How do big gifts affect rival charities and their donors?

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Abstract

This paper studies crowd-out in the non-profit sector by examining how charities respond to the activities of their rivals. Combining novel data on big gifts with the IRS Form 990, I find evidence of crowd-in such that a big gift to a rival increases charitable activities by 3.8% one year following the gift, and 4.7% two years following. This seems to be driven by both an increase in donations and a reduction in fundraising expenditure. These results help us to rule out models of pure charity altruism.

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1 Introduction

The idea of crowd-out has been explored in several contexts, from insurance markets[1], to foreign direct investment[2]. However, as of yet, we know little about the ways in which these forces affect the non-profit sector. This paper uses newly-collected data on big gifts to ask whether the activities of one charity in a sector crowd out the activities of others. As well as offering a credible identification strategy, big gifts are an important phenomenon to study. Recent work has documented a shift in charitable giving, such that an increasing share of households are "non-givers", while major donors are giving more[3]. We know that this has changed the distribution of giving, but we know less about how it is affecting the non-profit landscape. Combining data on big gifts with information from the IRS Form 990, I find evidence of crowd-in such that, on average, a big gift to one charity increases the charitable activities of others. In particular, a big gift to a rival increases charitable activities by 3.8% one year following the gift, and 4.7% two years following. This appears to be driven by an increase in donations and a reduction in fundraising expenditure. I also find evidence to suggest that donors view some charities as complements, and other as substitutes, depending on how "close" they are.

In order to think about crowd-out in the non-profit sector, we need some notion of a charity objective function. The non-profit status of charities ensures that managers receive no direct reward from maximizing net revenues[4]. But if non-profit firms are unmotivated by profit, then what are they motivated by? Weisbrod (1988) suggests that, instead of being profit-maximizers, charities are in fact profit satisficers, whereby they fundraise in order to maximize some other objective. Glaeser and Shleifer (2001) argue that non-profit entrepreneurs choose the charitable sector in order to commit to higher quality products and softer incentives for cost reduction.

[1] Cutler and Gruber (1996), for example

[2] De Backer and Sleuwaegen (2003)

[3] Meer et al (2017)

[4] Salaries can depend upon performance, but managers receive no reward in the form of equity appreciation or distributions

Indeed, the non-profit sector is preferable as long as the benefits of committing to higher quality outweigh the costs of having to earn profits in the form of “perquisites” (lower effort levels, shorter workdays, better benefits etc) rather than cash. Andreoni and Payne (2011) present empirical evidence of the fact that charities behave differently from profit-maximizing firms. In particular, they find that a dollar spent on fundraising yields over $5.50 in new donations. This implies that charities leave considerable slack in their fundraising potential.

Although there exists a literature on crowd-out in the non-profit sector, it has so far focussed on the effect of government spending. Andreoni (1993) designs a laboratory experiment to examine the effect of government provision of public goods on voluntary contributions, and finds evidence of incomplete crowd-out. Andreoni and Payne (2003) ask what happens to fundraising expenditure when a charity receives a government grant? Using IRS Form 990 data, they find government grants cause charities to substitute away from fundraising towards provision of charitable services.

This paper builds on previous work but shifts the focus away from government spending, and instead studies how charities react to the activities of their rivals. In this context, we can still appeal to existing models, and ask what they predict on crowd-out. Traditional models based on the idea of pure or impure altruism predict complete and incomplete crowd-out, respectively. Specifically, the pure altruism model implies that a $1 lump-sum tax used to increase rivals' charity output reduces a charity's output one-for-one, while the impure altruism model predicts a less than one-for-one reduction in output. However, adapting Andreoni's (1998) framework of non-convex provision of public goods to include “warm glow” donors generates a level of public good provision that is higher than under the standard model with convex provision. The results of this paper rule out pure altruism models[5], and instead call for a framework that implies that a big gift to a rival increases charitable activities.

[5]Kotchen and Wagner (2019) argue that evidence of crowd-in is still consistent with impure altruism

The rest of the paper proceeds as follows: Section 2 sets out the theoretical frameworks, Section 3 describes the data and Section 4, the empirical strategy. Section 5 presents the results and Section 6 concludes.

2 Theoretical framework

There exist several models that can help us predict how the activities of one charity can affect those of its rivals. I first discuss a class of models that predict complete or incomplete crowd-out, and then a model that predicts crowd-in.

2.1 Crowd-out?

One possibility is that charities are purely altruistic. If a purely altruistic donor is one whose preferences only depend on the total supply of the public good, a purely altruistic charity should care only about furthering their cause, and not the survival, prominence or reputation of their organization[6]. For example, a purely altruistic cancer charity cares only that we find a cure for cancer. If a purely altruistic charity lies at one end of the spectrum, then at the other end, is a charity that is entirely motivated by "warm glow." Models of donor "warm glow" were first described by Andreoni (1989, 1990) to capture the idea that donors gain utility from the act of giving as well as from the charity's output. Thus, a warm glow charity[7] is one that favors its own output relative to other providers. For example, a warm glow cancer charity is concerned only with its own efforts to cure cancer[8]. An impurely altruistic charity derives utility from both its own efforts to cure cancer and those of others.

[6]Some charities, such as Friends of the Global Fight Against AIDS, Tuberculosis, and Malaria, describe their mission as a "global fight"

[7]Scharf (2014) also considers the notion of warm glow charities, arguing that warm glow motives in provision can lead to inefficient charity selection

[8]George Omiros, the executive vice president of Leukemia and Lymphoma Society, is quoted as saying that the struggle is to "steal market share from other organizations to continue to grow"

We can draw on the models of Becker (1974), Bergstrom, Blume and Varian (1986) and Andreoni (1989, 1990), to help formalize these ideas. In particular, we can apply the donor models of pure and impure altruism to the charity side, and derive the corresponding testable predictions of complete versus incomplete crowd-out.

In the pure altruism model, a charity j in sector s derives utility $U(x_{js}, C_s)$ from private consumption x_{js} and from total charitable output, C_s. Henceforth dropping the s subscript for clarity, x_j can be regarded as expenditure on fundraising, wages and administration, or just fundraising (abstracting from the latter two expenses). Normalizing prices, charities are subject to the budget constraint $x_j + c_j = y_j$, where c_j is expenditure on charitable activities and y_j is total resources i.e. revenue from donations, government grants and other sources. Noting that $C = c_j + C_{-j}$, where $C_{-j} = \sum_{i \neq j} c_i$, the utility function can be re-written as $U(y_j - c_j, c_j + C_{-j})$. Maximizing with respect to c_j yields the interior first order condition

$$-U_x(x_j, C) + U_C(x_j, C) = 0$$

In words, a purely altruistic charity should set its marginal utility of fundraising equal to its marginal utility of total charitable output. Note that the implications of the model are qualitatively the same whether we regard x_j as expenditure that is complementary to C, or expenditure that helps to increase y_j. Specifically, if y_j is assumed to be a function of x_j, the first order condition above would include additional terms, but the interpretation would remain unchanged. Charity j's preferred level of total output is given by the implicit demand function

$$C^* = f(y_j + C_{-j})$$

where preferred total output only depends on "social income" $(y_j + C_{-j})$, and own charitable output is a perfect substitute for the charitable output of others: $\frac{dC^*}{dy_j} = \frac{dC^*}{dC_{-j}} \equiv f_1$. c_j^* and x_j^* are as follows:

$$c^* = f(y_j + C_{-j}) - C_{-j} \qquad\qquad x^* = y_j - f(y_j + C_{-j}) + C_{-j}$$

From this, it is straightforward to see that an increase in C_{-j} funded by a lump-sum tax on j ($dC_{-j} = -dy_j$) alters the composition but not the level of social income, thereby leaving C^* unchanged. Charity j's response is thus characterized by a one-for-one reduction in charitable activity, implying complete crowd-out: $\frac{dc^*}{dC_{-j}}\Big|_{dy_j=-dC_{-j}} = -1$. And, expenditure on fundraising remains unchanged: $\frac{dx^*}{dC_{-j}}\Big|_{dy_j=-dC_{-j}} = 0$.

These stark implications of the purely altruistic model result from the fact that charities derive no utility directly from their own activities. This seems unlikely. Thus, a more realistic model may be one of impure altruism, where charities derive utility both from their own activities as well as total output in their sector. Again, dropping the sector subscript, such impurely altruistic charities have preferences of the form $U(x_j, C, c_j)$. Now, c_j increases utility both via its contribution to C, and directly, via a warm-glow benefit. Again using the example of a cancer charity, this utility function allows for charities to care that they are the ones to cure cancer, not a rival charity. The first order condition becomes:

$$-U_x(x_j, C, c_j) + U_C(x_j, C, c_j) + U_c(x_j, C, c_j) = 0$$

such that charities set their marginal utility of fundraising equal to their marginal utility of total charitable output plus their own output. By adding warm-glow, the implicit demand functions now have two arguments:

$$C^* = f(y_j+C_{-j}, C_{-j}) \qquad c^* = f(y_j+C_{-j}, C_{-j})-C_{-j} \qquad x^* = y_j-f(y_j+C_{-j}, C_{-j})+C_{-j}$$

The first element derives from the public goods dimension of the utility function, the second, from the private goods dimension. Now, the charity's own activity and that of others are no longer perfect substitutes: $\frac{dC^*}{dy_j} \equiv f_1$ but $\frac{dC^*}{dC_{-j}} \equiv f_1 + f_2$.

Assuming that warm-glow is a normal good, $f_2 > 0$, the charity's desired total output increases more in response to an increase in output from others than in response to an increase in resources. Importantly, the impure altruism model predicts incomplete crowd-out: an increase in C_{-j} funded by a lump-sum tax on j ($dC_{-j} = -dy_j$) increases C^* by f_2 such that $\frac{dc^*}{dC_{-j}}\Big|_{dy_j=-dC_{-j}} = -1 + f_2 > -1$. And, expenditure on fundraising declines: $\frac{dx^*}{dC_{-j}}\Big|_{dy_j=-dC_{-j}} = -f_2 < 0$. In other words, if charities are impurely altruistic, they do not reduce their activities one-for-one and in fact cut back on fundraising expenditure.

Pure warm glow implies that charitable activity by others has no impact on charity j's output. Thus, desired total output increases one-for-one with an increase in others' charitable activity: $\frac{dC^*}{dC_{-j}}\Big|_{dy_j=0} = f_1 + f_2 = 1$. In addition, charitable activities and fundraising remain unchanged: $\frac{dc^*}{dC_{-j}}\Big|_{dy_j=0} = f_1 + f_2 - 1 = 0$ and $\frac{dx^*}{dC_{-j}}\Big|_{dy_j=0} = -(f_1 + f_2) + 1 = 0$.

2.2 Crowd-in?

A recent working paper by Kotchen and Wagner (2019) argues that the normality assumptions in the impure altruism model are not directly comparable to those in the pure altruism model. The implicit joint production assumption in the impure altruism model conflates normality based on preferences with income effects on demand. One consequence is that assuming normality in the usual sense of preferences means that crowd-in is also a plausible consequence of impure altruism. Under their framework, crowd-in is consistent with impure altruism, but not pure altruism.

Another model that predicts crowd-in is one that is inspired by Andreoni's (1998) concept of non-convex provision of public goods. In this model, public good provision (G) features an important nonconvexity: $G = \sum_{i=1}^{N} g_i$ if $\sum_{i=1}^{N} g_i \geq \overline{G}$, and 0 otherwise. In other words, there is a minimum threshold, $\overline{G}$, that donations (g_i) must meet for the public good to be provided. In the standard model, this threshold applies to the total provision of public goods. However, if the threshold is interpreted as applying to a charity sector, donations can move the market into the region of increasing returns.

Furthermore, adding warm-glow donors into this framework means that any effort to move the sector to $\overline{G}$ generates a higher level of public good provision than in the standard model with convex provision. This is because warm-glow donors will be incompletely crowded out. Therefore, the resultant equilibrium will feature a level of public good provision that is higher than under the standard model.

3 Data

3.1 IRS Form 990

Data on charity revenue and expenses are derived from federal tax returns filed by IRS Section 501(c)(3) organizations for the period 1998 to 2017. 501(c)(3) nonprofits are organizations whose mission relates to charity, education, science or public safety testing, with all those with gross receipts of over $50,000 required to file. The IRS Form 990 identifies the amount the nonprofit receives in private donations, government grants, and fundraising expenditures for the year for which the return is filed. Private donations may come from individuals, estates, corporations, and/or other nonprofit organizations. Government grants include grants received from all levels of government, excluding reimbursements for services provided by the nonprofit under a government contract[9]. Fundraising includes both expenditures associated with fundraising events as well as professional fundraising fees[10]. Expenditure on charitable activities is deduced from information on income and expenditures.

The period of analysis starts in 1998 because, prior to then, only a random sample of Form 990 filings were available. But, from 1998 onwards, all filings were digitized and made available by the National Center for Charitable Statistics (NCCS). The

[9]These types of payments are reported as program service revenue

[10]These are payments made to external organizations for conducting fundraising or for consulting on fundraising

organizations are classified in the National Taxonomy of Exempt Entities (NTEE) by a three digit code[11]. The NTEE classification system divides nonprofit organizations into 26 major groups (1-digit codes) under 10 broad categories. Within the major groups, organizations are allocated decile- and centile-level codes. Those that exist across all or most of the 26 major groups are treated separately[12]. During the period of analysis, 19% of charities operate in the Education sector, 13% in Human Services and 11% in Arts, Culture and Humanities.

Given that this project involves studying expenditure on charitable activities, the following rules are applied sequentially to exclude organizations from the sample: (i) all organizations with three years or fewer of observations (153,665 organizations); (ii) organizations that report zero revenue for all years that they exist in the sample (13 organizations); and (iii) organizations that report zero expenses for all years that they exist in the sample (311 organizations). This leaves 393,088 organizations to form an unbalanced panel. Table 1 reports summary statistics, with amounts reported in constant dollars (1995 is the base year). Average revenue is $2.4 million, with contributions accounting for $0.5 million. $1.4 million is spent on charitable activities and just over $20,000 on fundraising[13].

3.2 Chronicle of Philanthropy

IRS Form 990 data are combined with information on big gifts. These data are collected from The Chronicle of Philanthropy and Slate magazine, which collaborate

[11]NTEE codes are subject to change: an organization may change its primary purpose, the IRS and/or NCCS may decide that a different code better fits the organization's primary purpose, or in some instances a particular organization may note that they have been misclassified and request a change by NCCS. I use the classifications as they existed in 2015.

[12]See `https://nccs.urban.org/publication/irs-activity-codes` for a full list of NTEE codes

[13]The relationship between fundraising expenditures and total revenues is increasingly used as a measure of nonprofit "efficiency". As such, charities may have an incentive to underreport fundraising expenditures to keep this ratio low. To the extent the nonprofit adopts a consistent method of reporting its fundraising expenditures during the sample period, the charity fixed effects will help to control for this.

to produce a list of America's top 50 to 60 donors[14]. The annual ranking counts donations made to organizations with charity or foundation status under Section 501(c)(3), and is based primarily on gifts and pledges of cash, land, and stock. Philanthropists are not legally required to publicly disclose their gifts, meaning that some large gifts are omitted from the rankings. Multiyear pledges are only counted once, as a lump sum in the year the commitment is made.

I restrict attention to gifts to charities that file a Form 990, meaning that gifts to foundations, universities and hospitals are excluded from the analysis. Thus, I am left with 218 big gifts, 61 of which are bequests. Table 2 describes the data in more detail, but the median gift in the sample is $5 million. Two-thirds of big gifts are donated to organizations operating in the Arts, Culture and Humanities sector, and charities located in California or New York receive 35% of gifts.

4 Empirical strategy

The testable predictions from the models described in Section 2 are that, if a charity is purely altruistic, an increase in C_{-j} funded by a lump-sum tax on j ($dC_{-j} = -dy_j$) results in charity j reducing its charitable activity (c_j) one-for-one, and leaving expenditure on fundraising (x_j) unchanged. If a charity is impurely altruistic, an increase in C_{-j} will result in a less than one-for-one decline in charitable activity and a reduction in fundraising expenditure. If crowd-out is rejected entirely, then the altruism models are inappropriate, and one that features non-convex provision is a possible alternative.

Given that the altruism models have such stark predictions, it is perhaps useful to speculate on the circumstances under which these predictions hold. Namely, are there some sectors that are more likely to behave in a manner consistent with altruism? I would argue that organizations engaged in scientific research are most

[14] The Chronicle of Philanthropy interviews dozens of charities, philanthropists, and their representatives, in order to compile the annual lists

likely to reduce charitable activities following an increase in the activities of rivals. If funding is essential for scientific breakthroughs and rivals have access to more resources, then it seems prudent for charity j to cut back and focus its efforts on alternative avenues/research. Museums, by contrast, may behave differently. If rival art museums increase their charitable activities, it seems less likely that art museum j would be induced to scale back its collection. Thus, we might expect scientific research charities to behave in a manner consistent with altruism, and museums, warm glow.

In order to empirically test the models of crowd-out, I would ideally estimate the following specification:

$$CharitableActivities_{jkst} = \alpha_j + \lambda_t + \beta OthersActivities_{-jkst} + \epsilon_{jkst} \qquad (1)$$

where "charitable activities" is the real level of grants and other assistance paid by charity j located in region k, operating in sector s in year t. The organization fixed effects, α_j, are designed to capture the time-invariant heterogeneity in charities such as their reputation, age, type, and/or method of operation that affects their capacity to fulfil their mission. The year fixed effects control for macro-level time-varying shocks that affect all charities similarly.

Under this specification, assuming $dC_{-j} = -dy_j$, $\beta = -1$ would be evidence of complete crowd-out, and indicate a model consistent with pure altruism. $0 < \beta < -1$ would suggest incomplete crowd-out, and indicate a model of impure altruism. $\beta = 0$ would mean that the activities of charity j are unaffected by their rivals, and suggest a model of pure warm-glow, and $\beta > 0$ would be evidence of crowd-in. With fundraising expenditure as the dependent variable, $\beta = 0$ would indicate a model consistent with either pure altruism or pure warm glow[15], and $0 < \beta < -1$ would indicate impure altruism.

However, if charity j is in high demand (for example in the aftermath of a hurricane),

[15]Whether pure altruism or pure warm glow is the correct model depends on the magnitude of the estimated β coefficient in 1

then its competitors are also likely to be in high demand. In other words, there may be unobserved factors that increase both the charitable activities of charity j and the charitable activities of others. Thus, in order to correct for this positive bias, it will be important to find an instrument for "other charities' activities". In particular, I need an instrument that affects rival charities' activities, but not the activities of charity j directly.

4.1 Big gifts

The exogenous shock to rival charities' activities I use is a "big gift"[16]. These very large gifts from private donors generate a spike in revenues, the timing of which is arguably random. For identification, I require that a big gift to a rival charity directly affects their decisions, but does not directly affect the decisions of charity j. Using the example above, the big gift must affect the charitable activities of the rival, but be uncorrelated with demand for charity j. This would be violated if the gift is received during a period of high demand for both the rival and charity j. To allay any validity concerns, I use both information on lifetime gifts and bequests. In particular, if we can not be certain about the validity of lifetime gifts, the timing of bequests is as good as random.

In order to assess the effect of a big gift on rival charities, I need to define the market in which they operate. I do this at three different levels, focusing on organizations based in the same city. The narrowest definition labels two charities as rivals if they share the same exact NTEE classification (at the centile-level) and are located in the same city. So, orchestras based in New York City are assumed to operate in the same market. A slightly broader definition of a market labels charities as rivals if they operate in the same city and share the same NTEE classification at the decile-level. For example, performing arts organizations in New York City would be defined as operating in the same market. Finally, the broadest definition of a market is at

[16] Several charity bosses express surprise at the receipt or size of the gift. The executive director of one charity is quoted as saying "I'm sure he [the donor] was laughing all the way to the grave thinking about how surprised we'd all be".

the major group-level. So, Arts, Culture and Humanities charities in New York City would be classified as rivals.

I focus on markets at the city-level due to the difficulty of defining the rivals of charities with a broader remit. In particular, they may have international rivals, which lie outside of the data. Thus, the sample is limited to those that operate locally. Specifically, organizations are omitted if they (i) change their state of filing any time between 1998 and 2017, since this suggests that they are not committed to the provision of goods or services to a local area; (ii) the organization's name or mission statement on the Form 990 includes key words such as "international" or "global" that signal a focus of provision outside their local area; or (iii) the charity ever files a return on behalf of a group of affiliated charities, since these returns may include financial data for out-of-state affiliated groups.

Defining markets at different levels also relates to the validity of big gifts. As mentioned above, a big gift is an invalid instrument if it is received at a time in which both the recipient and charity j are in high demand. When markets are defined more broadly, the instrument is more likely to be valid. In particular, if a natural history museum receives a big gift due to high demand, the dance company operating in the same market is less likely to also be experiencing high demand. In this way, there is a trade off between the "closeness" implied by the definition of rival charities and the validity of the instrument.

The panel structure of the data means that both sector and time variation can be exploited. In order to allow for a flexible time path of responses, a generalized event-study regression is used. This relies on the assumptions that the outcomes of organizations in the same market would evolve similarly in the absence of any big gifts, and that there are no contemporaneous changes that affect recipients and non-recipients differentially. Specifically, at the centile-level, the quasi-experiment to consider is the following: if the Chicago Philharmonic receives a big gift, and this affects the Chicago Symphony Orchestra, the control group is all orchestras located in cities where no orchestra received a big gift.

Thus, separately for each definition of a market, m, I run regressions of the form:

$$\log Y_{jkt} = \alpha_j + \lambda_t + \sum_{s \in \mathcal{S}} \beta_{ms} BG_{imt} \mathbb{1}\{t = s\} + \gamma_m BG_{imt} \mathbb{1}\{t \neq s\} + \epsilon_{jkt} \qquad (2)$$

where Y_{jkt} is the outcome for charity j in city k at time t and β_{ms} is the effect of big gifts to rival firms in the market m, s periods after the gift. BG_{imt} is a dummy variable equal to one if any charity $i \neq j$ in market m at time t receives a big gift, and $\mathbb{1}\{t = s\}$ is an indicator equal to one if t is s periods away from the gift, where $\mathcal{S} = \{-2, -1, 0, 1, 2, 3\}$. The single parameter γ_m captures the effect of the gift in periods outside $\mathcal{S}$. α_j is a charity fixed effect, λ_t is a time fixed effect, and ϵ_{jkt} is the error term.

The effect of the total value of big gifts on Y_{jkt} can also be studied by running regressions of the form:

$$\begin{aligned} \log Y_{jkt} = \alpha_j + \lambda_t + \sum_{s \in \mathcal{S}} \beta_{ms} \log[(TBG_{imt}/MarketSize_{mt-1}) + 1] \mathbb{1}\{t = s\} + \\ \gamma_m \log[(TBG_{imt}/MarketSize_{mt-1}) + 1] \mathbb{1}\{t \neq s\} + \epsilon_{jkt} \end{aligned} \qquad (3)$$

where TBG_{imt} is the total value of big gifts received by charities $i \neq j$ in market m at time t. This value is normalized by the size of market m in period t-1[17], where market size is measured as total revenue[18]. Market size can be thought of as reflecting the visibility of the cause. If the market is large, then that means that there are either several charities operating in the market, or one large rival. Either way, a larger market is associated with greater awareness of the cause. The normalization is done for ease of comparison across the major group-, decile-, and centile-level markets.

[17] I exclude charity j in the calculation of market size and use the value in t-1 to ensure it does not reflect any big gifts

[18] I also look for heterogeneous effects across market size, without normalizing the total value of the big gifts

Furthermore, if charities are not motivated entirely by warm glow, then information relating to other charities in the market should matter for charity j's response.

The main outcome of interest is log(charitable activities + 1000)[19]. Charitable activities are measured as the real level of grants and other assistance paid out by the organization, and deduced from information on income and expenditure on non-charitable activities[20]. Other outcome variables are log(fundraising expenses + 1000) and log(contributions + 1000), where fundraising expenses are measured as expenditure on fundraising events and professional fundraising fees, and total contributions as the sum of contributions, gifts and grants.

Power becomes an issue when the market is defined at narrower levels. When the market is defined at the major group level, there are 11,914 organizations that are "exposed" to a big gift. However, at the decile- and centile-levels, this number drops to 3,310 and 709 respectively. This drop in exposure creates imprecise estimates if the full sample is used. Therefore, regressions are run on different samples for the different market definitions. In particular, when the market is defined at the major group-level, the sample includes all major groups that ever receive a big gift (these are the sectors listed in Table 2), and when it is defined at the decile (centile)-level, the sample is all deciles (centiles) that ever receive a big gift. The practical reason for this is to increase power, but it also restricts attention to organizations that are most comparable. Namely, the relevant comparison should be all charities that are in contention to receive a big gift. Sectors that never receive big gifts may be meaningfully different in a way that is unobservable to the econometrician[21]. Notwithstanding this observation, the pattern of results is unchanged if the same sample is used throughout the analysis.

[19]A log transformation is used for all outcome variables to avoid dropping observations. The constant was chosen as 1000 to avoid placing too much implicit weight on extensive-margin changes, but the results are insensitive to alternative transformations

[20]This includes expenses such as fundraising, compensation of officers, payroll taxes and rental expenses

[21]Examples of sectors that never receive a big gift are Public Safety, Disaster Preparedness and Relief, and International, Foreign Affairs and National Security.

5 Results

The main results report the estimates of equation 2, where BG_{imt} is a dummy variable equal to one if any charity $i \neq j$ in market m at time t receives a big gift. Table 3 reports the OLS esimates with log(charitable activities + 1000) as the dependent variable. Column 1 shows the results when the market is defined at the major group level. Column 2 defines the market at the decile-level. Across the two market definitions, the results suggest that a big gift to a rival charity in the market increases charity j's activity. On average, when the market is defined at the major group level, a big gift to a rival in period t increases charity j's activity by 3.8% in t+1 and 4.7% in t+2. When the market is defined at the decile-level, charity j's activity increases by 2.6% in t+1. This result is largely driven by lifetime gifts (as opposed to bequests[22]), and is stronger for those charities exposed to more than one big gift. There is also some heterogeneity across sectors, with estimated coefficients higher in magnitude in the Arts, Culture and Humanities, and Education sectors, and lower in Health sectors. The centile-level results are quantitatively similar, but imprecise.

Crucially, the positive coefficients on BG_{imt} conflict with the predictions of the altruism models. Under the original specification of the altruism models, a coefficient of -1 would have indicated that charities are purely altruistic, a coefficient between -1 and 0 would have indicated impurely altruistic, and 0 would have meant that charities are motivated entirely by warm glow. Under the Kotchen and Wagner (2019) specification, a positive coefficient on BG_{imt} is still consistent with impure altruism, but inconsistent with pure altruism. Thus, these results are definitive in ruling out the idea that charities are purely altruistic, but may still be consistent with impurely altruistic charities, depending on which version of the model is preferred.

Of course, the next question is what is generating this increase in charitable activities? Referring to the charity budget constraint $x_j + c_j = y_j$[23], where c_j is expenditure

[22]The estimated coefficients follow the same pattern when gifts are restricted to bequests, but are mostly imprecise

[23]Ignoring the savings decisions of charities is a limitation here. Charities are not required to detail their savings decisions, so any calculations would have to be imputed from changes in net

on charitable activities, x_j is expenditure on non-charitable activities and y_j is total resources. This equation suggests that a rise in charitable activities is either driven by an increase in resources, a reduction in non-charitable expenditure, or both. Total resources comprise contributions, programme service revenue and dues, as well as income from investments and inventory sales. Given that contributions are likely to be most sensitive[24] to big gifts to rival charities, I focus on these[25]. On the expenditure side, compensation of officers makes up the largest share of non-charitable expenditure, but wages are slow-moving. Fundraising expenditure on the other hand, is more responsive to contemporaneous events[26]. Thus, Tables 4 and 5 report the estimates of equation 2 from the OLS regression with log(contributions + 1000) and log(fundraising + 1000) as the dependent variables respectively.

Again, column 1 reports the results when the market is defined at the major group level, and column 2 at the decile-level. Table 4 shows that, across both market definitions, a big gift to a rival charity increases the contributions received by charity j. This result is supportive of a model with non-convex provision of services and warm-glow donors. If donors only wish to donate to a "successful" market, then a big gift could push the market into the region of increasing returns, meaning that donors receive positive marginal utility from any additional donations they make. Furthermore, the publicity generated by a big gift may alert more donors to the cause.

On average, when the market is defined at the major group level, a big gift to a rival in period t increases contributions to charity j by 5.4% in t+1 and 4.8% in t+2. When the market is defined at the decile-level, contributions to charity j increase by 5.8% in t+1 and 3.8% in t+2. Again, this result is largely driven by lifetime gifts, and is stronger for those charities exposed to more than one big gift. Estimated coefficients

assets.

[24]Heavy publicity means that many big gifts are visible to other potential donors, with the philanthropist(s) often earning named recognition.

[25]It is also not entirely obvious how donations should respond, since a big gift can provide information on the quality of the recipient, but also the "worthiness" of the cause in general.

[26]Furthermore, the results of Andreoni and Payne (2003) suggest that fundraising would be the mediating pathway that explains any response in donations

are also higher in magnitude for those charities operating in the Arts, Culture and Humanities, and Environment sectors. The centile-level results are imprecise but in fact work in the opposite direction: a big gift to a rival decreases contributions to charity j. Although these results are insignificant, the different signs for the centile-level regressions could be suggestive of a story of substitutes versus complements. Namely, donors consider two orchestras based in New York City as substitutes, such that when one receives a big gift, donations to the other fall. Whereas, when a New York opera company receives a big gift, New York orchestras considered as complementary experience an increase in donations.

Finally, Table 5 shows that, across both market definitions, a big gift to a rival charity reduces charity j's fundraising expenditure. On average, when the market is defined at the major group level, a big gift to a rival in period t reduces fundraising by charity j by 8.8% in t+1 and 6.9% in t+2[27]. This reduction in fundraising is true for both lifetime gifts and bequests. The estimated coefficients follow a similar pattern at the decile- and centile-levels, but are less precise. However, when the sample is restricted to markets that only receive one big gift during the time period, charity j's fundraising expenditure increases. This may be related to publicity and visibility. If a rival in the market receives a big gift, charity j's response may be to spend more on fundraising in order to take advantage of the attention the cause is receiving. However, when rivals are receiving several big gifts, the publicity means that fundraisers do not have to exert as much effort to maintain the same level of charitable activities. This hypothesis is probed further in the results by market size, but of course, I can not test it directly.

5.1 Total value of big gifts

As well as analysing the impact of the presence of a big gift, we can also examine the effect of the total value of big gifts in a market. Table 6 reports the OLS estimates

[27] These magnitudes are smaller for charities operating in the Arts, Culture and Humanities sector.

of equation 3 with log(charitable activities + 1000) as the dependent variable. As before, the columns reflect the different market definitions. The results at the decile- and centile-level are insignificant, but again, the major-group level results indicate that big gifts to rival charities increase charity j's activity. In particular, a 10% increase in (big gifts/market size) in period t increases the charitable activities of charity j by 0.8% in t+1 and 1.1% in t+2. This pattern is fairly consistent regardless of whether total big gifts are normalized by market size or not[28]. In other words, a big gift increases charitable activities across markets of all sizes.

Table 7 reports the estimates of equation 3 with log(contributions + 1000) as the dependent variable. Consistent with the earlier results, the estimated coefficients are mostly positive but insignificant across all market definitions. This suggests that the effect varies across market size, and in fact, the alternative specification without any normalization reveals a more interesting pattern. Appendix Tables 2 present these results, reporting the coefficients at different market sizes[29]. Focussing on the 10th and 90th percentiles of market size, the results suggest that donation spillovers are positive at the major group- and decile-level, especially when the market is small. When the market is defined at the decile-level, and the market size is less than \$500,000, a 10% increase in big gifts to rivals in period t increases contributions to charity j by 0.1% in period t+2. However, at the centile-level, when the market is small, the effect works in the opposite direction: a big gift to a rival decreases contributions to charity j. In particular, when the market size is less than \$300,000, contributions to charity j decrease by 0.4% in period t. We can not know the exact mechanism, but the positive spillovers at the decile-level and negative spillovers at the centile-level again support the notion that donors view charities operating at the same decile-level as complements, and those at the same centile-level as substitutes.

Finally, Table 8 reports the estimates of equation 3 with log(fundraising + 1000) as the dependent variable. Consistent with the earlier results, the estimated coefficients

[28]See Appendix Table 1 for the specification without normalization

[29]The 10th percentile of market size is around \$500,000 at the major group- and decile-levels, and \$30,000 at the centile-level. The 90th percentile is roughly \$10 million at the major group- and decile-levels, and \$5 million at the centile-level.

are mostly negative but insignificant across all market definitions. Yet again, considering the alternative specification reveals differences across market sizes. Appendix Tables 3 show that, at the major group- and decile-level, charities operating in thin markets increase fundraising expenditure in response to big gifts, whereas charities operating in large markets decrease fundraising. At the centile-level, the estimated coefficients are negative.

5.2 Heterogeneity analysis

The previous sections illustrate how the effect of a big gift to a rival charity varies across different market definitions and sizes. However, the estimated effect is also likely to vary across a range of other dimensions. In particular, I shall focus on heterogeneous effects by charity size and donation size.

Using specification 2, and defining a small charity as one with real annual revenue of less than $25,000, and a large charity as one with real annual revenue of at least $3 million[30], Appendix Tables 4 show that, at the major group level, the effect of a big gift on charitable activities is largest for smaller charities. The positive effect on donations documented above seems to be driven by medium-sized charities, and the decline in fundraising following a big gift to a rival charity is strongest for larger charities.

It is also reasonable to expect that charity responses vary by the size of the gift. A $500,000 gift to a rival is a very different prospect from a $50 million gift. Using specification 2, and defining small gifts as those under $500,000 and very large gifts as over $50 million[31], Appendix Tables 5 show that, at the major group level, a small gift to a rival charity has a greater effect on charitable activities than a very large gift. This may be because charities are better able to compete with a rival that has received $500,000 versus one that has been gifted $50 million. The results also suggest that the effect on donations is positive when the gift is small, but negative

[30]These roughly correspond to the 10th and 90th percentiles, respectively

[31]Again, these roughly correspond to the 10th and 90th percentiles, respectively

when the gift is large. Relating this back to the model of non-convex provision, this suggests that these non-convexities exist, but that there may even be two thresholds. In particular, there may be a second threshold above which donors see a declining marginal utility of donating. Finally, fundraising increases when a rival receives a small gift. In other words, the reduction in fundraising expenditure reported above is driven by larger gifts. One possible explanation is, given that very large gifts are extremely rare, charity j has little incentive to increase fundraising expenditure in the hope of attracting another large gift. However, if a rival receives a \$500,000 gift, there may be other potential donors that charity j can attract by devoting more resources to fundraising. Also, it may be the case that smaller gifts are viewed as a signal of donor interest in the cause. Whereas, large gifts often just reflect the idiosyncratic preferences of the donor.

5.3 Robustness checks

The event study design rests on the assumption that, absent treatment, the time paths of the outcome variables in the treated and control groups would evolve in parallel. Figures 1, 2 and 3 plot the coefficients on BG_{imt} to illustrate the pre-trends in the outcomes studied for several years prior to exposure to a big gift. The figures show the pre-trends for when the market is defined at the major group level, but the patterns are similar at the decile-level[32]. There is little indication of pre-trends when the outcome variables are log(charitable activities + 1000) and log(fundraising expenses + 1000). And, in the case of charitable activities, there is a clear break in trend between period t (the year the rival receives the big gift) and t+1. However, there may be some evidence of a pre-trend when the dependent variable is log(contributions + 1000). It is possible that the cause is receiving some attention prior to the big gift, but notwithstanding this, there is still evidence of a break in trend.

In order to allay any concerns over the invalidity of big gifts as an exogenous shock

[32]The estimated coefficients are more imprecise at the centile-level

to charitable activities, I also restrict the sample to just bequests. The coefficients are less precisely estimated, but the signs and pattern of results remain the same. Other robustness checks involve expanding the sample to include non-local charities, and also estimating 2 maintaining the same sample for each market definition. The latter reduces the precision of the estimated coefficients, but neither affects the results substantively.

6 Discussion

This paper uses new data on big gifts to study crowd-out. I find that a big gift to a rival increases charity j's activity. This appears to be driven by both an increase in donations and a reduction in fundraising expenditure. These results suggest that charity behavior is inconsistent with pure altruism.

Heterogeneity analysis reveals some further nuances. In particular, taking the results at the decile- and centile-level together suggests that donors consider charities operating at the same decile-level as complements, and at the same centile-level as substitutes. This is especially true in thin markets. We also see that a big gift to a rival increases the activities of smaller charities by more, while larger charities cut back even further on fundraising. Finally, the impact on charitable activities, donations and fundraising is more pronounced following a smaller gift. This may be unsurprising if smaller gifts better reflect a wider interest in the cause, while large gifts are often just a product of the idiosyncratic preferences of the donor.

One limitation of the analysis is that it does not account for charities' savings decisions. Duquette (2017) finds that, while charities spend revenue from program services, they overwhelmingly save revenue from donations. Therefore, I may be misattributing some savings to spending on charitable activities. Detailed data on assets and liabilities are only available for later years, making it hard to control for savings without losing power.

However, aside from savings, the results appear robust to various sample restrictions. So, the next question to ask is what can explain these findings? The results on crowd-in are consistent with Kotchen and Wagner's model of impure altruism, and also Andreoni's model of non-convex provision of public goods. In particular, non-convex provision combined with warm-glow donors can generate levels of provision that are higher than under the standard model. To explain the increase in donations, we can also appeal to the model proposed by Vesterlund (2003). Namely, when there is imperfect information regarding the value of a public good, an announcement strategy leads to high-quality charities receiving contributions that exceed those that would result had the quality of the charity been common knowledge. Again, interpreting the public good as being provided at the market-level, a highly publicised big gift can encourage donations to all (high-quality) charities in the market. Finally, the reduction in fundraising expenditure is in part predicted by Andreoni and Payne (2003). They study the effect of government grants on fundraising and find that, for arts organizations, an additional \$1000 in government grants decreases fundraising expenditures by \$265, on average. Thus, if a big gift to a rival generates more donations to charity j, it means they can produce the same level of charitable services with less effort, causing them to cut back on fundraising.

The insights of these papers, as well as my own analysis, suggest that any future models should try to capture the following features: (i) a big gift has informational value regarding the quality of the specific charity that receives it, but also the cause as a whole; (ii) competition between donors means that a big gift to the Detroit Symphony induces the supporters of the Detroit Opera House to increase donations (this could also be interpreted as whether donors view two charities as complements or substitutes); and (iii) charities dislike fundraising such that, if a big gift brings publicity to their cause, they have an incentive to decrease fundraising efforts.

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8 Tables

Table 1: Form 990 Summary Statistics

	Mean (Std Dev)
Revenue	2,373,456
	(19,126,710)
Contributions	425,588
	(2,509,106)
Programme service revenue and dues	1,803,509
	(17,739,163)
Investment income	53,657
	(747,785)
Fundraising expenditure	19,771
	(4,859,586)
Professional fundraising fees	1,239
	(89,498)
Compensation of officers	986,495
	(57,523,816)
Expenditure on charitable activities	1,337,362
	(59,100,436)
Observations	3,351,490

Notes: All dollars are constant ($1995)
Standard deviations are in parentheses

Table 2: Big Gift Summary Statistics

	All gifts	Lifetime gifts	Bequests
Average Big Gift ($1,000s)	24,523	18,554	39,885
NTEE Major Group			
A	143	105	38
B	20	15	5
C	13	6	7
D	7	6	1
E	2	2	
F	3	1	2
G	1	1	
I	1	1	
J	1	1	
K	4	3	1
L	4	4	
N	3	2	1
O	2	2	
P	6	1	5
S	2	2	
T	4	3	1
X	1	1	
Y	1	1	
Observations	218	157	61

Notes: All dollars are constant ($1995) and reported in thousands

Table 3: Big Gift Spillover Effects - Charitable Activities

	Log(Charitable activities + 1000) Major group	Log(Charitable activities + 1000) Decile-level
Big Gift * Period t	-0.0129	-0.0160
	(0.0165)	(0.0217)
Big Gift * Period t+1	0.0384***	0.0259**
	(0.0145)	(0.0122)
Big Gift * Period t+2	0.0468**	0.0203
	(0.0200)	(0.0193)
Big Gift * Period t+3	0.0162	0.0139
	(0.0225)	(0.0187)
Charity Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	2248851	1400312
R-Squared	.0396101	.0405905

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Big Gift Spillover Effects - Contributions

	Log(Contributions + 1000) Major group	Log(Contributions + 1000) Decile-level
Big Gift in Market * Period t	0.0129	0.00987
	(0.00802)	(0.0179)
Big Gift in Market * Period t+1	0.0538***	0.0576***
	(0.0197)	(0.0179)
Big Gift in Market * Period t+2	0.0483***	0.0384***
	(0.0121)	(0.0147)
Big Gift in Market * Period t+3	0.0117	-0.00718
	(0.0130)	(0.0280)
Charity Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	2398113	1483029
R-Squared	.0028754	.0032551

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Big Gift Spillover Effects - Fundraising

	Log(Fundraising + 1000)	Log(Fundraising + 1000)
	Major group	Decile-level
Big Gift in Market * Period t	-0.0408	-0.104
	(0.0490)	(0.0729)
Big Gift in Market * Period t+1	-0.0884*	-0.0872
	(0.0470)	(0.0574)
Big Gift in Market * Period t+2	-0.0687**	0.0204
	(0.0337)	(0.0523)
Big Gift in Market * Period t+3	-0.134***	-0.256***
	(0.0458)	(0.0808)
Charity Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	2262244	1408271
R-Squared	.0682173	.0689028

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Total Big Gifts Spillover Effects - Charitable Activities

	Log(Activities + 1000) Major group	Log(Activities + 1000) Decile-level
Log[(Total Big Gifts/Market Size) + 1] * t	0.0458	0.0499
	(0.0442)	(0.0318)
Log[(Total Big Gifts/Market Size) + 1] * t+1	0.0823*	-0.0205
	(0.0455)	(0.0290)
Log[(Total Big Gifts/Market Size) + 1] * t+2	0.109***	0.0319
	(0.0378)	(0.0365)
Log[(Total Big Gifts/Market Size) + 1] * t+3	0.0143	-0.0224
	(0.0337)	(0.0526)
Charity Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	1449079	726579
R-Squared	.0343926	.0342285

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Total Big Gifts Spillover Effects - Contributions

	Log(Contributions + 1000) Major group	Log(Contributions + 1000) Decile-level
Log[(Total Gifts/Market Size) + 1] * t	0.0327	0.0417
	(0.0534)	(0.0501)
Log[(Total Gifts/Market Size) + 1] * t+1	-0.0356	-0.0215
	(0.0680)	(0.0439)
Log[(Total Gifts/Market Size) + 1] * t+2	0.00853	0.0850
	(0.0892)	(0.0547)
Log[(Total Gifts/Market Size) + 1] * t+3	-0.0461	0.0604
	(0.0711)	(0.0889)
Charity Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	1537553	764284
R-Squared	.0040772	.0051494

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Total Big Gifts Spillover Effects - Fundraising

	Log(Fundraising + 1000) Major group	Log(Fundraising + 1000) Decile-level
Log[(Total Big Gifts/Market Size) + 1] * t	0.153	-0.0370
	(0.128)	(0.127)
Log[(Total Big Gifts/Market Size) + 1] * t+1	-0.0803	-0.217
	(0.196)	(0.175)
Log[(Total Big Gifts/Market Size) + 1] * t+2	0.0716	-0.158
	(0.214)	(0.202)
Log[(Total Big Gifts/Market Size) + 1] * t+3	0.0599	-0.0535
	(0.182)	(0.188)
Charity Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Observations	1457421	730539
R-Squared	.0876335	.0937092

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9 Figures

Figure 1

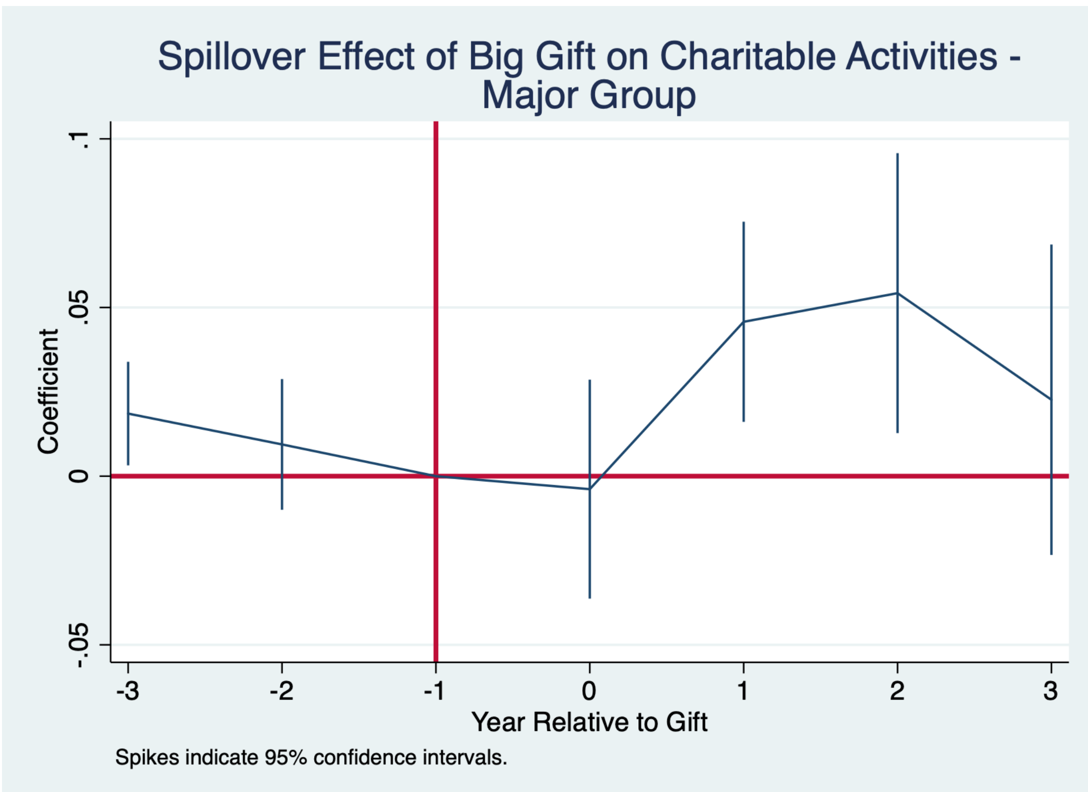

Spillover Effect of Big Gift on Charitable Activities -
Major Group
Coefficient
.1
.05
0
-.05
-3
-2
-1
0
1
2
3
Year Relative to Gift
Spikes indicate 95% confidence intervals.

Figure 2

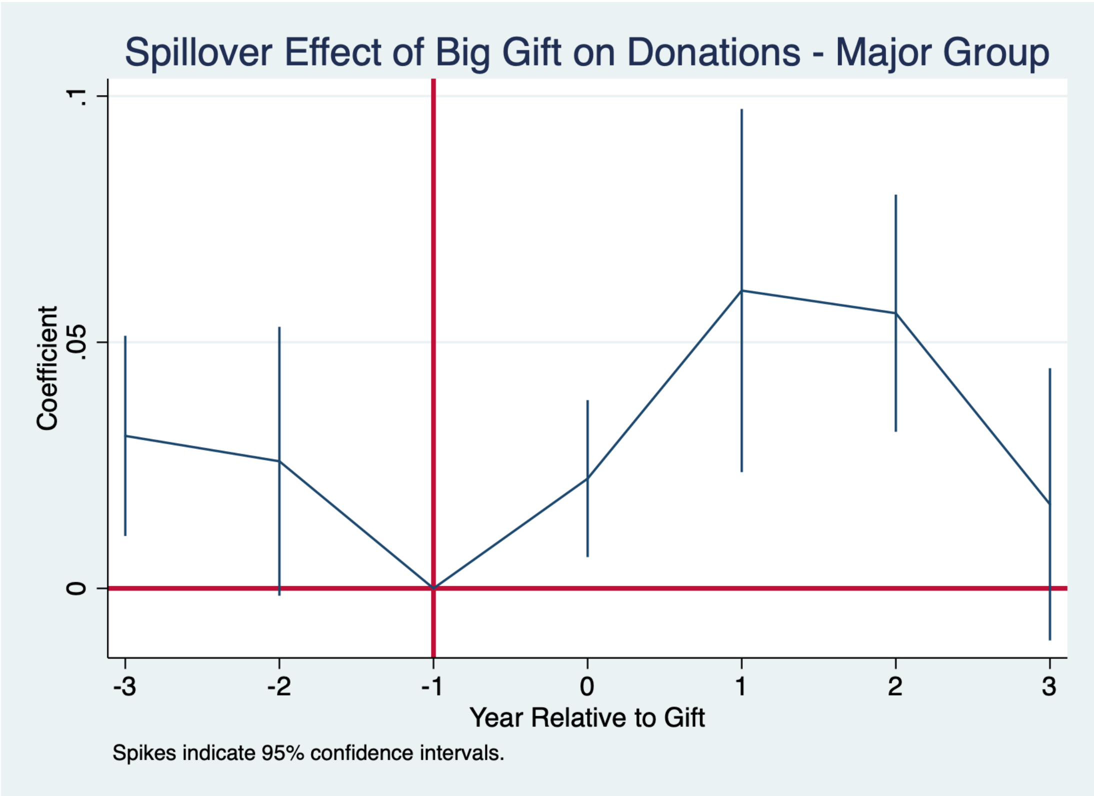
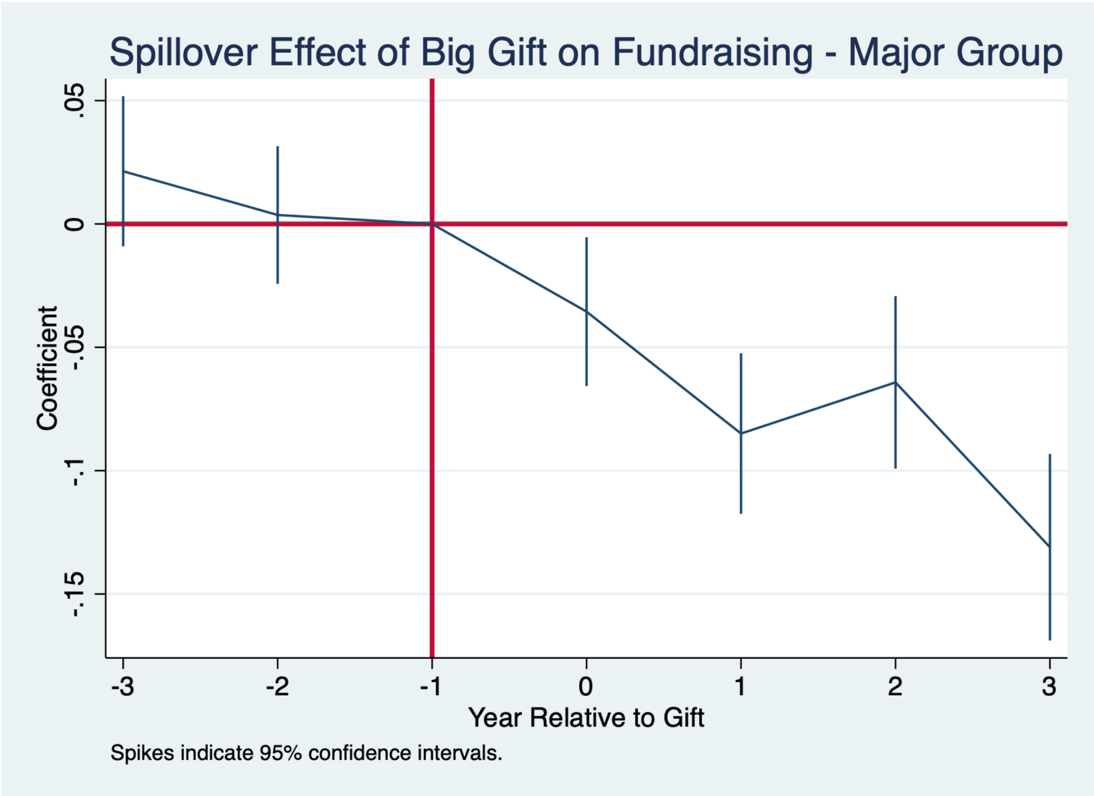

Spillover Effect of Big Gift on Donations - Major Group
Coefficient
.1
.05
0
-3
-2
-1
0
1
2
3
Year Relative to Gift
Spikes indicate 95% confidence intervals.

Figure 3



Spillover Effect of Big Gift on Fundraising - Major Group
Coefficient
.05
0
-.05
-.1
-.15
-3
-2
-1
0
1
2
3
Year Relative to Gift
Spikes indicate 95% confidence intervals.

A Appendix Tables

Table A.1.1: Total Big Gifts Spillover Effects - Charitable Activities at the Major Group Level

	Log(Activities + 1000) All	Log(Activities + 1000) 10th percentile market	Log(Activities + 1000) 90th percentile market
Log(TBG + 1) * t	0.000526	-0.0394***	0.000230
	(0.000842)	(0.000585)	(0.000858)
Log(TBG + 1) * t+1	0.00360***	0.0202	0.00355***
	(0.000918)	(0.0265)	(0.000889)
Log(TBG + 1) * t+2	0.00372***	0.0191***	0.00328**
	(0.00139)	(0.00228)	(0.00139)
Log(TBG + 1) * t+3	0.00206	0	0.00156
	(0.00139)	(.)	(0.00130)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2248851	251518	1552787
R-Squared	.03959	.0322393	.042858

Notes: Standard errors (in parentheses) clustered at the treatment level
The omitted reference period is the period prior to the big gift being received
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.1.2: Total Big Gifts Spillover Effects - Charitable Activities at the Decile-Level

	Log(Activities + 1000) All	Log(Activities + 1000) 10th percentile market	Log(Activities + 1000) 90th percentile market
Log(TBG + 1) * t	-0.000559	-0.00936*	-0.00129
	(0.00160)	(0.00505)	(0.00174)
Log(TBG + 1) * t+1	0.00200**	-0.0205	0.00196*
	(0.00100)	(0.0167)	(0.00104)
Log(TBG + 1) * t+2	0.00150	0.0303	0.00108
	(0.00143)	(0.0316)	(0.00151)
Log(TBG + 1) * t+3	0.00137	0	0.00115
	(0.00136)	(.)	(0.00131)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	1400312	167319	967836
R-Squared	.0405885	.0277604	.045298

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.1.3: Total Big Gifts Spillover Effects - Charitable Activities at the Centile-Level

	Log(Activities + 1000) All	Log(Activities + 1000) 10th percentile market	Log(Activities + 1000) 90th percentile market
Log(TBG + 1) * t	0.00120	-0.00485***	0.000867
	(0.00225)	(0.000763)	(0.00246)
Log(TBG + 1) * t+1	0.00253	0.0116***	0.00238
	(0.00323)	(0.00106)	(0.00340)
Log(TBG + 1) * t+2	0.00158	-0.00713***	0.00206
	(0.00330)	(0.00163)	(0.00345)
Log(TBG + 1) * t+3	0.00123	-0.0278***	0.000978
	(0.00269)	(0.00373)	(0.00286)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	689844	56929	533751
R-Squared	.0488746	.0385726	.0528603

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.1: Total Big Gifts Spillover Effects - Contributions at the Major Group Level

	Log(Contributions + 1000) All	Log(Contributions + 1000) 10th percentile market	Log(Contributions + 1000) 90th percentile market
Log(TBG + 1) * t	0.00181***	-0.0557***	0.00187***
	(0.000565)	(0.000856)	(0.000538)
Log(TBG + 1) * t+1	0.00411***	0.0458**	0.00421***
	(0.000936)	(0.0194)	(0.000971)
Log(TBG + 1) * t+2	0.00353***	0.0535***	0.00360***
	(0.000796)	(0.00175)	(0.000828)
Log(TBG + 1) * t+3	0.00164	0	0.00154
	(0.00102)	(.)	(0.000993)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2398113	272077	1650649
R-Squared	.0028682	.0029566	.0028477

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.2: Total Big Gifts Spillover Effects - Contributions at the Decile-Level

	Log(Contributions + 1000) All	Log(Contributions + 1000) 10th percentile market	Log(Contributions + 1000) 90th percentile market
Log(TBG + 1) * t	0.00305**	-0.00208	0.00329**
	(0.00142)	(0.00191)	(0.00131)
Log(TBG + 1) * t+1	0.00526***	0.00244	0.00569***
	(0.00107)	(0.00382)	(0.00109)
Log(TBG + 1) * t+2	0.00386***	0.0130***	0.00433***
	(0.000831)	(0.00469)	(0.000895)
Log(TBG + 1) * t+3	0.00120	0	0.00148
	(0.00205)	(.)	(0.00205)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	1483029	178939	1024475
R-Squared	.0032473	.0052864	.002738

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.3: Total Big Gifts Spillover Effects - Contributions at the Centile-Level

	Log(Contributions + 1000) All	Log(Contributions + 1000) 10th percentile market	Log(Contributions + 1000) 90th percentile market
Log(TBG + 1) * t	0.00487	-0.0399***	0.00474
	(0.00475)	(0.00252)	(0.00488)
Log(TBG + 1) * t+1	0.00619	-0.00304	0.00704
	(0.00466)	(0.00864)	(0.00488)
Log(TBG + 1) * t+2	0.00507	0.0337*	0.00498
	(0.00635)	(0.0176)	(0.00671)
Log(TBG + 1) * t+3	0.00363	-0.00344	0.00296
	(0.00638)	(0.0180)	(0.00656)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	731013	60416	566139
R-Squared	.0030575	.0043487	.0027866

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3.1: Total Big Gifts Spillover Effects - Fundraising at the Major Group Level

	Log(Fundraising + 1000) All	Log(Fundraising + 1000) 10th percentile market	Log(Fundraising + 1000) 90th percentile market
Log(TBG + 1) * t	-0.00151	0.0775***	-0.00148
	(0.00291)	(0.00113)	(0.00274)
Log(TBG + 1) * t+1	-0.00435*	-0.0375	-0.00387*
	(0.00235)	(0.0249)	(0.00222)
Log(TBG + 1) * t+2	-0.00320	0.0525***	-0.00295
	(0.00232)	(0.00234)	(0.00222)
Log(TBG + 1) * t+3	-0.00705***	0	-0.00654***
	(0.00240)	(.)	(0.00235)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2262244	252870	1562377
R-Squared	.0682047	.0635796	.0702055

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3.2: Total Big Gifts Spillover Effects - Fundraising at the Decile-Level

	Log(Fundraising + 1000) All	Log(Fundraising + 1000) 10th percentile market	Log(Fundraising + 1000) 90th percentile market
Log(TBG + 1) * t	-0.00644	0.0153	-0.00669*
	(0.00401)	(0.0103)	(0.00399)
Log(TBG + 1) * t+1	-0.00552*	0.0160	-0.00566*
	(0.00299)	(0.0180)	(0.00298)
Log(TBG + 1) * t+2	0.00119	0.0101	0.00151
	(0.00335)	(0.0279)	(0.00341)
l_big_gifts_L3	-0.0162***	0	-0.0167***
	(0.00411)	(.)	(0.00386)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	1408271	168264	973432
R-Squared	.0689052	.0721946	.0673709

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3.3: Total Big Gifts Spillover Effects - Fundraising at the Centile-Level

	Log(Fundraising + 1000) All	Log(Fundraising + 1000) 10th percentile market	Log(Fundraising + 1000) 90th percentile market
Log(TBG + 1) * t	-0.00694	0.101***	-0.00767
	(0.00653)	(0.0131)	(0.00690)
Log(TBG + 1) * t+1	-0.00809	-0.132**	-0.00799
	(0.00653)	(0.0659)	(0.00673)
Log(TBG + 1) * t+2	0.00212	-0.159***	0.00204
	(0.00571)	(0.0563)	(0.00581)
Log(TBG + 1) * t+3	-0.0122	0.0787**	-0.0147
	(0.00981)	(0.0336)	(0.0103)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	694067	57278	537032
R-Squared	.0828089	.1051761	.0781298

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4.1: Big Gift Spillover Effects by Charity Size - Charitable Activities at the Major Group Level

	Log(Activities + 1000) All	Log(Activities + 1000) 10th percentile charity	Log(Activities + 1000) 90th percentile charity
Big Gift in Market * t	-0.0129	-0.00548	0.00192
	(0.0165)	(0.0400)	(0.0152)
Big Gift in Market * t+1	0.0384***	0.113***	0.0157
	(0.0145)	(0.0411)	(0.0209)
Big Gift in Market * t+2	0.0468**	0.0307	0.0476***
	(0.0200)	(0.0527)	(0.0173)
Big Gift in Market * t+3	0.0162	0.0614	0.0478
	(0.0225)	(0.0418)	(0.0348)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2248851	177264	203350
R-Squared	.0396101	.0013443	.1382302

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4.2: Big Gift Spillover Effects by Charity Size - Contributions at the Major Group Level

	Log(Contributions + 1000) All	Log(Contributions + 1000) 10th percentile charity	Log(Contributions + 1000) 90th percentile charity
Big Gift * t	0.0129	-0.0851**	-0.0582
	(0.00802)	(0.0350)	(0.0416)
Big Gift * t+1	0.0538***	-0.0540	-0.0510
	(0.0197)	(0.0570)	(0.0482)
Big Gift * t+2	0.0483***	0.0617	-0.0976**
	(0.0121)	(0.0510)	(0.0386)
Big Gift * t+3	0.0117	-0.183**	-0.107**
	(0.0130)	(0.0747)	(0.0496)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2398113	197405	204542
R-Squared	.0028754	.0072095	.0049018

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4.3: Big Gift Spillover Effects by Charity Size - Fundraising at the Major Group Level

	Log(Fundraising + 1000) All	Log(Fundraising + 1000) 10th percentile charity	Log(Fundraising + 1000) 90th percentile charity
Big Gift in Market * t	-0.0408	-0.0228	-0.0494
	(0.0490)	(0.0300)	(0.118)
Big Gift in Market * t+1	-0.0884*	-0.00871	-0.349***
	(0.0470)	(0.0345)	(0.105)
Big Gift in Market * t+2	-0.0687**	0.0321	-0.286***
	(0.0337)	(0.0336)	(0.0909)
Big Gift in Market * t+3	-0.134***	-0.0190	-0.322**
	(0.0458)	(0.0259)	(0.127)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2262244	178775	203769
R-Squared	.0682173	.0459661	.1823891

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5.1: Small Gift Spillover Effects at the Major Group Level

	Log(Activities + 1000)	Log(Contributions + 1000)	Log(Fundraising + 1000)
Small Gift * Period t	0.000857	-0.0263***	0.0163
	(0.0132)	(0.00733)	(0.0457)
Small Gift * Period t+1	0.148***	0.0529***	0.0655***
	(0.00182)	(0.00235)	(0.00254)
Small Gift * Period t+2	0.130***	0.0396***	0.0748***
	(0.00167)	(0.00219)	(0.00190)
Small Gift * Period t+3	0.0979***	0.0118***	0.0655***
	(0.00149)	(0.00224)	(0.00239)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2248851	2398113	2262244
R-Squared	.0604087	.0039998	.0706621

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5.2: Mega Gift Spillover Effects at the Major Group Level

	Log(Activities + 1000)	Log(Contributions + 1000)	Log(Fundraising + 1000)
Mega Gift * Period t	-0.0217**	-0.0415***	-0.0250
	(0.0109)	(0.0121)	(0.0236)
Mega Gift * Period t+1	0.0476*	-0.0200	-0.131
	(0.0288)	(0.0208)	(0.198)
Mega Gift * Period t+2	0.0319	-0.0161	-0.166
	(0.0373)	(0.0210)	(0.196)
Mega Gift * Period t+3	-0.00830	-0.0414*	-0.0330
	(0.0379)	(0.0230)	(0.0814)
Charity Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	2248851	2398113	2262244
R-Squared	.0395366	.002843	.0681527

Notes: Standard errors (in parentheses) clustered at the treatment level

The omitted reference period is the period prior to the big gift being received

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$