Why give if others will?
Evidence of crowd-out in a crowdfunding platform

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Current Version

October 2024

Abstract

The increasing use of dynamic fundraising schemes such as crowdfunding has given rise to a relatively small but growing body of literature focusing on understanding the effectiveness of such techniques. In this paper, we first present a simple model of dynamic fundraising as a sequential-move threshold public goods game. We demonstrate that donors have an incentive to free-ride on expected future contributions, which leads to the following testable hypotheses for our empirical analysis: Donations are, all else equal, decreasing in accumulated past donations and increasing in time from the beginning of fundraising. We analyze a rich dataset from a prominent crowdfunding platform and find evidence that supports our hypotheses and shows the presence of a small but statistically significant forward-looking crowd-out among donors. On average, a one-percentage-point increase in past cumulative donations leads to a reduction of 0.05 percentage points in the amount contributed, while a one-percentage-point increase in time passed results in an increase of 0.03 percentage points in the amount contributed. In short, we observe that an increased prospect of future provision crowds out earlier contributions.

JEL Classifications: H00, H41, D64, I22

Keywords: public goods, philanthropy, fundraising, crowdfunding, free-riding, crowd-out

*Authors' emails are hedieh.tajali@ed.ac.uk and psaboury2@uh.edu. We are grateful for assistance from Oliver Hurst-Hiller, Andi Muskaj, Mohammad Radiyat, and Ali Rosen at Donorschoose.org. We received helpful comments from Nicolas J. Duquette, Tatiana Kornienko, Sarah Smith, and seminar participants at the ASSA 2023 Annual Meeting, the 2023 Asian Meeting of the Econometric Society, the 25th Applied Economics Meeting, the Italian Society of Public Economics, the Association of Southern European Economic Theorists (ASSET), the University of Aberdeen, Royal Economic Society 2024 Annual Conference, 3rd Naples School of Economics Workshop, and the University of Edinburgh.

1 Introduction

Traditional fundraising techniques often entail soliciting potential donors without revealing much about previous donations or the fundraising timeline. Thus, the resulting environment is, in effect, a static public good game between donors who simultaneously choose their donation size. However, in recent years, some fundraisers have adopted new methods, such as crowdfunding, that include sequential solicitation, where donors observe past contributions before deciding on their own donations. Such techniques change the donation game to a dynamic sequential move one that, based on classic fundraising theory, should exacerbate the free-rider problem and lead to less giving compared to simultaneous move settings (Varian, 1994). However, despite this potential for free-riding, also known as giving crowd-out in the charitable giving literature, crowdfunding, and other dynamic fundraising techniques are becoming more prevalent, which mandates further scientific inquiry into their effectiveness. In this paper, we first theoretically demonstrate that in a sequential move threshold public goods game, free-riding takes a forward-looking form, such that donors' giving decisions are driven by their expectations of future giving. We then present an empirical test for the presence of crowd-out in a dynamic fundraising environment using rich observational data. We find evidence supporting the notation that expected future donations crowd out earlier donations.

The focus of our research is crowdfunding, which is an increasingly popular dynamic fundraising tool and provides a great setting to observe donor behavior and test for crowd-out in a dynamic contribution game. We use a rich crowdfunding dataset from DonorsChoose.org[1] to test our hypotheses of crowd-out behavior. In DonorsChoose.org, donors can choose to donate to any of the posted projects that have a publicly observable requested amount (determined by the fundraiser) and expiration date (four months from the project's public posting date). Moreover, each donor can observe the sum of past contributions before deciding how much to give. In the end, a project receives the sum of contributions only if their total amount reaches the requested amount before the expiration date. Thus, each project is a threshold public good that is funded by sequentially moving donors and, as such, is susceptible to crowd-out behavior.

We develop a simple theoretical model of donor behavior in a crowdfunding platform to formally demonstrate that under sequential giving, donors have the propensity to free-ride on expected upcoming donations when they are likely to occur. The intuition for this form of forward-looking crowd-out behavior is that a potential donor can infer the probability of future donors providing the public good (funding the project up to the threshold) from the cumulative past giving and time left to the project's expiration. In particular, when a given donor observes

[1] DonorsChoose.org.org is an online crowdfunding platform extensively used by public school teachers across the USA to raise money for their classrooms by posting various projects. Given the scope and broad use of DonorsChoose.org among low-income communities, DonorsChoose.org is referred to as "the PTA Equalizer" (Rivero, 2018). Moreover, this platform has the criteria the National School Board Association sets for best-in-class crowdfunding sites, such as financial transparency and accountability, privacy and safety, and integrity controls. For more details, see: https://help.donorschoose.org/hc/en-us/articles/360002942094-Resources-for-School-Board-Members.

high past contributions and/or a lot of time left to expiration, she infers a high probability that the public good will be provided by future donors, which reduces the donor's giving incentives. In contrast, observing a project with little accumulated donations and/or nearing its expiration date implies that the project is not very likely to reach its fundraising goal in time by future donations, which in turn, increases the giving motives of the donor in question. This theoretical finding provides two main testable hypotheses: A donor's giving is, all else equal, decreasing in accumulated past donations and increasing in time from the beginning of fundraising.

We estimate the effects of cumulative past donations and time elapsed from project posting on the size of each donor's contribution. Our identification strategy takes advantage of the fact that donors would be unaware of the time left and accumulated donations prior to browsing the website; hence, these variables are exogenous to any arriving donors' characteristics. We find evidence supporting the hypotheses that cumulative past donations have a negative effect on donation size and that time passed from a project posted date has a positive effect. These results indicate that expected future donations crowd out earlier donations. In particular, a one percentage point increase in past collected contributions (relative to the project provision threshold) leads to a reduction of 0.05 percentage points in the amount contributed on average. More interestingly, a one percentage point increase in time passed (relative to the total project posting period) will increase the amount contributed by 0.03 percentage points (relative to the project provision threshold).

Our results are robust to various specifications, such as controlling for the urgency of a project, the requested amount, the type of project specified by a teacher, and the number of donations by a donor. However, when we drop the first donations (due to their peculiarity) from our dataset, the statistical significance of the impact of total accumulated past donations on donation size diminishes. In other words, while later donations are much smaller than the initial donation, there is no evidence of a further decrease in donation size as cumulative past donations grow. Nevertheless, the positive response of donation size to the time passed since the project's posting date persists in the absence of initial donations. This evidence supports the presence of forward-looking free-riding or crowd-out in crowdfunding platforms.

Our study adds to the literature on dynamic fundraising and public good provision. Cornes and Sandler (1996) provide one of the earliest comprehensive reviews of the classical theory of public goods and a detailed analysis of dynamic models. Marx and Matthews (2000) characterize the equilibria of a dynamic voluntary contribution threshold public good game, and establish the conditions that lead to full provision. Based on the theory developed by Marx and Matthews (2000), Duffy et al. (2007) investigate dynamic public good provision in a laboratory experiment and find contributions to be larger in the dynamic multiple-round game relative to the static game. Using a lab-in-the-field experiment, Ansink et al. (2017) examine various crowdfunding designs and demonstrate the importance of signals to mitigate cheap-riding and coordination failure.[2]

[2]According to Ansink et al. (2017) cheap-riding occurs whenever agents contribute to the public good but try to reach an outcome where their own relative contribution is low.

We also contribute to the growing literature on the application of crowdfunding to charitable fundraising. While the use of crowdfunding in entrepreneurship has been studied extensively, crowdfunding for charitable causes is more recent and, due to its unique characteristics, requires specific scholarly attention that is developing into a distinct strand of literature.[3] Meer (2014, 2017) empirically investigates the price elasticity of giving, competition, and substitution between causes in crowdfunding. Corazzini et al. (2015) study crowdfunding in a lab experiment and find that the presence of multiple public goods decreases coordination and total contributions. In another empirical research, Wu et al. (2020) find evidence of a negative relationship between the cumulative amount of donations and subsequent individual donation size that is consistent with our free-riding and crowd-out results. There are also a number of studies that focus on various giving motives and other factors influencing donor behavior in crowdfunding, such as goal gradient helping[4](Cryder et al., 2013), peer effects (Smith et al., 2015), the importance of early days of a fundraising campaign (Beier and Wagner, 2016), the role of charity outcomes and interaction (Gleasure and Feller, 2016), default giving options (Altmann et al., 2019), conformity to the majority gift size (Sasaki, 2019), and completion effect[5] (Argo et al., 2020; Wash, 2021). Lastly, it is worth noting that this literature includes studies on charitable crowdfunding in the context of public policy, such as the crowd-out effects of school spending on crowdfunding (Meer and Tajali, 2021) and higher education funding (Horta et al., 2022), and the impact of charitable crowdfunding on educational outcomes (Keppler, Li, and Wu, 2022).

Our work is also related to the literature on charitable giving motives. Why people give to charities has been a long-standing subject of inquiry among economists (Vesterlund, 2006; Andreoni and Payne, 2013). The broadest distinction in the economics literature has traditionally been between pure altruism (utility from the provision of the public good) and various other-regarding motives (gaining utility from the act of giving). In the classic models that assume pure altruism, donors are expected to free-ride on early donations (Varian, 1994). However, Vesterlund (2003), Andreoni (2006), Krasteva and Saboury (2021) show that under information asymmetry about the quality of the public good, purely altruistic donors infer quality from the size of lead donor's gift and, as a result, contribute more when a large leadership gift is observed. Other-regarding motives can be divided into the warm-glow of giving (Andreoni, 1988, 1989, 1990) that depends only on the size of one's donation, and social motives that stem from considering how one's gift compares to others' contributions (Bénabou and Tirole, 2006; Vesterlund, 2016). While warm-glow does not induce any response to giving by others, social motives lead to conditional cooperation, i.e., responding positively to others' contributions. Researchers have used laboratory or field experiments to investigate these motives, such as Fehr

[3]For instance, Boudreau et al. (2015) study the role of various motives in mitigating the free-rider problem in entrepreneurial crowdfunding. Strausz (2017) explain the emergence of entrepreneurial crowdfunding through the lens of mechanism design as an innovation to alleviate moral hazard under demand uncertainty. In a recent study by Deb et al. (2019), they design a reward-based crowdfunding model for a private good and empirically examine the dynamic interactions between buyers and donors using data collected from Kickstarter. Alegre and Moleskis (2021) and van Teunenbroek et al. (2023) provide systematic reviews of this literature.

[4]Donors contribute a larger amount in the last stage of a fundraising campaign.

[5]Donors contributing more to reach their personal fundraising targets.

and Schmidt (1999); Bolton and Ockenfels (2000); Charness and Rabin (2002); Ariely et al. (2009); Konow (2010); Gneezy et al. (2012, 2014); Cooper and Kagel (2016); Ottoni-Wilhelm et al. (2017) to name a few.[6]

This article proceeds as follows: in Section 2, we discuss our theoretical model and the implied testable hypotheses. We then describe the data and lay out our empirical strategy in Section 3, which is followed by the results and robustness checks in Sections 4 and 5. Section 6 concludes.

2 Theory

In this section, we introduce a partial equilibrium model of an individual donor's giving behavior in a crowdfunding platform. We model the behavior of a donor who visits DonorsChoose.org to make a donation but is not particularly familiar with any specific project, and has no prior knowledge of any project's timeline. While it is not very likely that such a donor chooses a project randomly, it is plausible to assume that whatever project they choose, their visit time is exogenous to the chosen project's characteristics and timeline. Moreover, it is also reasonable to assume that donors' preferences are diverse, and any project has its fair share of potential donors who may choose to visit DonorsChoose.org at any point in time. Thus, from the viewpoint of any given project, there are some interested donors out there, who visit the project's page at a pace that is, effectively, as good as random.

Furthermore, for the purpose of mathematical tractability, we assume a discrete timeline where in each discrete piece of the fundraising period, a maximum of one donor may randomly show up with a publicly known probability. In other words, we have assumed a partition of the fundraising period into a finite number of short periods where each has a publicly known chance of being occupied by a donor. While this assumption is not entirely realistic, it approximates a continuous crowdfunding game closely enough for the purpose of our analysis.

Lastly, we only analyze the behavior of the last 3 donors and use the results as the theoretical grounds for our empirical hypotheses. Our reasoning is that while the logic is extendable to earlier donors, finding a closed-form solution for the giving behavior of earlier donors is mathematically complex and beyond the scope of this paper. Therefore, we leave the analysis of the full model to future research.

2.1 Model

Fundraising for a threshold public good occurs over a finite length of time that starts at time zero and ends at time T. The length of time is divided into $\bar{t}$ periods, such that period t starts

[6] Gee and Meer (2020) explore whether increasing donations to one non-profit organization affects donations to others, questioning if the altruism budget is fixed or flexible.

at time $\dfrac{(t-1)T}{\bar{t}}$ and ends at time $\dfrac{tT}{\bar{t}}$. During each time period, a maximum of one potential donor may arrive. The probability of a donor arriving during each period is $\nu \in (0,1)$ that is fixed and publicly known, and otherwise, there will be no donor during that period. Thus, the number of actual donors that arrive over the whole fundraising timeline can be any integer from 0 to $\bar{t}$. Let g^t represent the contribution in time period $t \in \{1, 2, 3, ..., \bar{t}\}$.[7] The public good will be provided if the sum of all donations $G = \sum_{t=0}^{\bar{t}} g^t$ is no less than a threshold G_0, and each donor i's utility will depend on their own contribution g_i and total contribution G as follows:

$$u_i = \mathbb{1}_{G \geq G_0}[v_i(w_i - g_i) + V_i] + \mathbb{1}_{G<G_0} v_i(w_i) \tag{1}$$

In the following subsections, we will use backward induction to find the equilibrium behavior of the last 3 donors, given the behavior of past donors and the number of potential donors that are expected to arrive.

2.2 Last Donor's Contribution

Consider donor i that arrives in the last time period $\bar{t}$, and let $g_{-i} = \sum_{t=1}^{\bar{t}-1} g^t$ represent what has already been contributed by previous donors. Furthermore, let's focus on the case where $g_{-i} < G_0$.[8] Donor i compares the payoff of contributing $G_0 - g_{-i}$ and providing the public good to that of no contribution and does the former if the following holds:

$$V_i \geq v_i(w_i) - v_i(w_i - G_0 + g_{-i}) \tag{2}$$

Inequality (2) simply states that the last donor will donate $G_0 - g_{-i}$, and provide the public good if her valuation of the public good is higher than the utility cost of covering the gap until the provision threshold G_0.

2.3 The Impact of Cumulative Past Donations

Consider donor i that arrives in the time period $\bar{t} - 1$, and let $g_{-i} = \sum_{t=1}^{\bar{t}-2} g^t$ represent what has already been contributed by previous donors. Furthermore, let's focus on the case where $g_{-i} < G_0$.[9] Donor i, expects another donor j (as discussed in Section 2.2) to arrive in the last period with probability ν. Moreover, conditional on donor j's arrival, she will contribute $G_0 - g_{-j} = G_0 - g_{-i} - g_i$ if Inequality (2) holds for her, the probability of which depends on the distribution of donor types. Let's denote the latter probability as follows:

$$p(g_{-j}, \bar{t}) = Prob(V_j \geq v_j(w_j) - v_j(w_j - G_0 + g_{-j})) \tag{3}$$

[7] If no donor shows up in a given period t, then $g^t = 0$.

[8] The other case is trivial.

[9] The other case is trivial.

Since $g_{-j} = g_{-i} + g_i$, donor i's expected utility in period $\bar{t}-1$ will be:

$$E(u_i(g_i, g_{-i})|\bar{t}-1) = \begin{cases} v_i(w_i) + \nu p(g_{-i}+g_i,\bar{t})[V_i - v_i(w_i) + v_i(w_i - g_i)] \text{ if } g_i < G_0 - g_{-i} \\ v_i(w_i - g_i) + V_i \text{ if } g_i \geq G_0 - g_{-i} \end{cases} \tag{4}$$

Donor i will never give more than $G_0 - g_{-i}$ as giving any higher amount reduces their utility of wealth without changing the level of the public good. Giving $G_0 - g_{-i}$ leads to a utility of $v_i(w_i - G_0 + g_{-i}) + V_i$ that donor i compares to the expected utility of giving $g_i^*(g_{-i}, \bar{t}-1)$ that satisfies the following first order condition:

$$\frac{p_1(g_{-i} + g_i^*(g_{-i},\bar{t}-1),\bar{t})}{p(g_{-i} + g_i^*(g_{-i},\bar{t}-1),\bar{t})} = \frac{v_i'(w_i - g_i^*(g_{-i},\bar{t}-1))}{V_i - v_i(w_i) + v_i(w_i - g_i^*(g_{-i},\bar{t}-1))} \tag{5}$$

$g_i^*(g_{-i},\bar{t}-1)$ is the gift where donor i balances the trade-off between increasing the probability of provision by giving more and increasing the net benefit of provision by giving less.[10] More intuitively, the donor is weighing whether to support the provision of the public good or free-ride on the expected subsequent donor's willingness to provide the public good. Donor i donates $g_i^*(g_{-i},\bar{t}-1)$ if and only if the following holds:[11]

$$v_i(w_i) + \nu p(g_{-i} + g_i^*(g_{-i},\bar{t}-1),\bar{t})[V_i - v_i(w_i) + v_i(w_i - g_i^*(g_{-i},\bar{t}-1))] \geq v_i(w_i - G_0 + g_{-i}) + V_i$$

Otherwise, she gives $G_0 - g_{-i}$ that is the whole contribution gap needed to provide the public good. Since $v_i()$ is an increasing and concave function, it follows that the right-hand-side of Equation (5) is increasing in $g_i^*(g_{-i},\bar{t}-1)$. Thus, the following proposition holds:

Proposition 1 *If and only if* $\frac{p_1(.,\bar{t})}{p(.,\bar{t})}$ *is non-increasing in its argument, i.e.,* $ln(p(.,\bar{t}))$ *is a concave function,* $g_i^*(g_{-i},\bar{t}-1)$ *is decreasing in* g_{-j}*.*

Proposition 1 states that as long as donor j does not switch to a corner solution, her gift will be decreasing in cumulative past donations for a large set of distributions of donor wealth and preferences. Thus, the following testable hypothesis is implied:

Hypothesis 1 *Donations that do not reach the provision threshold of the public good are decreasing in the sum of past donations.*

Rejection of hypothesis 1 implies that either $ln(p(.,\bar{t}))$ is strictly convex or the pure altruistic donor utility model does not fully capture donors' preferences.[12]

[10] In more technical terms, at $g_i^*(g_{-i},\bar{t}-1)$ the donor optimizes her giving where the provision probability and the net benefit are equally sensitive to the marginal gift.

[11] The left-hand-side is the expected utility of giving $g_i^*(g_{-i},\bar{t}-1)$.

[12] While the term altruism has been used in various senses, we follow the standard terminology in charitable giving theory, e.g., Ottoni-Wilhelm et al. (2017).

The full picture of donor i's behavior is not limited to the interior solution $g_i^*(g_{-i}, \bar{t}-1)$, and includes the case where her optimal choice is the corner solution, i.e., contributing $G_0 - g_{-i}$. Interestingly, while $g_i^*(g_{-i}, \bar{t}-1)$ is decreasing in g_{-i}, donor i becomes more likely to switch to a corner solution as g_{-i} grows.[13] The following proposition formalizes this argument:

Proposition 2 *There exists $\bar{g}_i(\bar{t}-1)$ such that for any $g_{-i} \geq \bar{g}_i(\bar{t}-1)$, donor i will contribute $G_0 - g_{-i}$ in period $\bar{t}-1$.*

Proposition 2 implies that the probability of a corner solution is increasing in cumulative past donations, which leads to the following testable hypothesis:

Hypothesis 2 *The probability of a donor giving the full amount left to the provision threshold is increasing in the sum of past donations.*

2.4 The Impact of Time

Consider donor i that arrives in the time period $\bar{t}-2$, and let $g_{-i} = \sum_{t=1}^{\bar{t}-3} g^t$ represent past donations. Furthermore, as before, we focus on the case where $g_{-i} < G_0$.[14] Donor i expects two other donors j and k to arrive, each with probability ν, in the remaining two periods. These subsequent donors are expected to behave as discussed in Sections 2.2 and 2.3. Therefore, donor i's expected utility can be written as:

$$E(u_i(g_i, g_{-i})|\bar{t}-2) = \begin{cases} v_i(w_i) + \nu p(g_{-i} + g_i, \bar{t}-1)[V_i - v_i(w_i) + v_i(w_i - g_i)] \text{ if } g_i < G_0 - g_{-i} \\ v_i(w_i - g_i) + V_i \text{ if } g_i \geq G_0 - g_{-i} \end{cases} \tag{6}$$

where $p(., \bar{t}-1)$ is the expected probability of public good provision on or after period $\bar{t}-1$ as a function of cumulative contributions, conditional on a final donor's arrival:

$$p(g_{-j}, \bar{t}-1) = Prob(g_{-j} \geq \bar{g}_j(\bar{t}-1)) + \nu E\left(p(g_{-j} + g_j^*(g_{-j}, \bar{t}-1), \bar{t})|g_{-j} < \bar{g}_j(\bar{t}-1)\right) + (1-\nu)p(g_{-j}, \bar{t}) \tag{7}$$

As in Subsection 2.3, donor i will never give more than $G_0 - g_{-i}$. Moreover, donor i compares the corner solution to the optimal interior solution $g_i^*(g_{-i}, \bar{t}-2)$ that satisfies the following first order condition:

$$\frac{p_1(g_{-i} + g_i^*(g_{-i}, \bar{t}-2), \bar{t}-1)}{p(g_{-i} + g_i^*(g_{-i}, \bar{t}-2), \bar{t}-1)} = \frac{v_i'(w_i - g_i^*(g_{-i}, \bar{t}-2))}{V_i - v_i(w_i) + v_i(w_i - g_i^*(g_{-i}, \bar{t}-2))} \tag{8}$$

[13] The reason is that as g_{-i} increases, $g_{-j} = g_{-i} + g_i^*(g_{-i}, \bar{t}-1)$ converges to G_0. Therefore, there is not much left for the last donor j to contribute. Thus, $p(g_{-j}, \bar{t})$ converges to 1, and donor i's expected utility of donating $g_i^*(g_{-i}, \bar{t}-1)$ converges to $(1-\nu)v_i(w_i) + \nu[V_i + v_i(w_i - g_i^*(g_{-i}, \bar{t}-1))]$. However, the utility of donating $G_0 - g_{-i}$ converges to $V_i + v_i(w_i - g_i^*(g_{-i}, \bar{t}-1))$ that is strictly higher. Therefore, above a high enough level of g_{-i}, donor i finds it worthwhile to donate $G_0 - g_{-i}$ and provide the public good for sure (corner solution).

[14] The other case is trivial.

Analogously to the case analyzed in Section 2.3, the right-hand side of Equation (8) increases in $g_i^*(g_{-i}, \bar{t}-2)$, and Proposition 1 would extend to this period. Furthermore, by the same logic explained in Section 2.3, donor i becomes more likely to contribute $G_0 - g_{-i}$ (corner solution) at higher levels of g_{-i}. Hence, Proposition 2 would also extend to period $\bar{t}-2$. Therefore, at first glance, the behavior of donor i looks very similar in periods $\bar{t}-1$ and $\bar{t}-2$. However, a closer examination of Equations (3) and (7) reveals that for a given level of past giving and donor contribution, the provision probability is higher in the earlier period:

$$p(g_{-i} + g_i, \bar{t}-1) > p(g_{-i} + g_i, \bar{t}) \tag{9}$$

This result is intuitive, as earlier in the timeline, more subsequent donors are expected to show up and contribute to the public good leading to a higher provision probability that increases the current donor's incentives to free-ride on expected future donations. As a result, comparing Equations (5) and (8) reveals that for a given level of past donations, $g_i^*(g_{-i}, \bar{t}-2) < g_i^*(g_{-i}, \bar{t}-1)$, which is formalized in the following proposition:[15]

Proposition 3 *For a given level of past contributions, the optimal interior gift is increasing in time, i.e.,* $\forall g_{-i} < G_o \quad g_i^*(g_{-i}, \bar{t}-2) < g_i^*(g_{-i}, \bar{t}-1)$.

Proposition 3 states that as long as donor j does not switch to a corner solution, her gift will be increasing in time, which implies the following testable:

Hypothesis 3 *For a given level of past donations, the size of donations that have not reached the provision threshold is increasing in time.*

Rejection of hypothesis 3 implies that the pure altruistic donor utility model does not fully capture donors' preferences.

Turning to the corner solution, Proposition 2 extends to period $\bar{t}-2$ analogously. Thus, there exists $\bar{g}_i(\bar{t}-2)$ such that for any $g_{-i} \geq \bar{g}_i(\bar{t}-2)$, donor i prefers contributing $G_0 - g_{-i}$ to giving $g_i^*(g_{-i}, \bar{t}-2)$. It can be established that $\bar{g}_i(\bar{t}-2) > \bar{g}_i(\bar{t}-1)$.[16] This result can be summarized in the following proposition:

Proposition 4 *The full provision threshold* $\bar{g}_i(t)$ *is decreasing in* t*, i.e.,* $\bar{g}_i(\bar{t}-2) > \bar{g}_i(\bar{t}-1)$

Proposition 4 implies that the probability of a corner solution is increasing in time, which leads to the following testable hypothesis:

[15] Since both probabilities $p(., \bar{t}-1)$ and $p(., \bar{t})$ converge to 1 as their first argument (total contributions) approaches G_0, Inequality (9) implies $p_1(g_{-i} + g_i, \bar{t}-1) < p_1(g_{-i} + g_i, \bar{t})$.

[16] The logic is as follows. Donor i prefers contributing $G_0 - g_{-i}$ to giving $g_i^*(g_{-i}, \bar{t}-2)$, i.e., $u_i(G_0 - g_{-i}, g_{-i}) > E(u_i(g_i^*(g_{-i}, \bar{t}-2), g_{-i})|\bar{t}-2)$. Consider $g_{-i} \geq \bar{g}_i(\bar{t}-2)$. From Equation (9), $p(g_{-i} + g_i^*(g_{-i}, \bar{t}-1), \bar{t}) < p(g_{-i} + g_i^*(g_{-i}, \bar{t}-1), \bar{t}-1)$. Therefore, $E(u_i(g_i^*(g_{-i}, \bar{t}-1), g_{-i})|\bar{t}-1) < E(u_i(g_i^*(g_{-i}, \bar{t}-1), g_{-i})|\bar{t}-2) < E(u_i(g_i^*(g_{-i}, \bar{t}-2), g_{-i})|\bar{t}-2) < u_i(G_0 - g_{-i}, g_{-i})$ which implies that if donor i prefers the corner solution in period $\bar{t}-2$, they must prefer it in period $\bar{t}-1$ for the same level of past contributions.

Hypothesis 4 *For a given level of past donations, the probability of full provision of the public good is increasing in time.*

In short, as the fundraising deadline approaches, all else equal, donors give more and are more likely to fully provide the public good. The intuitive explanation is that earlier in the timeline, a donor expects more future donors to show up. Thus, the donor has an incentive to free-ride on expected future donations.

2.5 Other Giving Motives

Our model's main assumption is that each individual donor is purely altruistic, i.e., she enjoys the public good regardless of who provides it and independent of the size of her own contribution. This assumption is the main driver of our results that can be summarized as: expected future donations crowd out today's giving. Therefore, the rejection of the 4 hypotheses stated in the previous sections would imply that donors' giving behavior is not, at least primarily, governed by pure altruism.

Warm glow is arguably the earliest established other-regarding giving motive that ascribes giving to the "joy of giving."(Andreoni, 1988, 1989, 1990) Warm glow is the utility one gets from their own gift irrespective of other donors' behavior, which reduces a donor's incentive to change their donation in response to past or potential future giving by others. Thus, it follows that as warm glow motives strengthen, $g_i^*(g_{-i}, t)$ becomes less sensitive to changes in g_{-i} and t.

There is also evidence of various giving motives that lead to "conditional cooperation," such as social norm compliance, social pressure, peer pressure, moral obligation, reciprocity, inequality aversion, and self-image concerns. In the presence of any of these motives, a donor incurs some disutility from donating below what she believes to be the acceptable gift size, which is determined based on her perception of others' donations. In the context of our crowdfunding model, expected cumulative past giving per past donor for the period t can be calculated as $\frac{g_{-i}}{\nu(t-1)}$ that a donor would gravitate towards with any of the giving motives just described. As a result, with strong enough conditional cooperation motives, $g_i^*(g_{-i}, t)$ would become increasing in g_{-i} and decreasing in t.

Lastly, strategic "quality signaling" has also been established as a determinant of giving behavior when donors' giving is observable by subsequent donors. (Vesterlund, 2003; Andreoni, 2006; Krasteva and Saboury, 2021) demonstrate that when the quality of the public good is uncertain, an informed donor has an incentive to move early and signal quality to downstream donors via the size of her gift. As a result, the downstream donor reads a larger donation as a stronger signal of quality and increases her donation in response. In the context of our model, the implication is that higher cumulative past giving in a shorter time span is interpreted as a signal of quality and leads to more giving. Thus, $g_i^*(g_{-i}, t)$ could become increasing in g_{-i} and decreasing in t.

Our empirical strategy is designed to test whether pure altruism (as opposed to any of the three above-described motives) is the dominant giving motive of crowdfunding donors and as we show in Section 4, our empirical results support our hypotheses. Thus, while we do not rule out the presence of any of the three above-mentioned motives, we find evidence that, at least in the context of the DonorsChoose.org platform, pure altruism (and the resultant crowd-out) is the main driver of giving behavior. In fact, previous studies have shown that altruism and other motives (particularly warm-glow) can coexist (Andreoni et al., 2008).

3 Data and Empirical Strategy

3.1 Data

We use a dataset from DonorsChoose.org, an online crowdfunding platform extensively used by public school teachers across the USA to post projects and collect funding directly from the public.[17] Since the founding of the platform in 2000, teachers at 86% of public schools in the United States have used it to post a project and have attracted more than $1.5 billion in donations from more than 5.5 million donors. The database of DonorsChoose.org contains detailed data on teacher project postings and donation dates and times.

Each project posting includes a detailed list of costs and supplies that would be purchased if the fundraising is successful, along with a written description of the project, student needs, and the proposed use of the supplies. The project page also includes school information (such as its location and poverty level) and a photograph of the classroom. Moreover, Donorschoose.org staff and volunteers screen each project before it is posted publicly. Approved projects can be browsed by anyone who visits the website. Figure A1 shows the page of a representative project. If a project reaches its goal, DonorsChoose.org purchases the materials and ships them directly to the teacher. Otherwise, once a project expires prior to being funded,[18] donors have the option to receive a refund, contribute to another project, or allow DonorsChoose.org to select a project for them.

Our dataset contains detailed information on project posting by teachers (until the end of 2020), including project posted date, amount requested, and school location, as well as detailed data on donation amount and timing (date and time). After dropping donations whose recorded date is after the project expiration date due to a recording error,[19] our final sample includes 14,735,787 donation-day observations (with 4,154,494 donors) and 2,297,177 posted projects by

[17]DonorsChoose.org is available to all public school teachers free of charge. Thus, teachers do not incur any direct fundraising expenditures.

[18]Projects that do not reach their goal expire after four months.

[19]According to the representative of DonorsChoose.org, such observations are due to an error in coding the data. Hence, we drop 215,220 observations (less than 1.5% of the total 14,735,787 donation-date observations).

710,955 teachers from 87,256 schools. Table 1 presents summary statistics of the sample.

Table 1: Summary statistics

	Mean	Std. Dev.	Median
First donation amount	69.02	297.19	27.80
Last donation amount	193.96	1288.84	78.40
Donation amount	81.75	294.49	28.25
Requested amount	785.19	5170.23	502.38
Day passed from the posted date	20.06	26.78	6.56
Amount donated before the posted date	2.33	128.81	0.00
Amount donated on the same date as the posted date	78.71	312.89	0.00
Number of donations	19.38	38.53	11.00
Number of funded projects	0.89	0.31	1.00

Total observations 14,735,787. Donations and requested amounts are in January $2020.

3.2 Empirical Strategy

Our goal is to test whether donors free-ride on expected future contributions in a crowdfunding platform. Equation (10) represents our baseline empirical model to test Hypotheses 1 and 3 by estimating the effect of time from the project posting date and accumulated past donations on a donor's contribution (in cases that have not reached the contribution threshold):

$$g_{ipd} = \alpha_{my} + \beta_1(t_{pd}) + \beta_2(g_{-ipd}) + \beta_3(g_{-ipd} \times t_{pd}) + \beta_4 Donor_{-ipd} + \epsilon_{ipd} \tag{10}$$

where i and p are indexed for donor and project, and d is the donation date (as day-month-year). g_{ipd} is the donation size relative to the amount requested by the fundraiser (hereafter, normalised donation):

$$g_{ipd} = \left(\frac{Amount\ donated_{ipd}}{Amount\ requested_p}\right) \times 100 \tag{11}$$

g_{-ipd} is the total amount donated before donor i arrives relative to the amount requested by the fundraiser (hereafter, normalised cumulative donations):

$$g_{-ipd} = \left(\frac{Cumulative\ past\ donations_{ipd}}{Amount\ requested_p}\right) \times 100 \tag{12}$$

and t_{pd} represents the percentage of the project posting period that has passed at the time of a particular donation (hereafter, normalised time):[20]

$$t_{pd} = \left(\frac{donation\ date_{pd} - project\ posted\ date_p}{expiration\ date_p - project\ post\ date_p}\right) \times 100 \tag{13}$$

In Equation (10), the main explanatory variables are t_{pd} and g_{-ipd}, which are both directly observable by the donors before they make their contribution decisions. Hence, the two

[20] As mentioned in Section 3.1, projects expire after four months if they are not fully funded. Hence, we create the expiration date as four months after the posting date.

main coefficients of interest are β_1 and β_2. In addition, we add the interaction term between these two variables to control for their effect on one another. We control for the time effects by including month-year fixed effects (α_{my}), and cluster the standard errors at the project level. We also include the number of donors who contributed to a specific project up to time t ($Donor_{-ipd}$). Note that DonorsChoose.org does not reveal the amount contributed by each previous donors to new donors. A new donor only observes the sum of past donations, project expiration date, and the number of donors who contributed so far.

To test our two other Hypotheses 2 and 4, we estimate the effect of time from the project posting date and accumulated past donations on the probability of a corner solution by estimating the following model:

$$I_{ipd} = \alpha_{my} + \beta_1(t_{pd}) + \beta_2(g_{-ipd}) + \beta_3(g_{-ipd} \times t_{pd}) + \beta_4 Donor_{-ipd} + \epsilon_{ipd} \tag{14}$$

where I_{ipd} is an indicator function of whether a donor contributed the full remaining amount to complete a project, i.e., $I_{ipd} = \mathbb{1}_{g_{ipd} \geq G_0 - g_{-ipd}}$.

Our empirical design is based on an across-project variation in our main explanatory variables since time and cumulative past donations are correlated within a single project. Hence, the appropriate approach is to investigate how donors behave across projects, which is why we normalize the explanatory variables, and exclude any project fixed effects that absorb across-project variation. We argue that there is as good as random variation in both cumulative past donations and time across projects since the majority of donors in our dataset are one-time donors.[21] Therefore, while donors' decision to browse DonorsChoose.org might not be random, information on the website regarding the projects would come to them as random. In other words, donors choose to browse the platform at a certain time, but they do not have any prior knowledge about the amount collected thus far and the time left to expire for any of the projects. Thus, these two variables would be exogenous to the characteristics of a potential donor. Our identification strategy takes advantage of this plausibly exogenous variation.

We recognize that project-specific characteristics can potentially lead to a biased estimate in the absence of a fixed-effects model. In particular, a project's attractiveness can cause both an increase in cumulative past donations and current donation size. However, such bias leads to a lower estimate of the true level of crowd-out. In other words, any evidence of crowd-out in our findings would be a lower-bound estimate. Moreover, our across-group specification precludes the possibility of the bias of a fixed-effects estimator (Nickell bias (Nickell, 1981)).

Another potential caveat to our identification strategy is that DonorsChoose.org does not present donors with listings randomly; rather, it sorts projects by the most urgent. That means projects with the lowest cost to complete, the highest economic need, and the fewest days left will appear on the main search page. We control for these criteria by constructing an index for the likelihood of showing up on the first page, which includes an indicator for i)

[21] Out of 4,154,494 donors, about 71% of donors contributed one time (ever) to DonorsChoose.org platform by the end of 2020. In addition, the majority of donors contributed only once to a project (see Figure 7).

school poverty level, ii) projects with only 10 percent or lower time left to expiration, and iii) projects with less than USD20 left to reach their funding target. Our first-page likelihood index takes the value of 1 if a project satisfies all three criteria and is zero otherwise.[22] Hence, we can rewrite our baseline models as follows:

$$g_{ipd} = \alpha_{my} + \beta_1(t_{pd}) + \beta_2(g_{-ipd}) + \beta_3(g_{-ipd} \times t_{pd}) + \beta_4 Donor_{-ipd} + \delta \mathbb{1}_{first-page_{pd}} + \epsilon_{ipd} \quad (15)$$

$$I_{ipd} = \alpha_{my} + \beta_1(t_{pd}) + \beta_2(g_{-ipd}) + \beta_3(g_{-ipd} \times t_{pd}) + \beta_4 Donor_{-ipd} + \delta \mathbb{1}_{first-page_{pd}} + \epsilon_{ipd} \quad (16)$$

where "first-page" is our first-page likelihood index representing the urgency of a project. δ is the associated coefficient.

One more concern about the identification strategy is that teachers can potentially advertise their postings and attract donors with prior knowledge about their projects. Luckily, DonorsChoose.org formalizes this potential and provides an opportunity for teachers to spread the word and start pre-funding through the "Friends & Family Pre-Funding" option.[23] All pre-funding contributions are applied to the project once it is posted on the website.[24] All such contributions are observable in our dataset, and only 12,869 donations (around 0.09% of total donation observations) are related to the pre-funding period. Thus, given their small size and number, donations from friends and family have an insignificant impact on our results.[25]

4 Results

In this section, we present the empirical results of testing for crowd-out in the crowdfunding platform DonorsChoose.org, i.e., Hypotheses 1 to 4. The binscatter plot in Figure 1 shows that normalised donation (g_i) is generally decreasing in normalized cumulative donations (g_{-i}) which supports Hypothesis 1.[26]

[22] In our final sample, about 76% of the observations (donation-date) include only one of these factors, less than 6% have two of them, and only 0.08% satisfy all 3 criteria.

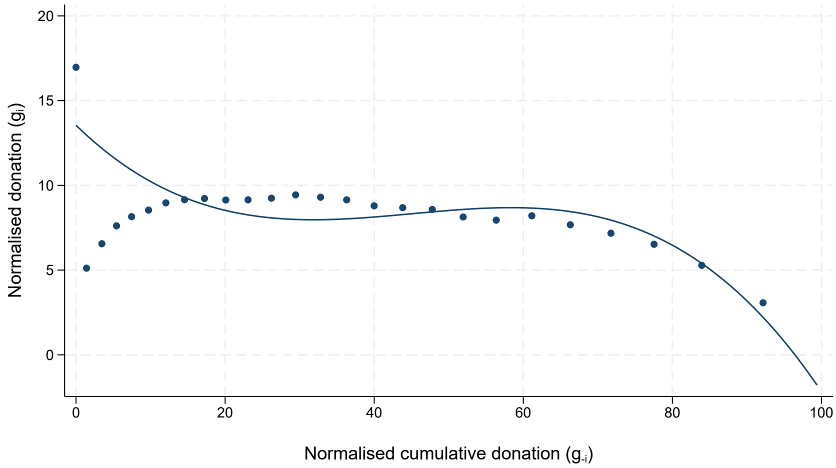
[23] This option allows private fundraising to occur before the DonorsChoose.org team reviews a project and posts it publicly.

[24] For details see: https://help.donorschoose.org/hc/en-us/articles/226500648-Friends-Family-Pre-Funding

[25] According to Table 1, average donation contributed before the posting date of a project is just USD2.33.

[26] Figure A2 depicts the same relationship after excluding the first donations to all projects.

Figure 1: Normalised donation (g_i) by normalised cumulative donations (g_{-i})

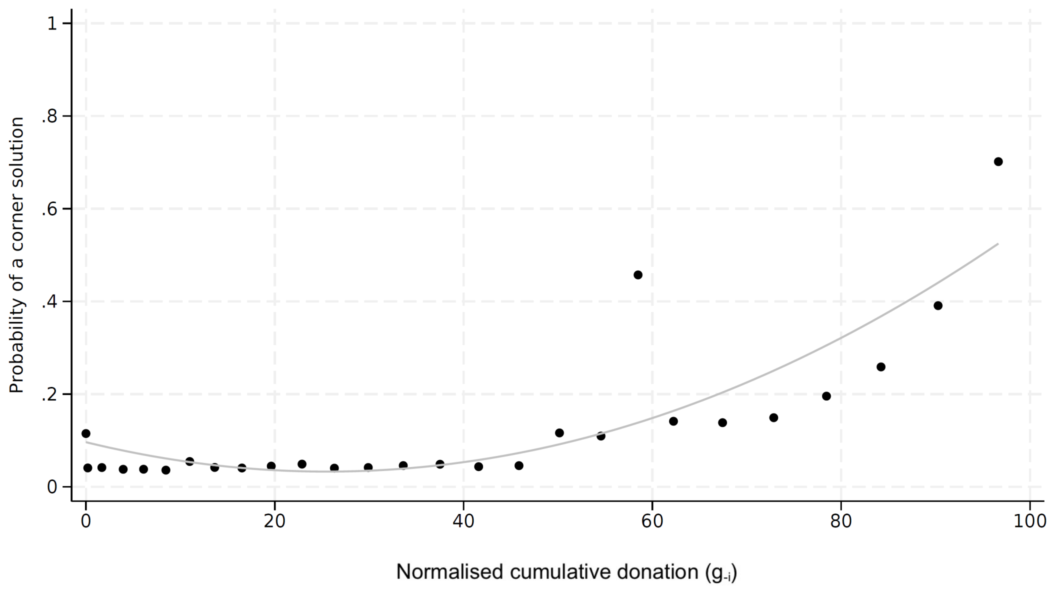


Note: This figure shows a nonlinear relationship of the third degree of a polynomial regression model. The sample excludes observations that the donation amount is greater or equal to the amount left to the provision threshold.

We also explore the relationship between the proportion of observations in which the donor contributed the full remaining amount to complete a project (mean of I_i) and the normalized cumulative donations (g_{-i}), which is presented in Figure 2. The upward slope supports Hypothesis 2 stating that the probability of a donor contributing the full amount left (a corner solution) is increasing in the sum of past donations.[27]

[27] Figure A3 provides the same relationship for a given point in the project posting timeline.

Figure 2: Proportion of observations where the donor completed a project (mean of I_i) by the normalised cumulative donations (g_{-i})



Note: The sample excludes the observations where normalised cumulative donations have exceeded 100.

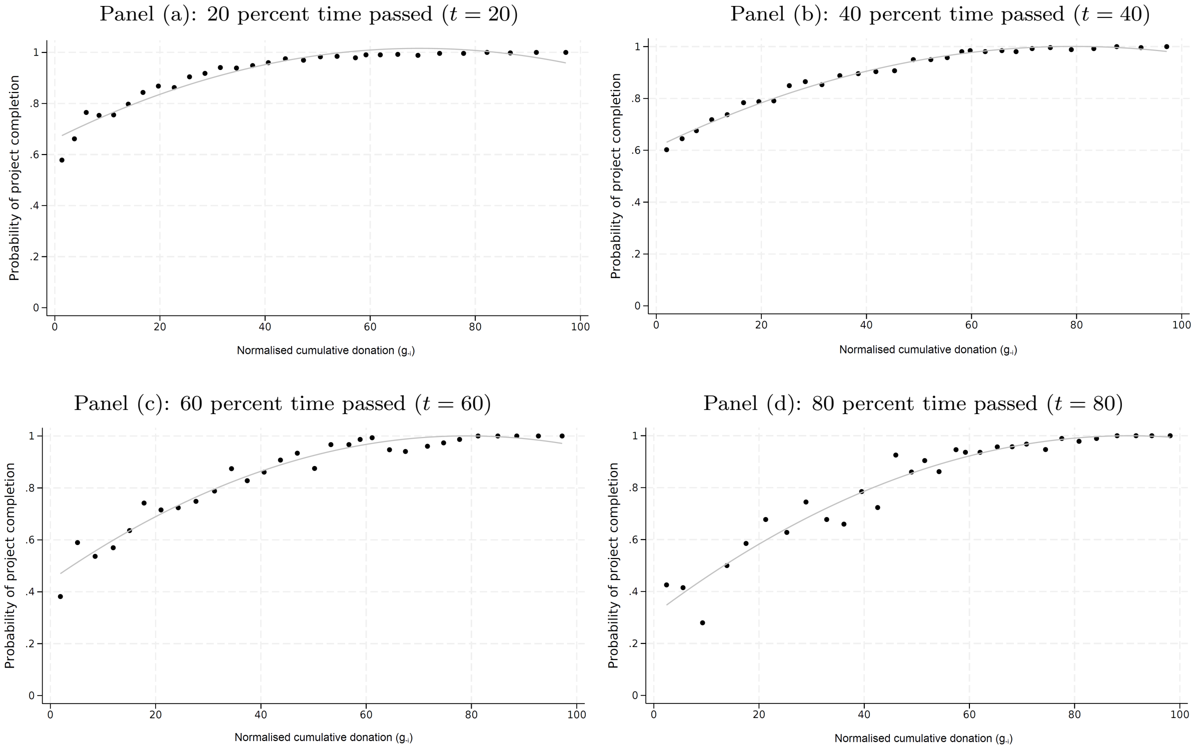
Figure 3: Probability of project completion by normalised donations ($g_{-i} + g_i$)

Panel (a): 20 percent time passed ($t = 20$)

Panel (b): 40 percent time passed ($t = 40$)

Panel (c): 60 percent time passed ($t = 60$)

Panel (d): 80 percent time passed ($t = 80$)

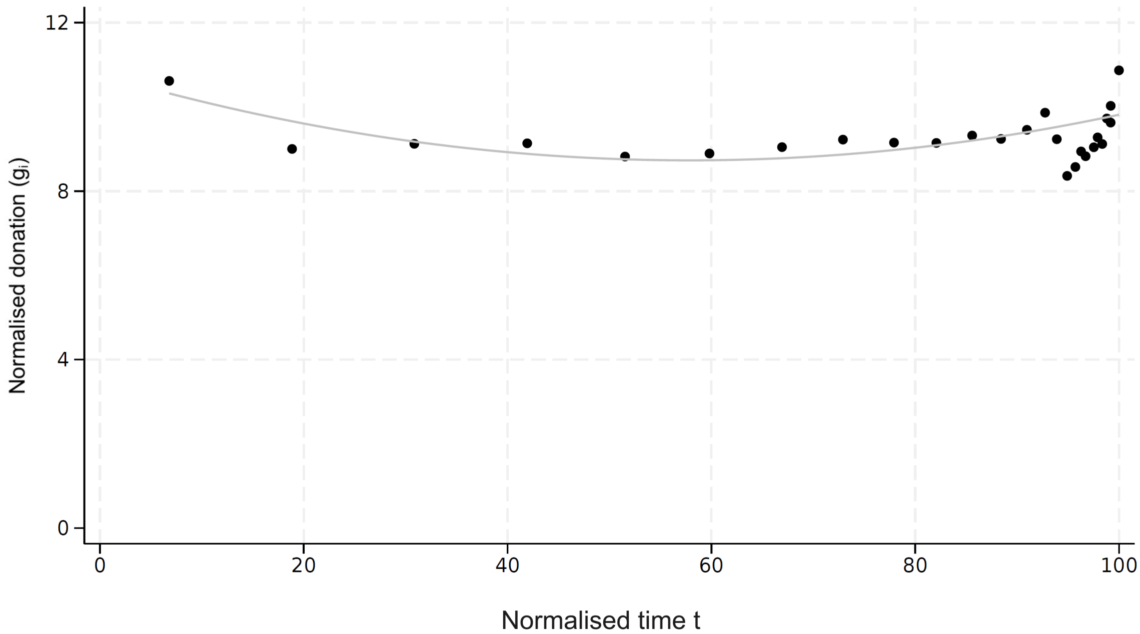


Note: The sample excludes the observations where normalised cumulative donations have exceeded 100.

In addition, we plot the relationship between a project getting fully funded before its expiration date and the sum of normalised donations ($g_{-i} + g_i$) at a given time in Figure 3 to verify that the probability function introduced in Equation 3 is strictly concave, which satisfies the technical condition in Proposition 1.

Turning to Hypothesis 3, we present the relationship between normalised time and normalised donation in Figure 4, where giving is increasing in time, which provides evidence in support of the Hypothesis 3.

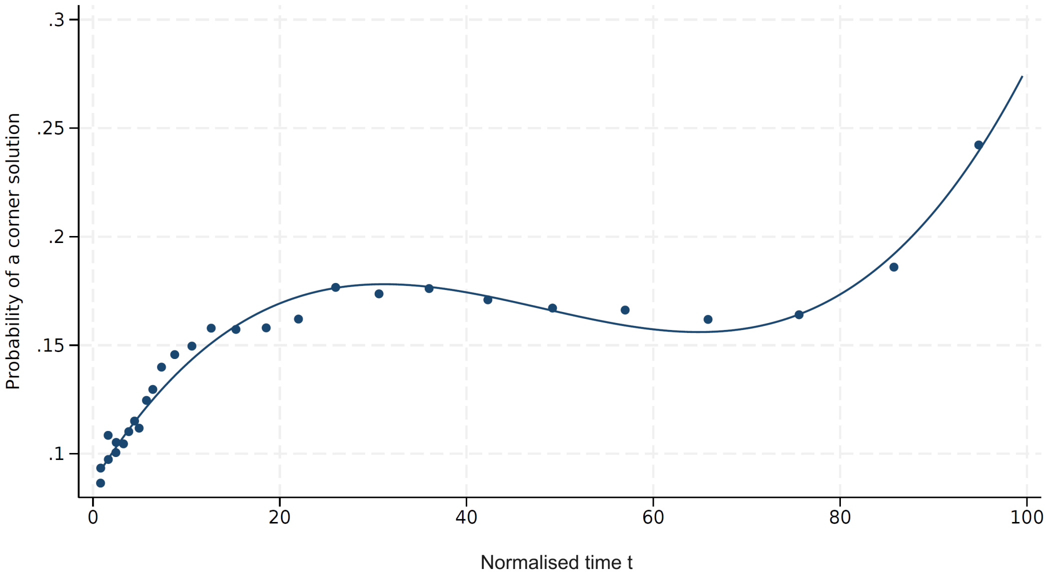
Figure 4: Normalised donation (g_i) by normalised time (t)



Note: The sample excludes observations that the donation amount is greater or equal to the amount left to the provision threshold.

Similarly, we investigate the relationship between the proportion of observations, in which the donor contributed the full remaining amount to complete a project (mean of I_i) and the normalised time (t) in Figure 5, where the probability of a corner solution is increasing in time confirming Hypothesis 4.

Figure 5: Proportion of observations where the donor completed a project (mean of I_i) by normalised time (t)



Note: This figure shows a nonlinear relationship of the third degree of a polynomial regression model. The sample excludes the observations where normalised cumulative donations have exceeded 100 and also donations before the official project posted date.

To formally test our hypotheses, we estimate Equations 10 and 15 to explore the impact of both normalised cumulative donations and normalised time on normalised donation using our preferred sample (excluding corner solution observations). The results are presented in Table 2. Column 1 contains the result from estimating Equation 10 and shows that as the normalized time increases by one percentage point, normalised donation increases by about 0.03 percentage points. Furthermore, a one percentage point increase in normalised cumulative donations leads to a reduction of 0.05 percentage points in normalised donation. These findings demonstrate that a donor has less incentive to give with longer time left to the campaign's expiration date or with larger past contributions up to the time they visit the website. This result is consistent with our Hypotheses 1 and 3 and provides evidence in support of forward-looking crowd-out.[28] These results are robust after controlling for project urgency by estimating Equation 15, i.e., after controlling for the possibility that a project is listed on the first page (Column 2). Although urgency does seem to have an impact on donation, the crowd-out hypotheses evidence persists.

[28] In Table A1, we show the results from estimating Equations 10 and 15 using all the observations in our final sample (including corner solution observations).

Table 2: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) on normalised donation (g_i) - preferred sample

	Normalised donation (g_i)	
	(1)	(2)
Normalised time (t)	0.0270***	0.0268***
	(0.0004)	(0.0004)
Normalised cumulative donations (g_{-i})	-0.0520***	-0.0520***
	(0.0020)	(0.0020)
Number of donors up to t	-0.0742***	-0.0742***
	(0.0093)	(0.0093)
(Normalised time) × (Normalised cumulative donations)	-0.0005***	-0.0005***
	(0.0000)	(0.0000)
First page		0.8457***
		(0.2324)
N	12,128,794	12,128,794
Donation-month-year FEs	Yes	Yes

$*p < 0.1 **p < 0.05 ***p < 0.01$.

This table presents the estimation of Equation 10 (Column 1) and Equation 15 (Column 2) for our preferred sample (dropping corner solution observations). Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

Table 3: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) on the probability of a corner solution - final sample

	Probability of a corner solution	
	(1)	(2)
Normalised time (t)	0.0005***	0.0004***
	(0.0000)	(0.0000)
Normalised cumulative donations (g_{-i})	0.0045***	0.0045***
	(0.0000)	(0.0000)
Number of donors up to t	-0.0024***	-0.0024***
	(0.0003)	(0.0003)
(Normalised time) × (Normalised cumulative donations)	0.0000***	0.0000***
	(0.0000)	(0.0000)
First page		0.1462***
		(0.0037)
N	13,505,912	13,505,912
Donation-month-year FEs	Yes	Yes

$*p < 0.1 **p < 0.05 ***p < 0.01$.

This table presents the estimation of Equation 14 (Column 1) and Equation 16 (Column 2) for our final sample. Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

In Table 3, we present the results of estimating how normalised time and normalised cumulative donations impact the probability that a donor contributes the full remaining amount to complete a project, i.e., estimating Equations 14 and 16. The probability of a donor contributing the remaining amount needed to complete a project is increasing in both normalised cumulative donations and normalised time. A one percentage point increase in normalised cumulative donations increases the probability of a corner solution by 0.0045, and a one percentage point increase in normalised time increases the probability of the corner solution by 0.0005. These results support Hypotheses 2 and 4, and provide further evidence in support of our theoretical analysis. Moreover, these findings are robust after controlling for project urgency by estimating Equation 16 (Column 2).

5 Robustness

In this section, we investigate issues that may threaten our identification strategy. First, we exclude the first donation to all projects as such contributions might have been made by those familiar with the project and guided by more complicated incentives. Table 4 shows how normalised time and normalised cumulative donations impact normalised donation and the probability that a donor contributes the full remaining amount to complete a project (corner solution) by estimating Equations 15 and 16, excluding the first donations received by all projects. We find that when we drop the first donations, the evidence in support of Hypothesis 1 disappears (Column 1). However, as explained in Section 3.2, there is a potential downward bias in estimating the impact of normalized cumulative donations, and our estimates are to be considered as a lower bound. Moreover, one can still observe an even stronger impact of normalised time (an estimated coefficient of 0.04 in Column 1) in support of Hypothesis 3. Thus, the presence of forward-looking crowding-out cannot be rejected. In Column 2, we find that our findings related to the impacts of normalised time and normalised cumulative donations on the probability of a corner solution are robust to excluding the first donations from the sample, which provide further support for Hypotheses 2 and 4.

Table 4: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) - excluding the first donations

	Normalised donation (g_i) (1)	Probability of a corner solution (2)
Normalised time (t)	0.0418***	0.0008***
	(0.0005)	(0.0000)
Normalised cumulative donations (g_{-i})	0.0051**	0.0049***
	(0.0019)	(0.0000)
Number of donors up to t	-0.0727***	-0.0023***
	(0.0090)	(0.0003)
(Normalised time) × (Normalised cumulative donations)	-0.0008***	-0.0000*
	(0.0000)	(0.0000)
First page	2.5709***	0.1352***
	(0.2328)	(0.0047)
N	10095930	11644585
Donation-month-year FEs	Yes	Yes

$*p < 0.1 **p < 0.05 ***p < 0.01$.

This table presents the estimation of Equation 15 (Column 1) for our preferred sample and Equation 16 (Column 2) for our final sample, excluding the first donation contributed to a project. Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

Table 5: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) - controlling for the requested amount

	Normalised donation (g_i) (1)	Probability of a corner solution (2)
Normalised time (t)	0.0270***	0.0004***
	(0.0004)	(0.0000)
Normalised cumulative donations (g_{-i})	-0.0526***	0.0045***
	(0.0020)	(0.0000)
Number of donors up to t	-0.0710***	-0.0024***
	(0.0093)	(0.0003)
(Normalised time) × (Normalised cumulative donations)	-0.0005***	0.0000***
	(0.0000)	(0.0000)
First page	0.8168***	0.1445***
	(0.2324)	(0.0043)
Project requested amount	-0.0001*	0.0000
	(0.0000)	(0.0000)
N	12128794	13505912
Donation-month-year FEs	Yes	Yes

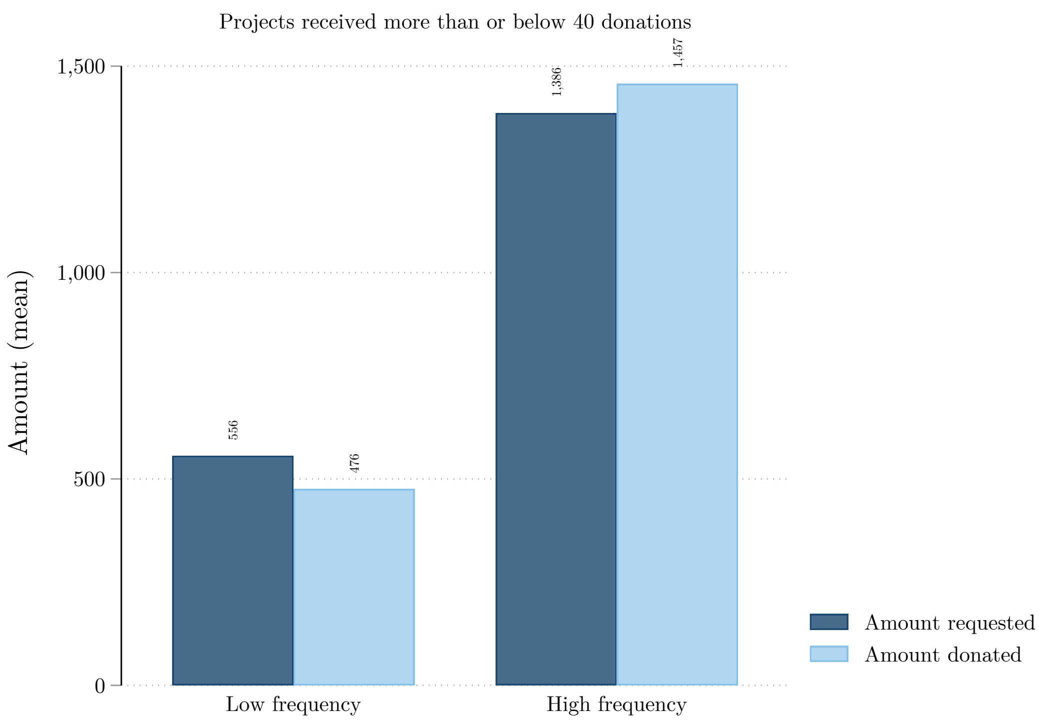
$*p < 0.1 **p < 0.05 ***p < 0.01$.

This table presents the estimation of Equation 15 (Column 1) for our preferred sample and Equation 16 (Column 2) for our final sample, controlling for the project requested amount. Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

Since we consider the across-project variation, one concern could be whether the results hold after controlling for all the observable characteristics of a project. To do so, we control for the requested amount and re-estimate Equations 15 and 16. The results in Table 5 show that the evidence in support of our crowd-out hypotheses is robust to observable project characteristics.

In our sample, on average, projects received about 19 donations. However, we also observe that some projects received relatively large numbers of donations. Figure 6 presents descriptive statistics about such projects. Considering a threshold of 40 donations, we observe that those projects with a higher frequency of contributions have had higher amounts requested. On average, the requested amount for those projects is about 1,400 USD, which is twice the average requested amount in our final sample (Table 1). This number is also significantly higher than projects with a lower frequency of contributions. First, this reassures that the higher number of visits or contributions to these projects is not related to some nonrandom factors. Second, out of 2,297,177 posted projects, only 0.87 percent are high frequencies with a threshold of 40 donations. Therefore, only an insignificant portion of our sample consists of those projects. Nonetheless, we run a robustness check to ensure the results are not driven by those projects with high frequencies in contributions. The results shown in Table 6 confirm our previous findings.

Figure 6: Projects with high and low frequencies of contributions



High frequency is defined as those receiving more than 40 donations.

Table 6: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) - excluding projects with higher frequencies of contributions

	Normalised donation (g_i) (1)	Probability of a corner solution (2)
Normalised time (t)	0.0268***	0.0004***
	(0.0004)	(0.0000)
Normalised cumulative donations (g_{-i})	-0.0520***	0.0045***
	(0.0020)	(0.0000)
Number of donors up to t	-0.0742***	-0.0023***
	(0.0093)	(0.0003)
(Normalised time) $\times$ (Normalised cumulative donations)	-0.0005***	0.0000***
	(0.0000)	(0.0000)
First page	0.8457***	0.1443***
	(0.2324)	(0.0043)
N	10095930	11644585
Donation-month-year FEs	Yes	Yes

$*p < 0.1 **p < 0.05 *** p < 0.01$.

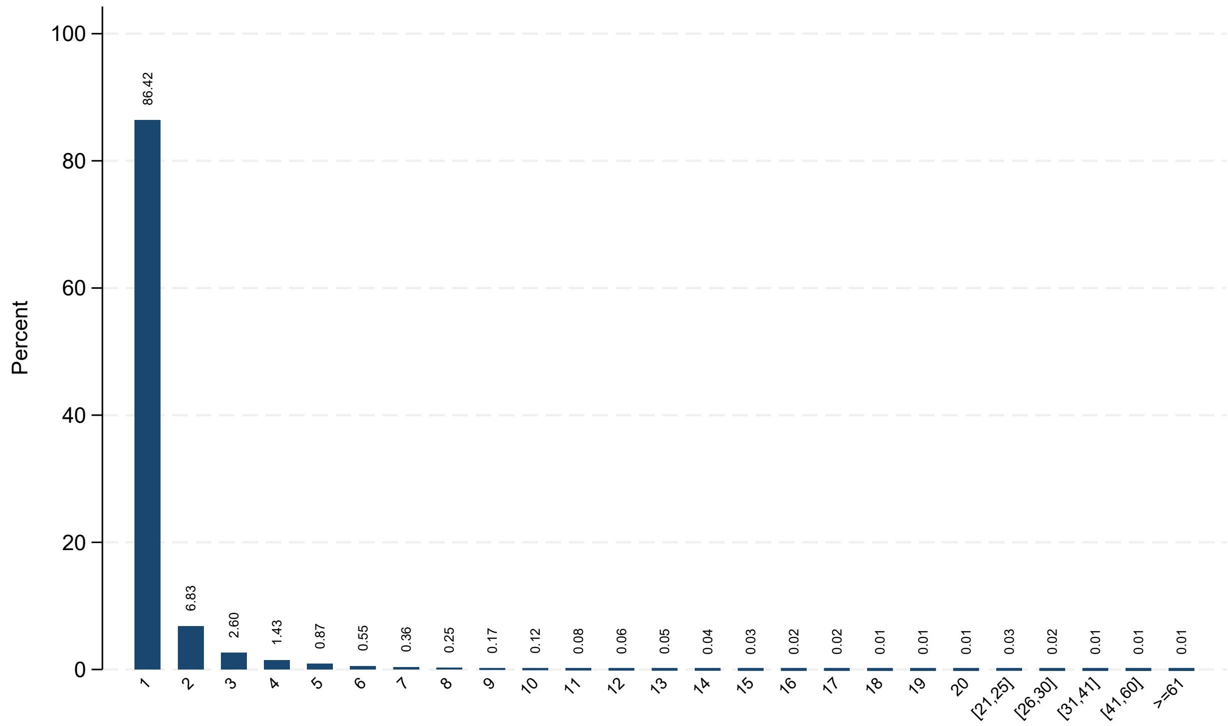
This table presents the estimation of Equation 15 (Column 1) for our preferred sample and Equation 16 (Column 2) for our final sample, excluding those projects with more than 40 contributions (defined as higher frequencies). Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

Another concern about our identification strategy is that some donors might be strategic and contribute to a project multiple times. The incentives behind such behavior can be a concern for our identification. Figure 7 presents how often a donor contributed to a specific project, which shows that in 86.42% of projects, donors contributed only once, and multiple contributions to a project by a donor do not occur very often. Moreover, our main findings are robust to limiting the sample to those donors who contributed to a project only once (Table 7).

In the DonorsChoose.org platform, teachers ask for different resources for their classroom projects, such as art, technology, supplies, etc. We investigate whether donors behave differently depending on the type of teachers' requests by grouping projects into four categories: enrichment, classroom supplies, technology, and other needs. The results are consistent with previous findings that support our hypotheses (Table A2).

Donors from all over the United States (or outside) can donate to this platform. However, there can be some differences between local donors and non-locals. Local donors may be more familiar with the school or have s stronger preference to give to the classroom projects in their geographic location. To examine whether local and non-local donors behave differently, we separate our sample by whether donations are from the same state as the school or from a different state. Table A3 shows the impact of normalised time and normalised cumulative donations by geographic location of the contributions. Our findings are robust to this consideration.

Figure 7: Number of donations to a project by a donor



It shows the frequency of contributions to a project by a donor (relative to 10,846,082 project-donor observations).

Table 7: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) - excluding donors with multiple contributions to a project

	Normalised donation (g_i) (1)	Probability of a corner solution (2)
Normalised time (t)	0.0287***	0.0007***
	(0.0005)	(0.0000)
Normalised cumulative donations (g_{-i})	-0.0697***	0.0048***
	(0.0022)	(0.0001)
Number of donors up to t	-0.1013***	-0.0036***
	(0.0126)	(0.0004)
(Normalised time) $\times$ (Normalised cumulative donations)	-0.0004***	0.0000
	(0.0000)	(0.0000)
First page	1.6952***	0.1422***
	(0.2689)	(0.0054)
N	7490512	8470530
Donation-month-year FEs	Yes	Yes

$*p < 0.1 **p < 0.05 *** p < 0.01$.

This table presents the estimation of Equation 15 (Column 1) for our preferred sample and Equation 16 (Column 2) for our final sample, excluding those donors with multiple contributions to a project. Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

6 Conclusion

We develop a simple theoretical model of donor behavior in charitable crowdfunding and demonstrate a forward-looking form of crowding-out behavior. Based on our theoretical analysis, we hypothesize that all else equal, a donor's contributions decrease with accumulated past donations and increase with time elapsed since the start of the fundraising. We use a rich crowdfunding database from DonorsChoose.org to empirically test our hypotheses. We find evidence consistent with our hypotheses of crowd-out behavior. Our results are robust to adding various controls and specifications. The only exception is that excluding the first donations renders the impact of past cumulative donations less significant, which is due to a downward bias inherent in that estimate, making it a lower bound.

The intuition behind our findings is that in a dynamic sequential-move threshold public goods game, a donor can infer the probability that subsequent donors provide the public good from past contributions and time, and the higher that probability, the higher the free-riding incentives. Consequently, donors exhibit a forward-looking crowd-out behavior within a dynamic contribution framework, where they free-ride on anticipated future donations. Our results shed light on donor behavior in dynamic contribution settings and offer insights for charity practitioners and fundraising strategists.

The literature on this topic is relatively recent, indicating a need for further investigation. One of the limitations of our work is that on the theory front, we only present a partial equilibrium model that focuses on donor behavior. While our model does provide a formal argument for our hypotheses, we believe that future theoretical work should expand on our model and fully characterize the equilibrium of the crowdfunding game. The results could provide further intuition for our empirical findings. On the empirical side, our research is based on data from one specific crowdfunding platform. There are other dynamic fundraising and crowdfunding platforms that exhibit unique features, which may influence free-riding and crowding-out behaviors. Thus, there is a need for further research to examine how specific crowdfunding designs impact donor behavior and the level of crowd-out. Additionally, our dataset lacks information on donor characteristics due to confidentiality restrictions. Future research is needed to explore heterogeneity in giving behaviors, especially based on donors' demographics, in dynamic fundraising contexts.

References

Alegre, I., and Moleskis, M. (2021). "Beyond financial motivations in crowdfunding: A systematic literature review of donations and rewards." *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, *32*(2), 276–287.

Altmann, S., Falk, A., Heidhues, P., Jayaraman, R., and Teirlinck, M. (2019). "Defaults and Donations: Evidence from a Field Experiment." *The Review of Economics and Statistics*, *101*(5), 808–826.

Andreoni, J. (1988). "Why Free Ride?: Strategies and Learning in Public Goods Experiments." *Journal of Public Economics*, *37*(3), 291–304.

Andreoni, J. (1989). "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence." *Journal of Political Economy*, *97*(6), 1447–1458.

Andreoni, J. (1990). "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving." *The Economic Journal*, *100*(401), 464–477.

Andreoni, J. (2006). "Leadership Giving in Charitable Fund-Raising." *Journal of Public Economic Theory*, *8*(1), 1–22.

Andreoni, J., Harbaugh, W. T., and Vesterlund, L. (2008). *Altruism in Experiments. In: The New Palgrave Dictionary of Economics*. London: Palgrave Macmillan UK.

Andreoni, J., and Payne, A. A. (2013). *Charitable Giving*, 1–50. Handbook of Public Economics.

Ansink, E., Koetse, M. J., Bouma, J., Hauck, D., and van Soest, D. (2017). "Crowdfunding Public Goods: An Experiment." *Tinbergen Institute Discussion Paper 2017-119/VIII.*

Argo, N., Klinowski, D., Krishnamurti, T., and Smith, S. (2020). "The Completion Effect in Charitable Crowdfunding." *Journal of Economic Behavior & Organization*, *172*, 17–32.

Ariely, D., Bracha, A., and Meier, S. (2009). "Doing Good or Doing Well? Image Motivation and Monetary Incentives in Behaving Prosocially." *American Economic Review*, *99*(1), 544–55.

Beier, M., and Wagner, K. (2016). "User behavior in crowdfunding platforms – exploratory evidence from switzerland." In *2016 49th Hawaii International Conference on System Sciences (HICSS)*, 3584–3593.

Bolton, G. E., and Ockenfels, A. (2000). "ERC: A Theory of Equity, Reciprocity, and Competition." *American economic review*, *90*(1), 166–193.

Boudreau, K., Jeppesen, L., Reichstein, T., and Rullani, F. (2015). "Crowdfunding as 'donations': Theory & evidence." *SSRN Electronic Journal.*

Bénabou, R., and Tirole, J. (2006). "Incentives and Prosocial Behavior." *American Economic Review*, *96*(5), 1652–1678.

Charness, G., and Rabin, M. (2002). "Understanding Social Preferences with Simple Tests*." *The Quarterly Journal of Economics*, *117*(3), 817–869.

Cooper, D. J., and Kagel, J. H. (2016). "Other-regarding preferences." *The handbook of experimental economics*, *2*, 217.

Corazzini, L., Cotton, C., and Valbonesi, P. (2015). "Donor Coordination in Project Funding: Evidence from a Threshold Public Goods Experiment." *Journal of Public Economics*, *128*, 16–29.

Cornes, R., and Sandler, T. (1996). *The Theory of Externalities, Public Goods, and Club Goods*. Cambridge University Press, 2 edn.

Cryder, C. E., Loewenstein, G., and Seltman, H. (2013). "Goal Gradient in Helping Behavior." *Journal of Experimental Social Psychology*, *49*(6), 1078–1083.

Deb, J., Oery, A., and Williams, K. R. (2019). "Aiming for the Goal: Contribution Dynamics of Crowdfunding." Working Paper 25881, National Bureau of Economic Research.

Duffy, J., Ochs, J., and Vesterlund, L. (2007). "Giving Little by Little: Dynamic Voluntary Contribution Games." *Journal of Public Economics*, *91*(9), 1708–1730.

Fehr, E., and Schmidt, K. M. (1999). "A Theory of Fairness, Competition, and Cooperation*." *The Quarterly Journal of Economics*, *114*(3), 817–868.

Gee, L. K., and Meer, J. (2020). *24. The Altruism Budget: Measuring and Encouraging Charitable Giving*, 558–565. Redwood City: Stanford University Press.

Gleasure, R., and Feller, J. (2016). "Does heart or head rule donor behaviors in charitable crowdfunding markets?" *International Journal of Electronic Commerce*, *20*(4), 499–524.

Gneezy, A., Imas, A., Brown, A., Nelson, L. D., and Norton, M. I. (2012). "Paying to Be Nice: Consistency and Costly Prosocial Behavior." *Management Science*, *58*(1), 179–187.

Gneezy, U., Imas, A., and Madarász, K. (2014). "Conscience Accounting: Emotion Dynamics and Social Behavior." *Management Science*, *60*(11), 2645–2658.

Horta, H., Meoli, M., and Vismara, S. (2022). "Crowdfunding in higher education: evidence from uk universities." *Higher Education*, *83*(3), 547–575.

Keppler, S., Li, J., and Wu, D. A. (2022). "Crowdfunding the Front Lines: An Empirical Study of Teacher-Driven School Improvement." *Management Science*.

Konow, J. (2010). "Mixed Feelings: Theories of and Evidence on Giving." *Journal of Public Economics*, *94*(3-4), 279–297.

Krasteva, S., and Saboury, P. (2021). "Informative Fundraising: The Signaling Value of Seed Money and Matching Gifts." *Journal of Public Economics*, *203*, 104501.

Marx, L. M., and Matthews, S. A. (2000). "Dynamic Voluntary Contribution to a Public Project." *The Review of Economic Studies*, *67*(2), 327–358.

Meer, J. (2014). "Effects of the Price of Charitable Giving: Evidence from an Online Crowdfunding Platform." *Journal of Economic Behavior & Organization*, *103*, 113–124.

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

Meer, J., and Tajali, H. (2021). "Charitable Giving Responses to Education Budgets." Working Paper 29331, National Bureau of Economic Research.

Nickell, S. (1981). "Biases in Dynamic Models with Fixed Effects." *Econometrica*, *49*(6), 1417–1426.

Ottoni-Wilhelm, M., Vesterlund, L., and Xie, H. (2017). "Why Do People Give? Testing Pure and Impure Altruism." *American Economic Review*, *107*(11), 3617–33.

Rivero, V. (2018). "The Great PTA Equalizer." *EdTech Digest*, https://www.edtechdigest.com/2018/11/14/the-great-pta-equalizer/.

Sasaki, S. (2019). "Majority size and conformity behavior in charitable giving: Field evidence from a donation-based crowdfunding platform in japan." *Journal of Economic Psychology*, *70*, 36–51.

Smith, S., Windmeijer, F., and Wright, E. (2015). "Peer Effects in Charitable Giving: Evidence from the (Running) Field." *The Economic Journal*, *125*(585), 1053–1071.

Strausz, R. (2017). "A Theory of Crowdfunding: A Mechanism Design Approach with Demand Uncertainty and Moral Hazard." *American Economic Review*, *107*(6), 1430–76.

van Teunenbroek, C., Dalla Chiesa, C., and Hesse, L. (2023). "The contribution of crowdfunding for philanthropy: A systematic review and framework of donation and reward crowdfunding." *Journal of Philanthropy and Marketing*, *28*(3), e1791.

Varian, H. R. (1994). "Sequential Contributions to Public Goods." *Journal of Public Economics*, *53*(2), 165–186.

Vesterlund, L. (2003). "The Informational Value of Sequential Fundraising." *Journal of Public Economics*, *87*(3), 627–657.

Vesterlund, L. (2006). *24. Why Do People Give?:* , 568–588. Yale University Press.

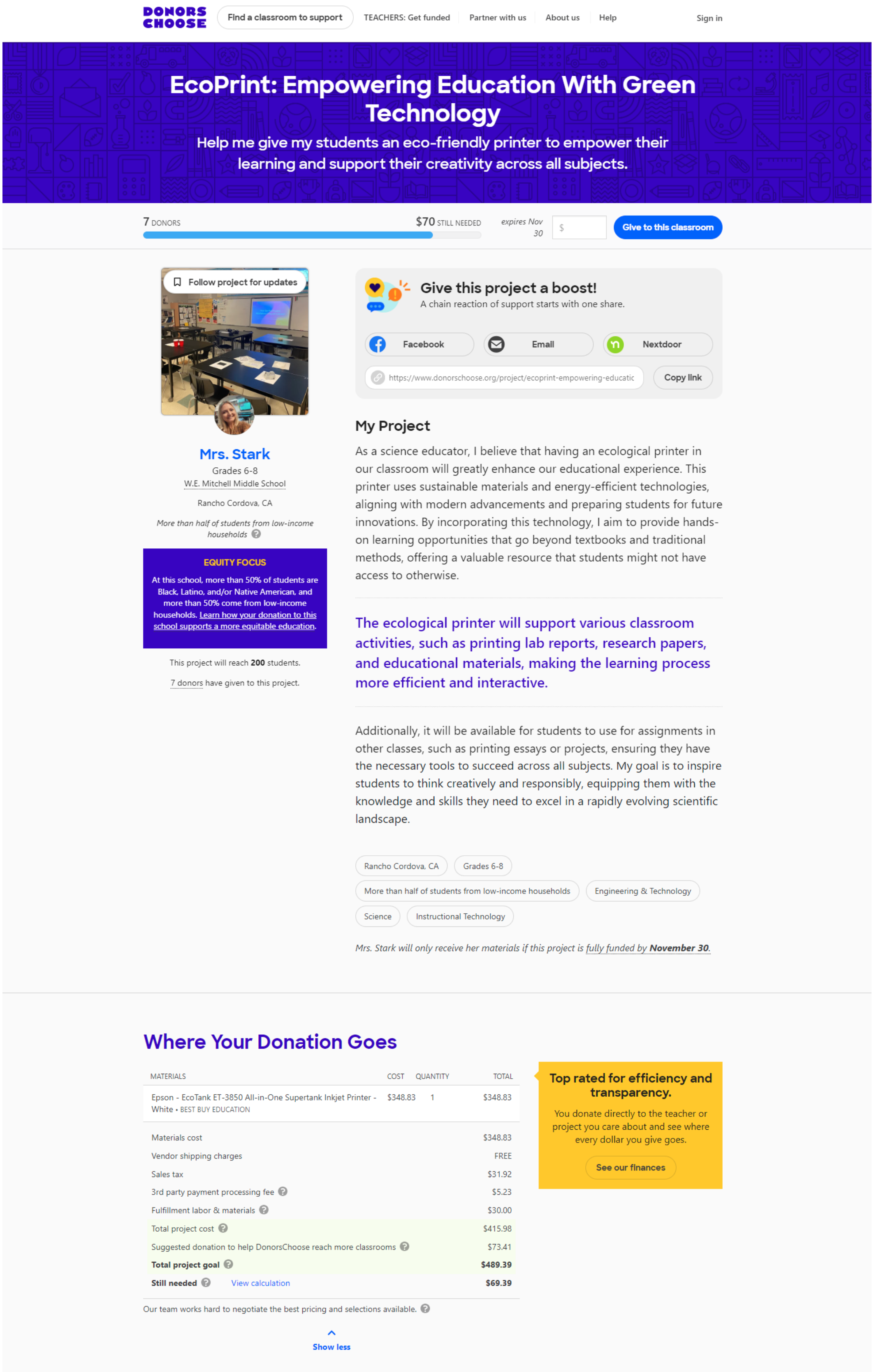
Vesterlund, L. (2016). *2. Using Experimental Methods to Understand Why and How We Give to Charity:* , 91–152. Princeton University Press.

Wash, R. (2021). "The Value of Completing Crowdfunding Projects." *Proceedings of the International AAAI Conference on Web and Social Media*, *7*(1), 631–639.

Wu, Y., Xie, X., and Zheng, K. (2020). "Conformity or Counter-Conformity Behavior? The Effect of Prior Charitable Giving in Donation-Based Crowdfunding." *International journal of business and social research*, *10*, 39–54.

A Appendix

Figure A1: Sample of DonorsChoose.org Requested Project



DONORS CHOOSE

Find a classroom to support | TEACHERS: Get funded | Partner with us | About us | Help | Sign in

EcoPrint: Empowering Education With Green Technology

Help me give my students an eco-friendly printer to empower their learning and support their creativity across all subjects.

7 DONORS $70 STILL NEEDED *expires Nov 30* $ Give to this classroom

Follow project for updates

Mrs. Stark

Grades 6-8

W.E. Mitchell Middle School

Rancho Cordova, CA

More than half of students from low-income households

EQUITY FOCUS

At this school, more than 50% of students are Black, Latino, and/or Native American, and more than 50% come from low-income households. Learn how your donation to this school supports a more equitable education.

This project will reach **200** students.

7 donors have given to this project.

Give this project a boost!

A chain reaction of support starts with one share.

Facebook Email Nextdoor

https://www.donorschoose.org/project/ecoprint-empowering-educatic Copy link

My Project

As a science educator, I believe that having an ecological printer in our classroom will greatly enhance our educational experience. This printer uses sustainable materials and energy-efficient technologies, aligning with modern advancements and preparing students for future innovations. By incorporating this technology, I aim to provide hands-on learning opportunities that go beyond textbooks and traditional methods, offering a valuable resource that students might not have access to otherwise.

The ecological printer will support various classroom activities, such as printing lab reports, research papers, and educational materials, making the learning process more efficient and interactive.

Additionally, it will be available for students to use for assignments in other classes, such as printing essays or projects, ensuring they have the necessary tools to succeed across all subjects. My goal is to inspire students to think creatively and responsibly, equipping them with the knowledge and skills they need to excel in a rapidly evolving scientific landscape.

Rancho Cordova, CA | Grades 6-8 | More than half of students from low-income households | Engineering & Technology | Science | Instructional Technology

Mrs. Stark will only receive her materials if this project is fully funded by ***November 30.***

Where Your Donation Goes

MATERIALS	COST	QUANTITY	TOTAL
Epson - EcoTank ET-3850 All-in-One Supertank Inkjet Printer - White • BEST BUY EDUCATION	$348.83	1	$348.83
Materials cost			$348.83
Vendor shipping charges			FREE
Sales tax			$31.92
3rd party payment processing fee			$5.23
Fulfillment labor & materials			$30.00
Total project cost			$415.98
Suggested donation to help DonorsChoose reach more classrooms			$73.41
Total project goal			**$489.39**
Still needed View calculation			**$69.39**

Our team works hard to negotiate the best pricing and selections available.

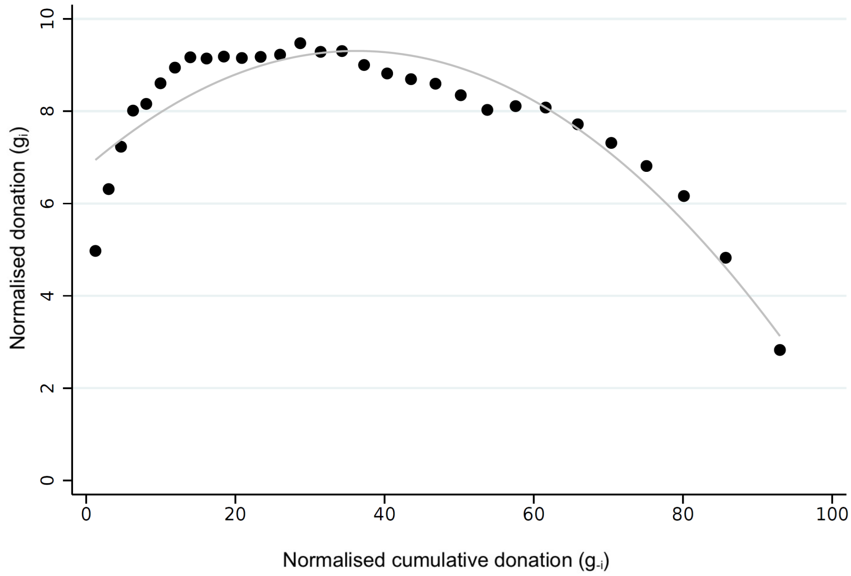
Show less

Top rated for efficiency and transparency.

You donate directly to the teacher or project you care about and see where every dollar you give goes.

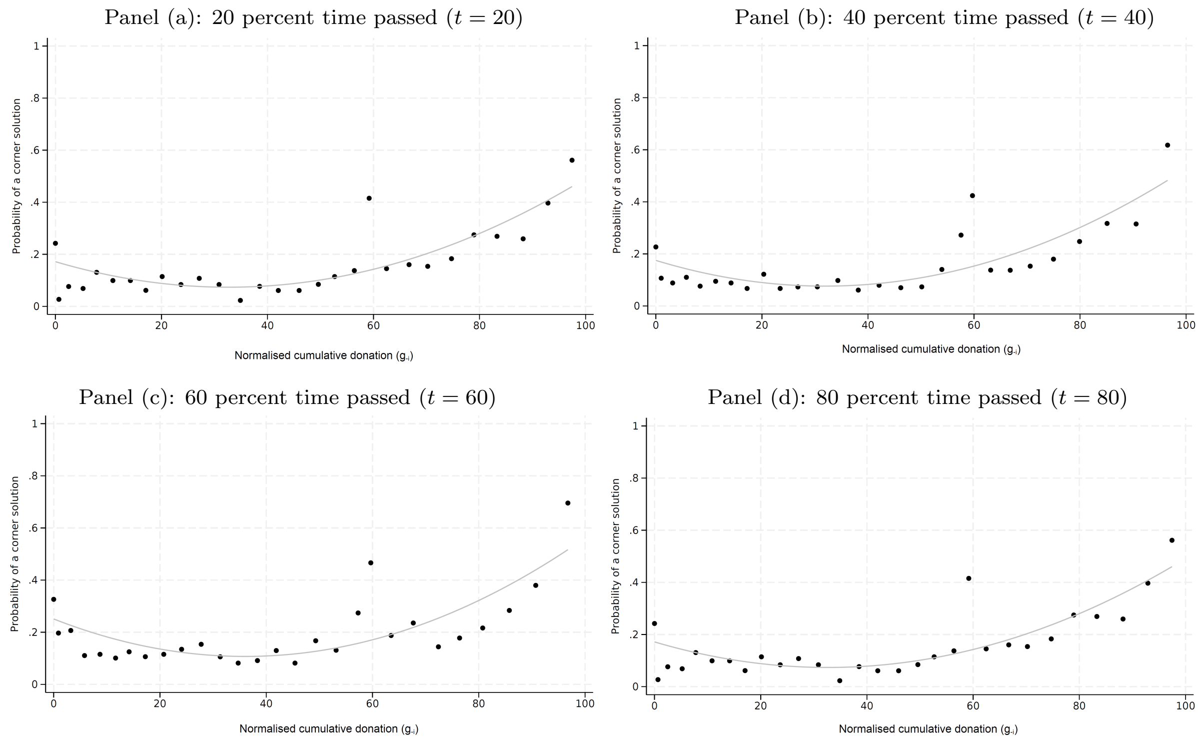
See our finances

Figure A2: Normalised donation (g_i) by normalised cumulative donation (g_{-i})



Note: This figure shows a nonlinear relationship of the third degree of a polynomial regression model. The sample excludes observations that the donation amount is greater or equal to the amount left to the provision threshold and the first donations to the projects.

Figure A3: Proportion of observations where the donor completed a project (mean of I_i) by the normalised cumulative donations (g_{-i}) at a given time



Note: The sample excludes the observations where normalised cumulative donations have exceeded 100.

Table A1: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) on normalised donation (g_i) - final sample

	Normalised donation (g_i)	
	(1)	(2)
Normalised time (t)	0.1473***	0.1471***
	(0.0062)	(0.0063)
Normalised cumulative donations (g_{-i})	-0.0481***	-0.0481***
	(0.0040)	(0.0040)
Number of donors up to t	-0.1265***	-0.1265***
	(0.0163)	(0.0163)
(Normalised time) × (Normalised cumulative donations)	-0.0016***	-0.0015***
	(0.0001)	(0.0001)
First page		0.8897
		(0.6134)
N	14735786	14735786
Donation-month-year FEs	Yes	Yes

$*p < 0.1 **p < 0.05 ***p < 0.01$.

This table presents the estimation of Equation 10 (Column 1) and Equation 15 (Column 2) for our final sample. Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

Table A2: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) by project resource types

	Normalised donation (g_i)				Probability of a corner solution			
Resource Type	Enrichment	Supplies	Technology	Others	Enrichment	Supplies	Technology	Others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Normalised time (t)	0.0375***	0.0200***	0.0284***	0.0211***	0.0004*	0.0004***	0.0004***	0.0005***
	(0.0014)	(0.0013)	(0.0006)	(0.0007)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Normalised cumulative donations (g_{-i})	-0.0611***	-0.0476***	-0.0548***	-0.0376***	0.0042***	0.0046***	0.0048***	0.0042***
	(0.0037)	(0.0030)	(0.0017)	(0.0016)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Number of donors up to t	-0.0421***	-0.0953***	-0.0921***	-0.0838***	-0.0014***	-0.0029***	-0.0029***	-0.0027***
	(0.0124)	(0.0192)	(0.0099)	(0.0074)	(0.0004)	(0.0005)	(0.0003)	(0.0002)
(Normalised time) × (Normalised cumulative donations)	-0.0006***	-0.0004***	-0.0005***	-0.0004***	0.0000	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
First page	-0.5914	1.1645	0.5586	1.6221***	0.1705***	0.1300***	0.1514***	0.1256***
	(0.7484)	(0.7224)	(0.3241)	(0.4293)	(0.0202)	(0.0112)	(0.0053)	(0.0065)
N	1714555	1184130	5855834	3374025	1903075	1315658	6591156	3695754
Donation-month-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

$*p < 0.1 **p < 0.05 ***p < 0.01$.

This table presents the estimation of Equation 15 (Column 1) for our preferred sample and Equation 16 (Column 2) for our final sample, by resource types requested by teachers. Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.

Table A3: The impact of normalised cumulative donations (g_{-i}) and normalised time (t) by geographic location

	Normalised donation (g_i)		Probability of a corner solution	
	Same state	Different state	Same state	Different state
	(1)	(2)	(3)	(4)
Normalised time (t)	0.0297***	0.0004***	0.0400***	0.0008***
	(0.0006)	(0.0001)	(0.0007)	(0.0000)
Normalised cumulative donations (g_{-i})	-0.0503***	0.0035***	-0.0265***	0.0054***
	(0.0014)	(0.0000)	(0.0025)	(0.0001)
Number of donors up to t	-0.0930***	-0.0023***	-0.0601***	-0.0025***
	(0.0082)	(0.0002)	(0.0096)	(0.0004)
(Normalised time) $\times$ (Normalised cumulative donations)	-0.0005***	0.0000**	-0.0008***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
First page	0.9926**	0.1194***	0.5551	0.1385***
	(0.3582)	(0.0072)	(0.3565)	(0.0060)
N	5026445	5390147	4735628	5567586
Donation-month-year FEs	Yes	Yes	Yes	Yes

$*p < 0.1 **p < 0.05 ***p < 0.01$.

This table presents the estimation of Equation 15 (Column 1) for our preferred sample and Equation 16 (Column 2) for our final sample, based on donation geographic locations. Standard errors are in parentheses and clustered at the project level. All the columns include donation-month-year fixed effects.