The extent to which government grants to nonprofit organizations crowd-out or crowd-in private giving to them: An unresolved debate revisited within a strategic fundraising setting

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9 April 2024

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This draft: April 9, 2024
First draft: April 9, 2024

Abstract

This study examines the extent to which government grants to nonprofits crowd-out or crowd-in private giving to them. Grants influence private giving via two channels: (*i*) "directly" through donors' preference-induced optimal change in their giving in response to the grants; and (*ii*) "indirectly" through nonprofits' optimally changing their fundraising efforts, which in turn influence private giving. I use a structural model that disentangles the two channels and explains the mixed empirical results in the literature on the crowd-out/crowd-in hypothesis. Relative strengths of the "direct" and "indirect" channels depend on the presence of strategic interaction among nonprofits with respect to fundraising.

Keywords: Nonprofit Organizations; Crowd-out; Crowd-in; Government Grants; Private Donations; Fundraising

JEL Classification Codes: L30; L13; L22

**Researcher's own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Acknolegements: This paper benefited greatly from …

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1. Introduction

A long-standing debate in the literature on the economics of the private provision of public goods through charitable organizations is the extent to which government grants to these organizations crowd-out (i.e., decrease), crowd-in (i.e., increase), or have no effect on private giving to them. Several theoretical studies predict that government grants to nonprofits (NP) will "completely" crowd-out private giving [Warr (1982, 1983); Roberts (1984, 1987); Bergstrom, Blume, and Varian (1986)], while other theoretical studies predict that government grants to NPs will "incompletely" crowd-out private giving [Andreoni (1989, 1990); and Duncan (1999)]. "Complete" crowd-out here simply means that private giving to nonprofits will fall by *at least* a dollar for each dollar of government grant provided to the nonprofits, while "incomplete" crowd-out means that private giving to nonprofits will fall by *less* than a dollar for each dollar of government grant provided to the nonprofits.

As pointed out in Borgonovi (2006), empirical evidence on the direction and intensity of the crowding effect of public support on private donations is mixed. For example, at the institutional level, there exists evidence of a complete crowding out effect (Roberts, 1984); others report an incomplete (or partial) crowding out effect in the social services field (Steinberg, 1985; Andreoni and Payne, 2003), public radio stations (Kingma, 1989) and a variety of non-profit organizations (Payne, 1998). Schiff (1985) presents evidence that in certain circumstances a moderate crowding in effect can occur. Other studies that find evidence of a crowd-in effect include, Payne (2001); Brooks (2000a, 2000b); Okten and Weisbrod (2000); Smith (2003, 2007); Heutel (2014); Andreoni, Payne, and Smith (2014); and Neto (2018). However, a set of empirical studies [Reece (1979); Lindsey and Steinberg (1990); Khanna, Posnett, and Sandler (1995); Brooks (1999); and Manzoor and Straub (2005)] have found that government grants to NPs have had no effect on private donations to them, suggesting that there is neither a crowd-out nor crowd-in effect in contrast to what other studies have argued. Brooks (2003) argues that such neutrality results, which are often based on measuring the impact on total private donations, mask actual effects on individual private giving behavior. Specifically, the author argues that government grants to NPs do separately impact giving amounts (the intensive margin) and number of givers (the extensive margin) in countervailing ways such that total private donations is unchanged. Accordingly, Brooks (2003) finds evidence that government grants to NPs reduce mean donation per donor but increase the number of donors. Furthermore, the evidence suggests that these countervailing changes in private giving are of relative magnitudes to yield no statistically measurable changes in total private donations.

However, as I show in this study, due to heterogeneity in donor preferences, it is possible that each individual donor's private giving may respond differently to the provision of government grants to the NP. Some donors may optimally choose to increase their giving while others optimally choose to decrease their giving such that aggregate, and average, donations remain unchanged. In other words, even if the number of donors remains the same it is possible to still obtain the neutrality result of no effect on total private donations to the NP in response to it receiving government grants since current donors with heterogeneous preferences may respond differently with offsetting changes in their giving to yield no change in total private donations. In this case both number of donors and average donation will be unchanged after provision of government grants even though this is not evidence of "true" neutrality of private giving in response to the provision of government grants.

In this study I build on the Gayle and Harrison (2023) framework to capture more fully the extent to which government grants to nonprofits impact the private donations they receive. As first formally argued in Andreoni and Payne (2003), government grants to nonprofits can influence private giving to the nonprofits through two channels: (*i*) "directly" through donors' preference-induced optimal change in their giving behavior in response to the grants provided to the nonprofits; and (*ii*) "indirectly" through nonprofits' optimally changing their fundraising efforts in response to the grants provided, which in turn influence private giving. However, up until now no study has structurally disentangled these two channels through which government grants can affect private giving.

In the case of channel (*i*), if the potential donor perceives government grants to nonprofits as a substitute for their own private donation, then an increase in government grants to a given nonprofit will cause such a donor to reduce their own private giving to the grant-receiving nonprofit, a "direct" crowd-out effect. Donors may perceive government grants to nonprofits as a substitute for their own private donation because it is often the donors' tax dollars that the government uses to provide grants to nonprofits. Accordingly, from this perspective, government grant provision is simply an alternate and involuntary way tax-paying potential donors support NPs, and therefore potential donors may trade-off their voluntary private support with their involuntary support. On the other hand, if the potential donor perceives government grants to nonprofits as a complement to their own private donation, then an increase in government grants to a given nonprofit will cause such a donor to increase their own private giving to the grant-receiving nonprofit, a "direct" crowd-in effect. As argued in Payne (2001), the government through its grant awards may provide a signal of quality of the NP to donors that is less noisy than other information sources typically available to private donors.[1] In addition, there may be positive spillover effects from government funding to private donations if donors are aware that the NP uses private and public funding in different but complementary ways.

Channel (*ii*) is based on the premise that a nonprofit's fundraising intensity positively influences private giving and that a grant-receiving nonprofit will optimally change their fundraising intensity in response to receiving government grants. If a nonprofit reduces its fundraising intensity in response to receiving government grants, as argued in Andreoni and Payne (2003, 2011), then the lower fundraising intensity will induce lower levels of private giving, an "indirect" crowd-out effect. However, I illustrate in this study that in principle it is also possible in the indirect channel for nonprofits to optimally respond to receiving government grants by increasing their fundraising intensity, which in turn will induce higher levels of private giving, in this case an "indirect" crowd-in effect. Accordingly, the indirect channel is invoked by nonprofits changing their fundraising intensity induced by receiving government grants. In summary, the "direct" grant crowd-out/crowd-in of private giving channel is driven by a change in donors' giving behavior without any change in nonprofits' fundraising intensity, while the "indirect" grant crowd-out/crowd-in of private giving channel is driven by a change in nonprofits' fundraising intensity in response to government grants provided.

The analysis begins by laying out a donor demand model in the spirit of Gayle and Harrison (2023), with an important distinguishing feature of the model in this study being its ability to capture heterogeneity in preferences across potential donors. I then use this model to measure the impact of determinants of donors' optimal direct giving responses to the provision of government grants to NPs. To complement the donor demand model, I specify a strategic interactive framework in which rival nonprofits optimally determine their fundraising intensity/spending levels conditional on government grants provided to them. Accordingly, the modelling framework has two key features that are important for capturing more fully the extent to which government grants to nonprofits impact the private donations they receive: (*i*) it captures NPs' strategic responses to rivals' fundraising decisions; and (*ii*) it captures how each NP optimally adjust its fundrasing intensity in response to receiving a governemnt grant. Given that government grants to a NP indirectly influence private donations to the NP via influencing the NP's optimal fundraising intensity, feature (*i*) implies that government grants to NP j will also indirectly

[1] Heutel (2014) provides an empirical test of the argument that government grants crowd in private giving because the grants serve as a signal of NP's quality to donors and finds systematic evidence consistent with grants serving as a signal of NPs' quality to donors.

influence private giving to rival NPs via their strategic fundraising response to NP *j*'s government grant-induced change in it's fundraising intensity.

I then take the parametrized structural model to real-world data to: (*i*) econometrically estimate the parameters; (*ii*) draw inference on donor preferences from the parameter estimates; and (*iii*) use the estimated model to perform counterfactual experiments designed to measure the extent to which the provision of government grants to nonprofits crowd-out or crowd-in private giving to the nonprofits. The donor demand parameter estimates suggest that there exists heterogeneity in private donor preference for the provision of government grants to nonprofits and consequently whether the provision of government grants induces "direct" crowd-out or crowd-in of private giving to grant-receiving nonprofits will depend on the preference profile of the population of potential donors to the nonprofit. Furthermore, the estimates suggest that potential donors' income and race are important demographic factors that directly determine their private giving response to the provision of government grants. An important implication of this finding is that empirical evidence of crowd-out versus crowd-in likely depend on the demographic mix of private donors to the sample of nonprofits being empirically studied, and consequently it is not surprising for the literature to present mixed results on the crowd-out hypothesis, as have been the case.

Second, equilibrium analysis using the estimated model reveals that government grants to nonprofits can either crowd-out or crowd-in fundraising spending of the grant-receiving nonprofit, but the likelihood and magnitude of crowd-out crucially depend on whether competition and strategic interaction among NPs with respect to fundraising are present in the local donor market. Regarding the full impacts on private giving that account for these changes in NPs' fundraising spending induced by government grants, I find that government grants to nonprofits can either crowd-out or crowd-in private donations of the grant-receiving nonprofits, but the likelihood of grant crowd-out and the relative magnitudes of the "direct" and "indirect" channels of crowd-out crucially depend on whether competition and strategic interaction with respect to fundraising are present in the local donor market. Specifically, it is apparent that the strategic interaction among NPs with respect to fundraising serves to attenuate the magnitude of the "indirect" grant crowd-out effect, a new finding in the literature. Furthermore, I find that grant crowd-out of private donations through the "indirect" channel consistently and substantially dominates the "direct" channel only when competition and strategic interaction among NPs with respect to fundraising are absent from the local donor market, but the "indirect" channel is often marginally dominated by the "direct" channel with the presence of competition and strategic interaction, another new finding in the literature. In the conclusion I discuss what these results imply for designing policies to mitigate grant crowd-out.

The remainder of the paper is organized as follows. Section 2 lays out the model framework I use for analyzing the impact on private giving to nonprofits induced by the provision of government grants to them. In Section 3 I describe the data used for the empirical analysis. Section 4 presents and discusses parameter estimates from the donor demand model. Section 5 conceptually describes the counterfactual experiments implemented, while Section 6 discusses the results from the counterfactual experiments. Concluding remarks are gathered in Section 7.

2. A Model to Analyse the Impact on Private Giving of Government Grants to Nonprofits

2.1 Donor Demand

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

$$\max_{j \in \{0,1,\dots,J_{mt}\}} \left\{ U_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt} \right\} \tag{1}$$

where U_{ijmt} is the indirect utility donor i gets from donating to nonprofit firm j located in market m during period t. The indirect utility of donor i, U_{ijmt}, comprises three components, δ_{jmt}, μ_{ijmt}, and ε_{ijmt}. Component δ_{jmt} is the mean utility level across all donors who donate to firm j; component μ_{ijmt} captures donor $i's$ utility deviation from the market mean utility due to donor $i's$ unique preference value placed on particular firm attributes; and component ε_{ijmt} captures idiosyncratic shocks to donor $i's$ preference, which I assume to be distributed type I extreme value.

The mean utility level, δ_{jmt}, and deviation from the mean utility level, μ_{ijmt}, are functions that are parameterized as follows:

$$\delta_{jmt} = \gamma ln(f_{jmt}) + \sum_{k=1}^{K} \lambda_k \left(G_{jmt} \times I_k \right) + x_{jmt}\beta + \xi_{jmt} \tag{2}$$

$$\mu_{ijmt} = \sigma^c v_i^c + \sigma^G\left(v_i^G \times G_{jmt}\right) + \phi^{Income}\left(Income_i \times G_{jmt}\right) + \phi^{White}\left(White_i \times G_{jmt}\right) \quad (3)$$

where f_{jmt} represents fundraising/solicitation intensity measured in dollars of spending for nonprofit firm j in market m during period t; and γ is an estimable parameter that measures the average change in donors' satisfaction induced by a change in the nonprofit's solicitation intensity. G_{jmt} is a measure of the monetary value of government grants received by nonprofit j during period t; I_k is a zero-one dummy variable that is equal to 1 only if nonprofit j belongs to sector k; and λ_k for $k = 1,2, \ldots K$ are the associated sector-specific parameters to be estimated. In this application each NP falls into one of seven (7) distinct sectors. Parameter λ_k measures the marginal impact on donors' mean utility obtained from donating to nonprofit j induced by its receipt of government grants G_{jmt}. If a sufficiently large number of potential donors perceive government grants to nonprofit j as a substitute for their own private donation, then I expect $\lambda_k < 0$, i.e., an increase in government grants to nonprofit j will cause such donors to reduce their own private giving to the nonprofit, a "direct" crowd-out effect. On the other hand, if a sufficiently large number of potential donors perceive government grants to nonprofit j as a complement to their own private donation, then I expect $\lambda_k > 0$, i.e., an increase in government grants to nonprofit j will cause such donors to increase their own private giving to the nonprofit, a "direct" crowd-in effect. Accordingly, whether government grants to NPs in a sector directly crowd-out or crowd-in private giving is an empirical question that is in part answered by the estimate of parameter λ_k.

Vector x_{jmt} contains measurable attributes of nonprofit j, with corresponding parameters in vector β that measure the marginal utility to donors of the respective attributes. Mean utility component ξ_{jmt} captures utility-influencing firm, market, and period characteristics that are observed by nonprofits and donors but unobserved to me the researcher.

Heterogeneity in donor preferences is in part captured by μ_{ijmt}. Equation (3) shows that μ_{ijmt} is a function of donor-specific random preference shocks for donating to a grant-receiving NP per unit of government grant provided, as well as how a donor's preference for donating to a grant-receiving NP per unit of government grant provided is correlated with the donor's income level and race. Specifically, v_i^c is a taste shock for donor i that influences this donor's likelihood of donating to one of the available nonprofit alternatives versus not donating to any of them, with associated estimable parameter σ^c that measures taste heterogeneity, i.e., variation in tastes across donors with respect to their proclivity to donate to one of the available nonprofit alternatives versus not donating to any of them. Second, taste shock v_i^G captures part of donor $i's$ unique preference for government grants being provided to nonprofits that influences this donor's giving decision, with the associated estimable parameter σ^G that measures variation in tastes across donors with respect to their preference for government grants being provided to nonprofits as it relates to their giving decision to these nonprofits. Third, $Income_i$ is a measure of potential donor $i's$ income level, with the associated estimable parameter ϕ^{Income} that measures income-driven variation in tastes across donors with respect to their preference for donating to a grant-receiving NP per unit of government grant provided to the NP. Last, $White_i$ is an indicator measure of whether potential donor $i's$ race is white, with the associated estimable parameter ϕ^{White} that measures race-correlated variation in tastes across donors with respect to their preference for donating to a grant-receiving NP per unit of government grant provided to the NP.

Last, following much of the Empirical Industrial Organization literature on random coefficients logit demand models [see Berry (1994); Berry, Levinsohn, Pakes (1995); and Nevo (2000)], I assume that the preference shocks, $v_i = \begin{pmatrix} v_i^c \\ v_i^G \end{pmatrix}$, are distributed standard normal across donors, i.e., $v_i \sim N(0, I)$, while demographic variables, $D_i = \begin{pmatrix} Income_i \\ White_i \end{pmatrix}$ are random draws from the distribution of the actual population of potential donors in the local market. Draws of D_i are based on the NielsenIQ Consumer Panel databased published and maintained by The University of Chicago, Booth School of Business.[2] In addition, with the assumption that ε_{ijmt} is distributed type I extreme value, the solution to the utility maximizing donation choice problem in equation (1) is the following equation that yields the unconditional probability of donors in market m choosing to donate to nonprofit firm j:

$$s_{jmt}(\boldsymbol{f}_{mt}, \boldsymbol{G}_{mt}; \theta) = \int \frac{exp\left(\delta_{jmt} + \mu_{ijmt}\right)}{1 + \sum_{r=1}^{J_{mt}} exp(\delta_{rmt} + \mu_{irmt})} d\Phi(v) dF(D) \qquad (4)$$

where $\theta = (\gamma, \lambda, \beta, \sigma, \phi)$ is a vector of estimable parameters; $\boldsymbol{f}_{mt}$ is a vector of solicitation intensities measured in dollars of spending for the nonprofit firms in market m during period t, i.e., $f_{jmt} \in \boldsymbol{f}_{mt} \forall j \in J_{mt}$; $\boldsymbol{G}_{mt}$ is a vector of government grants measured in dollars provided to the nonprofit firms located in market m during period t, i.e., $G_{jmt} \in \boldsymbol{G}_{mt} \forall j \in J_{mt}$; $\Phi(\cdot)$ is the standard normal distribution function, and $F(D)$ is the distribution of demographic measures of potential donors in the local markets. $s_{jmt}(\cdot)$ is also defined as the model-predicted donation share of nonprofit j in market m during period t.

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[2] The Consumer Panel Data comprise a representative panel of households that continually provide information about their purchases in a longitudinal study. The panel has 40,000–60,000 active panelists (varies by year), projectable to the total United States. Household demographic and geographic variables are included, as well as select demographics for the heads of household and other members.

It is well-known in the Empirical Industrial Organization literature that there is no closed-form solution for the integral problem in equation (4), which requires it be approximated numerically using random draws of v_i and D_i from $\Phi(\cdot)$ and $F(\cdot)$, respectively. Accordingly, s_{jm} in equation (4) is numerically approximated as follows:

$$s_{jmt}(\boldsymbol{f}_{mt}, \boldsymbol{G}_{mt}; \theta) = \frac{1}{ns}\sum_{i=1}^{ns} s_{ijmt}(\boldsymbol{f}_{mt}, \boldsymbol{G}_{mt}; \theta) \tag{5}$$

with

$$s_{ijmt}(\boldsymbol{f}_{mt}, \boldsymbol{G}_{mt}; \theta) = \frac{exp(\delta_{jm}+\mu_{ijmt})}{1+\sum_{r=1}^{J_{mt}} exp(\delta_{rm}+\mu_{irmt})} \tag{6}$$

where ns in equation (5) is the number of individual random draws from $\Phi(\cdot)$ and $F(\cdot)$ used for the approximation;[3] and $s_{ijmt}(\boldsymbol{f}_{mt}, \boldsymbol{G}_{mt}; \theta)$ in equation (6) is the donor-specific probability that donor i chooses to donate to nonprofit j during period t.

2.2 Using the Model to Compute Impacts on Private Giving induced by Government Grants to Nonprofits

As first formally argued in Andreoni and Payne (2003), government grants to nonprofits can influence private giving to the nonprofits through two channels: (i) "directly" through donors' preference-induced optimal change in their giving behavior in response to the grants provided to the nonprofits; and (ii) "indirectly" through nonprofits' optimally changing their fundraising efforts in response to the grants provided, which in turn influence private giving. In the case of channel (i), if the potential donor perceives government grants to nonprofits as a substitute for their own private donation, then an increase in government grants to a given nonprofit will cause such a donor to reduce their own private giving to the grant-receiving nonprofit, a "direct" crowd-out effect. On the other hand, if the potential donor perceives government grants to nonprofits as a complement to their own private donation, then an increase in

[3] In estimation I use $ns = 1{,}000$. The NielsenIQ Consumer Panel data provide demographic information on the panelists. For example, a panelist's household income in the data is reported to fall within one of 30 income categories. For a given zip code area, which is how I delineate local markets in this study, I compute from the Consumer Panel the proportion/share of panelists that fall within each of the 30 income categories. I then assume the distribution of the income categories is governed by a multinomial probability distribution, where the proportions of the panelists that fall within each income category correspond to probabilities associated with the possible outcomes from the multinomial probability distribution. Accordingly, with the proportions of the panelists that fall within each income category for a given market in hand, I then use the multinomial probability distribution to generate ns random draws of individuals with their associated income categories. This method of obtaining ns random income category draws is repeated in each zip code market. An analogous process is used to obtain random draws of individuals' race across zip code markets.

government grants to a given nonprofit will cause such a donor to increase their own private giving to the grant-receiving nonprofit, a "direct" crowd-in effect.

Channel (*ii*) is based on the premise that a nonprofit's fundraising intensity positively influences private giving and that a grant-receiving nonprofit will optimally change their fundraising intensity in response to receiving government grants. As argued in Andreoni and Payne (2003, 2011), if a nonprofit reduces its fundraising intensity in response to receiving government grants, then the lower fundraising intensity will induce lower levels of private giving, an "indirect" crowd-out effect. As I subsequently illustrate, in principle it is also possible in the indirect channel for nonprofits to optimally respond to receiving government grants by increasing their fundraising intensity, which in turn will induce higher levels of private giving, in this case an "indirect" crowd-in effect. Accordingly, the indirect channel is invoked by nonprofits changing their fundraising intensity in either direction in response to receiving government grants.

The "direct" crowd-out/crowd-in effect can be measured from the donor demand model described above by simply computing the following derivatives holding constant fundraising intensities:

$$\left.\frac{ds_{jm}}{dG_{jm}}\right|_{f_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\frac{\partial s_{ijm}}{\partial G_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\left[\left(\frac{\partial \delta_{jm}}{\partial G_{jm}} + \frac{\partial \mu_{ijmt}}{\partial G_{jm}}\right) s_{ijm}\left(1 - s_{ijm}\right)\right]$$

$$= \frac{1}{ns}\sum_{i=1}^{ns}\left[\left(\lambda_k + \sigma^G v_i^G + \phi^{Income} Income_i + \phi^{White} White_i\right) s_{ijm}\left(1 - s_{ijm}\right)\right] \qquad (7)$$

$$\left.\frac{ds_{rm}}{dG_{jm}}\right|_{f_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\frac{\partial s_{irm}}{\partial G_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\left[-\left(\frac{\partial \delta_{jm}}{\partial G_{jm}} + \frac{\partial \mu_{ijmt}}{\partial G_{jm}}\right) s_{ijm} s_{irm}\right]$$

$$= \frac{1}{ns}\sum_{i=1}^{ns}\left[-\left(\lambda_k + \sigma^G v_i^G + \phi^{Income} Income_i + \phi^{White} White_i\right) s_{ijm} s_{irm}\right] \qquad (8)$$

where $\left.\frac{ds_{jm}}{dG_{jm}}\right|_{f_{jm}}$ in equation (7) captures the own-firm "direct" effect, while $\left.\frac{ds_{rm}}{dG_{jm}}\right|_{f_{jm}}$ in equation (8) captures the cross-firm "direct" effect. The signs of these derivatives depend on the signs, and possibly the relative magnitudes, of parameters λ_k, σ^G, ϕ^{Income}, and ϕ^{White}. However, irrespective of the signs and relative magnitudes of parameters λ_k, σ^G, ϕ^{Income}, and ϕ^{White}, the sign of the own-firm "direct" effect is opposite of the sign of the cross-firm "direct" effect. For example, if donor i perceives government grants to nonprofit j as a substitute for their own private donation, i.e., $\left(\lambda_k + \sigma^G v_i^G + \phi^{Income} Income_i + \phi^{White} White_i\right) < 0$, then an increase in government grants to nonprofit j, i.e., an increase in G_{jm}, will cause donor i to reduce their own private giving to nonprofit j, a "direct" crowd-out effect, but increase their private giving to rival nonprofit r. In other words, donor i will transfer a portion of their private giving from nonprofit j to nonprofit r. If a sufficiently large number of donors in the market behave in this way, then we will have $\left.\frac{ds_{jm}}{dG_{jm}}\right|_{f_{jm}} < 0$ and $\left.\frac{ds_{rm}}{dG_{jm}}\right|_{f_{jm}} > 0$. Conversely, if donor i perceives government grants to nonprofit j as a complement for their own private donation, i.e., $\left(\lambda_k + \sigma^G v_i^G + \phi^{Income} Income_i + \phi^{White} White_i\right) > 0$, then an increase in government grants to nonprofit j, i.e., an increase in G_{jm}, will cause donor i to increase their own private giving to nonprofit j, a "direct" crowd-in effect, but reduce their private giving to rival nonprofit r. In other words, donor i will transfer a portion of their private giving from nonprofit r to nonprofit j. If a sufficiently large number of donors in the market behave in this way, then we will have $\left.\frac{ds_{jm}}{dG_{jm}}\right|_{f_{jm}} > 0$ and $\left.\frac{ds_{rm}}{dG_{jm}}\right|_{f_{jm}} < 0$.

The following derivatives jointly capture both the "direct" and "indirect" effects on private giving of government grants:

$$\frac{ds_{jm}}{dG_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\left[\underbrace{\frac{\partial s_{ijm}}{\partial G_{jm}}}_{direct\ effect} + \underbrace{\frac{\partial s_{ijm}}{\partial f_{jm}}\frac{\partial f_{jm}}{\partial G_{jm}} + \sum_{\forall r \neq j}\frac{\partial s_{ijm}}{\partial f_{rm}}\frac{\partial f_{rm}}{\partial G_{jm}}}_{indirect\ effect}\right] \tag{9}$$

$$\frac{ds_{rm}}{dG_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\left[\underbrace{\frac{\partial s_{irm}}{\partial G_{jm}}}_{direct\ effect} + \underbrace{\frac{\partial s_{irm}}{\partial f_{jm}}\frac{\partial f_{jm}}{\partial G_{jm}} + \sum_{\forall g \neq j \neq r}\frac{\partial s_{irm}}{\partial f_{gm}}\frac{\partial f_{gm}}{\partial G_{jm}}}_{indirect\ effect}\right] \tag{10}$$

Note that the "indirect" effect requires measuring partial derivatives, $\frac{\partial f_{jm}}{\partial G_{jm}}$ and $\frac{\partial f_{rm}}{\partial G_{jm}}\ \forall r \neq j$. In other words, computing the "indirect" effect not only requires information on how NP j optimally changes its fundraising spending in response to receiving a grant, captured by $\frac{\partial f_{jm}}{\partial G_{jm}}$, but in addition requires information on how rivals to NP j will optimally change their fundraising intensities in response to NP j receiving a government grant, captured by $\frac{\partial f_{rm}}{\partial G_{jm}}\ \forall r \neq j$. Quantifying the partial derivatives, $\frac{\partial f_{jm}}{\partial G_{jm}}$ and $\frac{\partial f_{rm}}{\partial G_{jm}}\ \forall r \neq j$, requires specifying how nonprofits strategically interact with each other with respect to optimally setting their fundraising intensities, a task to which I now focus discussion.

2.3 The Solicitation Game Between Rival Nonprofits

The modeling framework used in this section for specifying NPs' net revenue from their solicitation operations is in the spirit of Gayle and Harrison (2023) and accounts for the crucial role of strategic interaction in NPs' fundraising decisions. In what follows I often omit the time subscript only to avoid a clutter of notation. Therefore, each equation is still to be interpreted in a time-specific manner.

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

$$ED_{jm} = s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta) \times PD_m \tag{11}$$

where $s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)$ is the donation share of nonprofit j in market m, which is defined in equations (5) and (6) above as being equivalent to the unconditional probability a potential donor in the local market donates to nonprofit j; and PD_m is a measure of the aggregate potential money donations, i.e., the private donative capacity of local market m. Based on the donor demand model laid out above, the reader is reminded that the donation share of NP j is a function of a vector of solicitation intensities, $\boldsymbol{f}_m$, measured in dollars of spending for the nonprofit firms in market m, i.e., $f_{jm} \in \boldsymbol{f}_m \forall j \in J_m$, as well as a vector of government grants, $\boldsymbol{G}_m$, received by the nonprofits in market m, i.e., $G_{jm} \in \boldsymbol{G}_m \forall j \in J_m$.

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

$$TC_{jm} = VC_{jm}(f_{jm}) + FC_{jm} \tag{12}$$

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

The net revenue or return to the solicitation operations of nonprofit firm j in market m is

given by:

$$NR_{jm}(f_{jm}, f_{-j,m}, \boldsymbol{G}_m) = s_{jm}(f_{jm}, f_{-j,m}, \boldsymbol{G}_m; \theta) \times PD_m - TC_{jm} \tag{13}$$

where the net return for nonprofit firm j is a function of its own solicitation intensity, f_{jm}, as well as the solicitation intensities of rival nonprofit firms, i.e., $f_{-j,m} = \boldsymbol{f}_m \backslash f_{jm}$.

As in Gayle and Harrison (2023), I assume each NP chooses its solicitation spending to maximize net revenue from its solicitation operations:

$$\max_{f_{jm}} NR_{jm}\left(f_{jm}, f_{-j,m}, \boldsymbol{G}_m\right) \tag{14}$$

The optimization problem in (14) implies that a Nash equilibrium in solicitation intensities must satisfy the following first-order conditions:

$$\frac{\partial s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm}} \times PD_m - mc_{jm} = 0 \qquad \forall j \in J_m \tag{15}$$

where term $\frac{\partial s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm}} \times PD_m$ in equation (15) measures the marginal change in donations received by nonprofit firm j in market m due to a marginal change in its solicitation spending; and $mc_{jm} = \frac{\partial VC_{jm}}{\partial f_{jm}}$ measures the marginal change in the composite of implicit and explicit costs incurred by the nonprofit due to a marginal change in its solicitation spending.

Solicitation Spending Reaction Functions

Nonprofit $j's$ solicitation spending reaction function, $R_j(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)$, is obtained by using the first-order conditions in equation (15) to express f_{jm} as a function of rival nonprofits' solicitation spending such that:

$$f_{jm} = R_j(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta) \tag{16}$$

Likewise, rival nonprofit $r's$ solicitation spending reaction function is analogously defined as:

$$f_{rm} = R_r(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta) \tag{17}$$

A Nash equilibrium in solicitation spending occurs where these reaction functions intersect when plotted in solicitation spending of competing nonprofits space [see Gayle and Harrison (2023) for a more detailed treatment of solicitation spending reaction functions.]. Since I am interested in understanding how the provision of government grants influences the Nash equilibrium in solicitation/fundraising spending, then it is necessary to learn how the reaction functions in equations (16) and (17) shift in response to a change in G_{jm} when these functions are plotted in solicitation spending of competing nonprofits space.

Totally differentiating the first-order conditions in equation (15), yields:

$$\frac{\partial^2 s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm}^2} PD_m df_{jm} - \frac{\partial mc_{jm}}{\partial f_{jm}} df_{jm} + \frac{\partial^2 s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm} \partial G_{jm}} PD_m dG_{jm} = 0 \tag{18}$$

which can be rearranged as follows:

$$\left[\frac{\partial^2 s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm}^2} PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}\right] df_{jm} + \frac{\partial^2 s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm} \partial G_{jm}} PD_m dG_{jm} = 0$$

$$\left[\frac{\partial^2 s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm}^2} PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}\right] df_{jm} = -\frac{\partial^2 s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm} \partial G_{jm}} PD_m dG_{jm}$$

$$\left[\frac{\partial^2 s_{jm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{jm}^2} PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}\right]\frac{df_{jm}}{dG_{jm}} = -\frac{\partial^2 s_{jm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{jm}\partial G_{jm}} PD_m$$

$$\frac{df_{jm}}{dG_{jm}} = \frac{\frac{\partial^2 s_{jm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{jm}\partial G_{jm}} PD_m}{-\left[\frac{\partial^2 s_{jm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{jm}^2} PD_m - \frac{\partial mc_{jm}}{\partial f_{jm}}\right]} \tag{19}$$

The sign of the derivative, $\frac{df_{jm}}{dG_{jm}}$, in equation (19) informs us of the direction in which nonprofit $j's$ reaction function shifts in response to receiving government grants, G_{jm}. Since the denominator of the right-hand side expression in equation (19) will be positive due to assumed concavity of the net revenue function with respect to the NP own solicitation spending, the sign of $\frac{df_{jm}}{dG_{jm}}$ depends on the sign of the numerator.

Note that the second-order partial, $\frac{\partial^2 s_{jm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{jm}\partial G_{jm}}$, in the numerator of equation (19) can be written as $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}}$, which measures how first-order partial, $\frac{\partial s_{jm}}{\partial f_{jm}}$, is influenced by a marginal change in G_{jm}. The first-order partial, $\frac{\partial s_{jm}}{\partial f_{jm}}$, measures the effectiveness or efficiency of nonprofit $j's$ solicitation activities in securing donations for fulfilling its mission. Accordingly, $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}}$ measures how the provision of government grants to nonprofit j influences the efficiency/effectiveness of its solicitation activities in securing donations for fulfilling its mission.

Based on the donor demand model laid out above, it can be shown that

$$\frac{\partial s_{jm}}{\partial f_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\frac{\gamma}{f_{jm}} s_{ijm}\left[1 - s_{ijm}\right] \tag{20}$$

Therefore,

$$\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\frac{\gamma}{f_{jm}}\left[\frac{\partial s_{ijm}}{\partial G_{jm}} - 2s_{ijm}\frac{\partial s_{ijm}}{\partial G_{jm}}\right]$$

$$\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns}\frac{\gamma}{f_{jm}}\frac{\partial s_{ijm}}{\partial G_{jm}}\left[1 - 2s_{ijm}\right] \tag{21}$$

The task now is to sign the expression on the right-hand side of equation (21). Throughout, I will assume that fundraising intensity positively impacts private giving, which implies $\gamma > 0$, an assumption that is later supported by the parameter estimates in the donor demand model. In addition, recall that the partial derivative, $\frac{\partial s_{ijm}}{\partial G_{jm}}$, measures own-firm "direct" grant crowd-out/crowd-in of donor $i's$ private giving as discussed above and shown in equation (7).

First, consider the case in which a sufficiently large number of donors in the market perceive government grants as a substitute for their own private giving, i.e., $\frac{\partial s_{ijm}}{\partial G_{jm}} < 0$ for a sufficiently large number of donors resulting in "direct" crowd-out. In addition, the right-hand side of equation (21) suggests that the sign of $[1 - 2s_{ijm}]$ for these sufficiently large number of donors with "direct" grant crowd-out type preferences will determine the sign of $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}}$. Specifically, if $s_{ijm} > 0.5$ holds for these donors in the market, i.e., enough donors with "direct" grant crowd-out type preferences also have a greater than 0.5 probability of donating to nonprofit j, which implies $[1 - 2s_{ijm}] < 0$ for these donors, then we will have $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}} > 0$. However, if instead $s_{ijm} < 0.5$ holds for these donors in the market, which implies $[1 - 2s_{ijm}] > 0$ for them, then we will have $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}} < 0$.

Conversely, now consider the case in which a sufficiently large number of donors in the market perceive government grants as a complement to their own private giving, i.e., $\frac{\partial s_{ijm}}{\partial G_{jm}} > 0$ for a sufficiently large number of donors resulting in "direct" crowd-in. In addition, if $s_{ijm} > 0.5$ holds for these sufficiently large number of donors with "direct" grant crowd-in type preferences in the market, i.e., they have a greater than 0.5 probability of donating to nonprofit j, which implies $[1 - 2s_{ijm}] < 0$ for these donors, then we will have $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}} < 0$. However, if instead $s_{ijm} < 0.5$ holds for these donors in the market, which implies $[1 - 2s_{ijm}] > 0$ for them, then we will have $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}} > 0$.

The discussion above illustrates that the sign of $\frac{\partial\left(\frac{\partial s_{jm}}{\partial f_{jm}}\right)}{\partial G_{jm}} = \frac{\partial^2 s_{jm}(\boldsymbol{f}_m, \boldsymbol{G}_m; \theta)}{\partial f_{jm} \partial G_{jm}}$ may be either positive or negative depending on whether there is "direct" crowd-in or "direct" crowd-out in combination with the sign of $[1 - 2s_{ijm}]$ for enough donors, where the sign of $[1 - 2s_{ijm}]$ for each donor is determined by the value of the probability with which the donor donates to the nonprofit. Therefore, the sign of the derivative,

$\frac{df_{jm}}{dG_{jm}}$, in equation (19) may be either negative or positive, revealing that the provision of government grants to nonprofit j may shift its solicitation reaction function in either direction.

In the strategic setting I consider, government grants provided to nonprofit j will also shift the solicitation reaction function of nonprofits that are rivals to nonprofit j, *ceteris paribus*. Using arguments analogous to the ones above, it can be shown that:

$$\frac{df_{rm}}{dG_{jm}} = \frac{\frac{\partial^2 s_{rm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{rm}\partial G_{jm}} PD_m}{-\left[\frac{\partial^2 s_{rm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{rm}^2} PD_m - \frac{\partial mc_{rm}}{\partial f_{rm}}\right]} \quad (22)$$

The sign of the derivative, $\frac{df_{rm}}{dG_{jm}}$, in equation (22) informs us of the direction in which rival nonprofit $r's$ solicitation reaction function shifts in response to government grants, G_{jm}, provided to nonprofit j. Again, applying arguments analogous to the ones provided above, it is the case that the sign of $\frac{df_{rm}}{dG_{jm}}$ depends on the sign of the numerator in equation (22).

The second-order partial, $\frac{\partial^2 s_{rm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{rm}\partial G_{jm}}$, can be written as $\frac{\partial\left(\frac{\partial s_{rm}}{\partial f_{rm}}\right)}{\partial G_{jm}}$, which measures how first-order partial, $\frac{\partial s_{rm}}{\partial f_{rm}}$, is influenced by a marginal change in G_{jm}. The second-order partial, $\frac{\partial\left(\frac{\partial s_{rm}}{\partial f_{rm}}\right)}{\partial G_{jm}}$ measures how the provision of government grants to nonprofit j influences the efficiency/effectiveness of rival nonprofit $r's$ solicitation activities in securing donations for fulfilling nonprofit $r's$ mission. Based on my donor demand model:

$$\frac{\partial s_{rm}}{\partial f_{rm}} = \frac{1}{ns}\sum_{i=1}^{ns} \frac{\gamma}{f_{rm}} s_{irm}[1 - s_{irm}] \quad (23)$$

Therefore,

$$\frac{\partial\left(\frac{\partial s_{rm}}{\partial f_{rm}}\right)}{\partial G_{jm}} = \frac{1}{ns}\sum_{i=1}^{ns} \frac{\gamma}{f_{rm}} \frac{\partial s_{irm}}{\partial G_{jm}} [1 - 2s_{irm}] \quad (24)$$

Given the similarity in structure of equations (21) and (24), arguments analogous to those used for equation (21) imply that the sign of $\frac{\partial\left(\frac{\partial s_{rm}}{\partial f_{rm}}\right)}{\partial G_{jm}} = \frac{\partial^2 s_{rm}(\boldsymbol{f}_m,\boldsymbol{G}_m;\theta)}{\partial f_{rm}\partial G_{jm}}$ may be either positive or negative depending on whether there is "direct" crowd-in or "direct" crowd-out in combination with the sign of $[1 - 2s_{irm}]$ for enough donors in the market. Therefore, the sign of the derivative, $\frac{df_{rm}}{dG_{jm}}$, in equation (22) may be either negative or positive, revealing that the provision of government grant to nonprofit j may shift the solicitation reaction function of rival nonprofit r in either direction.

In summary, how the provision of government grants influences the Nash equilibrium in fundraising spending is an empirical question since in principle the solicitation reaction functions for the grant-receiving firm and its rivals may shift in either direction. Accordingly, I now take the model to real-world data to understand how the systematic patterns in the data translate into empirical predictions on government grant crowd-out or crowd-in of private giving to nonprofit firms.

3. Data

The donation, fundraising, and government grants data, measured in dollars, are for 501(c)3 public organizations that filed tax returns over the period 2008 through 2015.[4] These annual frequency data are obtained from the National Center on Charitable Statistics (NCCS) at The Urban Institute. Although most nonprofits are exempt from federal income taxation, the United States Internal Revenue Service (IRS) requires them to file a 990 tax return form annually if their gross receipts are greater than $25,000.

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

A NP attribute that is most important for this study is the amount of government grants provided to each nonprofit organization in each year. These data contain the aggregate dollar value of government grants received by each nonprofit organization in each year. A nonprofit organization may not receive government grants every year, so this variable is zero in some years for many nonprofits. However, based on the primary focus of this study, I restrict the sample to NPs that receive government grants at least once throughout the 2008-2015 sample period.

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

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

Table 1: Description of Nonprofits and Sectors in the Sample

Sector Number	Sector Name	Examples of Nonprofit Organizations	Mean Annual NP Count	Mean % of Sample NP Count
1	Arts	AUGUSTA MINI THEATRE INC; CENTER THEATRE GROUP OF LOS ANGELES; BALTIMORE MUSEUM OF ART; BEVERLY ARTS CENTER; BOSTON BALLET INC; FORT WORTH MUSEUM OF SCIENCE AND HISTORY	328 - - -	9.59 - - -
2	Education	ANN ARBOR DISTRICT LIBRARY; AURORA CHRISTIAN SCHOOL INC; BARBARA CHAMBERS CHILDREN CENTER INC; BAY AREA SCHOOL FOR INDEPENDENT STUDY	788 - - -	23.09 - - -
3	Environmental & Animal	BOTANICAL RESEARCH INSTITUTE OF TEXAS; CAPITAL AREA HUMANE SOCIETY; CENTER FOR NATURAL LANDS MANAGEMENT; Chicago Zoological Society	108 - - -	3.15 - - -
4	Health	JOSEPH P ADDABBO FAMILY HEALTH CENTER; James A Eddy Memorial Geriatric Center; KANE COMMUNITY HOSPITAL; KIDS COMMUNITY CLINIC OF BURBANK	1105 - - -	32.39 - - -
5	Human & Social Services	DOMESTIC VIOLENCE INTERVENTION SERVICES; GREAT MIAMI VALLEY YMCA; FOOD BANK OF NORTHEAST LOUISIANA INC; KIPS BAY BOYS AND GIRLS' CLUB INC; GIRL SCOUTS OF GREATER ATLANTA INC.	788 - - -	23.06 - - -
6	International	US MEXICO FOUNDATION FOR SCIENCE INC; EDUCATION DEVELOPMENT CENTER INC; Heifer Project International; INTERNATIONAL JUSTICE MISSION	48 - - -	1.40 - - -
7	Civil Rights & Advocacy	BLACK VETERANS FOR SOCIAL JUSTICE; COMMUNITY ACTION OF SKAGIT COUNTY; DISABILITY RIGHTS CALIFORNIA; FLORIDA DIVERSITY BUSINESS COUNCIL INC; THE CENTER FOR COMMUNITY SOLUTIONS	250 - - -	7.31 - - -

Notes: This table describes the sector classifications for the sample of nonprofits and provides a few examples of the nonprofits. The panel spans the period 2008 through 2015.

Local geographic markets in this study are delineated by zip code area. To facilitate computing each nonprofit's donation share within a given local market for a given year, I first determine the donative capacity of each market, a variable denoted as PD_m first defined above in equation (11). The donative capacity of a local market, PD_m, is computed as 2.5 times the maximum aggregate donations observed in the relevant zip code area in a given year over the sample years of the study. An advantage of using this method to measure the donative capacity of each market is that this method captures the variation across local markets of their populations' propensity to donate. For example, two local markets with the same number of individuals may have very different propensities to donate based on differences across the markets with respect to their populations' demographic characteristics such as income, race, etc. However, a caveat of the method is that the 2.5 multiplicative factor is an arbitrary number. Accordingly, it is prudent to assess the extent to which results are sensitive to the multiplicative factor used for approximating the donative capacities. To this end, I have re-estimated the demand model using multiplicative factors less than and greater than 2.5 and find that key qualitative results are largely robust to the resulting donative capacity changes. Estimation results based on the multiplicative factors 1.5 and 5, respectively, are reported in Table A1 in the Appendix.

With measures of PD_m in hand, I then compute each nonprofit's observed donation share within a given local market for a given year as, $S_{jmt} = Donations_{jmt}/PD_m$, where $Donations_{jmt}$ is the dollar amount of private donations received by nonprofit j located in market m during period/year t. Accordingly, the observed share of the outside option, S_{0mt}, i.e., the observed mean probability that potential donors choose not to donate to one of the nonprofits in the local market is computed as, $S_{0mt} = 1 - \sum_{j=1}^{J_{mt}} S_{jmt}$, [5] where as previously defined, J_{mt} is the number of nonprofits in the local market.

Organizations reporting negative contributions, program service revenues, or assets are deleted. The sample has 27,321 observations generated from 3,655 nonprofit organizations across 15,609 market-year combinations. Table 2 reports summary statistics on the key variables used in the empirical analysis.

Table 2: NP-level Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Market share of Donations (S_{jmt})	0.122	0 .1318	0.00000005	0.40
Donations (000 of $)	8591.42	38100	0.000924	1,190,000
Government Grants (000 of $)	7,979.01	65,600	0	4,150,000
Solicitation spending (000 of $)	130.80	1,015.28	0	39,000
Program service revenue (000 of $)	109,000	657,000	0	41,200,000
Assets (000 of $)	232,000	1,020,000	0.143	40,000,000
Number of nonprofits per local market	3.46	3.651	1	28
Number of observations	27,321			

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

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

4. Results from Donor Demand Estimation

I draw upon the discrete-choice demand model literature, following Berry (1994); Berry, Levinsohn and Pakes (1995) (BLP); and Nevo (2000) to estimate the parameters in my random coefficients logit donor demand model using generalized method of moments (GMM). I follow the nonlinear GMM estimation algorithm proposed in Nevo (2000) to obtain estimates of the demand parameters, $\theta = (\gamma, \lambda, \beta, \sigma, \phi)$, that enter the GMM objective function linearly, (γ, λ, β), and nonlinearly, (σ, ϕ).

It is likely that nonprofits' fundraising spending, f_{jmt}, and the government grants they receive, G_{jmt}, are correlated with NP attributes captured in ξ_{jmt} that are unobserved by me the researcher but observed by donors, nonprofits, and government officials responsible for making grant award decisions. For example, it is not difficult to imagine that nonprofits in the sample with well-managed operational infrastructure unobserved to me are likely the recipients of relatively more government grants and are relatively more efficient in securing private donations from their fundraising efforts. Even with the included NP-level fixed effects in the demand model that help control for time-invariant NP-level attributes that are unobserved to me the researcher, as well as period/year fixed effects to control for occurrences of time-varying events that are unobserved to me the researcher but uniformly impact donors, NPs, and government grant agencies, there may exists NP-specific factors that: (*i*) change over time; (*ii*) influence either f_{jmt}, G_{jmt}, or both; and (*iii*) are unobserved to me. Accordingly, econometric estimation of the demand parameters needs to account for the likelihood that f_{jmt} and G_{jmt} are endogenous variables, and therefore instruments for these variables are needed to achieve consistent estimates of the parameters associated with them.

Following Gayle and Harrison (2023), I construct and use well-known BLP-motivated type instruments for firms' fundraising intensity variable. Such BLP-motivated instruments include the means of asset value and program service revenues across a NP's rivals. Additional instruments used for the solicitation intensity variable include the number of competing nonprofits in the local market. The rationale for this instrument is that the number of competing nonprofits is a measure of the competitive intensity a given nonprofit faces to secure donations. The degree of competitive intensity a NP faces to secure donations should influence its optimal choice of solicitation intensity. Given that the number of competing nonprofits in a market during period t is determined by rival nonprofits' entry decisions in some previous period, then I do not expect the number of competing nonprofits in period t is correlated with ξ_{jmt}, making this a valid instrument for f_{jmt}.

To instrument for the government grants a NP receives within a given year I follow Harrison, Henderson, Ozabaci, and Laincz (2023) and use the aggregate value of government grants awarded to a NP's rivals within the local market for the relevant year. The rationale is that a government often predetermines at the beginning of the year the total amount of grant money that will be allocated to nonprofits. From this predetermined fixed pot of grant money, the amount of grant money secured by a given nonprofit is inversely related to the amount secured by the nonprofit's rivals.

To obtain estimates of the random coefficients, recall from my previous discussion of the donor demand model that I include in the specification interactions of potential donors' observed demographics, $D_i = \begin{pmatrix} Income_i \\ White_i \end{pmatrix}$, with government grants, as well as interactions of potential donors' unobserved preference shocks, $v_i = \begin{pmatrix} v_i^C \\ v_i^G \end{pmatrix}$, with the intercept and government grants, respectively. The coefficients of these interaction variables serve to distinguish the estimated donation substitution patterns from those implied by a standard logit model, and better capture the heterogeneity in preferences across potential donors. Similar in spirit to the product differentiation instruments suggested in Gandhi and Houde (2020), to identify the random coefficients I construct nonprofit differentiation instruments along the dimensions of various measured nonprofit attributes. For example, a differentiation instrument used is constructed by computing the Euclidian distance between a nonprofit's predicted government grants and predicted government grants of rival nonprofits, where the predicted grants are generated from an ordinary least square (OLS) estimated reduced-form grant regression.[6]

Table 3 reports parameter estimates of the donor demand model. In columns (1) and (2) of the table I report parameter estimates for the standard logit version of the demand model that does not account for heterogeneity in donor preferences.[7] Instruments for the endogenous variables f_{jmt} and G_{jmt} are not used

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[6] For the construction of these differentiation instruments, I refer the reader to Table 12 in Gandhi and Houde (2020). The predicted government grants are obtained from a reduced-form regression of government grants on all the measured nonprofit attributes as well as firm and period fixed effects. Similar in spirit to the formulas in Gandhi and Houde (2020), the Euclidian distance instrument for grants in this study is defined as: $\sqrt{\sum_{j' \neq j \in J_t} \left(\hat{G}_{j't} - \hat{G}_{jt}\right)^2}$.

[7] Estimating the standard logit version of the donor demand requires simply estimating the following linear equation: $ln(S_{jmt}) - ln(S_{0mt}) = \gamma ln(f_{jmt}) + \sum_{k=1}^{K} \lambda_k \left(G_{jmt} \times I_k\right) + \beta x_{jmt} + \xi_{jmt}$, where S_{jmt} is the observed market share of donations received by firm j in market m during period t computed as the value of donations received by firm j as a proportion of the donative capacity (measured by PD_m, first defined in equation (11)) of the market; S_{0mt} is the observed proportion of the donative capacity of market m during period t that is not secured by the nonprofit firms in the market.

when obtaining the parameter estimates in column (1), but instruments for the endogenous variables are used when obtaining the parameter estimates reported in column (2). It is evident that the values of the parameter estimates associated with the endogenous variables are very different across columns (1) and (2), suggesting that instruments are needed to address the endogeneity challenges posed by variables f_{jmt} and G_{jmt}. A formal statistical test reported in the table confirms the endogeneity of f_{jmt} and G_{jmt}.

The parameter estimates in column (2) that capture donors' direct marginal giving response to government grants received by nonprofits are statistically significant at conventional levels of statistical significance for nonprofits in sectors 1, 4, 5, and 6, respectively. The signs of these parameter estimates ($\lambda_1 < 0$, $\lambda_4 < 0$, $\lambda_5 > 0$, $\lambda_6 > 0$) suggest that donors' direct response is to reduce their private giving to grant-receiving nonprofits in sectors 1 and 4 but increase their private giving to grant-receiving nonprofits in sectors 5 and 6. These results suggest that on average donors perceive government grants to nonprofits in sectors 1 and 4 as substitutes for their own private giving, but as a complement to their own private giving to nonprofits in sectors 5 and 6. However, it is important to recall that the demand model in column (2) does not account for heterogeneity in donor preferences. In other words, the model in column (2) does not have the flexibility to capture the likelihood that private donors to a set of same-sector nonprofits may change their giving behavior differently in response to government grants provided to these nonprofits, i.e., some donors may perceive the government grants as substitutes for their own giving while others perceive the government grants as complementary to their own giving. To capture such likely heterogeneity in donor preferences, I turn to estimates from the full random coefficients model reported in column (3).

As expected, the positive and statistically significant parameter estimate on fundraising intensity in the donor demand model, i.e., $\gamma > 0$, suggests that by increasing its fundraising intensity, a nonprofit firm can increase the private donations it receives as well as its market share among these donations. In addition, taste variation parameter, σ^c, associated with the constant is statistically significant, revealing heterogeneity in preferences across donors with respect to their proclivity to donate to one of the available nonprofit alternatives versus not donating to any of them.

Table 3: Donor Demand Model Estimates

	Standard Logit Specification		Random Coefficients Logit Specification
	OLS Estimation	2SLS Estimation	GMM Estimation
Factors influencing mean utility	Parameter estimate (std. error)	Parameter estimate (std. error)	Parameter estimate (std. error)
Constant	-5.25*** (0.254)	-11.18* (6.35)	-22.82*** (6.55)
Solicit (γ)	0.044*** (0.004)	2.339** (0.974)	2.147** (0.920)
Gov Grants × Sector 1 (λ_1)	0.113 (0.074)	-20.322** (8.343)	-3.784 (8.528)
Gov Grants × Sector 2 (λ_2)	0.010 (0.009)	0.247 (0.456)	-0.278 (0.479)
Gov Grants × Sector 3 (λ_3)	-0.094*** (0.038)	-4.027 (7.528)	4.549 (9.340)
Gov Grants × Sector 4 (λ_4)	-0.007 (0.018)	-7.939*** (2.639)	-2.481 (2.695)
Gov Grants × Sector 5 (λ_5)	-0.010 (0.017)	8.110*** (2.426)	3.638 (2.667)
Gov Grants × Sector 6 (λ_6)	0.143*** (0.036)	18.553** (7.899)	4.559 (8.348)
Gov Grants × Sector 7 (λ_7)	0.011 (0.009)	2.067 (1.637)	-0.996 (1.812)
Program service revenue	-0.033*** (0.005)	0.295*** (0.106)	0.077 (0.119)
Assets	0.150*** (0.017)	-0.498 (0.337)	-0.009 (0.368)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Taste Variation Controls			
v × Constant (σ^c)	-	-	62.55*** (7.181)
v × Gov Grants (σ^G)	-	-	-0.567*** (0.083)
Income × Gov Grants (ϕ^{Income})	-	-	0.794*** (0.115)
White × Gov Grants (ϕ^{White})	-	-	-0.094*** (0.037)
R-squared	0.7183		
Number of Observations	27,321		
Test of endogeneity: Wu-Hausman		$F(8, 23464) = 139.47$; p-value = 0.000	
GMM Objective Function Value	-	-	22.55

Notes: Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level of significance, respectively.

The sector-specific parameters, λ_k, that measure the marginal impact on donors' mean utility obtained from donating to a nonprofit induced by its receipt of government grants are not statistically significant at conventional levels of statistical significance. However, this does not imply that donors have no preference for adjusting their private giving in response to government grants provided to nonprofits. In fact, the statistical significance of the taste variation parameters (σ^G, ϕ^{Income}, ϕ^{White}) associated with the provision of government grants suggests quite the opposite. Specifically, $\sigma^G < 0$ suggests that the larger is a donor's preference draw in favor of the provision of government grants the more likely is such a donor to perceive their private giving as a substitute for government grant and consequently government grants are more likely to induce a "direct" crowd-out of the private giving from such donors, *ceteris paribus*. Second, $\phi^{Income} > 0$ suggests that higher income donors are more likely to perceive their private giving as a complement to government grants and consequently government grants are more likely to induce a "direct" crowd-in of the private giving from higher income donors, *ceteris paribus*. Third, $\phi^{White} < 0$ suggests that donors who identify their race as being white are more likely to perceive their private giving as a substitute to government grants and consequently government grants are more likely to induce a "direct" crowd-out of the private giving from such donors, *ceteris paribus*.

Hungerman (2009) finds systematic reduced-form regression evidence that the magnitude of crowd-out varies by the racial diversity of local donor markets. Specifically, he finds that the crowd-out of private funding of charitable services by government funding of these services is attenuated the more racially diverse is the local donor market. In other words, there is less crowd-out in local markets with a larger presence of minority races. This finding in Hungerman (2009) is somewhat consistent and complementary with the finding in this study that donors who identify their race as being white are more likely to perceive their private giving as a substitute to government grants and consequently government grants are more likely to induce a "direct" crowd-out of the private giving from such donors.

In summary, the model estimates suggest that there exists heterogeneity in private donor preference for the provision of government grants to nonprofits and consequently whether the provision of government grants induces "direct" crowd-out or crowd-in of private giving to grant-receiving nonprofits will depend on the preference profile of the population of potential donors to the nonprofit. Furthermore, the estimates suggest that potential donors' income and race are important demographic factors that directly determine their private giving response to the provision of government grants. An important implication of this finding is that empirical evidence of crowd-out versus crowd-in likely depend on the demographic mix of private donors to the sample of nonprofits being empirically studied, and consequently it is not surprising for the literature to present mixed results on the crowd-out hypothesis, as have been the case.

Next, I use the estimated model to perform counterfactual experiments designed to measure the extent to which the provision of government grants to nonprofits crowd-out or crowd-in private giving to the nonprofits. The remainder of the paper focuses on these counterfactual experiments.

5. Implementing the Counterfactuals

The counterfactual experiments I run can be classified into three types: (*i*) *Experiment 1*, which is designed to measure the "direct" government grant crowd-out or crowd-in of private giving; (*ii*) *Experiment 2*, which is designed to measure government grant crowd-out or crowd-in of nonprofits' fundraising/solicitation spendings; and (*iii*) *Experiment 3*, which is designed to measure the combined "direct" and "indirect" effects of government grant crowd-out or crowd-in of private giving. I now describe how each of these experiments is implemented.

Experiment 1

To implement *Experiment 1* I first counterfactually increase by 20% the government grants provided to a single firm in each market for a given year. Even though the period subscript t is omitted from model components below, this omission is only for the purpose of avoiding a clutter of notation. Accordingly, for a given market and year I use the factual menu of government grants provided to nonprofits to obtain the counterfactual menu of government grants provided. Specifically, let $\boldsymbol{G}_m = (G_{jm}, G_{-j,m})$ represent the factual vector of dollar value of government grants provided to the nonprofits in market m, where G_{jm} denotes the grants provided to nonprofit j; and $G_{-j,m}$ denotes the vector of grants provided to the nonprofits that compete with nonprofit j, i.e., $G_{-j,m} = \boldsymbol{G}_m \backslash G_{jm}$. I define the counterfactual vector of grants provided as $\widetilde{\boldsymbol{G}}_m = (1.20 \times G_{jm}, G_{-j,m})$, i.e., among the rival nonprofits in market m, only nonprofit j experiences a 20% counterfactual increase in government grants provided. The nonprofit that gets to be firm j is randomly selected in each market.

With $\boldsymbol{G}_m$ and $\widetilde{\boldsymbol{G}}_m$ in hand, as well as the vector of demand parameter estimates, $\hat{\theta}$, reported in column (3) of Table 3, I then compute private donation share vectors $\boldsymbol{s}_m(\boldsymbol{f}_m, \boldsymbol{G}_m; \hat{\theta})$ and $\tilde{\boldsymbol{s}}_m(\boldsymbol{f}_m, \widetilde{\boldsymbol{G}}_m; \hat{\theta})$ using the model-predicted share function described in equations (5) and (6). Note that $\tilde{\boldsymbol{s}}_m(\boldsymbol{f}_m, \widetilde{\boldsymbol{G}}_m; \hat{\theta})$ is the counterfactual vector of private donation shares across rival nonprofits in the market when only donors optimally respond to the new government grants provided to one of the nonprofits. Since the vector of fundraising intensities, $\boldsymbol{f}_m$, is held fixed at their factual levels throughout *Experiment 1*, the comparison of $\boldsymbol{s}_m$ with $\tilde{\boldsymbol{s}}_m$ reveals the extent of the "direct" government grant crowd-out or crowd-in of private giving driven purely by optimizing donor choice behavior.

Experiment 2

To discuss implementation of *Experiment 2*, it is convenient to first represent in matrix notation the system of first-order conditions illustrated in equation (15) from the Nash equilibrium solicitation spending game. Let Δ_m be a $J_m \times J_m$ matrix that captures the response of donation shares to changes in solicitation intensities, where J_m is the number of rival nonprofit firms in the relevant market. Specifically, matrix Δ_m contains first-order partial derivatives of donation shares with respect to solicitation intensities:

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

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

The system of first-order conditions in equation (15) can now be represented in matrix notation as follows:

$$[(\boldsymbol{I} * \Delta_m) \times Ones(J_m, 1)] \times PD_m - \boldsymbol{mc}_m = \boldsymbol{0} \tag{25}$$

where $\boldsymbol{I}$ in equation (25) is a $J_m \times J_m$ identity matrix; $\boldsymbol{I} * \Delta_m$ is an element-by-element multiplication of the two matrices; $Ones(J_m, 1)$ is a $J_m \times 1$ vector of ones; PD_m is a scalar measure of the donative capacity of the local market; $\boldsymbol{mc_m}$ is a $J_m \times 1$ vector of marginal costs across the NPs in the local market; and $\boldsymbol{0}$ is a $J_m \times 1$ vector of zeros.

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

$$\left[\left(\boldsymbol{I} * \Delta_m\left(\boldsymbol{f}_m, \boldsymbol{G}_m; \hat{\theta}\right)\right) \times Ones(J_m, 1)\right] \times PD_m = \widehat{\boldsymbol{mc}}_{\boldsymbol{m}} \tag{26}$$

I assume the estimated marginal costs captured in vector $\widehat{\boldsymbol{mc}}_{\boldsymbol{m}}$ do not change with any counterfactual change in government grants provided. Accordingly, with $\widehat{\boldsymbol{mc}}_{\boldsymbol{m}}$ in hand, I then solve for the vector of optimal NP solicitation spendings, $\boldsymbol{f}_m^G$, that satisfy:

$$\left[\left(\boldsymbol{I} * \Delta_m\left(\boldsymbol{f}_m^G, \widetilde{\boldsymbol{G}}_m; \hat{\theta}\right)\right) \times Ones(J_m, 1)\right] \times PD_m - \widehat{\boldsymbol{mc}}_{\boldsymbol{m}} = \boldsymbol{0} \qquad (27)$$

Note the key difference between equation (26) and equation (27) is that factual $\boldsymbol{G}_m$ in equation (26) is replaced with counterfactual $\widetilde{\boldsymbol{G}}_m$ in equation (27). Last, a corresponding comparison of $\boldsymbol{f}_m$ with $\boldsymbol{f}_m^G$ across all nonprofits in the relevant market will reveal the extent to which the counterfactual change in the provision of government grants impacts equilibrium solicitation spendings.

Experiment 3

Now with $\widetilde{\boldsymbol{G}}_m$ and $\boldsymbol{f}_m^G$ in hand from *Experiment 1* and *Experiment 2*, respectively, I can implement *Experiment 3* simply by computing $\bar{\bar{\boldsymbol{s}}}_m\left(\boldsymbol{f}_m^G, \widetilde{\boldsymbol{G}}_m; \hat{\theta}\right)$ and comparing it with $\boldsymbol{s}_m\left(\boldsymbol{f}_m, \boldsymbol{G}_m; \hat{\theta}\right)$ across all nonprofits in the relevant market. Note that $\bar{\bar{\boldsymbol{s}}}_m\left(\boldsymbol{f}_m^G, \widetilde{\boldsymbol{G}}_m; \hat{\theta}\right)$ is the counterfactual vector of private donation shares across rival nonprofits in the market when both donors and nonprofits optimally respond to the new government grants provided to one of the nonprofits. Accordingly, the comparison of $\boldsymbol{s}_m$ with $\bar{\bar{\boldsymbol{s}}}_m$ reveals the extent to which the combined "direct" and "indirect" effects of government grant crowds-out or crowds-in private giving.

6. Results from the Counterfactual Experiments

I begin by reporting and discussing results from *Experiment 1*. The results are broken down by whether the local market has a single nonprofit, which I call monopoly donor markets, versus markets with two or more competing nonprofits, which I call oligopoly donor markets. Approximately 67% of the local markets in the sample are monopoly donor markets but these markets only account for 38% of the nonprofit-level observations in the data. Therefore, a substantial majority of the nonprofits in the data are in oligopoly donor markets. Competition and strategic interaction among nonprofits with respect to fundraising are absent from the monopoly markets but present in the oligopoly markets. Accordingly, decomposing the results based on the presence of fundraising competition will better facilitate comparisons later when nonprofit responses to the provision of government grants are considered.

Table 4 reports model-predicted changes in private giving to nonprofits in local monopoly donor markets driven by a 20% counterfactual increase in government grants to the nonprofit in the relevant local market. The predictions in this table assume that the nonprofit does not change its fundraising spending in response to the government grants provided, i.e., the change in private giving is driven only by a change in donors' donation choice behavior. The estimates reveal that in most cases (approximately 71%) the grants crowd-out private giving to the grant-receiving nonprofits, with private giving expected to fall by a mean 2.76% among the grant-receiving nonprofits. The declines in private giving correspond to NP-level grant crowd-out mean elasticity of -0.138, i.e., private giving fall by a mean 0.138% for each 1% increase in new government grants provided to the nonprofits. As the last row in the table shows, these "direct" grant crowd-out changes measured in dollar terms correspond to a mean 4 cents decline in private donations to the grant-receiving NP for each additional dollar of grant provided. Measured in terms of dollars, there is also evidence of "direct" grant crowd-in. Specifically, the last row in the table shows that for the "direct" grant crowd-in cases private donations to grant-receiving NPs are expected to increase by a mean 43 cents for each additional dollar of grant provided to them.

Table 4: Model-predicted NP-level Direct Crowd-out/Crowd-in effects on private giving caused by government grants to the single nonprofit in each local monopoly donor market. (**Monopoly Markets**)

	Cases showing crowd-out of private giving to the nonprofit that counterfactually received 20% more grants	Cases showing crowd-in of private giving to the nonprofit that counterfactually received 20% more grants	% of crowd-out cases
	Mean (Std. error of mean)	Mean (Std. error of mean)	
NP-level % change in private donations	-2.76*** (0.095)	537.36 (507.75)	71.11
NP-level grant crowding of private donations Elasticity	-0.138*** (0.005)	26.87 (25.39)	-
NP-level grant crowding of private donations (in $/cents) per dollar of additional grant provided	-0.04*** (0.002)	0.43*** (0.06)	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level.

Table 5 reports model-predicted changes in private giving to nonprofits in local oligopoly donor markets driven by a 20% counterfactual increase in government grants to one of the nonprofits in the relevant local market. Like Table 4, the predictions in Table 5 assume that nonprofits do not change their fundraising spending in response to the government grants provided, i.e., the change in private giving is driven only by a change in donors' donation choice behavior. The estimates reveal that in most cases (approximately 88%) the grants crowd-out private giving to the grant-receiving nonprofits. The table shows that private giving is expected to fall by a mean 5.81% among the grant-receiving nonprofits. The declines in private giving to the grant-receiving nonprofits correspond to NP-level grant crowd-out mean elasticity of -0.29, i.e., private giving fall by a mean 0.29% for each 1% increase in new government grants provided to the nonprofits. As the last row in the table shows, these "direct" grant crowd-out changes measured in dollar terms correspond to a mean 34 cents decline in private donations to the grant-receiving NP for each additional dollar of grant provided.

It is important to note that in a setting where nonprofits compete for private donations, rival nonprofits that did not receive additional grants nevertheless will experience a change in their private donations as I have illustrated in discussing equation (8). For example, the estimates in Table 5 show that nonprofits that are rivals to the nonprofit that experienced crowd-out of private giving due to receiving additional government grants will experience an increase in their private donations by a mean 6%. In other words, there is evidence that some donors are likely to switch their donations from the firm that receives additional grants to its rivals who did not receive additional grants.

Table 5: Model-predicted NP-level Direct Crowd-out/Crowd-in effects on private giving caused by government grants to a single nonprofit in each local oligopoly donor market. (**Oligopoly Markets**)

	Cases showing crowd-out of private giving to the NPs that counterfactually received additional grants		Cases showing crowd-in of private giving to the NPs that counterfactually received additional grants		% of crowd-out cases
	Among NPs that counterfactually received 20% more grants	Among rival NPs that did not have a change in their grants	Among NPs that counterfactually received 20% more grants	Among rival NPs that did not have a change in their grants	
	Mean (Std. error of mean)	Mean (Std. error of mean)	Mean (Std. error of mean)	Mean (Std. error of mean)	
NP-level % change in private donations	-5.81*** (0.222)	6.18*** (0.480)	509.53** (232.54)	-11.45*** (1.07)	88.54
NP-level grant crowding of private donations Elasticity	-0.290*** (0.011)	-	25.48** (11.63)	-	-
NP-level grant crowding of private donations (in $/cents) per dollar of additional grant provided	-0.34*** (0.023)	-	0.64*** (0.128)	-	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level.

It is evident from the model predictions in Table 5 that government grants can crowd-in private giving to grant-receiving nonprofits, i.e., there exist private donors with a preference for donating more to nonprofits that receive additional government grants. The last row in the table shows that the "direct" grant crowd-in changes measured in dollar terms correspond to a mean 64 cents increase in private donations to the grant-receiving NP for each additional dollar of grant provided. Furthermore, the table shows that private donations to rivals of the nonprofits that experienced "direct" grant crowd-in will decline by a mean 11%, that is, some private donors are predicted to switch their donations from rivals of the grant-receiving NP to partly finance the crowd-in that the grant-receiving NP has experienced.

Unlike Table 5 with predictions focused on NP-level metrics, Table 6 reports model-predicted changes in private giving aggregated across rival nonprofits in the relevant local oligopoly donor market. However, like Table 5, the predictions in Table 6 assume that nonprofits do not change their fundraising spending in response to the government grants provided, i.e., the change in private giving is driven only by a change in donors' behavior. Table 6 reveals that the provision of government grants to NPs will crowd-out private giving in the majority (approximately 88%) of local donor markets. The mean market-level "direct" crowd-out elasticity is -0.281, i.e., aggregate private giving in the local donor market will decrease by 0.281% for each percentage point increase in government grants provided to a subset of nonprofits in the local market. Furthermore, the market-level "direct" grant crowd-out changes measured in dollar terms correspond to a mean 15 cents decrease in private donations for each additional dollar of grant provided to nonprofits across these local oligopoly donor markets.

Table 6 also shows that there exist markets that are predicted to experience aggregate "direct" grant crowd-in of private donations. Specifically, the market-level "direct" grant crowd-in changes measured in dollar terms correspond to a mean 49 cents increase in private donations for each additional dollar of grant provided to nonprofits across these local donor markets.

Several early theoretical studies are built on the assumption that potential donors are "purely" altruistic, i.e., donors only derive satisfaction from the aggregate level of the public good provided, which implies that for any given aggregate level of the public good provided a donor perceives their own donation as perfectly substitutable with other private donations and government grants to the nonprofit [Warr (1982, 1983); Roberts (1984, 1987); Bergstrom, Blume, and Varian (1986)]. Consequently, these theoretical studies predict that government grants to nonprofits will "completely" crowd-out private giving, where "complete" here simply means that private giving to nonprofits will fall by *at least* a dollar for each dollar of government grant provided to the nonprofits, which as illustrated in the example in the footnote at the end of this sentence does not imply that private donations to grant-receiving nonprofits are necessarily driven to zero with the provision of grants.[8] However, subsequent theoretical studies argue that potential donors' altruism is "impure" because donors also receive private satisfaction, termed a "warm glow" in the literature, from their own donations to nonprofits [see Andreoni (1989, 1990)]. The "warm glow" causes private donors to be less responsive to the provision of government grants to the extent that crowd-out will necessarily be "incomplete", where "incomplete" here means that private giving to nonprofits will fall by *less* than a dollar for each dollar of government grant provided to the nonprofits.

Table 6: Model-predicted local market-level Direct Crowd-out/Crowd-in effects on private giving caused by government grants to a single nonprofit in each local oligopoly donor market. (**Oligopoly Markets**)

	Cases showing market-level crowd-out of private giving	Cases showing market-level crowd-in of private giving	% of crowd-out cases
	Mean (Std. error of mean)	Mean (Std. error of mean)	
Market-level % change in private donations	-1.58*** (0.102)	35.48*** (8.06)	88.39
Market-level grant crowding of private donations Elasticity	-0.281*** (0.018)	2.52*** (0.49)	-
Market-level grant crowding of private donations (in $/cents) per dollar of additional grant provided	-0.15*** (0.010)	0.49*** (0.125)	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level.

Both the "pure" and "impure" altruism theoretical frameworks are built to explain donors' optimal private giving response to the provision of government grants to nonprofits without any consideration for nonprofits' optimal fundraising response to the provision of government grants, and how the fundraising responses feedback to impact private donations. Accordingly, both the "pure" and "impure" altruism theoretical frameworks are built only to explain the "direct" channel of government grant crowd-out of private giving. The empirical predictions in Table 4, Table 5, and Table 6 reveal that government grant crowd-out of private giving is "incomplete" in the "direct" channel, i.e., private giving to nonprofits will fall by *less* than a dollar for each dollar of government grant provided to the nonprofits. Accordingly, the

[8] As the following example illustrates, the definition of "complete" crowd-out does not imply that private donations to a NP are necessarily driven to zero once government grants are provided to the NP. For example, if the "complete" crowd-out effect is a decline of $2 of private giving for each dollar of government grant provided, then a NP that receives $500,000 in private donations prior to receiving $100,000 in government grants will continue to receive $300,000 in private donations in periods after receiving the government grants since only $200,000 of the private donations will be crowded out.

empirical results here on "direct" grant crowd-out of private giving are more supportive of the "impure" altruism theoretical framework.

As first formally argued by Andreoni and Payne (2003), government grants to nonprofits can cause them to optimally choose to reduce their fundraising efforts, i.e., government grants can crowd-out NPs' fundraising spending. Following *Experiment 2*, Table 7 reports model-predicted changes in nonprofits' optimal fundraising spending caused by a 20% increase in government grants to the single NP in the relevant monopoly donor market. The estimates in the table reveal that government grants can either crowd-out or crowd-in fundraising spending of the grant-receiving NP, though in almost all cases (approximately 99%) crowd-out of fundraising spending occurs. The NP-level government grant crowd-out elasticities of fundraising spending are a mean -5.81 among grant-receiving NPs, while the relatively few NP-level government grant crowd-in elasticities of fundraising spending are a mean 0.43 among grant-receiving NPs. In terms of model-predicted dollar changes in the fundraising spending of grant-receiving nonprofits induced by the additional grants provided to them, the table shows that most monopoly nonprofits will decrease their fundraising spending by a substantial mean $3.74 for each additional dollar of grant provided.

Table 7: Model-predicted NP-level Crowd-out/Crowd-in effects on solicitation spending caused by government grants to the single nonprofit in each local monopoly donor market. (**Monopoly Markets**)

	Cases showing crowd-out of solicitation spending among NPs that counterfactually received 20% more grants	Cases showing crowd-in of solicitation spending among NPs that counterfactually received 20% more grants	% of solicitation crowd-out cases
	Mean (Std. error of mean)	Mean (Std. error of mean)	
NP-level % change in solicitation spending	-116.25*** (0.843)	8.56*** (1.14)	98.82
NP-level grant crowding of solicitation spending Elasticity	-5.81*** ((0.042)	0.43*** (0.057)	-
NP-level grant crowding of solicitation spending (in $/cents) per dollar of additional grant provided	-3.74*** (1.04)	0.008 (0.005)	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level.

Now focusing on nonprofits in oligopoly donor markets, Table 8 reports model-predicted changes in nonprofits' optimal fundraising spending caused by a 20% increase in government grants to a NP in the relevant oligopoly market. The estimates in the table reveal that government grants can either crowd-out or crowd-in fundraising spending of the grant-receiving NP, with crowd-out of fundraising spending occurring in less than half of the cases (approximately 46%). In other words, once competition and strategic interaction among nonprofits with respect to fundraising are considered, which is appropriate in oligopoly donor markets, substantially less cases of government grant crowd-out of fundraising spending occurs. The NP-level government grant crowd-out elasticities of fundraising spending are a mean -0.18 among grant-receiving NPs, while the NP-level government grant crowd-in elasticities of fundraising spending are a mean 0.19 among grant-receiving firms. In terms of dollar value measured responses, grant-receiving NPs are predicted to reduce (increase) their fundraising spending by 3 cents (5 cents) for each additional dollar of government grant provided to them. Accordingly, grant crowd-out versus crowd-in of fundraising spending are relatively balanced both in terms of cases of occurrences and absolute magnitudes of effects, suggesting that nonprofits are almost equally likely to increasing their fundraising spending as they are to reduce their fundraising spending with relatively similar magnitudes in optimally responding to receiving government grants. Importantly, owing to the strategic interaction among rival nonprofits with respect to optimally setting their fundraising spending, Table 8 reveals that grant-receiving nonprofits that optimally decreased (increased) their fundraising spending in response to receiving additional grants will spur their rivals to also decrease (increase) their fundraising spending.

Borgonovi (2006) argues that government funding may incentivize some grant-receiving nonprofits to invest in planning more ambitious activities that require additional private donations, which in turn induces them to increase their solicitation spending. Also consistent with the argument that government grants can induce some grant-receiving nonprofits to invest in planning more ambitious activities, using a data set on nonprofits located in the United Kingdom, Andreoni, Payne, and Smith (2014) find evidence that nonprofits' expenses increase in response to receiving government grants (see regression results in Panel g of Table 6 on page 82 of their paper).

Table 8: Model-predicted NP-level Crowd-out/Crowd-in effects on solicitation spending caused by government grants to a single nonprofit in each local oligopoly donor market. (**Oligopoly Markets**)

	Cases showing crowd-out of solicitation spending among NPs that counterfactually received additional grants		Cases showing crowd-in of solicitation spending among NPs that counterfactually received additional grants		% of solicitation crowd-out cases
	Among the NPs that counterfactually received 20% more grants	Among the rival NPs that did not have a change in their grants	Among NPs that counterfactually received 20% more grants	Among the rival NPs that did not have a change in their grants	
	Mean (Std. error of mean)	Mean (Std. error of mean)	Mean (Std. error of mean)	Mean (Std. error of mean)	
NP-level % change in solicitation spending	-3.54*** (0. 264)	-5.44*** (0.455)	3.79*** (0.282)	1.90*** (0.330)	46.39
NP-level grant crowding of solicitation spending Elasticity	-0.18*** ((0.013)	-	0.19*** (0.014)	-	-
NP-level grant crowding of solicitation spending (in $/cents) per dollar of additional grant provided	-0.03*** (0.004)	-	0.05*** (0.007)	-	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level.

Now that the evidence provided in Table 7 and Table 8 has established that the provision of government grants does influence NPs optimal choice of fundraising intensity, and we know from the donor demand model estimates that fundraising intensities influence private giving, consistent with arguments first formally made in Andreoni and Payne (2003) it is clear that crowd-out or crowd-in of private giving caused by the provision of government grants have both a “direct” effect through changes in donors’ giving behavior as well as an “indirect” effect through changes in NPs’ optimal fundraising efforts. Following *Experiment 3*, Table 9 reports model-predicted changes in private giving to NPs caused by a 20% increase in government grants to the single NP in the relevant monopoly donor market when both grant-induced changes in donors’ giving behavior as well as changes in NPs’ optimal fundraising spending are jointly considered. In other words, unlike Table 4 that only considers changes in donors’ giving behavior, i.e., “direct” crowd-out/crowd-in effects, the predictions in Table 9 are driven by the combination of both “direct” and “indirect” crowd-out/crowd-in effects on private giving caused by the provision of government grants to NPs.

The estimates in Table 9 reveal that in almost all cases (approximately 98%) the increased provision of government grants crowd-out private giving to the grant-receiving nonprofits. The NP-level grant crowd-out of private giving elasticities in the table are a mean -4.6. It is notable that this mean grant-crowd-out of private giving elasticity is in the elastic range, and therefore substantially larger in absolute magnitude than the inelastic grant crowd-out mean elasticity reported in Table 4. Specifically, among grant-receiving nonprofits, the mean grant crowd-out elasticity in Table 9 is approximately 33 times larger (= -4.6/-0.138) than its counterpart in Table 4. Put differently, the "direct" grant crowd-out of private giving elasticity is only 3% (= 100*(-0.138/-4.6)) of the full (combined "direct" and "indirect") grant crowd-out of private giving elasticity. A key takeaway message here is that the majority of crowd-out of private giving that occurs due to the provision of government grants is attributed to grant-induced changes in NPs' optimal fundraising intensities, i.e., the "indirect" effect. However, it is important to note that the results in Table 4 and Table 9 focus on monopoly donor markets in which there is no competition and strategic interaction among nonprofits with respect to fundraising. I next focus attention on the oligopoly donor markets to reveal the extent to which competition and strategic interaction among nonprofits with respect to fundraising influence the results.

Table 9: Model-predicted NP-level combined Direct and Indirect Crowd-out/Crowd-in effects on private giving caused by government grants to the single nonprofit in each local monopoly market. (**Monopoly Markets**)

	Cases showing crowd-out of private giving to the NPs that counterfactually received 20% more grants	Cases showing crowd-in of private giving to the NPs that counterfactually received 20% more grants	% of crowd-out cases
	Mean (Std. error of mean)	Mean (Std. error of mean)	
NP-level % change in private donations	-91.93*** (0.126)	7713.14 (7580.99)	97.94
NP-level grant crowding of private donations Elasticity	-4.60*** (0.006)	385.66 (379.05)	-
NP-level grant crowding of private donations (in $/cents) per dollar of additional grant provided	-118.56*** (32.11)	0.23** (0.082)	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level, while ** indicates statistical significance at the 5% level.

Table 10 reports model-predicted changes in private giving to NPs caused by a 20% increase in government grants to a single NP in the relevant oligopoly donor market when both grant-induced changes in donors' giving behavior as well as changes in NPs optimal fundraising spending are jointly considered.

Interestingly, the estimates in Table 10 reveal that in a minority of cases (approximately 44%) the increased provision of government grants crowd-out private giving to the grant-receiving nonprofits. The NP-level grant crowd-out of private giving elasticities in the table are a mean -0.54. It is notable that this mean grant-crowd-out of private giving elasticity is inelastic but larger in absolute magnitude than the grant crowd-out mean elasticity reported in Table 5. Specifically, among grant-receiving nonprofits, the mean grant crowd-out elasticity in Table 10 is only 1.9 times larger (= -0.54/-0.29) than its counterpart in Table 5. Put differently, the "direct" grant crowd-out of private giving elasticity is 54% (= 100*(-0.29/-0.54)) of the full (combined "direct" and "indirect") grant crowd-out of private giving elasticity.

Table 10: Model-predicted NP-level combined Direct and Indirect Crowd-out/Crowd-in effects on private giving caused by government grants to a single nonprofit in each local oligopoly market. (**Oligopoly Markets**)

	Cases showing crowd-out of private giving to the NPs that counterfactually received additional grants		Cases showing crowd-in of private giving to the NPs that counterfactually received additional grants		% of crowd-out cases
	Among NPs that counterfactually received 20% more grants	Among rival NPs that did not have a change in their grants	Among NPs that counterfactually received 20% more grants	Among rival NPs that did not have a change in their grants	
	Mean (Std. error of mean)	Mean (Std. error of mean)	Mean (Std. error of mean)	Mean (Std. error of mean)	
NP-level % change in private donations	-10.89*** (0.447)	3.77 (3.67)	285.06* (166.42)	119.10** (60.02)	44.70
NP-level grant crowding of private donations Elasticity	-0.54*** (0.022)	-	14.25* (8.32)	-	-
NP-level grant crowding of private donations (in $/cents) per dollar of additional grant provided	-0.59*** (0.045)	-	0.87*** (0.070)	-	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level, while ** indicates statistical significance at the 5% level.

Measured in dollars, Table 10 shows that private donations to grant-receiving nonprofits will decline by a mean 59 cents for each dollar of additional grant provided. It is notable that the "direct" grant crowd-out of private giving effect measured in dollars reported in Table 5 is as much as 58% (= 100*(34 cents/59 cents)) of the combined "direct" and "indirect" grant crowd-out effect reported in Table 10. Importantly, once competition and strategic interaction among nonprofits with respect to fundraising are considered, as they should in local oligopoly donor markets, then I get the result that a minority of the crowd-out of private giving that occurs due to the provision of government grants is attributed to grant-induced changes in NPs' optimal fundraising intensities, i.e., the "indirect" effect. Accordingly, it is apparent that the strategic interaction among NPs with respect to fundraising serves to attenuate the magnitude of the "indirect" grant crowd-out effect.

As pointed out in Andreoni and Payne (2013), more recent econometric studies find evidence of government grant crowd-out ranging from about 70 cents to 1 dollar of private giving for each dollar of grant provided, which helps put in context the magnitude of the full grant crowd-out effect of 59 cents reported in Table 10 relative to findings in other econometric studies. However, unlike this study, none of the existing studies use a structural empirical model to disentangle and use counterfactual experiments to separately measure the "direct" and "indirect" channels through which grant crowding of private donations occur. Andreoni and Payne (2011) is the only empirical study that attempts to disentangle the "direct" and "indirect" channels and find that grant crowd-out of private giving via the "direct" channel is approximately 30%, with the remaining 70% attributed to the "indirect" channel. Accordingly, in contrast to the findings in this study for most nonprofits, they find that the vast majority of crowd-out is attributed to the "indirect" channel. However, their study uses a "reduced form" regression methodological approach and does not explicitly analyze the extent to which competition and strategic interaction among NPs with respect to fundraising affect the relative strengths of the "direct" and "indirect" channels.

Why might counterfactual experiments with an estimated structural model provide advantages, relative to using a "reduced form" regression analysis approach, in examining the extent to which government grants to nonprofits crowd-out/crowd-in the private donations they receive? Since the provision of government grants, or increases in grants, are typically not randomly assigned to nonprofits, it is difficult to tease out from the actual data the true causal impact of government grants on nonprofits' fundraising intensities and the private donations they receive. Consider the likely scenario that a government's grant funding decisions are based on several attribute metrics of nonprofits, such as: (*i*) nonprofits' efficiency/effectiveness in fundraising; and (*ii*) demonstrated levels of private support across the nonprofits. Specifically, suppose grants have a higher chance of been awarded to nonprofits that are less able to secure sufficient private funding for their mission. This would show up in the actual data as nonprofits with relatively lower fundraising intensities receiving more grants, which poses a challenge to empirically identify the extent to which the grant provision causes relatively lower fundraising intensities versus relatively lower fundraising intensities driving more grants to be awarded to these nonprofits based on the government's grant award decision-making process. Counterfactual experiments with an estimated structural model allow the researcher to randomly assign which nonprofits will experience the counterfactual increase in grants, and holding all other factors constant, use the model to measure the causal impact of the increases in government grants on nonprofits' optimal fundraising intensities and private donors' optimal donation choices.

It is evident from the model predictions in Table 10 that government grants can also crowd-in private giving to grant-receiving nonprofits. Importantly, the results in Table 10 reveal that once grant-induced optimal changes in competing NPs' fundraising spending are considered, crowd-in of private giving to the grant-receiving nonprofits can occur in the majority of cases. The last row in the table shows that the full grant crowd-in changes measured in dollar terms correspond to a mean 87 cents increase in private donations to the grant-receiving NP for each additional dollar of grant provided. Recall our observation from Table 8 that grant-receiving NPs that optimally increased their fundraising spending in response to receiving additional grants will spur their rivals to also increase their fundraising spending. Accordingly, the predictions in Table 10 show that private donations will also increase to rivals of a grant-receiving NP that experienced grant crowd-in of private giving even though the rivals were not provided with additional grants.

Unlike Table 10 with predictions focused on the NP-level, Table 11 reports model-predicted changes in private giving aggregated across rival nonprofits in each local oligopoly market. However, like Table 10, the predictions in Table 11 consider that the provision of government grants induces donors to change their giving behavior as well as nonprofits to change their optimal level of fundraising spending. The estimates in Table 11 reveal that the provision of government grants to nonprofits will crowd-out private giving in just over half (approximately 57%) of the local oligopoly donor markets, with a market-level mean crowd-out elasticity of -2. Furthermore, the market-level grant crowd-out changes measured in dollar terms correspond to a mean 78 cents decrease in private donations for each additional dollar of grant provided to nonprofits across these local oligopoly donor markets.

Table 11 also shows that there exist a substantial number of markets (approximately 43% of the oligopoly markets) that are predicted to experience aggregate grant crowd-in of private donations. Specifically, the market-level grant crowd-in changes measured in dollar terms correspond to a mean 62 cents increase in private donations for each additional dollar of grant provided to nonprofits across these local donor markets.

Table 11: Model-predicted local market-level combined Direct and Indirect Crowd-out/Crowd-in effects on private giving caused by government grants to a single nonprofit in each local oligopoly donor market.
(**Oligopoly Markets**)

	Cases showing market-level crowd-out of private giving	Cases showing market-level crowd-in of private giving	% of crowd-out cases
	Mean (Std. error of mean)	Mean (Std. error of mean)	
Market-level % change in private donations	-6.61*** (0.305)	17.74*** (3.94)	57.27
Market-level grant crowding of private donations Elasticity	-2.0*** (0.235)	1.92*** (0.281)	-
Market-level grant crowding of private donations (in $/cents) per dollar of additional grant provided	-0.78*** (0.058)	0.62*** (0.058)	-

Notes: Standard error of mean is in parentheses. *** indicates statistical significance at the 1% level.

7. Conclusion

Using a strategic fundraising setting, this study revisited an unresolved debate on the extent to which the provision of government grants to nonprofit organizations crowd-out or crowd-in private giving to them. As first formally argued in Andreoni and Payne (2003), government grants to nonprofits can influence private giving to the nonprofits through two channels: (*i*) "directly" through donors' preference-induced optimal change in their giving behavior in response to the grants provided to the nonprofits; and (*ii*) "indirectly" through nonprofits' optimally changing their fundraising efforts in response to the grants provided, which in turn influence private giving. Since most nonprofits compete for private donations with their fundraising efforts, the strategic fundraising framework I use for the analysis is necessary to properly capture the "indirect" channel. In fact, the strategic fundraising framework makes clear a new theoretical result to the literature that in principle nonprofits may optimally respond to receiving government grants by either increasing or decreasing their fundraising efforts, which in turn influences private giving. Accordingly, the framework makes clear that how the provision of government grants influences NPs' fundraising spending and ultimately private giving is an empirical question that can only be answered by rigorous analysis of real-world data.

I then take the parametrized structural model to real-world data to: (*i*) econometrically estimate the parameters; (*ii*) draw inference on donor preferences from the parameter estimates; and (*iii*) use the estimated model to perform counterfactual experiments designed to measure the extent to which the provision of government grants to nonprofits crowd-out or crowd-in private giving to the nonprofits. The donor demand parameter estimates suggest that there exists heterogeneity in private donor preference for the provision of government grants to nonprofits and consequently whether the provision of government grants induces “direct” crowd-out or crowd-in of private giving to grant-receiving nonprofits will depend on the preference profile of the population of potential donors to the nonprofit. Furthermore, the estimates suggest that potential donors’ income and race are important demographic factors that directly determine their private giving response to the provision of government grants. An important implication of this finding is that empirical evidence of crowd-out versus crowd-in likely depend on the demographic mix of private donors to the sample of nonprofits being empirically studied, and consequently it is not surprising for the literature to present mixed results on the crowd-out hypothesis, as have been the case.

Next, I use the estimated donor demand model to examine donors’ preference-induced optimal change in their giving behavior in response to the grants provided to the nonprofits, i.e., the “direct” crowding effect channel. Consistent with the “impure” altruism theoretical framework that predicts government grant crowd-out of private giving will be “incomplete” [see Andreoni (1989, 1990)], I find evidence of market-level “direct” grant crowd-out of a mean 15 cents decrease in private donations for each additional dollar of grant provided to competing nonprofits across the local donor markets predicted to experience crowd-out (approximately 88% of the local oligopoly donor markets). Across the remaining local oligopoly donor markets, I find evidence of market-level “direct” grant crowd-in of a mean 49 cents increase in private donations for each additional dollar of grant provided to nonprofits in these local donor markets.

Equilibrium analysis using the estimated model reveals that government grants to nonprofits can either crowd-out or crowd-in fundraising spending of the grant-receiving nonprofit, but the likelihood and magnitude of crowd-out crucially depend on whether competition and strategic interaction among NPs with respect to fundraising are present in the local donor market. Specifically, I find that in local monopoly donor markets in almost all cases (approximately 99%) crowd-out of fundraising spending occurs, with the fundraising spending of grant-receiving nonprofits falling by a substantial mean $3.74 for each additional dollar of grant provided. However, in local oligopoly donor markets that contain the majority of nonprofits, grant crowd-out of fundraising spending occurs in less than half of the cases (approximately 46%), with grant-receiving NPs predicted to reduce (increase) their fundraising spending by 3 cents (5 cents) for each additional dollar of government grant provided to them. Importantly, owing to the strategic interaction among rival nonprofits with respect to optimally setting their fundraising spending, I find that grant-receiving nonprofits that optimally decreased (increased) their fundraising spending in response to receiving additional grants will spur their rivals to also decrease (increase) their fundraising spending.

Regarding the full impacts on private giving that account for these changes in NPs' fundraising spending induced by government grants, I find that government grants to nonprofits can either crowd-out or crowd-in private donations of the grant-receiving nonprofits, but the likelihood of grant crowd-out and the relative magnitudes of the "direct" and "indirect" channels of crowd-out crucially depend on whether competition and strategic interaction among NPs with respect to fundraising are present in the local donor market. Specifically, I find that in local monopoly donor markets in almost all cases (approximately 98%) the increased provision of government grants crowd-out private giving to the grant-receiving nonprofits, with the "direct" grant crowd-out of private giving elasticity only accounting for 3% of the full (combined "direct" and "indirect") grant crowd-out of private giving elasticity. However, in local oligopoly donor markets that contain the majority of nonprofits, I find that in a minority of cases (approximately 44%) the increased provision of government grants crowd-out private giving to the grant-receiving nonprofits, with the "direct" grant crowd-out of private giving elasticity accounting for 54% of the full (combined "direct" and "indirect") grant crowd-out of private giving elasticity. Accordingly, it is apparent that the strategic interaction among NPs with respect to fundraising serves to attenuate the magnitude of the "indirect" grant crowd-out effect, a new finding in the literature.

In summary, I draw the conclusion that grant crowd-out of private donations through the "indirect" channel consistently and substantially dominates the "direct" channel in local monopoly donor markets, but the "indirect" channel is often marginally dominated by the "direct" channel in local oligopoly markets. Presuming that it is socially desirable to mitigate government grant crowd-out of private giving to nonprofits, the results of this study suggest that the optimal design of policies to mitigate grant crowd-out of private giving crucially depends on whether there exist competition and strategic interaction among nonprofits with respect to fundraising. Specifically, if competition and strategic interaction among nonprofits are absent from the local donor market, then policies to mitigate grant crowd-out of private giving will be most effective when targeted at how nonprofits optimally change their fundraising efforts in response to receiving government grants rather than how donors optimally change their private giving behavior in response to the government grants. On the other hand, if competition and strategic interaction among nonprofits are present in the local donor market, then policies to mitigate grant crowd-out of private giving should equally focus on incentives to prevent nonprofits from reducing their fundraising efforts and incentives to prevent donors from reducing their private giving. The encouraging news is that when competition and strategic interaction among nonprofits are present in the local donor market, there is less need for policies to mitigate grant crowd-out of private giving since the results of this study show that competition and strategic interaction among nonprofits increase the prevalence of grant crowd-in of private giving. Accordingly, future research may focus on the optimal design of grant crowd-out mitigation policies.

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Appendix

Table A1: Donor Demand Model Estimates based on Alternate Measures of the Donative Capacities of Local Markets

	Donative Capacities based on 1.5 times the Maximum Aggregate Donations Observed in the Relevant Local Market in a given Year Over the Sample Period	Donative Capacities based on 5 times the Maximum Aggregate Donations Observed in the Relevant Local Market in a given Year Over the Sample Period
Factors influencing mean utility	Parameter estimate (std. error)	Parameter estimate (std. error)
Constant	-20.58*** (6.75)	-27.73*** (6.59)
Solicit (γ)	2.68*** (1.050)	2.57*** (0.834)
Gov Grants × Sector 1 (λ_1)	-2.290 (9.430)	2.04 (8.074)
Gov Grants × Sector 2 (λ_2)	0.127 (0.500)	0.088 (0.395)
Gov Grants × Sector 3 (λ_3)	9.88 (8.935)	8.48 (8.116)
Gov Grants × Sector 4 (λ_4)	-4.46 (2.990)	-0.359 (2.376)
Gov Grants × Sector 5 (λ_5)	3.36 (2.737)	-0.745 (2.598)
Gov Grants × Sector 6 (λ_6)	7.07 (9.140)	2.800 (7.391)
Gov Grants × Sector 7 (λ_7)	-1.56 (1.862)	-1.303 (1.635)
Program service revenue	0.112 (0.123)	0.004 (0.102)
Assets	0.017 (0.389)	0.099 (0.339)
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Taste Variation Controls		
v × Constant (σ^c)	43.19*** (4.294)	77.57*** (12.109)
v × Gov Grants (σ^G)	0.486*** (0.104)	0.956*** (0.140)
Income × Gov Grants (ϕ^{Income})	-0.038* (0.020)	0.044 (0.090)
White × Gov Grants (ϕ^{White})	0.310*** (0.041)	-0.022 (0.723)
GMM Objective Function Value	15.067	22.605
Number of Observations	27,321	

Notes: Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level of significance, respectively.