

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 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:[13]

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

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

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.

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). We also note that while the model assumes homogeneous firms our empirical model builds richness into the demand and cost models which allows for nonprofit and donor heterogeneity.

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

We turn to the denominator in equation (8) 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 $\frac{\partial^2 s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}^2} < 0$.[14] Therefore, donations generated by soliciting more potential donors generates additional revenue, but each additional donor has a lower expected donation. Thus, we note that $-[\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}^2}PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}] > 0$ will occur when the change in marginal revenue from additional fundraising exceeds the change in marginal cost. With $\frac{\partial^2 s_{jm}(\mathbf{f}_m;\theta)}{\partial f_{jm}^2} < 0$, this will obviously hold when a NP's marginal cost are constant or increasing in its solicitation activities, i.e., $\frac{\partial mc_{jm}}{\partial f_{jm}} \geq 0$. However, even if marginal costs are decreasing as a function of increased fundraising effort ($\frac{\partial mc_{jm}}{\partial f_{jm}} < 0$), the denominator in equation (8) will be positive as long as the *change* in marginal revenue with increased fundraising declines at a faster rate than the *change* in marginal cost. In other words, when $\frac{\partial mc_{jm}}{\partial f_{jm}} < 0$, the necessary condition for a positive denominator in equation (8) is $\frac{\partial mc_{jm}}{\partial f_{jm}} > \frac{\partial^2 s_j m(f_m;\theta)}{\partial f_{jm}^2}PD_m$. Our theory condition that the denominator in equation (8) be positive is thus not very restrictive and also realistic given the common assumption that additional revenue from donors is harder to acquire as a NP moves away from donors that are more closely matched to the NPs mission (Andreoni and Payne, 2003a). We also note that this condition holds for all observations in our data at the estimated values of our demand and marginal cost parameters.

With the denominator in equation (8) positive, the sign of $\frac{df_{jm}}{df_{rm}}$ only 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). Formally, the second-order cross partial, $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}}$, measures how $\frac{\partial s_{jm}}{\partial f_{jm}}$ changes due to a marginal change in f_{rm}. The first-order partial, $\frac{\partial s_{jm}}{\partial f_{jm}}$, measures the effectiveness or efficiency of NP j's solicitation activities in securing donations for fulfilling its mission. Accordingly, $\frac{\partial^2 s_{jm}(f_m;\theta)}{\partial f_{jm}\partial f_{rm}} = \frac{\partial(\frac{\partial s_{jm}}{\partial f_{jm}})}{\partial f_{rm}}$ 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

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

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.

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.[15]

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.

2.1.3 Relating to Marginal Revenue and Marginal Cost

As another way of previewing our main results and emphasizing the importance of considering and quantifying the strategic interactions of nonprofits, 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.[16]

Second, as discussed above, our necessary condition for marginal costs is that marginal costs are either non-decreasing or if decreasing, the decline in marginal revenue as fundraising efforts increases is faster than the decline in marginal costs. We reflect this with three

[15] 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.

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

depictions of increasing, constant, and decreasing marginal costs (mc_I, mc_C, and mc_D respectively) 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 donor demand such that marginal revenue shifts to the right. Among several factors, this marginal revenue shift could be driven by: (*i*) a change to donor's preferences; or (*ii*) consistent with Andreoni and Payne (2003b) and our discussion and model a decrease in other revenue sources (e.g., a decrease in government grants); or (*iii*) as we subsequently consider in our counterfactuals and the converse of entry considered in Aldashev and Verdier (2010), a competitor is removed from the market. In any of these cases, 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 ($f_{I_j}^*$, $f_{C_j}^*$, or $f_{D_j}^*$) 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, ($f_{I_j}^* *$, $f_{C_j}^* *$, or $f_{D_j}^* *$), 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.

3 Initial Trends and Data

3.1 Data

The donation and fundraising data are for 501(c)3 public charities who filed a 990 tax return from 1989-2003 (National Center for Charitable Statistics, 1989-2003).[17] We intentionally focus our analysis during this time period with the goal of establishing a baseline model and empirical estimates that allow us to document the presence of strategic behavior. While there is mounting evidence of strategic *mis*-reporting behavior in fundraising once monitoring and

[17]Private foundations are also required to file a 990-PF but our focus is on organizations that produce rather than fund charitable products and services. Although most NPs are exempt from federal income taxation, the IRS requires that all public charities file a 990 tax return annually if their gross receipts are greater than $25,000.

rating of such expenses was introduced (Mayo, 2025), that type of strategic behavior is not the specific focus of this paper. Distinguishing between different types of strategic behavior (i.e., stemming from conventional competitive forces, increased donor sensitivity to higher fundraising,[18] or underreporting due to third-party monitoring) is clearly important, it would require a model of conduct related to monitoring and given the paucity of work in this area and our lack of existing empirical estimates with no third-party monitoring, we begin here.

We use this data to obtain information on a nonprofit's yearly donations and fundraising intensity. An advantage of this particular dataset is that we observe essentially the universe of all filing nonprofit public charities. A disadvantage however is that this dataset aggregates individual and corporate giving with government grants and thus we cannot distinguish between these two revenue sources. We however view this as a minor limitation given that nonprofits clearly expend effort on raising government grants and it is unclear where they report expenditures for these efforts as there is no corresponding line item in the tax return where NPs would report efforts expended to acquire government grants. Thus our measures of strategic interaction should be viewed as an aggregate measure for joint efforts for generating donations and grants. We note here that this dataset is therefore not well suited in disentangling strategic interaction in fundraising from the well-known indirect crowd-out identified by Andreoni and Payne (2003a).

The data also contain other financial characteristics. Firm size is correlated with fundraising levels but is a long-run decision; we proxy for size of the nonprofit 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.[19]

[18] We note that we estimated our demand model using 990 tax return data from 2011-2019 and indeed find evidence of increased donor sensitivity. Our coefficient on *solicit* is larger as is the own-fundraising elasticity. However, we also highlight here another potential source of differences in estimates; there was a major reform to the 990 tax form in 2008 and the place where fundraising expenses are reported moved. In the early years, there appears to be an issue with reporting this expense correctly and we cannot discern whether the lack of information on fundraising expenses to due to the NP not filling out the form correctly or difficulty by the data team (the IRS and/or Urban Institute where we source the data) in properly extracting the data. That is why this new data begins in 2011. Keeping these caveats in mind, we also calculate our second derivatives and indeed find evidence of strategic substitutes for more recent years. We provide these newest estimates and discussion in an online appendix but emphasize caution in drawing strong conclusions about donor sensitivity in light of our above discussion.

[19] In robustness checks provided upon request, we find similar demand estimates for our key parameters

Measurement error in the financial information exists, particularly given that most of the tax forms are not audited (Tinkelman, 2004). We delete firm-year observations reporting negative contributions, fundraising expenses, program service revenues, or assets. In addition, in all cases where we observe zero fundraising expenses, we observe positive donations. Indeed, of the firms reporting zero fundraising expenses at least once in the sample, more than 75 percent report zero fundraising expenses in more than 75% of their observed data. Given concerns about how an organization could collect donations if no fundraising effort is exerted and also because our demand model uses logged specifications, we also remove any observations reporting zero contributions, fundraising expenses, program service revenues, or assets.[20]

To calculate the market shares for each firm, we follow the convention in the literature and define the market as a local market area based on connecting zip codes as this decreases concerns about larger markets creating upward bias on the degree of competition.[21] We also define NPs based on their primary missions as reported by the National Taxonomy of Exempt Entities, similar to the NAICS codes.[22] Some industries could be classified in multiple sectors given the subjective nature of the classification.[23] Although we cannot ensure completely that we capture all of the NPs in a particular sector, choosing services that are well-defined with a clear mission decreases the measurement error of identifying all competitors.

Each NP's market share is therefore calculated as the ratio of its donations relative

when we estimate demand separately for nonprofits that have at least one year where earned revenues make up a larger proportion of total revenues than donations. The only exception is that, as expected, we find no significance on the coefficient on program service revenue for nonprofits that depend heavily on donations for revenues.

[20]Another concern relates to the possibility of under or over-reporting on donations and fundraising expenses to meet particular conventional thresholds (Mayo, 2025) and its potential subsequent impact on our within group share estimation. In particular, we recognize that we may be observing zero or negative values in one year because nonprofits may shift fundraising, etc. from one year to another. 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) and also limit our main analysis to years prior to increased scrutiny on fundraising expenses.

[21]To be more precise, we construct markets using Census places following the methodology in 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.

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

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

to potential donations in that market-year. The within group market shares are similarly calculated but use total donations in the chosen industry for that market-year. To close the empirical model, we need to calculate the market size or market potential, which recall in our setting we refer to as the donative capacity. We follow recommended standard practice as in Nevo (2000) and calculate the market size large enough to ensure that market shares are positive for all NPs. We therefore 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 local market for that year.[24] We test the sensitivity of our market size definition in Appendix A.2.3.

Table 1 lists the number of organizations by NTEE code and our broad seven industry types included in the estimation.[25] 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.

Because our demand and cost equations are logged, our sample only includes firm-year observations with positive values.[26] We therefore have 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.

[24] The donation rates are obtained from charitable giving by households that itemize deductions from Internal Revenue Service for 2006. The size of the population uses Census county population data aggregated to our market level for each year.

[25] 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.

[26] As a robustness check, we estimate Table 4 including observations with zero program service revenues by adding one before we log the variable. The results are qualitatively similar.

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:

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

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).[27] For example, the number of NPs in the market is clearly endogenous since 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.

[27] 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 elicit 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.[28]

[28] We note here that these results and our counterfactual results are similar in sign to estimates in the small

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 Donor's 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 $j = 1, \ldots, J_m$. As is typical for discrete demand models, Nevo (2000), we also specify an outside option, $j = 0$, such that donor i can choose to not donate to any of the J_m NP firms. 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, $j = 0, 1, \ldots, J_m$.[29]

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:

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

reduced form fundraising literature such as Thornton (2006) but also demonstrate that failure to account for the endogeneity of market structure produces underestimates of the effect of competition.

[29] 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.

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., $0 \leq \sigma < 1$, 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:

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

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 (firm and market) 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.[30] Donors will give to the charity that maximizes their utility.

In market m, let Γ_{km} be the set of 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:

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

[30] 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.

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 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 "short-run" marginal cost:

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

where estimable parameter ρ_f reflects the "short-run" cost technology embodied in NPs' solicitation activities, i.e., ρ_f determines the extent to which the relevant NP's marginal cost changes as it increases its own solicitation intensity; and c_{jmt} is a composite of other predetermined non-fundraising cost components that influence the level of marginal cost. The left-hand side to equation (18) is recovered from our demand estimation given our assumption of net-revenue maximization. To be specific, let term $\frac{\partial s_{jmt}(\mathbf{f}_m;\theta)}{\partial f_{jmt}} \times PD_{mt}$ in equation (5) at time t be denoted by mr_{jmt}, i.e.,

$$mr_{jmt} = \frac{\partial s_{jmt}(\mathbf{f}_m;\theta)}{\partial f_{jmt}} \times PD_{mt} \tag{19}$$

where the right-hand-side of equation (19) is a function of variables and parameter estimates in the donation share function, i.e., $mr_{jmt}(\mathbf{f}_m, \mathbf{x}_m; \theta)$. As such, with vector of variables $\mathbf{f}_m$ and $\mathbf{x}_m$ along with parameter estimates $\hat{\theta}$, we can use equation (19) to obtain estimates, $\widehat{mr}_{jmt}(\mathbf{f}_m, \mathbf{x}_m; \hat{\theta})$. The first-order condition in equation (5) along with equations (18) and (19) imply:

$$\widehat{mr}_{jmt} = exp(\rho_f f_{jmt} + c_{jmt}) \tag{20}$$

Our model thus measures how marginal costs change as the NP increases their solicitation intensity. Recall that f is measured as the dollar amount of solicitation activities. While a measure of the actual products produced in fundraising would be ideal, our measure of fundraising is analogous to production function settings that use total revenue for outputs (Syverson, 2004) and thus acknowledge that this dollar-based measure confounds the monetary costs with the choice of inputs. However, our model explicitly acknowledges this shortcoming and allows for greater flexibility in the role that fundraising plays in NP costs in that we incorporate 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, such that (suppressing our t index) i.e., $\frac{\partial mc_{jm}}{\partial f_{jm}} = \rho_f exp(\rho_f f_{jm} + c_{jm}) > 0$, and $\frac{\partial^2 mc_{jm}}{\partial f_{jm}^2} = \rho_f^2 exp(\rho_f f_{jm} + c_{jm}) > 0$. Like Aldashev and Verdier (2010), we explicitly consider the opportunity cost of fundraising. 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.[31]

[31] One can show that this also would imply an increasing returns to scale technology in our model. However,

We highlight that in addition to being a salient piece of modeling 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.

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

$$c_{jmt} = \rho_0 + \rho_1 w_{jmt} + \tau_j^c + \nu_t^c + \Sigma_{m=1}^{M} \phi_m^c (L_m \times T_t) + \epsilon_{jmt}^c \tag{21}$$

where w_{jmt} is a vector of year specific, cost-shifting variables, ρ_1 a vector of associated parameters and ϵ_{jmt}^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. Taking the logarithm of both sides of equation (20), and using equation (21) to substitute for c_{jm}, yields the following regression equation:

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

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 (17) 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 (17).

Consistent with our theoretical model, our empirical model is specified to explain "short-run" strategic interactions between NPs with respect to their choice of fundraising to secure private donations. Therefore, our empirical model envisions a short-run planning horizon for each NP in determining their optimal fundraising decisions. While non-fundraising firm

given that we do not estimate fixed costs, such an implication is likely biased so we refrain from such conclusions.

attributes (e.g., firm size; revenue portfolio choices; etc.) are no doubt the result of decisions made by each NP, analogous to similar arguments in the for-profit literature (Berry et al., 1995; Eizenberg, 2014), such attributes are optimally determined within the medium to long-run planning horizon before fundraising decisions. Therefore, we employ BLP-motivated instruments of the mean of asset values and program service revenues across a firm's rivals within the sector.[32] Again, analogous to other settings, these NP rival characteristics are correlated to a NP's fundraising and within sector donation shares through competitive pressures but are uncorrelated to unobserved donative demand shocks.

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}.

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}.

[32] 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 focus the main results in this paper on a nested logit estimation framework since (i) using a random coefficients model produced very similar estimates and (ii) the with-in group parameter in the nested logit provides a more intuitive approach to modeling within versus across sector competition.

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.[33] 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 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.

In our NP setting, when we discuss the properties of the fundraising marginal cost function, these properties relate to how the function behaves with respect to short-run changes in the level of fundraising, which is consistent with the short-run planning horizon focus of the model with respect to optimal fundraising decisions. Therefore, when we discuss whether NPs' fundraising marginal cost is increasing versus decreasing it is with respect to changes

[33] 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.

in a NP's level of fundraising, and therefore these are necessarily short-run properties of the cost function. While our analysis in the paper focuses on short-run equilibrium changes, to properly identify these short-run equilibrium changes it is important our model controls for long-run attributes (e.g., firm size, age, etc.) on marginal cost.

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 alternative instrument sets.[34] 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. The sign on assets is suggestive of some advantages of scale in the fundraising production function but we stop short of deeming this to be conclusive evidence given our prior discussions that the model is focused on short-term strategic interactions.

5.2 Fundraising Elasticities

Our model specification allows us to calculate own-NP and cross-NP fundraising elasticities. We give the precise formulas in Appendix A.2.1 but note here that they follow the conventional notion of measuring how market shares change for firm i as either that firm increases its own fundraising efforts (own-firm) or a competitor changes their fundraising efforts (cross-firm). We measure the cross-firm elasticity for competitors within the same sector as well as competitors across sectors.

Table 6 reports mean own-NP elasticities using our preferred demand specification from column (4), Table 4. Our own-NP fundraising elasticities are reported by sector. All elasticities are significantly different from and less than one, suggesting inelastic demand. The elasticities are closely grouped around 0.83. While inelastic demand may at first glance seem counterintuitive, as suggested by our discussion of strategic decisions, we should not antici-

[34] 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.

pate 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 (A5), 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.[35] 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.

5.3 Diversion Ratios

To get a more thorough understanding of donor substitution behavior across competing NPs, we also compute diversion ratios. Diversion ratios complement our fundraising elasticity estimates by quantifying how much donors divert giving from one NP to another when a NP increases its fundraising efforts.[36] 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

[35] A numerical table for the cross-firm fundraising elasticities is in the Appendix, Table A3.

[36] We discuss more precise details in Appendix A.2.2. 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).

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.[37] 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.[38]

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 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, i.e., fundraising effectiveness, for a NP changes as a competing NP increases its fundraising efforts. NP j's fundraising effectiveness (FRE) is captured by $\partial s_j/\partial f_j$. We can then consider how NP j's FRE is influenced by the solicitation spending of rival NPs which is captured by the second-order cross-partial, denoted as ΔFRE. Details on the calculations are in Appendix A.2.4.

Table 8, Panel A reports summary statistics on FRE for NPs by sector.[39] Human service NPs on average have the most effective fundraising campaigns relative to NPs in the other

[37] Appendix A.2.3 presents robust results with different scales for the donative capacity.

[38] 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%.

[39] 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.

sectors of our study. All the mean measures of the FRE index reported in the table are positive and statistically different from zero at conventional levels of statistical significance.

Table 8, 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 and statistically significant,[40] there exists a small set of within sector NP pairs, less than 1% among 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%.

Given that the vast majority of cases have a negative ΔFRE_{jr}, we can take this as strong evidence of strategic substitutes for NP fundraising. 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%. We also find strong evidence of strategic substitutability across sectors–the scaled metric ΔFRE_{jr} is negative for all cross-sector rival pairs of NPs, statistically significant 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.

[40] We bootstrap the standard errors for ΔFRE_{jr} to provide further statistical confidence of strategic substitutability. The bootstrap standard errors are computed using a parametric bootstrap procedure analogous to the one used and described in (Ivaldi and Verboven, 2005) (see footnote 25 on page 686 in that paper).

5.5 Implementing Counterfactuals

The demand and supply-side framework above can be used to perform various counterfactual experiments of interest. We use the framework to perform two counterfactual experiments, *Experiment 1* and *Experiment 2*, respectively. *Experiment 1* is designed to investigate the impact on NPs' optimal choice of their solicitation efforts due to elimination of one NP firm from the same sector in each market, while *Experiment 2* is designed to investigate how NPs' fundraising spending would change if rival NPs collude/coordinate, instead of compete, with respect to determining their fundraising spending. The implementation details of each experiment are discussed in Appendix A.3.

5.5.1 Counterfactual Predictions from Experiment 1

Per our discussion in Sections 2.1.2 and 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.[41] 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 Figure 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 7, the totality of the fundraising

[41] The table with estimates and standard errors is provided in Appendix Table A4.

changes are non-trivial. Back of the envelope calculations based on these estimates suggest that an 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.

Experiment 1 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.[42] 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

[42]Percentages disaggregated by sector are shown in the Appendix, Table A4.

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 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.

5.5.2 Counterfactual Predictions from Experiment 2

Figure 7 shows time series plots comparing observed mean local market-level solicitation spending to two alternatives where NPs coordinate their fundraising efforts. The first shows model-predicted mean market-level solicitation spending when there is only sector-level fundraising cooperation in a market and the second shows model-predicted mean market-level solicitation spending when *all* rival NPs in a local market practice fundraising cooperation.

Our results suggest that fundraising cooperation/collusion reduces solicitation spending. Specifically, in each year mean market-level actual solicitation spending exceeds the model-predicted mean solicitation spending when there is fundraising cooperation either at the sector level within a market or at the local market level. Actual fundraising spending is higher by a mean 23% (27%) as compared to the counterfactual scenario in which rival NPs practice sector-level (market-level) fundraising collusion. Therefore, the model-predicted evidence reveals that fundraising spending becomes lower with more extensive fundraising cooperation between rival nonprofits.

This counterfactual provides to our knowledge some of the first empirical evidence that coordinated fundraising campaigns can be successful at lowering fundraising efforts. These findings have implication for merger policy; such efficiency gains has not typically been a prominent argument when considering NP antitrust but perhaps should be more broadly considered as a benefit to NP mergers (Philipson and Posner, 2009). Our counterfactual gives in some sense an upper bound on the efficiency gains since it considers cooperation of all NPs in a sector/market but still points to consideration of such benefits. Moreover, coordinated fundraising campaigns such as those run by the United Way or the Giving Tuesday campaigns, have been promoted as a way to increase donations (Eckel et al., 2020). Our results suggest lower fundraising levels should be considered as a benefit to both market interventions. Of course, this is but one element of a full welfare analysis; our findings suggest that such additional research would be warranted to explore the complete cost/benefit analysis.

6 Discussion & Conclusion

Our paper provides a framework to gain better insight into competition and strategic interactions in nonprofit (NP) donative markets. We provide a new lens on important questions about the intensity and nature of competition within and across NP sectors. This paper links 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 and provide concrete empirical evidence of NPs behaving optimally and strategically in the competitive donation environment. Our estimates suggest that donors are relatively inelastic to the level of own-fundraising for our sample period 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. This insight is more apparent when competition between NPs is viewed from the lens of donative markets rather than NP's final services provided or their output market. 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 between NPs in a donative market setting. Increased fundraising by a NP can in theory decrease or increase a rival's fundraising efforts, defined as rival's fundraising being either strategic substitutes or strategic complements respectively, and we find evidence that they are predominantly strategic substitutes. Our framework highlights that strategic substitutes/complements is distinct from measuring donor's substitution patterns in their giving to NPs and that the NP framework warrants special consideration because it is different than what we typically assume in an oligopoly for-profit setting where prices often enter as strategic complements. Our analysis also suggests that equilibrium fundraising spending decreases with more extensive fundraising cooperation/collusion between rival nonprofits.

Taken together, these findings call greater attention to the role of NPs behaving optimally in a competitive environment and has implications for important questions in the donative space. As just a few examples, a line of experimental research, both in the field and the lab, have highlighted the benefits of particular fundraising approaches such as leadership gifts and matching grants (see Andreoni (2006); Karlan and List (2007); Filiz-Ozbay and Uler (2019); Huck et al. (2015); Diederich et al. (2022) just to name a few). To establish donor's incentives related to such fundraising techniques, the role of competitor's reactions is generally held constant. But our study suggests the following question: To what extent does the effectiveness of these techniques change when other NPs change their fundraising effort? Similarly, in Aldashev et al. (2014), inelastic fundraising and strategic substitutes are necessary conditions for the successful formation of coordinated fundraising amongst NPs. Our study provides confirmation that such an environment exists to support coordinated fundraising and also provides evidence from our counterfactual results that such coordination decreases total fundraising efforts. Finally, 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 fundraising decisions and donations at 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 that indeed NPs are acting strategically and that behavior should be taken seriously in future NP research and policy decisions. There are many avenues that warrant serious consideration. Within the specifics of NP markets, we believe our model can serve as a baseline to build additional analysis such as modeling strategic behavior in the presence of third-party monitoring of fundraising costs, modeling the optimal revenue portfolio mix (i.e., donations, grants, earned income, etc.) or incorporating endogenous entry and exit to more precisely study implications of mergers for philanthropic markets. Our model can also 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.

References

Aldashev, G., M. Marini, and T. Verdier (2014): "Brothers in alms? Coordination between nonprofits on markets for donations," *Journal of Public Economics*, 117, 182–200.

Aldashev, G. and T. Verdier (2010): "Goodwill bazaar: NGO competition and giving to development," *Journal of Development Economics*, 91, 48–63.

Andreoni, J. (2006): "Leadership giving in charitable fund-raising," *Journal of Public Economic Theory*, 8, 1–22.

Andreoni, J., J. List, and J. Meer (2022): "What Economists Give to Charitable Fundraising," *Working paper.*

Andreoni, J. and A. A. Payne (2003a): "Do Government Grants to Private Charities Crowd Out Giving or Fund-raising?" *American Economic Review*, 93, 792–812.

——— (2003b): "Do Government Grants to Private Charities Crowd Out Giving or Fund-raising?" *American Economic Review*, 93, 792–812.

Bagwell, K. (2007): "The economic analysis of advertising," *Handbook of industrial organization*, 3, 1701–1844.

Berry, S. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, 25, 242–262.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile prices in market equilibrium." *Econometrica*, 63, 841–890.

Bonnet, C., P. Dubois, S. B. Villas-Boas, and D. Klapper (2013): "Empirical Evidence on the Role of Nonlinear Wholesale Pricing and Vertical Restraints on Cost Pass-Through," *The Review of Economics and Statistics*, 95, 500–515.

Bresnahan, T. F. (1989): "Empirical Studies of Industries with Market Power," *Handbook of Industrial Organization, Edited by R. Schmalensee and R.D. Willig*, 2, 1011–1057.

Bresnahan, T. F. and P. C. Reiss (1990): "Entry in Monopoly Markets," *The Review of Economic Studies*, 57, 531–553.

——— (1991): "Entry and Competition in Concentrated Markets," *The Journal of Political Economy*, 99, 977–1009.

Bulow, J. I., J. D. Geanakoplos, and P. D. Klemperer (1985): "Multimarket oligopoly: Strategic substitutes and complements," *Journal of Political economy*, 93, 488–511.

Conlon, C. and J. H. Mortimer (2021): "Empirical properties of diversion ratios," *The RAND Journal of Economics*, 52, 693–726.

Dai, M., Q. Liu, and K. Serfes (2014): "Is the effect of competition on price dispersion non-monotonic? Evidence from the US airline industry," *Review of Economics and Statistics*, 96, 161–170.

Deryugina, T. and B. M. Marx (2021): "Is the supply of charitable donations fixed? evidence from deadly tornadoes," *American Economic Review: Insights*, 3, 383–98.

Diederich, J., C. C. Eckel, R. Epperson, T. Goeschl, and P. J. Grossman (2022): "Subsidizing unit donations: Matches, rebates, and discounts compared," *Experimental Economics*, 25, 734–758.

Eckel, C., B. Guney, and N. Uler (2020): "Independent vs. coordinated fundraising: Understanding the role of information," *European Economic Review*, 127, 103476.

Eizenberg, A. (2014): "Upstream innovation and product variety in the us home pc market," *Review of Economic Studies*, 81, 1003–1045.

Ekström, M. (2018): "Seasonal altruism: How Christmas shapes unsolicited charitable giving," *Journal of Economic Behavior & Organization*, 153, 177–193.

Filiz-Ozbay, E. and N. Uler (2019): "Demand for giving to multiple charities: An experimental study," *Journal of the European Economic Association*, 17, 725–753.

Gayle, P., T. D. Harrison, and J. Thornton (2017): "Entry, donor market size, and competitive conduct among nonprofit firms," *International Journal of Industrial Organization*, 50, 294–318.

Gayle, P. G. and X. Xie (2019): "Firms' Markup, Cost, and Price Changes when Policymakers Permit Collusion: Does Antitrust Immunity Matter?" *Journal of Economic Behavior and Organization*, 157, 680–707.

Gee, L. and J. Meer (2020): "The Altruism Budget: Measuring and Encouraging Charitable Giving," in *The Nonprofit Sector: A Research Handbook*, ed. by W. W. Powell and P. Bromley, Stanford University Press, 3rd ed.

Goldberg, P. and F. Verboven (2001): "The Evolution of Price Dispersion in the European Car Market," *The Review of Economic Studies*, 68, 811–848.

Harrison, T. D., D. J. Henderson, D. Ozabaci, and C. A. Laincz (2023): "Does one size fit all in the non-profit donation production function?" *Oxford Bulletin of Economics and Statistics*, 85, 373–402.

Harrison, T. D. and C. A. Laincz (2008): "Entry and Exit in the Nonprofit Sector," *The B.E. Journal of Economic Analysis & Policy*, 8.

Harrison, T. D. and K. Seim (2019): "Nonprofit tax exemptions, for-profit competition and spillovers to community services," *The Economic Journal*, 129, 1817–1862.

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

Internal Revenue Service, Statistics of Income Division (2023): "Nonprofit Charitable and Other Tax-Exempt Organizations, Tax Year 2019," Publication 5331, Department of the Treasury, Internal Revenue Service, revised July 2023.

Ivaldi, M. and F. Verboven (2005): "Quantifying the Effects from Horizontal Mergers in European Competition Policy," *International Journal of Industrial Organization*, 23, 669–691.

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

Katz, M. L. and C. Shapiro (2002): "Critical loss: Let's tell the whole story," *Antitrust*, 17, 49.

Lapointe, S., C. Perroni, K. Scharf, and Tukiainen (2018): "Does market size matter for charities?" *Journal of Public Economics*, 168, 127–145.

List, J. A. (2011): "The market for charitable giving," *Journal of Economic Perspectives*, 25, 157–80.

Mayo, J. (2021): "How do big gifts affect rival charities and their donors?" *Journal of Economic Behavior & Organization*, 191, 575–597.

——— (2025): "Navigating the notches: Charity responses to ratings," *Journal of Political Economy Microeconomics*, 3, 98–137.

Meer, J. (2017): "Does Fundraising Create New Giving?" *Journal of Public Economics*, 145C, 82–93.

Miller, N. H. and M. C. Weinberg (2017): "Understanding the price effects of the MillerCoors joint venture," *Econometrica*, 85, 1763–1791.

National Center for Charitable Statistics, . (1989-2003): "CORE data," *Urban Institute*.

Nevo, A. (2000): "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry," *The RAND Journal of Economics*, 31, 395–421.

Okten, C. and B. Weisbrod (2000): "Determinants of donations in private nonprofit markets," *Journal of Public Economics*, 75, 255–272.

Philipson, T. J. and R. A. Posner (2009): "Antitrust in the not-for-profit sector," *The Journal of Law and Economics*, 52, 1–18.

Ribar, D. C. and M. O. Wilhelm (2002): "Altruistic and Joy-of-Giving Motivations in Charitable Behavior," *Journal of Political Economy*, 110, 425–457.

Rose-Ackerman, S. (1982): "Charitable Giving and 'Excessive' Fund Raising," *Quarterly Journal of Economics*, 97, 193–212.

Scharf, K., S. Smith, and M. Ottoni-Wilhelm (2022): "Lift and shift: The effect of fundraising interventions in charity space and time," *American Economic Journal: Economic Policy*, 14, 296–321.

Schmalensee, R. (1989): "Inter-industry Studies of Structure and Performance," *Handbook of Industrial Organization, Edited by R. Schmalensee and R.D. Willig*, 2, 951–1009.

Schmitz, J. (2021): "Is charitable giving a zero-sum game? The effect of competition between charities on giving behavior," *Management Science*, 67, 6333–6349.

Seaman, B., A. L. Wilsker, and D. Young (2014): "Measuring Concentration and Competition in the U.S. Nonprofit Sector: Implications for Research and Public Policy," *Nonprofit Policy Forum*, 5.

Shapiro, B. T., G. J. Hitsch, and A. E. Tuchman (2021): "TV advertising effectiveness and profitability: Generalizable results from 288 brands," *Econometrica*, 89, 1855–1879.

Shapiro, C. (2010): "The 2010 horizontal merger guidelines: From hedgehog to fox in forty years," *Antitrust Law Journal*, 77, 701–759.

Sinkinson, M. and A. Starc (2019): "Ask your doctor? Direct-to-consumer advertising of pharmaceuticals," *The Review of Economic Studies*, 86, 836–881.

Syverson, C. (2004): "Market structure and productivity: A concrete example," *Journal of political Economy*, 112, 1181–1222.

Thomadsen, R. (2005): "The Effect of Ownership Structure on Prices in Geographically Differentiated Industries," *The RAND Journal of Economics*, 36, 908–929.

Thornton, J. (2006): "Nonprofit Fund-Raising in Competitive Donor Markets," *Nonprofit Voluntary and Sector Quarterly*, 35, 204–224.

Tinkelman, D. (2004): "Using nonprofit organization-level financial data to infer managers' fund-raising strategies," *Journal of Public Economics*, 88, 2181–2192.

Tirole, J. (1988): "The Theory of Industrial Organization," *MIT Press*, 10th edition, 207–208.

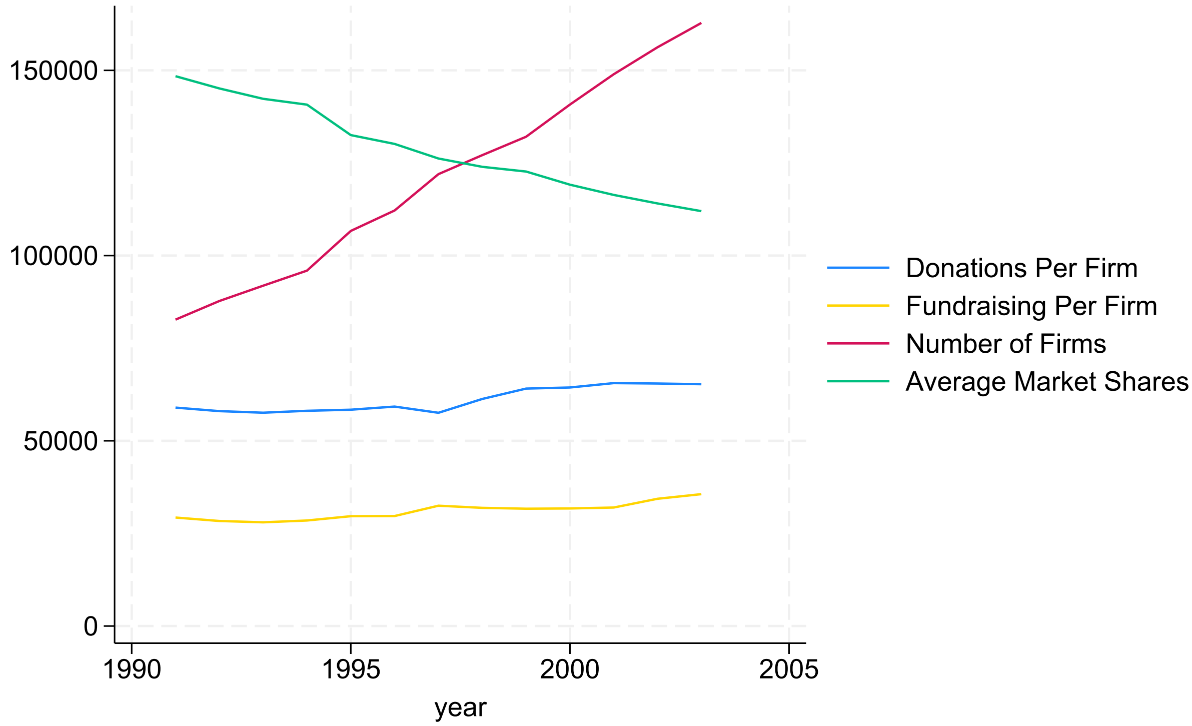
U.S. Census Bureau (2024): "Economic Census 2022: All Sectors, Summary Statistics for the U.S. (EC2200BASIC)," https://data.census.gov/, u.S. Census Bureau, Economic Census Basic Dataset, accessed December 5, 2025.

U.S. Department of Transportation, Bureau of Transportation Statistics (2020): "2019 Annual U.S. Airline Financial Data," https://www.bts.gov/newsroom/2019-annual-us-airline-financial-data, accessed: December 5, 2025.

Xu, D. (2024): "Spillovers in the charitable market: Evidence from reputation shocks," *Available at SSRN 4206456*.

Figures

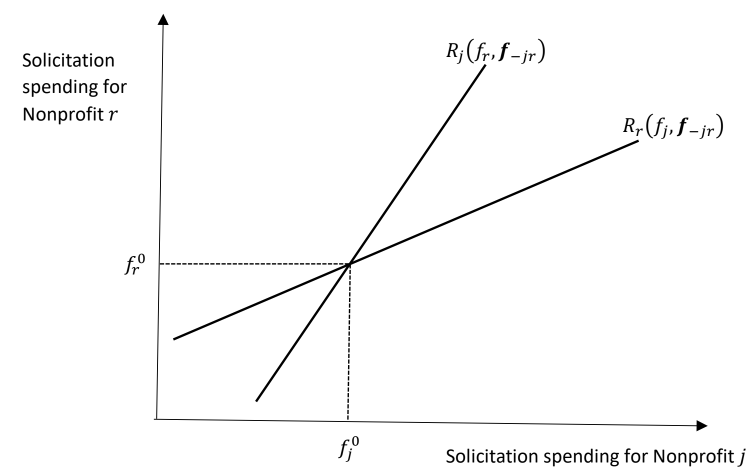
Figure 1: Trends in Donations and Fundraising



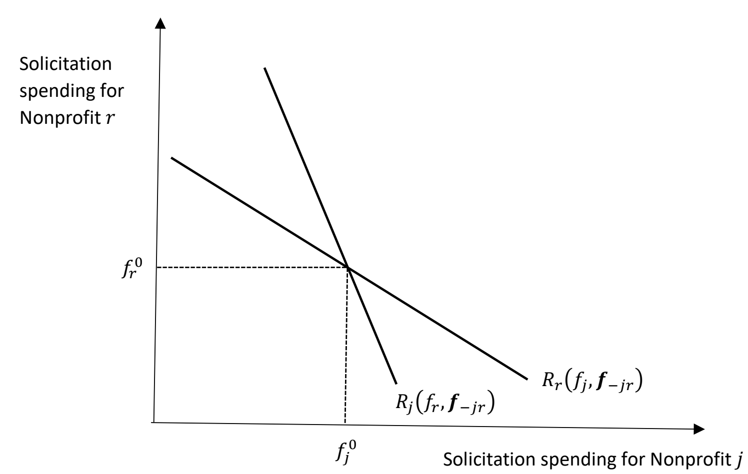
Note: The above presents trends over our sample of donations and fundraising intensity per firm, the number of firms, and the average market shares (scaled by a million) between 1991 and 2003. Financial variables are in 1989 dollars. Data source: 990 tax returns for public charities based on cleaning procedures described in Section 3.1.

Figure 2: Reaction functions for solicitation spending

(a) Strategic complements



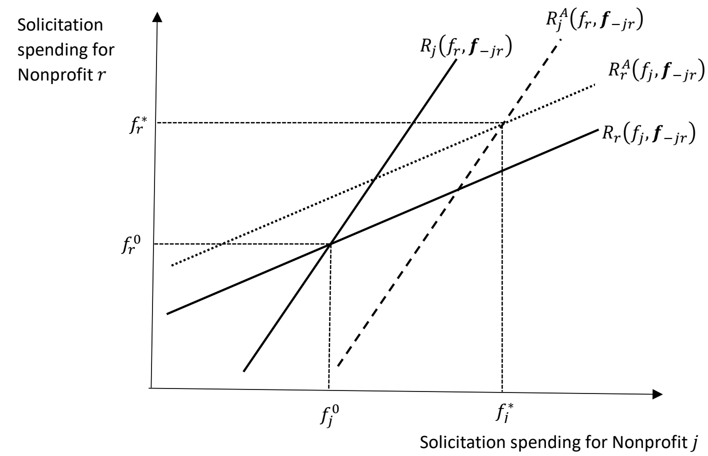
(b) Strategic substitutes



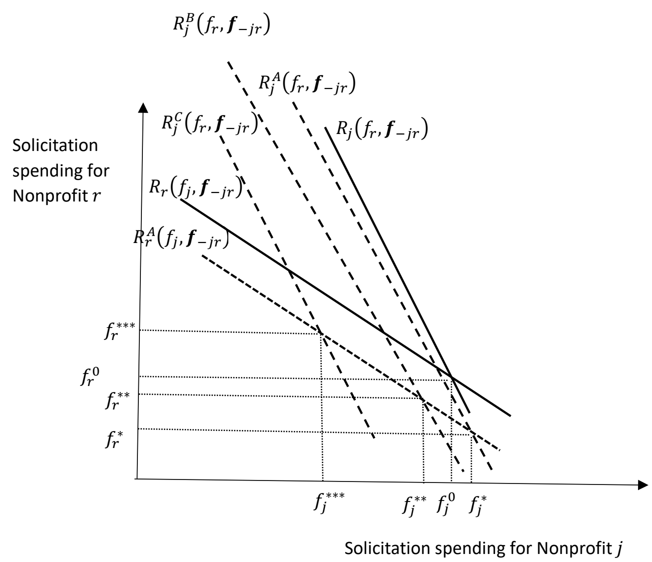
Note: The above presents reaction functions and the optimal level of fundraising if nonprofits demonstrate (a) strategic complementarity or (b) strategic substitutability in rivals' fundraising as detailed in Section 2.

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

(a) Strategic complements

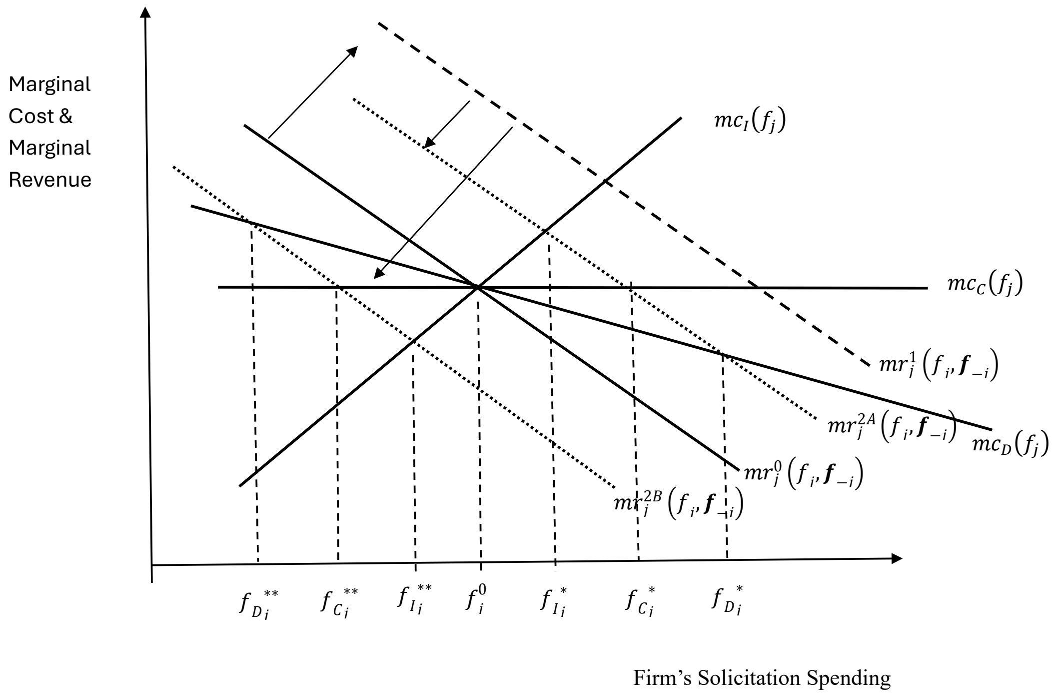


(b) Strategic substitutes



Note: The above presents changes in optimal fundraising levels for competing nonprofits when a third nonprofit increases its own fundraising level. Panels (a) and (b) demonstrate the equilibrium changes under strategic complementarity and strategic substitutability respectively based on the model presented in Section 2.

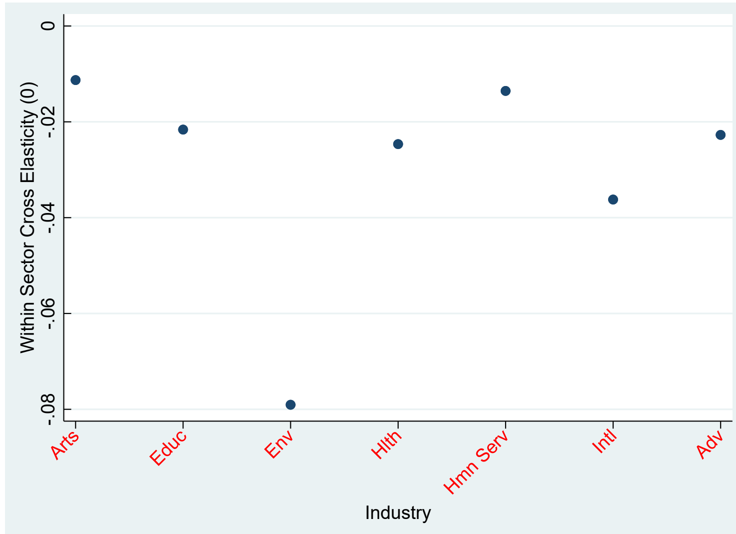
Figure 4: Strategic Fundraising Equilibria



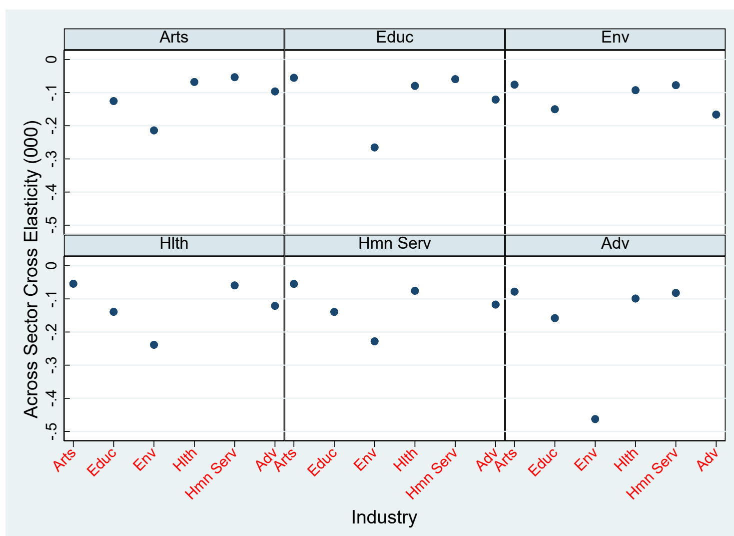
Note: The above presents changes in equilibrium fundraising levels for a nonprofit after a shift in their own marginal revenue to the right. $mr_j^1(f_j, \mathbf{f}_{-j})$ demonstrates the initial shift based on the direct effects. Under strategic substitutes, the equilibrium outcome could be represented by a shift to $mr_j^{2A}(f_j, \mathbf{f}_{-j})$ or $mr_j^{2B}(f_j, \mathbf{f}_{-j})$. Marginal costs is shown as increasing (mc_I), constant (mc_C), or decreasing with the slope smaller in magnitude than the mr slope (mc_D). Equilibrium fundraising can therefore increase for $mr_j^{2A}(f_j, \mathbf{f}_{-j})$ or decrease for $mr_j^{2B}(f_j, \mathbf{f}_{-j})$. See Section 2 and 2.1.3 for further discussion of the model and results.

Figure 5: Cross-firm Fundraising Elasticities

(a) Within sector



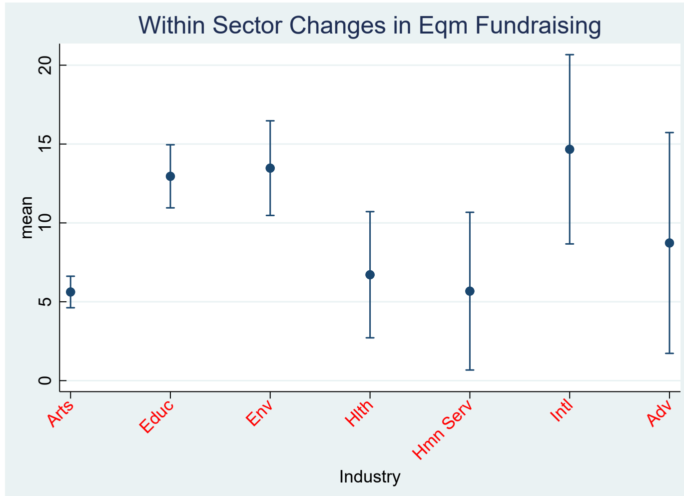
(b) Across sector



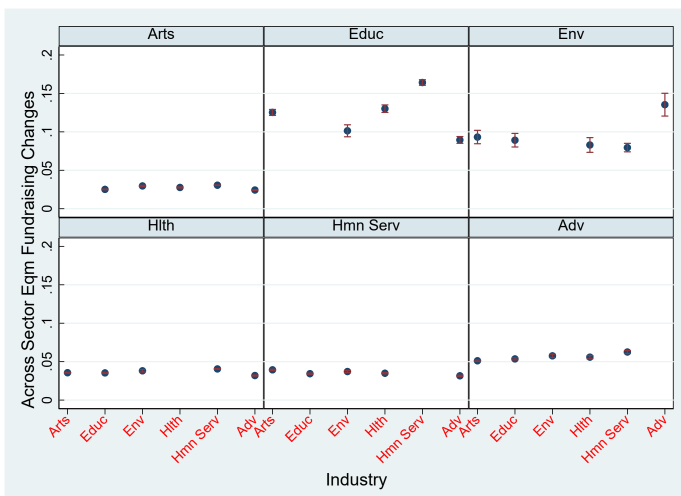
Note: The above presents the mean cross fundraising elasticities by NP sector, $e_{rjmt} = \frac{\partial s_{jmt}}{\partial f_{rmt}} \frac{f_{rmt}}{s_{jmt}}$ as described in section 5.2 and calculated as in equation A7 in Appendix A.2.1. The seven sectors are Arts, Education, Environmental & Animal, Health, Human & Social Services, International, and Civil Rights & Advocacy respectively. Confidence intervals are suppressed for clarity. All estimates are significant.

Figure 6: Counterfactual % Changes in fundraising when NP eliminated

(a) Within sector

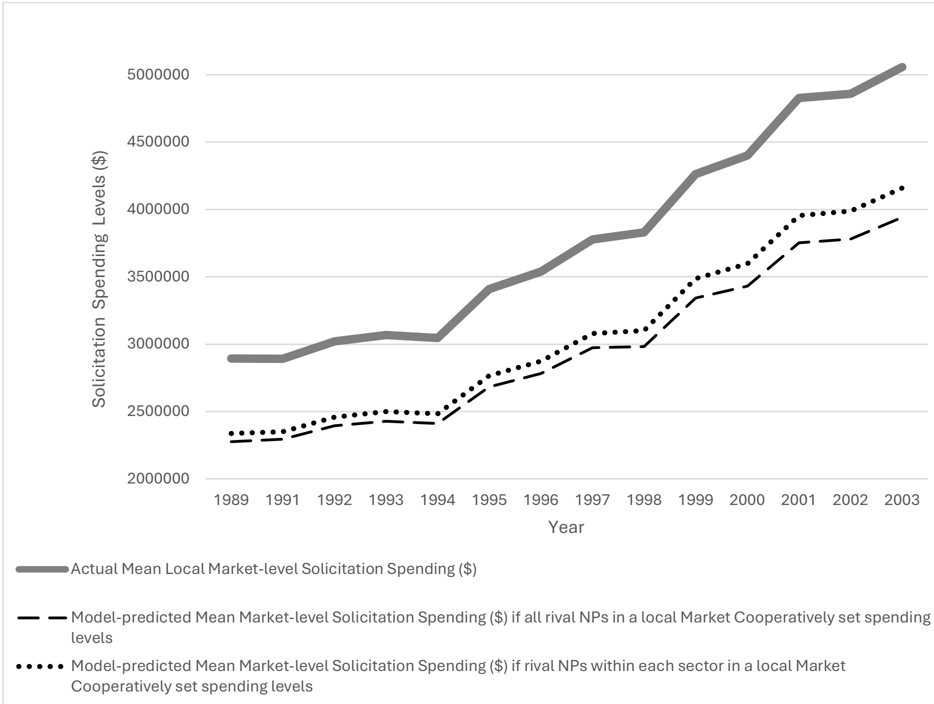


(b) Across sector



Note: The above presents our counterfactual estimates of predicted changes in equilibrium fundraising when we eliminate a firm in each sector-year market as discussed in Section 5.5 and Appendix A.3. The seven sectors are Arts, Education, Environmental & Animal, Health, Human & Social Services, International, and Civil Rights & Advocacy respectively. We present the averages with confidence intervals by NP sector.

Figure 7: Counterfactual with coordinated fundraising



Note: The above presents a time series plot of actual mean local market-level solicitation spending and model-predicted mean market-level solicitation spending for counterfactual coordinated fundraising of: (i) NPs within the same sector and local market and (ii) all NPs within the local market. Further details provided in Section 5.5 and Appendix A.3.

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: We provide market share information for our sample of nonprofit organizations categorized by primary industry NTEE classifications. Market shares are calculated based on the percentage of donations in a given market and year. Columns (4) and (5) calculate market shares corresponding to S_{jmt} and $S_{jmt/k}$ in our empirical model respectively. See equation (17) and the corresponding discussion for more details.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: By Firm				
Donation share in Mkt (%)	0.033	0.24	$1.88\text{x}10^{-8}$	33.70
Donation share in Sector (%)	10.2	20.5	$9.12\text{x}10^{-6}$	99.9
Donations (000)	1,570.44	10,919.86	0.02	879,214.00
Solicit (000)	129.56	826.05	0.001	96,286.22
Program service revenue (000)	3,709.49	30,729.47	0.001	1,501,986.25
Assets (000)	10,003.25	89,924.71	0.001	9,407,143.00
National organization	0.103	0.304	0	1
N	242,350			
Panel B: By Market-Year				
Donation share in Mkt (%)	0.104	0.391	$3.83\text{x}10^{-5}$	17.58
Donation share in Sector (%)	34.8	15.1	0.40	50.0
Donations (000)	782.22	1,610.41	1.49	61,329.83
Solicit (000)	69.33	127.24	0.034	1,800.01
Program service revenue (000)	2,384.53	6,300.39	0.214	161,784.06
Assets (000)	6,056.52	13,333.52	2.585	227,046.05
National organization	0.089	0.156	0	1
# of NPs	23.16	81.93	2	1,737
N	10,464			

Note: Source of data: 1989-2003 990 Tax Returns for US Public Charities. Market shares of donations are calculated based on the ratio of a nonprofit's donations relative to the total value of donations in their local market for all nonprofits and also by their sector. 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. All dollar-denominated values above reported in 1989 dollars.

Table 3: Descriptive Linear Regression Results

	Dependent variable: log of fundraising				
Variables	(1)	(2)	(3)	(4)	(5)
Number of NPs (000)	0.0456	0.6746**	0.1471*	−0.1275	1.1301*
	(0.1108)	(0.2296)	(0.0627)	(0.1136)	(0.4882)
Number of NPs^2(000)		−0.2960***	−0.0421		−0.4931*
		(0.0792)	(0.0237)		(0.1968)
Log Prog Serv Rev	0.0914***	0.0911***	0.0892***	0.0912***	0.0910***
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)
Log Assets	0.1788***	0.1779***	0.1743***	0.1792***	0.1773***
	(0.0103)	(0.0101)	(0.0106)	(0.0103)	(0.0101)
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
Instruments	No	No	No	Yes	Yes
Anderson Rubin				1.2415	58.3648
Anderson Rubin P-value				0.2657	0.0000
Exog P-value				0.1002	0.4997
Overid P-value				0.2051	−

Note: We report reduced form estimates from a regression of fundraising intensity on the number of nonprofit competitors and other firm and market level characteristics as 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 (market population and market population interacted with yearly time trends). *, **, *** p-value ≤ 10%, 5%, and 1%, respectively. Standard errors clustered at the market level are in parentheses.

Table 4: Nested Logit Demand Estimates

	Dep. var: log(S_{jmt})-log(S_{0mt})			
Variables	(1)	(2)	(3)	(4)
Solicit (f_{jmt})	0.383	1.003***	0.862***	0.726***
	(0.273)	(0.134)	(0.146)	(0.195)
Within group ($S_{jmt/k}$)	0.162**	0.310***	0.246***	0.138***
	(0.064)	(0.027)	(0.038)	(0.019)
Program service revenue	-0.056**	-0.109***	-0.098***	-0.085***
	(0.024)	(0.013)	(0.013)	(0.018)
Assets	0.064	-0.069**	-0.035	0.005
	(0.058)	(0.027)	(0.030)	(0.035)
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
Anderson Rubin	8.1896	236.1529	69.4856	72.2956
Anderson Rubin P-value	0.0849	0.0000	0.0000	0.0000
Exog P-value	0.0000	0.0000	0.0000	0.0000
Overid	0.9847	-	-	-
Overid P-value	0.8109	-	-	-
Observations	242350	242350	242350	242350
Number of NPs	47,887	47,887	47,887	47,887

Note: The above reports demand estimates based on specifications discussed in Section 4.1 and equation 17. All specifications instrument for solicitation intensities and the within group market share $S_{jmt/k}$. All columns use the number of nonprofits (N) in the local market and the own firm's sector as an instrument. Columns (2)-(4) interact measures of N with yearly time trends and column (4) includes rival nonprofits' asset values and program service revenues as instruments. We report the Anderson-Rubin underidentification test as well as tests for exogeneity and overidentification of our instruments. *, **, *** p-value $\leq$ 10%, 5%, and 1%, respectively. Standard errors clustered at the firm level are in parentheses.

Table 5: Marginal Cost Function Estimates

	Dep. var: $\log(\widehat{mr}_{jmt})$		
Variables	(1)	(2)	(3)
Solicit (f_{jmt})	2.525e-08	2.604e-08*	4.133e-08***
	(1.639e-08)	(1.517e-08)	(1.597e-08)
Age	0.0154*	0.0157**	0.0220***
	(0.0080)	(0.0076)	(0.0077)
Assets	-0.0369***	-0.0367***	-0.0311***
	(0.0094)	(0.0092)	(0.0089)
Assets*Age	-0.0008*	-0.0008*	-0.0012**
	(0.0005)	(0.0004)	(0.0005)
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;
Anderson Rubin	39.8834	81.5501	50.0578
Anderson Rubin P-value	0.0000	0.0000	0.0000
Exog	2.6246	1.0346	.
Exog P	0.1052	0.3091	.
Observations	242350	242350	242350

Note: The above reports cost estimates based on specifications discussed in Section 4.2 and equation 22. All specifications instrument for solicitation intensities with varied measures of the market specific donative capacity interacted with sector-specific and/or year indicators. We report the Anderson-Rubin underidentification test as well as tests for exogeneity of our instruments. *, **, *** p-value $\leq$ 10%, 5%, and 1%, respectively. Standard errors clustered at the market level are in parentheses.

Table 6: Own-firm Fundraising Elasticities

Sector	Mean	Std. Dev.	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: The above presents the distribution for fundraising elasticities by NP sector, $e_{jmt} = \frac{\partial s_{jmt}}{\partial f_{jmt}} \frac{f_{jmt}}{s_{jmt}}$ as described in Section 5.2 and equation A5 in Appendix A.2.1.
D:$_{f}und_{g}ayle_{h}arrison_{A}nalysis_{c}ode_{C}onstrained_{e}stimation_{o}f_{E}lasticities_{o}f_{E}lasticities_{t}dh_{V}2.doOwn_{f}irst_{o}rder$

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: The above presents 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: FRE elasticities (ΔFRE_{jr}) 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: FRE elasticities (ΔFRE_{jr}) 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 our fundraising effectiveness index (FRE) in Panel A and ΔFRE_{jr} in Panels B and C by NP sector discussed in Section 5.4 and calculated as in equation A8 in Appendix A.2.4. Panel A is scaled by 10,000,000,000 while Panels 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 errors are in parentheses. The details of the calculations are discussed in Appendix A.3.

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 NP's fundraising. Column (2)=Average percentage of NPs in each market-year with a 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:

$$\begin{aligned} NR_i &= d_i\gamma_i f_i - c\gamma_i f_i &\text{(A1)} \\ &= (A - bf_i - af_j)\gamma_i f_i - c\gamma_i f_i \end{aligned}$$

(A2)

Differentiating w.r.t f_i gives:

$$\frac{\partial NR_i}{\partial f_i} = (A - bf_i - af_j)\gamma_i - \gamma_i f_i b - c\gamma_i \quad \text{(A3)}$$

Setting equal to 0 and solving for f_i gives:

$$f_i = \frac{A - af_j - c}{2b} \quad \text{(A4)}$$

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 Further Details of Fundraising Elasticities, Diversion Ratios, and Fundraising Effectiveness

A.2.1 Own- and Cross-Fundraising Elasticity Formulas

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:

$$e_{jmt} = \frac{\partial s_{jmt}}{\partial f_{jmt}} \frac{f_{jmt}}{s_{jmt}} = \frac{\gamma}{1-\sigma}[1 - \sigma S_{jmt/k} - (1-\sigma) S_{jmt}]. \tag{A5}$$

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

$$e_{rjmt} = \frac{\partial s_{jmt}}{\partial f_{rmt}} \frac{f_{rmt}}{s_{jmt}} = -\frac{\gamma}{1-\sigma} \frac{S_{rmt}}{S_{jmt}} [\sigma S_{jmt/k} + (1-\sigma) S_{jmt}]. \tag{A6}$$

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

$$e_{rjmt} = \frac{\partial s_{jmt}}{\partial f_{rmt}} \frac{f_{rmt}}{s_{jmt}} = -\gamma S_{rmt}. \tag{A7}$$

A.2.2 Diversion Ratio Details

Diversion ratios complement our fundraising elasticity estimates by quantifying how much donors divert giving from one NP to another when a NP increases its fundraising efforts. To be precise, 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 $D_{jr} = \frac{\partial s_r / \partial f_j}{|\partial s_j / \partial f_j|}$.

A.2.3 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 A1 and Table A2, 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.

Table A1: 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 A2: 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

Diversion Ratio Robustness Checks–Estimates for Different Donative Capacities

A.2.4 Fundraising Effectiveness (FRE)

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., $FRE_j = \partial s_j/\partial f_j$.

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

$$\Delta FRE_{jr} = \frac{\partial(\frac{\partial s_j}{\partial f_j})}{\partial f_r} \frac{f_r}{(\frac{\partial s_j}{\partial f_j})} \tag{A8}$$

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

A.3 Counterfactual Details

Below we discuss more of the technical details of the two counterfactuals conducted in our paper. In what follows, it is convenient to use matrix notation to compactly represent the equations that characterize how the J rival nonprofits, indexed by $j = 1, ..., J$, within a local market compete for private donations via their fundraising.

A.3.1 *Experiment 1*

To discuss implementation of *Experiment 1*, let Δ be a $J \times J$ matrix that captures the response of donation shares to changes in solicitation intensities, where the rows and columns in matrix Δ correspond to the J distinct, and separately owned, rival NPs that operate within the relevant local market. 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:

$$\Delta = \begin{pmatrix} \frac{\partial s_1}{\partial f_1} & \vdots & \frac{\partial s_1}{\partial f_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_J}{\partial f_1} & \vdots & \frac{\partial s_J}{\partial f_J} \end{pmatrix} \tag{A9}$$

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

$$[(I * \Delta) \times Ones(J,1)] \times PD - \mathbf{mc} = 0 \tag{A10}$$

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 (A10) be denoted by vector $\mathbf{mr}$, i.e.,

$$\mathbf{mr} = [(I * \Delta) \times Ones(J,1)] \times PD. \tag{A11}$$

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 (A11) to obtain estimates, $\widehat{\mathbf{mr}}(\mathbf{f}, \mathbf{x}; \hat{\theta})$. Furthermore, the first-order conditions in (A10) 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:

$$\widehat{\mathbf{mc}} = exp(\hat{\rho}_f \mathbf{f} + \mathbf{c}) \tag{A12}$$

Using equation (A12), 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:

$$\hat{\mathbf{c}} = ln(\widehat{\mathbf{mc}}) - \hat{\rho}_f \mathbf{f} \tag{A13}$$

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

In implementing this 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, $\mathbf{f}^*$, that satisfy the following system of equations:

$$\mathbf{mr}(\mathbf{f}^*, \mathbf{x}; \hat{\theta}) - exp(\hat{\rho}_f \mathbf{f}^* + \hat{\mathbf{c}}) \quad = \quad \mathbf{0} \tag{A14}$$

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.

A.3.2 *Experiment 2*

We can also use the framework laid out above for *Experiment 1* to discuss how *Experiment 2* is implemented. The $J \times J$ identity matrix, I, in equation (A10) implies that rival NPs independently and non-cooperatively each set their optimal fundraising spending to maximize the net returns to their own solicitation operations. To instead counterfactually assume that a subset of rival NPs coordinate/collude with respect to setting their fundraising spending, we replace the identity matrix in equation (A10) with an alternate $J \times J$ matrix, Ω, such that the following is an appropriately updated version of equation (A10) that assumes cooperative fundraising:

$$[(\Omega * \Delta(\mathbf{f})) \times Ones(J, 1)] \times PD - exp(\hat{\rho}_f \mathbf{f} + \hat{\mathbf{c}}) \quad = \quad 0 \tag{A15}$$

where Δ is a function of $\mathbf{f}$, i.e., $\Delta(\mathbf{f})$; Ω is a matrix of appropriately positioned zeros and ones to reflect fundraising coordination between subsets of NPs; and $exp(\hat{\rho}_f \mathbf{f} + \hat{\mathbf{c}}) = \mathbf{mc}$ is the vector of marginal costs.

Let $\omega(i, j)$ represent an element in the i^{th} row and j^{th} column of matrix Ω, where the rows and columns in matrix Ω correspond to the J distinct, and separately owned, rival NPs that operate within the relevant local market. To be more specific, element $\omega(i, j) = 1$ if $i = j$, or if distinct NP i and NP j cooperatively set their fundraising levels, otherwise $\omega(i, j) = 0$.[43] In other words, all the main diagonal elements in Ω are equal to 1; while the subset of the off-diagonal elements in Ω that are equal to 1 corresponds to the pairwise combinations of NPs that we counterfactually assume cooperatively set their fundraising levels. Accordingly, this framework can accommodate fundraising coordination between any subset of rival nonprofits in the relevant local market. For example, all elements in Ω are equal to 1 in the case where we assume that all rival NPs in the relevant local market cooperatively set their fundraising.

Note that the composite marginal cost component, $\hat{\mathbf{c}}$, shown in equation (A15) was recovered from equations (A11) and (A13) based on the status quo of rival NPs independently and non-cooperatively each setting their optimal levels of fundraising. This therefore assumes that marginal costs are not influenced by cooperative fundraising behavior. Note however, that since $\mathbf{mc} = exp(\hat{\rho}_f \mathbf{f} + \hat{\mathbf{c}})$, our assumption here still allows marginal costs to change when NPs coordinate if coordination changes their level of fundraising, $\mathbf{f}$.

Effectively, *Experiment 2* is implemented by searching for the set of fundraising spendings, $\mathbf{f}^{**}$, that satisfy equation (A15). We then compare $\mathbf{f}$ with $\mathbf{f}^{**}$ to see how nonprofits' cooperation/collusion with respect to fundraising in each market is predicted to affect fundraising intensities. *Experiment 2* considers two levels of counterfactual fundraising cooperation/collusion between

[43] Analogous to the counterfactual merger analysis to predict price effects described in Nevo (2000) in the case of for-profit firms, our framework here can also be used to predict the potential effects on fundraising spending that may result from a counterfactual merger between separately owned rival nonprofits. In this context, Ω is interpreted as a nonprofit ownership structure matrix. Specifically, all the main diagonal elements in Ω are equal to 1; while the off-diagonal element that corresponds to distinct NP i and NP j is equal to 1 if these two NPs are commonly owned, or if the researcher wants to predict the counterfactual effects on equilibrium fundraising spending if these two NPs were to be commonly owned due to a proposed merger.

rival NPs: (i) the case of sector-level fundraising cooperation within each local market, i.e., rival NPs within the same sector and local market cooperate/collude with respect to setting their levels of fundraising but there is no cross-sector cooperation; and (ii) the case where all rival NPs within a local market cooperate/collude with respect to setting their levels of fundraising.

Counterfactual Tables Corresponding to Figures 5 & 6

Table A3: 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 A4: 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