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Journal of Public Economics

journal homepage: www.elsevier.com/locate/jpube



Does fundraising create new giving?☆



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ARTICLE INFO

Article history:
Received 25 March 2016
Received in revised form 11 November 2016
Accepted 11 November 2016
Available online 14 November 2016

Keywords: Altruism Philanthropy Charitable giving Competition

ABSTRACT

Despite an extensive literature on the impacts of a variety of charitable fundraising techniques, little is known about whether these activities increase overall giving or merely cause donors to substitute away from other causes. Using detailed data from Donorschoose.org, an online platform linking teachers with prospective donors, I examine the extent to which matching grants for donations to certain requests affect giving to others. Eligibility for matches is determined in entirely by observable attributes of the request, providing an exogenous source of variation in incentives to donate between charities. I find that, while matches increase giving to eligible requests, they do not appear to crowd out giving to similar ones, either contemporaneously or over time.

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1. Introduction

Despite the increased focus on the science of philanthropy in recent years (see Andreoni and A.A. Payne (2013) for an overview), charitable giving has remained fairly stable at around two percent of GDP in the United States (Perry, 2013). Given the vast literature on the efficacy of solicitation in general and of specific fundraising approaches on a charity's own donations, this observation raises the question of whether fundraising activities by a charity increase overall giving or merely crowds out some other part of an individual's altruism budget. The answer is of great importance to the theoretical and empirical literature on altruism and policy questions like the impact of tax preferences for charitable giving.

However, the prerequisites for a full answer to this question are daunting. To begin, a thorough accounting of the altruism budget requires data on all formal giving to both individual charities and potentially altruistic non-charity causes (such as campaigns to elect politicians who support policies that the donor believes have public goods aspects); all informal and casual giving (such as donations on

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the street or to door-to-door solicitors); intrafamily transfers motivated by altruism (Browning and Chiappori, 1998); volunteering (Brown et al., 2013); donations of blood or organs (Kessler and Roth, 2012; Lacetera, Macis, and Slonim, 2012); and willingness to pay more for charity-linked goods (Elfenbein and McManus, 2010), inter alia. One would then perturb donations to, say, an individual charity, either through random assignment or a natural experiment (to avoid the endogeneity inherent in charities' decisions to engage in fundraising activities) and monitor the effect within and across each form of giving over time – including bequests at the end of life. Such an exercise would allow one to fully assess whether increases in giving to one cause expand the total philanthropic budget or shift giving from one cause to another.

This approach is, to put it mildly, impractical. Yet, as an approximation, extremely detailed data on closely-related charities with exogenously-given incentives to donate to certain ones could, at least, answer the question within that context. DonorsChoose.org, an online platform that allows public school teachers to raise funds for projects, is well-suited for this approach. Donations to some projects posted on the site are matched by DonorsChoose.org's partners, usually foundations or corporations. Importantly, matches are made exclusively on the basis of observable characteristics of the project there is no scope to include or exclude a specific project if it does not meet the criteria specified by the match. For example, a match may be given to all mathematics-related projects in a particular state. Both projects already existing on the site and those posted afterwards receive the match; funds are dispensed when projects reach their goals, and the offer continues until the funds provided by the partner are exhausted.

[★] I have benefited from suggestions by Jim Andreoni, Jeffrey Clemens, Catherine Eckel, Tatyana Deryugina, Daniel Hungerman, Mark Hoekstra, Judd Kessler, Jason Lindo, John List, Harvey Rosen, and Ragan Petrie, as well as seminar participants at Duke University, Michigan State University, the Science of Philanthropy Initiative, the University of California – Santa Barbara, and the University of California – Santa Cruz. I am extremely grateful to David Crane, Vlad Dubovskiy, Jay Garlapati, Tea Ho, and Oliver Hurst-Hiller at DonorsChoose.org for providing data and for numerous clarifying conversations. Derek N. Welborn provided excellent research assistance.

I create a daily panel of DonorsChoose.org projects, comprising nearly 30 million observations on 350,000 projects. In specifications with project and day fixed effects, I document that, in line with the previous literature, matching grants increase giving to that charity. I then examine how the presence of similar projects with (and without) matches affects giving, both cross-sectionally on a given day, and over time. The identifying assumption is that there are no shocks to giving to a particular project on a particular day that are correlated with its likelihood of receiving a match; as described more fully in Section 3, the structure of the matching process at DonorsChoose.org is such that this type of correlation is unlikely. While it is certainly possible – and perhaps probable - that teachers increase their personal fundraising efforts in response to being matched, that is a mechanism by which charities may raise more funds in the presence of a matching grant. If matches crowd in givers who would not have otherwise made a donation, this is part of the outcome rather than a source of bias

I find no evidence that giving to a particular charity is reduced by the presence of inducements to give to others; most of the estimates are, in fact, positive and precisely-estimated, but quite small. This finding is robust to different definitions of the similarity of projects and alternative specifications. Restrictions on the types of donations considered (such as including only those who give to multiple schools) provide suggestive evidence that the results are not, in fact, being driven by increased teacher effort when matched. Finally, I aggregate the data to a daily time series and show that overall giving to DonorsChoose.org by non-partner donors increases when more projects are matched.

Of course, I cannot state whether the total amount given by donors to all possible causes increases (especially over long time horizons). However, the strong similarity of projects at DonorsChoose.org suggests that crowd-out from additional fundraising activities, in the form of matching, would be particularly high in this context. Finding little to no substitution of giving is an important piece of evidence on the economics of altruism and philanthropy, as well as an encouraging sign for fundraising professionals. In Section 2, I discuss the previous literature on solicitation, matching grants, and crowd-out of giving to related charities; in Section 3, I provide more details on the DonorsChoose.org data and describe the econometric approach. The results are presented in Section 4, and Section 5 concludes.

2. Previous literature

The literature on charitable giving highlights the importance of solicitation (Andreoni et al., 2011; Meer and Rosen, 2011; DellaVigna et al., 2012). The key result is that giving is rare without fundraising. Charities often look to spur donations through various inducements, like providing gifts (Falk, 2007; Alpizar et al., 2008; Eckel et al., 2015), recognition and prestige (Harbaugh, 1998), and, very commonly, matching grants (Eckel and Grossman, 2008; Karlan and List, 2007; Huck et al., 2015). In general, the existence of a match increases the likelihood of receiving a donation, though not on the size of the donation, and the rate of the match appears to have little impact. Yet while the charity with a match benefits, research on whether this giving crowds out donations to other charities is limited.

Theoretical models, primarily on the optimal regulation of charities, depend heavily on this issue. For example, Rose-Ackerman's (1982) findings on the regulation of fundraising depends on the degree to which donors "recognize that high levels of fundraising may be translated into higher donations from others," understanding that they "benefit little if fundraising simply shifts funds between charities that they find ideologically attractive." Similarly, Aldashev and Verdier (2010), developing a model of nongovernmental organizations, note that "the crucial question is how effective fundraising efforts are in attracting new donors," and that this is ultimately an empirical issue.

Laboratory experiments, offering the advantages of a controlled environment, can be used to examine the degree of crowd-out from additional choices or more intense solicitation for certain charities. Motivated by the seemingly-overwhelming number of projects on crowdfunding sites, Corazzini et al. (2015) design an experiment with multiple threshold public goods and show that increasing the number of competitors can decrease total contributions and the likelihood that any option reaches its goal. Krieg and Samek (2016), in a similar experiment with simultaneous public goods games, find that reducing the price of giving in one game increases giving to the untreated game, for an overall increase in total contributions. Using non-pecuniary incentives (like recognition) results in more crowd-out of giving to the untreated game. Harwell et al. (2015) give subjects a menu of charities to which they can donate, and examine within-subjects differences in giving after participants are shown a video promoting one of those charities. They find substantial shifting of donations to the targeted charity, but no impact on overall contributions. Finally, recent work by Filiz-Ozbay and Uler (2016) directly examine competition in the lab using differential rebate rates across charities; they also find a shift in donations towards the incentivized charity, but also those overall giving increases. Taken together, this recent literature suggests that results are dependent on context.

Field experiments have found mixed evidence as well. Meier (2007) shows that while donors who are randomly assigned to the offer of a match for their gift initially donate more, their giving rate falls after the match is removed. Ultimately, giving is lower in the long run for the treated group, highlighting the importance of examining effects beyond the initial period of an intervention. Conversely, Landry et al. (2010) find that donors initially attracted by a lottery (as opposed to a standard voluntary contribution mechanism) give more in future solicitations, without the offer of an incentive, and Bekkers (2015) finds that those offered a match do not give less in response to a natural disaster months later. In a somewhat different context, Lacetera, Macis, and Slonim (2012) find that economic incentives to give blood substantially increases donations. However, turnout is reduced at nearby and later drives, negating nearly half of the higher participation in response to the incentives and demonstrating the importance of accounting for spillover effects.

Papers using observational data find similarly divergent results. Cairns and Slonim (2011) examine the effects of multiple collections at Catholic Masses, finding that about a fifth of the second collection is cannibalized from the first. Diepen et al. (2009) combine the databases of three large charities in the Netherlands, finding that a charity's own mailings reduce revenue from subsequent solicitations, but mailings from competitor charities increase overall giving in the short run, with no long-run impacts. Meer (2014), also using data from DonorsChoose.org, finds that higher administrative costs for competitors, set in a plausibly exogenous manner, results in greater contributions to a given project, suggesting some degree of substitution in giving.

Using the Panel Study of Income Dynamics's charitable giving supplement, Brown et al. (2012) find that donations during 2004 had a positive association with giving to help victims of the December 2004 tsunami, and that giving to tsunami-related causes had a positive impact upon giving in the 2006 calendar year. They conclude that "there is no evidence in the analysis that giving to an unplanned natural disaster diverts future expenditure away from other types of giving." Reinstein (2010), also using the PSID, documents a similarly positive relationship between giving to different types of charities. After controlling for individual fixed effects (which would account for time-invariant altruistic preferences), though, he finds negative correlations between giving to certain categories, suggesting evidence of substitution. More to the point, the panel nature of the PSID offers many advantages, but the two year gap between waves, the self-reported, retrospective nature of the

questions, and the general lack of truly exogenous variation in giving limits its applicability to this question.

Finally, two very recent papers use natural disasters to examine whether greater need for certain causes (and perhaps attendant fundraising) crowd out giving to other causes. Using tax data, Deryugina and Marx (2015) show that giving increases in response to nearby tornadoes, particularly severe ones, and that the impact persists for several years. Scharf et al. (2015) use detailed data from the United Kingdom to examine giving in the aftermath of organized appeals for disaster appeal, finding no reduction in giving to other charities.

Even leaving aside the unattainable overarching puzzle of individuals' lifetime altruism budget, it is evident that there are unanswered questions in the literature. I use exogenously-assigned incentives to give to particular projects in the rich data from DonorsChoose.org, described in the next section, to estimate impacts both among charities at a given moment and over time.

3. Data and Econometric Specification

3.1. DonorsChoose.org

Founded in 2000, DonorsChoose.org is an online platform that allows public school teachers in the United States to post requests for funding. Donors, whose gifts are tax-deductible, can easily select projects to which to donate. The platform has raised nearly 400 million dollars from two million donors, for 270,000 teachers in 66,000 schools. Over two-thirds of the public schools in the United States have at least one teacher who has posted a project on the site. About 36% of projects request classroom supplies, 22% request books, and 30% request some type of technology.

A teacher selects supplies from lists of approved vendors (no requests for labor or capital improvements may be submitted). He or she writes several paragraphs regarding student needs and the purpose of the supplies, as well as posting a photograph of the classroom and students. The request's web page includes information about the school (such as its location and poverty level) and the project (such as its subject matter and the number of students reached). The request includes an itemized list of the materials requested, their price and quantity, and any additional charges. These projects are screened by the organization's staff.

If a project reaches its goal, DonorsChoose.org purchases the materials and ships them directly to the teacher to ensure quality. If the project expires prior to being funded, donors have the option to have the funds returned to their account (to select another project) or to have DonorsChoose.org select a project for them; in general, unfunded projects expire after five months. Screen captures of the main landing page, the search page, and sample requests are shown in Appendix A.²

My data extract consists of 346,136 projects posted between January 2008 and May 2012, of which 68.3% reached their goal and were funded. The mean request was \$602, with a median of \$472. On average, projects were live for 81 d (median of 73); among successful projects, the mean time to funding was 51 d (median of 34). Aggregating individual donations to a daily panel of projects yields 27.1 million day-project observations, of which 816,388 have at least one donation from a non-partner donor; that is, the gift comes

Table 1 Summary statistics.

	Mean	Standard deviation	Median
Panel A			
Funded	0.683	0.465	1
Number of non-partner donors	4.46	7.77	2
Days live	81.4	61.1	73
Project was ever matched	0.348	0.476	0
Total cost of project (including optional support)	\$602.32	\$21,264.25	\$472.18
Panel B			
Project is matched	0.208	0.406	0
Number of matched ZIP2-subject competitors	42.75	112.8	8
Number of total ZIP2-subject competitors	161.6	254.6	83
Average number of matched ZIP2-subject competitors over previous 60 d	41.2	99.0	8.88
Average number of total ZIP2-subject competitors over previous 60 d	154.6	233.4	81.0
Received a non-partner donation	0.030	0.171	0
Amount received from non-partner donations, conditional on receiving any	\$81.42	\$145.01	\$40.00
Number of non-partner donations, conditional on receiving any	1.89	2.75	1

Summary statistics in Panel A are listed for 346,136 projects, Summary statistics in Panel B are listed for 27,107,224 d-project observations.

from an individual not affiliated with DonorsChoose.org or its partner organizations. Conditional on receiving a donation on a given day, the average project receives 1.9 donations per day totaling \$81 (median of \$40).

Further summary statistics are shown in Table 1; summary statistics for the numerous time-invariant project attributes shown to prospective donors are not shown, as they are subsumed into the project fixed effects described in Section 3.4.

3.2. Matching grants

A number of foundations and corporations partner with DonorsChoose.org to provide matching grants for projects, selecting the eligibility criteria that define the matches. These matches come in two types. "Double Your Impact" (DYI) grants offer a standard dollarfor-dollar linear match;³ importantly, though, the funding is applied to gifts made prior to the start of the match. There are 316 dollar-fordollar matches in the sample, with an average amount of \$49,182 (median of \$20,000) in partner funds, totaling \$15.5 million. The other type of match is an "Almost Home" (AH) grant, in which the partner organization offers all but the last \$100 of funding to the project. There are 86 matches of this type, with an average of \$90,672 (median of \$33,432), totaling \$7.8 million.⁴ Projects that have already accumulated half or more of their target amount (DYI) or are within \$100 of the target (AH) are ineligible, regardless of whether they meet the match criteria. In both cases, funds are not committed by the partner unless the project fulfills its remaining need with others' donations. When the amount given by the partner to successfully completed projects is exhausted, the match ends. Projects that are still live return to being listed as unmatched.

Given that the identification strategy requires that the matches be unrelated to the project's unobserved attributes, it is worth highlighting the nature of matching data provided by DonorsChoose.org. These data consist of an identifier for the partner organization, the start date of the match, the amount of the grant, and the parameters of the match. These

¹ See http://www.donorschoose.org/about for more information. The organization has grown substantially in size since the end date of the sample in this paper.

² DonorsChoose.org made some changes to the layout of project pages after the data for this project was collected. The screen captures shown are of the site in early 2011. The default sorting when browsing or searching projects is by urgency, a metric determined by DonorsChoose.org based on the poverty level of the school and if the project was both relatively close to completion and to expiration.

³ "Double Your Impact" was renamed "Half Off" after the end date of the sample used in the paper. In early 2016, the site is altering the nature of dollar-for-dollar grants once again; the practices discussed here are as they existed during the sample period.

⁴ There are a number of promotions as well, totaling \$4.2 million in funds, but unlike the matches, these can by used by donors on any project.

parameters are determined entirely by project characteristics and are reported as a search URL tagging the relevant variables. ⁵ As such, there is no scope for unobservable attributes of the project to be correlated with whether or not it is matched. New projects entering after the match is live are matched as well, if they meet the criteria, though there is little scope for teachers to know the exact parameters and tailor their appeals to be eligible. ⁶

By comparing the match criteria to project characteristics and tracking the dates on which funds are committed by the partner organization's identifier, I am able to determine whether or not a project is matched on a particular day. Of the 27.1 million day-project observations in the data, 20.8% (5.65 million) are associated with a match. Importantly, there is substantial within-project variation; about 35% of projects are ever matched.

3.3. Competitors

It is not immediately obvious how to determine what comprises a project's set of competitors. DonorsChoose.org has thousands - and sometimes tens of thousands - of live projects at any given time. It stands to reason that users are not considering every possible project. Subject matter and geographic location are reasonable candidates. Based on search data on the DonorsChoose.org website during 2010, about 55% of searches or filters involve a geographic restriction and 29% involve a subject-area restriction (16% have both), far more than any other search criteria. Moreover, among donors who give more than once, the average donor gives 70% of their donations to projects in one subject area, with 39% giving to only one. Donors give 79% of their donations to projects in one twodigit ZIP area (that is, the area defined by the first two digits of the ZIP code), with 57% giving to only one ZIP2.8 I therefore define the competitor set as projects sharing the same subject and ZIP2, with an average size of 162 total projects per day (median of 83), of which 43 are matched (median of 8). 2 ZIP2 is an arbitrary choice, of course, but the results are robust to using geographic areas both generally larger (state) and smaller (threedigit ZIP or county), as seen in Table 3.

3.4. Econometric specification

To estimate the impact of matches on funds raised, I first measure the impact on the probability of receiving a gift on a given day.

```
\begin{split} &P(Donations_{it} = 1) = \beta_1 \cdot Matched_{it} + \beta_2 \cdot MatchedCompetitors_{it} \\ &+ \beta_3 \cdot TotalCompetitors_{it} + \beta_4 \cdot PreviousMatcedCompetitors_{it} \\ &+ \beta_5 \cdot PreviousTotalCompetitors_{it} + \beta_6 \cdot DaysLive_{it} + Project_i \\ &+ Date_t + \epsilon_{it} \end{split} \tag{1}
```

Matched $_{it}$ is an indicator for whether a project i has a match on a given day t. MatchedCompetitors $_{it}$ is the log of the number of other projects with a match in a given competitor group, while TotalCompetitors $_{it}$ is the log of total number of other projects in a given competitor group. 10 In that case, β_2 represents the impact of increasing the number of matched competitors while holding the total number of competitors

fixed – in essence, substituting matched competitors for unmatched ones – and β_3 is the impact of increasing the number of total competitors while holding the number of matched competitors fixed. Similarly, the PreviousMatchedCompetitors $_{it}$ and PreviousTotalCompetitors $_{it}$ variables are the log of the average number of matched and total competitors over a period prior to that day; in most specifications, I use sixty days. I also include the log of the number of days the project has been live.

Eq. (1) is estimated with ordinary least squares, and includes date fixed effects to control for time-specific factors that affect giving (such as increased news coverage that drives more donors to the site) and project fixed effects to account for any time-invariant project-specific attributes that impact giving. These include not only the observable characteristics of the project, such as the purpose of the funds or the poverty level of the school, but also unobservable characteristics such as the quality of the teacher's description or the photograph on the appeal page, as well as the overall popularity of the project.

Eq. (2), also estimated with ordinary least squares, estimates the impact of these variables on the log of the amount donated, conditional on raising any funds that day. It is straightforward to combine the estimates from Eqs. (1) and (2) to estimate the total impact on (the natural log of) donations.

$$\begin{aligned} & \text{Donations}_{it} = \beta_1 \cdot \text{Matched}_{it} + \beta_2 \cdot \text{MatchedCompetitors}_{it} \\ & + \beta_3 \cdot \text{TotalCompetitors}_{it} + \beta_4 \cdot \text{PreviousMatchedCompetitors}_{it} \\ & + \beta_5 \cdot \text{PreviousTotalCompetitors}_{it} + \beta_6 \cdot \text{DaysLive}_{it} + \text{Project}_i \\ & + \textit{Date}_t + \epsilon_{it} \quad \text{if Donations}_{it} > 0 \end{aligned} \tag{2}$$

The effects of the time-varying variables are identified from within-project changes in whether the project is matched and the number of its competitors. To ascribe a causal interpretation to those coefficients, project- and day-specific shocks cannot be correlated with those variables. Given the manner in which matches are made at DonorsChoose. org, this is a reasonable assumption. It is possible that lower-quality projects enter in response to a match, though project fixed effects will account for those factors, and excluding those projects from the data does not change the results. It is also possible that exogenous events, such as natural disasters, drive both matches to be made to projects in particular area and donors to seek out those types of projects. Specifications including ZIP2-by-month effects, which would account for any such shocks, are similar to the primary results.

A possible objection to this interpretation is that teachers may respond to being matched by increasing their off-site fundraising efforts – for example, by soliciting friends and family more intensely. A teacher's direct solicitations to friends and family for his or her own project as the result of being matched should not crowd out donations to other projects, because those donors only considered the project about which they were contacted. This is a plausible mechanism, but it is also part of the effect that I am investigating. The impact of a matching grant on a charity's funds is a combination of the impact on donors from the presence of the grant, with no reaction by the charity itself, and the impact on donors from the additional fundraising efforts that are concurrent with the grant itself. These two factors may be of independent interest, but, in practice, they do not occur independently. Nevertheless, in Section 4, I explore a number of alternative specifications in which the likelihood that donors were directly contacted by the teacher posting the project is low; the results are unchanged.

4. Results

4.1. Primary specification

I begin by examining the impact of receiving a matching grant for the project itself. Column 1 of Table 2 presents the results of estimating

 $^{^{\,5}\,}$ An example of the match criteria provided is

[&]quot;http://www.donorschoose.org/donors/search.html?subject4=-4&zone=104," which returns all math and science projects in upstate New York.

⁶ The results are unchanged when projects that were eligible for a match upon being posted are excluded from the sample.

⁷ Previous research has considered the impact of geographic distance on social distance, the perceived closeness between prospective donor and recipient, which in turn can play a role in donative behavior. See Brown et al. (2016), Chen and Li (2009), and Meer and Rigbi (2013).

⁸ A map of two-digit ZIP codes based on Census data is available in Appendix Fig. A5.

⁹ There is a good deal of variation in the number of competitors. About 21% of project-day observations had no matched competitors, while 0.4% had all competitor projects matched. Among ZIP2-subject groups, only 1.1% never had a match at all; a little under half of ZIP2-subject-day observations had no matched projects, while about 2% had all projects in the competitor group matched.

¹⁰ I add one to the number of competitors prior to taking logs.

Table 2 Main results: ZIP2-subject competitors.

	(1) Probability of receiving any donations	(2) Log amount conditional on receiving any donations	(3) Total effect on donations
Project is matched	0.0076***	-0.0151*	0.0276***
	(0.0003)	(0.0108)**	(0.0010)
Log number of matched current competitors	0.0009***	0.0112***	0.0036***
	(0.0001)	(0.0043)	(0.0004)
Log number of total current competitors	-0.0005	0.0028	-0.0019
	(0.0004)	(0.0138)	(0.0015)
Log average daily number of matched competitors over previous 60 d	0.0020*** (0.0002)	0.0368*** (0.0081)	0.0086*** (0.0007)
Log average daily number of total	- 0.0036***	-0.0142	-0.0138***
competitors over previous 60 d	(0.0005)	(0.0168)	(0.0019)
Observations	27,107,224	816,388	27,107,224

Columns (1) and (2) are estimated using OLS with project and day fixed effects, Specifications include the log of days the project has been live, project fixed effects, and date fixed. Column (3) combines the estimates from Columns (1) and (2). Standard errors are in parentheses and clustered by project.

Eq. (1) on the 27.1 million project-day observations, in which the outcome is a binary variable equaling one if the project received any donations from a non-partner donor on that day and zero otherwise; standard errors are clustered at the project level. Receiving a match increases the likelihood of receiving any funds by 0.76 percentage points (s.e. = 0.03 percentage points), a large effect relative to the baseline of 3%. In Column 2, I estimate the impact on the log of the amount conditional on receiving any donations. The effect is negative, but relatively small at -1.5% and statistically insignificant (s.e. = 1.1%). Combining these two effects in Column 3 shows that the average amount raised by matched projects increases by 2.8% (s.e. = 0.1%) on each day they are matched. These results are consistent with the previous literature on the impact of matches – matches matter, but their impact is concentrated on the extensive margin.

Turning to the impact of contemporaneous competitors, the second row of Table 2 shows that an increase in the number of matched competitors (holding the number of total competitors fixed) increases the funds raised by a particular project. While statistically significant, though, the impact is quite small in magnitude: a 10% increase in the number of matched competitors, all else equal, increases the likelihood of receiving a donation by one-onehundredth of a percentage point (about 3% of the baseline), increases the conditional average gift size by 1.1%, and has a total impact on donations of 0.4%. An increase in the total number of competitors in the same ZIP2-subject group on a given day has no impact, as seen in the third row of Table 2, with the coefficients both miniscule in magnitude and statistically insignificant; the confidence intervals are sufficiently narrow to exclude meaningful effects. Based on these results, it does not seem that an increase in competition reduces donations accruing to a particular charity.

This does not preclude, of course, intertemporal shifts in giving. The last two rows of Table 2 examine the impact of the average daily number of competitors over the previous sixty days. 11 Perhaps surprisingly, an

Table 3 Interactions: ZIP2-subject competitors.

	(1) Probability of receiving any donations	(2) Log amount conditional on receiving any donations	(3) Total effect on donations
Project is matched	0.0060*** (0.0009)	-0.1258*** (0.0356)	0.0186*** (0.0035)
Log number of matched current	0.0009***	0.0162***	0.0038***
competitors	(0.0001)	(0.0045)	(0.0004)
Project is matched x matched current competitors	-0.0002^* (0.0003)	-0.0694*** (0.0111)	-0.0027** (0.0011)
Log number of total current competitors	0.0022***	0.0111)	0.0086***
Log number of total current competitors	(0.0004)	(0.0151)	(0.0015)
Project is matched x total current	-0.0139^{***}	-0.0015	-0.0515^{***}
competitors	(0.0010)	(0.0259)	(0.0037)
Log average daily number of matched	0.0013***	0.0321***	0.0056***
competitors over previous 60 d	(0.0002)	(0.0083)	(0.0007)
Project is matched x matched 60 d competitors	0.0049*** (0.0003)	0.0357*** (0.0116)	0.0193*** (0.0011)
Log average daily number of total	-0.0061***	-0.0371^{**}	-0.0238^{***}
competitors over previous 60 d	(0.0004)	(0.0183)	(0.0018)
Project is matched x total 60 d	0.0109***	0.0541**	0.0420***
competitors	(0.0010)	(0.0259)	(0.0038)
Observations	27,107,224	816,388	27,107,224

Columns (1) and (2) are estimated using OLS with project and day fixed effects. Specifications include the log of days the project has been live, project fixed effects, and date fixed. Column (3) combines the estimates from Columns (1) and (2). Standard errors are in parentheses and clustered by project.

increase in the average daily number of matched competitors over that time period increases both the likelihood of receiving a donation and its size, with a 10% increase resulting in a 0.2 percentage point increase in probability of a gift (s.e. = 0.02 percentage points) and a 3.7% increase in the size of the gift (s.e. = 0.8%), for an overall impact of 0.9% (s.e. =0.07%). While fairly small in magnitude, this result, coupled with the effects of contemporaneous matched competitors, suggests that matched charities do not cannibalize donations from other charities. An increase in the total number of competitors over the previous sixty days does reduce giving somewhat, with a 0.36 percentage point reduction in the likelihood of receiving a gift (s.e. = 0.05 percentage points), resulting in a 1.4% reduction in average gift size.

Recall that if the positive effect of a project being matched is purely the result of teachers soliciting their social network for donations to their own project, then there should be no impact of competitors' matches either at the same time or over prior periods. Alternatively, if donations to one project come entirely at the expense of donations to others, then the effects of competitors should be negative and substantial enough to offset the effect of a project's own match. These effects are more easily seen in aggregate data, described in Section 4.4, which show no evidence of crowd out. Regardless, the positive effects of contemporaneous matched competitors suggests that matches induce donors to consider other, similar projects, and the positive effects of previous matched competitors suggest that donors are induced to return to projects of that type. 12

^{*} *p* < 0.1.

^{**} p < 0.05.

^{***} p < 0.01.

p < 0.1.

^{**} p < 0.05.

^{***} p < 0.01.

 $^{^{11}\,}$ I also used time horizons of fourteen, thirty, and ninety days. The results do not differ substantially.

 $^{^{12}\,}$ This result is consistent with Meer (2013), who shows that habit formation among donors is a strong driver of giving behavior.

Table 4AAlternative specifications probability of receiving any donations.

	Alternate competitor groups			Limited donors					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	ZIP3-subject	State-subject	County-subject	No teacher	No giving	No same	Donors to	Donors to	
	competitors	competitors	competitors	accounts	pages	ZIP3	multiple projects	multiple schools	
Project is matched	0.0073***	0.0078***	0.0073***	0.0068***	0.0066***	0.0037***	0.0052***	0.0044***	
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	
Log number of matched	0.0010***	0.0007***	0.0009***	0.0008***	0.0004***	0.0005***	0.0006***	0.0006***	
current competitors	(0.0001)*	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Log number of total current competitors	-0.0027*** (0.0003)	-0.0006 (0.0005)	-0.0027*** (0.0003)	-0.0002 (0.0004)	-0.0002 (0.0003)	-0.0021*** (0.0002)	-0.0037*** (0.0003)	-0.0032*** (0.0002)	
Log average daily number of matched competitors over previous 60 d	0.0030***	0.0017***	0.0035***	0.0018***	0.0018***	0.0005***	0.0014***	0.0009***	
	(0.0002)**	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Log average daily number of total competitors over previous 60 d	-0.0016*** (0.0003)	-0.0054^{***} (0.0005)	-0.0020*** (0.0003)	-0.0042^{***} (0.0004)	-0.0039*** (0.0004)	-0.0009*** (0.0002)	0.0002 (0.0003)	-0.0007*** (0.0002)	
Observations	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224	

Columns (1) and (2) are estimated using OLS with project and day fixed effects, as well as the log of days the project has been live. Column (3) combines the estimates from Columns (1) and (2). Standard errors are in parentheses and clustered by project.

One possible explanation for these results, particularly the impact of contemporaneous competitors, is based on the threshold nature of these projects. A long literature (see, for example, Andreoni, 1998; Bracha et al., 2011; and Cadsby and Maynes, 1999) has examined the nature of giving to threshold public goods. It is possible that the driving mechanism behind the increase in donative behavior with more matched competitors is due to donors giving multiple gifts to matched projects. This kind of splitting could occur because a smaller amount is necessary to reach the threshold for a matched project, leading a donor who wants to give a set amount to donate the balance to another project.

In this situation, one would expect the conditional amount given to a matched project to decrease substantially, as donors top up matched projects and move on to others with the balance of their planned donation. As seen in Table 2, this is not the case. To examine the issue further, I aggregated the data to the day level and looked at how the number of matched projects relates to the prevalence of multiple donations. There is a positive relationship between the number of matches and the

average number of donations made by a single donor in day. A 10% increase in the number of matches is associated with a 0.8% increase in the average number of donations per donor, or a 0.15 percentage point increase in the prevalence of multiple donations (about 0.5 percent of the baseline value). While the relationship is statistically significant, it is quite small, and though these findings are not conclusive, they do provide suggestive evidence that the threshold nature of these projects is not the primary mechanism behind the results.

4.2. Interactions

To investigate how the impact of competitors varies with the matching status of the project, I interact the indicator for matching with each of the four variables defining the number of matched and total competitors in Table 3.

There is no change in the impact of the number of contemporaneous matched competitors on the probability of receiving any donations

Table 4BAlternative specifications amount received conditional on any donations.

	Alternate competitor groups			Limited donors				
	(1) ZIP3-subject competitors	(2) State-subject competitors	(3) County-subject competitors	(4) No teacher accounts	(5) No giving pages	(6) No same ZIP3	(7) Donors to multiple projects	(8) Donors to multiple schools
Project is matched	-0.0104	-0.0041	-0.0113	-0.0223*	0.0059	-0.0043	0.0059	0.0067
	(0.0108)	(0.0107)	(0.0107)	(0.0114)	(0.0117)	(0.0157)	(0.0133)	(0.0141)
Log number of matched current competitors	0.0029	-0.0071	0.0035	0.0096**	0.0049	-0.0034	0.0020	-0.0010
	(0.0048)	(0.0045)	(0.0046)	(0.0045)	(0.0047)	(0.0063)	(0.0054)	(0.0057)
Log number of total current competitors	-0.0157	0.0506***	-0.0115	0.0073	0.0308**	0.0218	-0.0309^*	-0.0325^*
	(0.0095)	(0.0163)	(0.0102)	(0.0144)	(0.0146)	(0.0200)	(0.0171)	(0.0179)
Log average daily number of matched	0.0539***	0.0433***	0.0581***	0.0313***	0.0275***	0.0126	0.0294***	0.0193*
competitors over previous 60 d	(0.0085)	(0.0085)	(0.0085)	(0.0086)	(0.0088)	(0.0114)	(0.0099)	(0.0103)
Log average daily number of total	0.0080	-0.0832^{***}	-0.0019	-0.0339^*	-0.0687^{***}	0.0188	0.0144	0.0318
competitors over previous 60 d	(0.0126)	(0.0202)	(0.0131)	(0.0176)	(0.0179)	(0.0239)	(0.0208)	(0.0217)
Observations	816,388	816,388	816,388	721,059	557,674	290,803	448,116	372,085

Columns (1) and (2) are estimated using OLS with project and day fixed effects, as well as the log of days the project has been live. Column (3) combines the estimates from Columns (1) and (2). Standard errors are in parentheses and clustered by project.

^{*} *p* < 0.1.

^{**} p < 0.05.

^{***} p < 0.01.

^{*} p < 0.1.

^{**} p < 0.05.

^{***} p < 0.01.

Table 4CAlternative specifications effect on average giving.

	Alternate competitor groups			Limited donors				
	(1) ZIP3-subject competitors	(2) State-subject competitors	(3) County-subject competitors	(4) No teacher accounts	(5) No giving pages	(6) No same ZIP3	(7) Donors to multiple projects	(8) Donors to multiple schools
Project is matched	0.0267***	0.0288***	0.0267***	0.0248***	0.0246***	0.0140***	0.0192***	0.0163***
	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0008)	(0.0006)	(0.0007)	(0.0007)
Log number of matched current competitors	0.0038***	0.0024***	0.0034***	0.00319***	0.00175***	0.00190***	0.00243***	0.00220***
	(0.0005)*	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Log number of total current competitors	- 0.0106***	-0.0006	-0.0103***	-0.000734	0.0000348	-0.00767***	-0.0141***	-0.0124***
	(0.0010)	(0.0018)	(0.0010)	(0.0014)	(0.0013)	(0.0008)	(0.0010)	(0.0009)
Log average daily number of matched competitors over previous 60 d	0.0125***	0.0076***	0.0147***	0.00743***	0.00725***	0.00213***	0.00574***	0.00352***
	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Log average daily number of total	- 0.0058***	- 0.0225***	-0.0073***	-0.0166***	-0.0160***	- 0.00310***	0.00102	-0.00211**
competitors over previous 60 d	(0.0013)	(0.0021)	(0.0014)	(0.0018)	(0.0016)	(0.0009)	(0.0012)	(0.0010)
Observations	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224	27,107,224

Columns (1) and (2) are estimated using OLS with project and day fixed effects, as well as the log of days the project has been live. Column (3) combines the estimates from Columns (1) and (2). Standard errors are in parentheses and clustered by project.

when a project is matched, though an increase in the total number of projects reduces the likelihood of receiving a donation when the project itself is matched. On the intensive margin, though, a 10% increase in the number of matched competitors reduces the amount of donations when a project is matched, while it increases the amount received by unmatched projects slightly. There is no impact on the intensive margin of an increase in the total number of competitors. These results suggest that donors are stumbling across matched projects rather than seeking them out; if donors were seeking out matched projects, then an increase in the number of matched competitors would reduce the likelihood that any one matched project receives funding, while an increase in the number of total competitors would have no impact.

Turning to the effects of competition over the previous sixty days, an increase in the number of matched competitors over that time period has a more positive effect on fundraising for matched projects, again suggesting that donors develop a taste for matched projects of that type. Further evidence for this hypothesis is provided by the interaction with the total number of competitors; while greater previous competition reduces funds raise by unmatched projects, matched projects counteract this effect and, indeed, more previous competition has a somewhat positive impact.

4.3. Robustness

4.3.1. Alternative definitions of competitor groups

An important issue is whether the results are sensitive to the definition of the competition group. In Columns 1 to 3 of Tables 4A, 4B, and 4C, I show that this is not the case. I define competitors are those with both the same subject matter and the same ZIP3 (the area defined by the first three digits of the ZIP code, a far smaller area than ZIP2); those with the same subject and state; and those with the same subject and county. In each case, the results are essentially unchanged. 13

4.3.2. Restrictions on donors

As discussed above, the impact of matching is a combination of both the teacher's increased solicitation of his or her social network and the increased attention given to a matched project by donors who have no connection to the teacher. The results in Table 2 suggest that the former effect cannot be the only operative one, but it is possible to address this issue in another way. While there is relatively little data on the donors themselves, there are several attributes available that are likely to be correlated with being subject to increased fundraising efforts directly from the teacher that occur with the presence of a match.

First, donors can self-identify as teachers themselves on their account. I exclude these accounts when aggregating donations to the day-project panel level and estimate the three specifications in Table 2 in Column 4 of Tables 4A, B, and C. It is evident that there is little difference from the main results when using this sample.

Second, both donors and teachers can set up "giving pages," in which they highlight projects that they find particularly worthy. DonorsChoose.org tracks whether donors make their gifts through these giving pages; it stands to reason that these donors are more likely to be subject to additional solicitation when a project is matched. Excluding donations made in such a manner from the data also makes little difference to the results, as seen in Column 5.

Third, I exclude donations made from the same ZIP3 as the project. Given many donors' preference for giving to projects in close proximity, it is unsurprising that this restriction removes a large number of donations from the data. Nevertheless, the results, in Column 6, remain broadly similar to the primary specifications.

Finally, in Columns 7 and 8, I only include donors who give to more than one project and donors who give to more than one school. This removes individuals who only give in response to social pressure related to the project (though, of course, other one-time donors as well) and those who only give, for example, to their child's own school. Once again, the results are quite similar

The impact of a project's own match is similar across the five sets of results. This suggests that the impact of matching is not driven primarily by increased teacher solicitation, and provides additional evidence that the effects of additional matched competitors are not spurious.

4.3.3. Alternative specifications

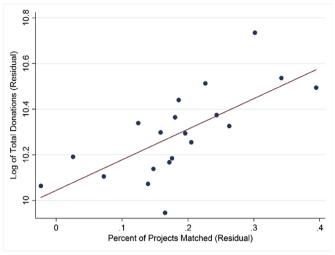
To check whether the log parameterization is masking patterns in the results, I also estimate the model using linear and quadratic terms,

^{*} n < 0.1

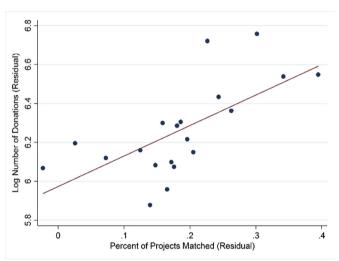
^{**} p < 0.05.

^{***} p < 0.03.

¹³ Since geographic area appears to be primary search criterion for many donors, as described in Section 3.3, I also estimated specifications in which the competitor group was defined as all projects in the same ZIP2 or ZIP3, irrespective of subject matter. The qualitative interpretation of the coefficients is unchanged: very small, precisely estimated impacts of competitors, with positive effects of additional matched competitors.



A: Total Donations



B: Total Number of Donations

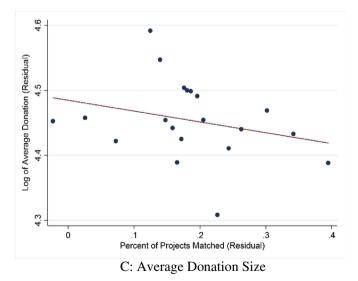


Fig. 1. Daily time series Each figure plots vingtile means of the daily outcome data against the daily percent of projects that are matched, both residual to a cubic time trend and day-of-week effects.

as well as partitioning the number of competitors into bins. These additional results, available in this paper's Web Supplement, show no indication that the results in Table 2 are driven by the log transformation of the number of competitors.

I also examine the probability that a project receives its first donation or that it reaches its threshold on a given day. In both cases, an increase in the number of matched projects both contemporaneously and over the previous sixty days increases the likelihood of a positive outcome; while the coefficients are precisely estimated, they are extremely small and economically insignificant. For example, a 10% increase in the number of matched competitors increases the likelihood that a project succeeds on a particular day by 0.009 percentage points (s.e. = 0.0005 percentage points). With an unconditional likelihood of success on a given day of 0.87%, this is a very small impact.

4.4. Time series evidence

If the results above are an accurate reflection of the impact of matching, then more dollars accrue to DonorsChoose.org when a larger proportion of projects are matched. I examine this directly, by aggregating the data to a daily panel for the 1611 days in the sample. To account for the growth of DonorsChoose.org and time patterns in giving, I regressed the log amount of total donations, the log number of donations, and the log of the average donation size on a linear, quadratic, and cubic time trend, along with day-ofweek effects. I compared the residuals of each variable in turn to the residual of the proportion of matched projects. In Fig. 1A, B, and C, I plot the vigintile (5% bin) means of these values against each other, with the mean of the variable added back in, including a regression line based on the full data sample. It is clear that there a positive correlation between a large share of projects matched and a greater number of dollars raised from more donations. The average donation size is somewhat smaller, but the relationship is weak. While the outcome of this exercise is not necessarily causal, coupled with the results above it is strongly suggestive that matches within DonorsChoose.org are not simply cannibalizing donations from other projects though, once again, I have no data on whether these additional funds reduce giving to other charitable causes.

5. Conclusion

One of the most important outstanding questions in the charitable giving literature is whether increases in fundraising by one charity reduce giving to others. Indeed, a necessary condition for fundraising to be effective overall is that it is effective on a subset of highly substitutable alternatives. Using data from DonorsChoose.org, however, I am able to determine how exogenously assigned incentives to donate to one cause affects giving to similar causes, both at the simultaneously and over time.

In line with the previous literature, I find that matching grants increase the likelihood that a given project receives donations and the overall amount it receives. I do not, however, find any evidence that a greater number of matched competitors crowds out giving to a particular charity. It does not appear that this effect is driven by increased fundraising efforts in response to the match, but rather by donors developing a taste for matched charities of that type.

DonorsChoose.org's platform is well-suited for investigating this question, yet it is only one sliver of the giving market. Indeed, I am unable to say whether the increase in donations in response to matching crowds out giving to other causes or increases individuals' overall giving budgets. Given the contradictory results in the literature, investigating this issue in other contexts and across multiple types of prosocial behavior is essential to a fuller understanding of the market for altruism.

Appendix A



Fig. A1. DonorsChoose.org home page.



Fig. A2. Sample search results.

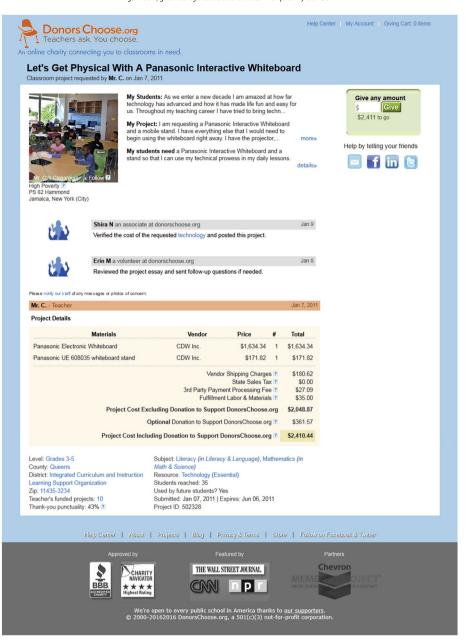


Fig. A3. Sample unmatched DonorsChoose.org request.

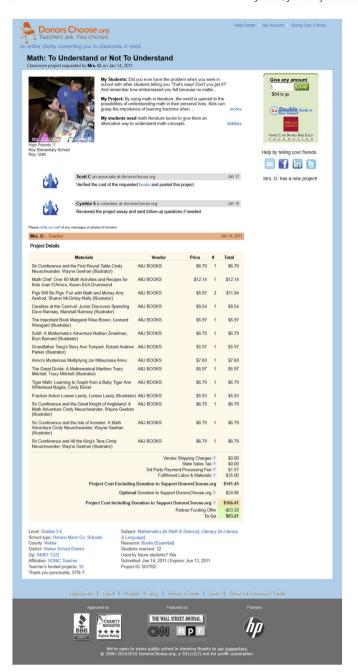


Fig. A4. Sample matched DonorsChoose.org request.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/i.ipubeco.2016.11.009.

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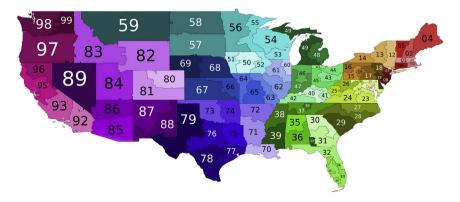


Fig. A5. ZIP2 zones.

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