Why give if someone else will? Evidence of crowd-out in a crowdfunding platform.

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Abstract

We study the application of crowdfunding to philanthropy. An important feature of crowdfunding platforms is that the fundraiser will only receive the donations if a minimum contribution threshold is met before a given deadline. Moreover, by construction, donors move sequentially, and potential donors observe the sum of past donations. Therefore, any potential donor can infer the probability that a posted project will be funded by future donors. In particular, the higher the sum of accumulated donations or the time left until the fundraising deadline, the more likely it is that the project is funded by future donors, which in turn, leads to less giving incentives for an altruistic potential donor. This phenomenon is a form of the well-known free-riding or crowd-out problem in the provision of public goods. Analyzing data from a prominent crowdfunding platform, we find evidence that supports the presence of this foreword-looking crowd-out behavior among donors.

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1 Introduction

Why people give to charities has been a long-standing subject of inquiry among economists. People have different motives for contributing to public goods in general and charitable giving in particular. 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 classic altruism-based models, 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, 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. 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 experiments to investigate these motives, such as Fehr and Schmidt (1999); Bolton and Ockenfels (2000); Charness and Rabin (2002); Konow (2010); Cooper and Kagel (2016) to name a few.

The focus of our study is altruism and the resulting crowd-out behavior in a crowdfunding platform, where donors can choose to donate to any of the posted projects. Each posted project has a publicly observable requested amount that is determined by the fundraiser and is the minimum donation required for the project to be funded. Additionally, each project has an expiration date. In short, a project is a threshold public good that is provided only if total contributions reach the requested amount before the expiration date, both of which are observable by any potential donor who visits the website. Therefore, once a potential donor arrives, she can infer the probability of public good provision (project being funded) based on cumulative past giving and time left to the project's expiration. Such a potential donor, if primarily altruistic, would respond to the increased prospect of future donations by reducing or even retracting her own giving. Consistent with this theory, we find that giving is decreasing in past contributions and increasing in time. These results indicate that expected future donations crowd out earlier donations. This evidence supports altruism and the resulting free-riding or crowd-out being the main drivers of donor behavior in crowdfunding platforms.[1]

We develop a simple theoretical model to formally demonstrate how pure altruism leads to crowd-out. Altruism, or the desire for the provision of the public good, is the earliest established motive for giving in economic theory. In the context of crowdfunding, we show that a purely altruistic donor's giving is, all else equal, decreasing in accumulated past donations. The intuition is simple: when a given donor arrives and observes higher past contributions, they infer a higher probability that the public good is provided, which reduces the donor's giving

[1] Free-riding is a term mainly used in public good theory, while crowd-out is the term used in charitable giving studies.

incentives. We also show that a donor can infer future donors' expected contributions from the time left to a project's expiration date. In particular, as a crowdfunding project nears its expiration date, it becomes less and less likely for future donors to show up, which, in turn, increases altruistic giving motives. Or, said backward, the more time left when a given donor arrives, the more likely it is for other potential donors to show up and contribute to the project. Thus, the donor in question would have less of an incentive to contribute. In short, all else equal, giving would be increasing in time. Both of these theoretical results stem from the propensity of a potential donor to free-ride on expected upcoming donations.

While altruism leads to crowd-out, there are two groups of opposing motives. First, it is reasonable to assume that when a project is posted, those who have inside information about it, such as friends and family of the fundraiser, will contribute first. Thus, as shown first by Vesterlund (2003), such early informed donors will have an incentive to signal project quality through the size of their donation. As a result, late-arriving donors interpret higher early donations as a signal of higher project quality, which, in turn, could alleviate free-riding behavior. Another counterbalance to altruism-based crowd-out is any social motive that takes into consideration the relative size of one's donation to others' donations and induces a sort of reciprocal behavior. The mechanism is as follows: Depending on the specific setup of a given platform, a potential donor can observe individual past contributions or at least infer the average past gift size by observing cumulative past contributions and the time elapsed from when the project was posted. In either case, higher past gifts induce more giving by a donor who has an incentive to reciprocate others' gifts. Such incentives can be derived from moral obligation, social pressure, social norm-compliance, inequality aversion, self-image concerns, or reciprocity (a tendency to reward kindness and punish unkind actions).

The relative weight of altruism-based crowd-out and the just-discussed countervailing forces is an empirical question. Thus, we examine whether altruism is the main driver of donor behavior by empirically testing for crowd-out in a rich crowdfunding database from DonorsChoose.org.[2] 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 test 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. Observing such effects supports altruism being the dominant giving motive. Otherwise, one can infer that other motives are stronger.

[2] DonorsChoose.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.

We find evidence in support of crowd-out. In particular, we estimate a statistically significant negative impact of total accumulated past donations on donation size. Our results show 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, we find that donation size responds positively to the time passed from the project posting date. On average, 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.

Our paper's main contribution is demonstrating a forward-looking form of crowd-out in charitable giving where one free-rides on anticipated future donations. We test our hypotheses using a rich dataset containing a large number of fundraising projects on a crowdfunding platform that can be observed and compared, making it an ideal setting for an empirical investigation of charitable giving behavior. Moreover, the rather recent prevalence of crowdfunding in charitable fundraising makes it a valuable subject of inquiry on its own. When compared to traditional fundraising through individual solicitations, crowdfunding platforms have two interesting characteristics that set them apart: 1) Sequential giving, i.e., each donor observes past contributions or the sum of past contributions (which is the case for DonorsChoose.org) 2) Threshold giving with an explicit deadline, i.e., projects will be funded only if contributions reach a given threshold (the amount asked by the fundraiser) by a given deadline (four months after posting in the case of DonorsChoose.org). These features differentiate crowdfunding platforms from more studied traditional fundraising techniques and warrant further investigation.

Our paper contributes to the broad literature on charitable giving and giving motives. In particular, we contribute to the small but growing literature on crowdfunding as a charitable fundraising mechanism. Of course, the use of crowdfunding in business and marketing has been studied extensively.[3] However, the use of crowdfunding in charitable fundraising is more recent

[3]For instance, Strausz (2017) provides a mechanism design for crowdfunding under uncertainty and moral hazard. Gleasure and Feller (2016) show that the goal and the donation amount were not related to individual fundraising projects. 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 of buyers and donors in crowdfunding using data collected from Kickstarter. Other studies in the area of entrepreneurial crowdfunding platforms include Belleflamme et al. (2015); Moritz and Block (2016); André et al. (2017); Cumming and Hornuf (2018); Ellman and Hurkens (2019); Zhou and Ye (2019); Chakraborty and Swinney (2021). Alegre and Moleskis (2021) present a systematic review of the literature on donation-based and reward-based crowdfunding (similarly, van Teunenbroek et al. (2023)).

and, unlike crowdfunding for businesses, entails the problem of free-riding. Therefore, the latter requires specific scholarly attention that has not yet been received broadly. Boudreau et al. (2015) provide a theory on crowdfunders' behavior and how the platform's design can help deal with free-rider problems. Recent studies have also explored donors' behavior in charitable giving crowdfunding platforms. Smith et al. (2015) find positive and sizable peer effects, but little evidence on signaling in online crowdfunding. Gleasure and Feller (2016) find that donations to organizations are more influenced by fundraising targets, while donations to individuals are more influenced by interaction-related factors. Beier and Wagner (2016) show the importance of the first days of a fundraising campaign in its success. Sasaki (2019) studies the causal effect of majority size on a donor's conformity behavior by using a dataset of donations on a donation-based crowdfunding platform in Japan and finds evidence of a subsequent donor giving a similar amount as the majority of donors mostly contribute the same amount.[4] Argo et al. (2020) find evidence of a "completion effect," i.e., donors contributing more to reach their personal fundraising targets. In a related study, Cryder et al. (2013) concentrate on the "goal gradient helping" motivation where donors contribute a larger amount in the last stage of a fundraising campaign. Similarly, Wash (2021) finds that individual donations are higher when they lead to project completion. In empirical research by Wu et al. (2020), they find anti-conformity behavior in charitable crowdfunding, demonstrating the negative relationship between the larger cumulative amount of donations and the subsequent individual donation amount.[5]

We also add to the literature on online charitable fundraising designs and their impacts on public finance. Meer (2014, 2017) investigates the price elasticity of giving, competition, and substitution between causes in crowdfunding. There are also papers that focus on crowd-out effects in crowdfunding (Meer and Tajali, 2021), higher education funding (Horta et al., 2022), and the impact of charitable crowdfunding on educational outcomes (Keppler, Li, and Wu, 2022). Altmann et al. (2019) show the impact of defaults on donors' behavior in online fundraising, while the aggregate donation levels are unaffected. Adena and Huck (2020) provide evidence of the role of the design of an online campaign in giving and how fundraising management should consider broader operational concerns.

This article proceeds as follows: in Section 2, we discuss our theoretical model and its implications. 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.

[4] Our study differs in terms of developing a theoretical mode, investing different motives, and looking at both the impact of time and accumulated donation using a large rich dataset.

[5] Some papers like Raihani and Smith (2015) show gender differences in competitive helping using an online fundraising page.

2 Theory

In this section, we introduce a partial equilibrium model of an altruistic 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 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 $t \in \{1, 2, 3, ..., \bar{t}\}$.[6] 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

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

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 $g_{-i} < G_0$.[7] 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 $g_{-i} < G_0$.[8] 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:

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

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:

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

[7] The other case is trivial.
[8] The other case is trivial.

$g_i^*(g_{-i}, \bar{t}-1)$ 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.[9] Donor i donates this amount if and only if the following holds:[10]

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

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 altruistic donor utility model does not fully capture donors' preferences.

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.[11] 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.*

[9] 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.

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

[11] 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).

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 $g_{-i} < G_0$.[12] 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:

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

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. 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:[13]

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

[12] The other case is trivial.

[13] 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 $p_1(g_{-i} + g_i, \bar{t}-1) < p_1(g_{-i} + g_i, \bar{t})$.

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 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 $\bar{g}_i(\bar{t}-2) > \bar{g}_i(\bar{t}-1)$.[14] 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:

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 Altruism vs. 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 altruism.

[14] 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.

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, 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 perceives to be the average gift. 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 early donor has an incentive to use the size of her gift to signal quality to a downstream donor. 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 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 altruism-based 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, altruism (and the resultant crowd-out) is the main driver of giving behavior.

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.[15] 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,[16] 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,[17] our final sample includes 14,735,787 donation-day observations (with 4,154,494 donors) and 2,297,177 posted projects by 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.

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

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

[17] 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).

3.2 Empirical Strategy

Our goal is to determine the relative importance of altruism (donors' focus on provision) compared to other motives (warm glow and conditional cooperation) in giving behavior in crowdfunding. 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):[18]

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

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 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., $I_{ipd} = \mathbb{1}_{g_{ipd} \geq G_0 - g_{-ipd}}$.

[18] 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.

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.[19] 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) 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.[20] 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

[19] 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).

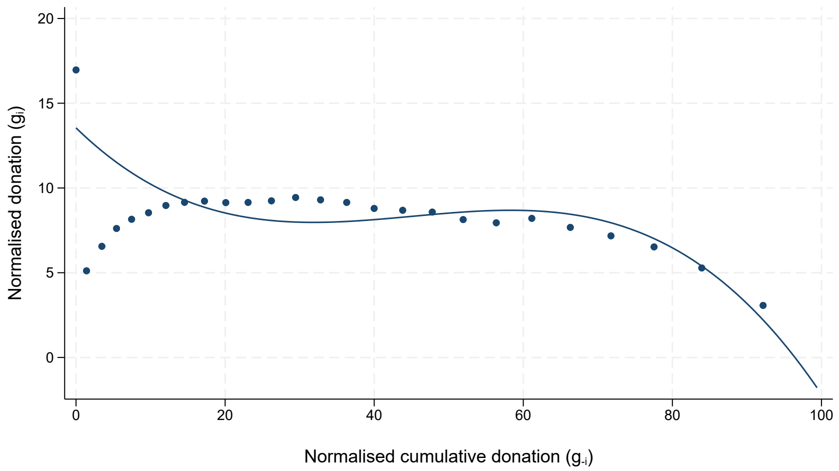
[20] In our final sample, about 76% of the observations (donation-date) include only one of these factors, less than 6% have two of them, and only 0.08% satisfy all 3 criteria.

the word and start pre-funding through the "Friends & Family Pre-Funding" option.[21] All pre-funding contributions are applied to the project once it is posted on the website.[22] 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.[23]

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.[24]

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.[25]

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

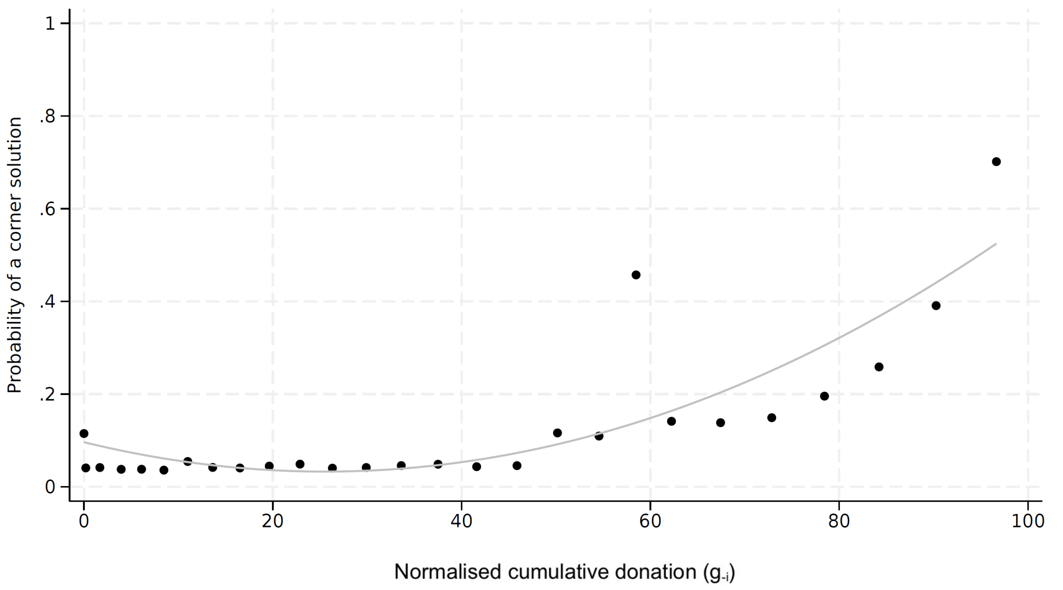
[22]For details see: https://help.donorschoose.org/hc/en-us/articles/226500648-Friends-Family-Pre-Funding

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

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

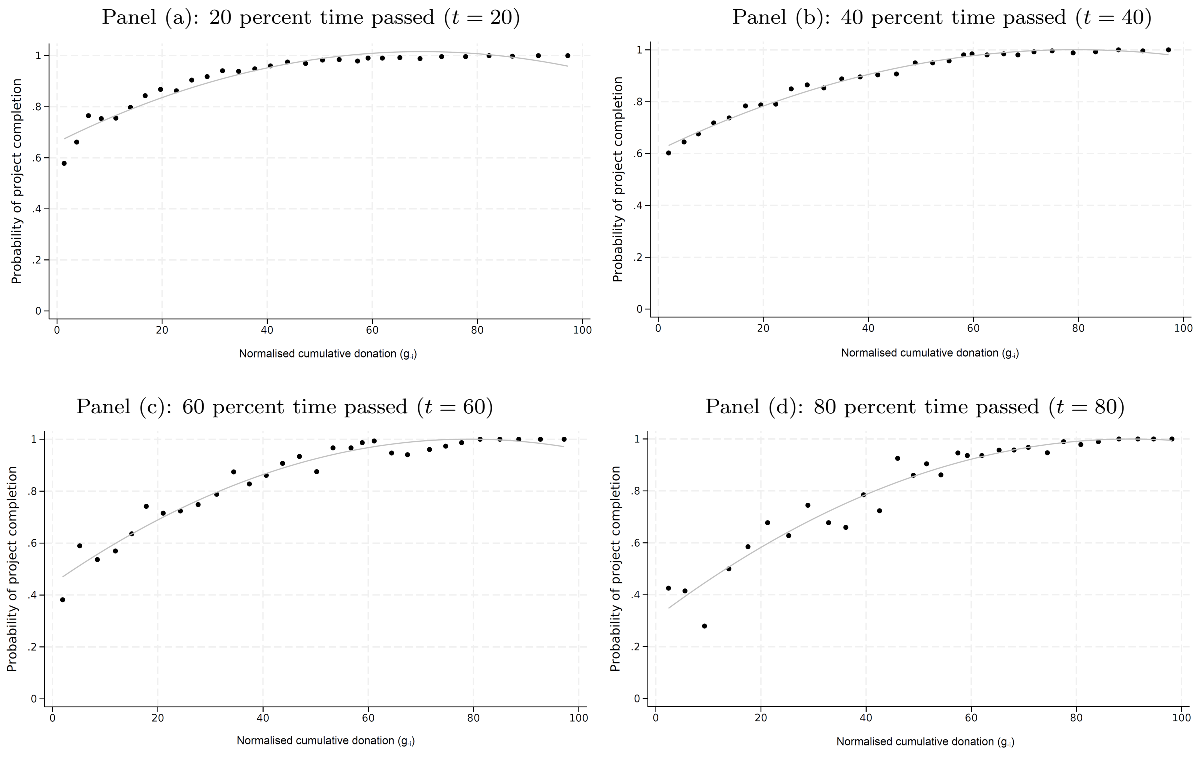
[25]Figure A3 provides the same relationship for a given point in the project posting timeline.

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 ($g_{-i} + g_i$)

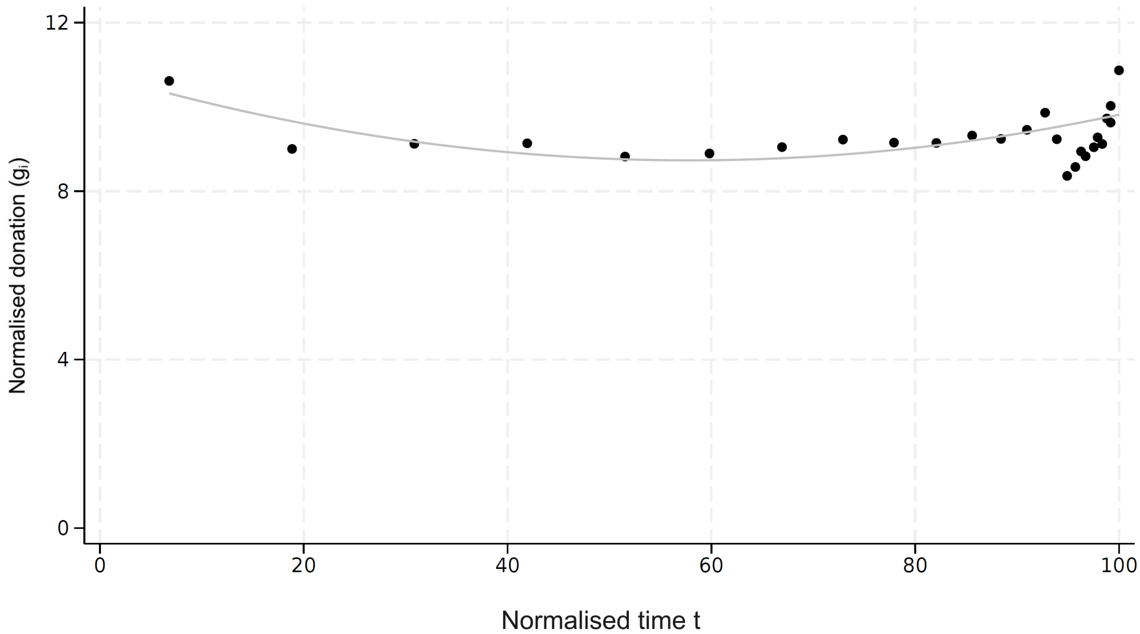


Note: The sample excludes the observations where normalised cumulative donations have exceeded 100.

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.

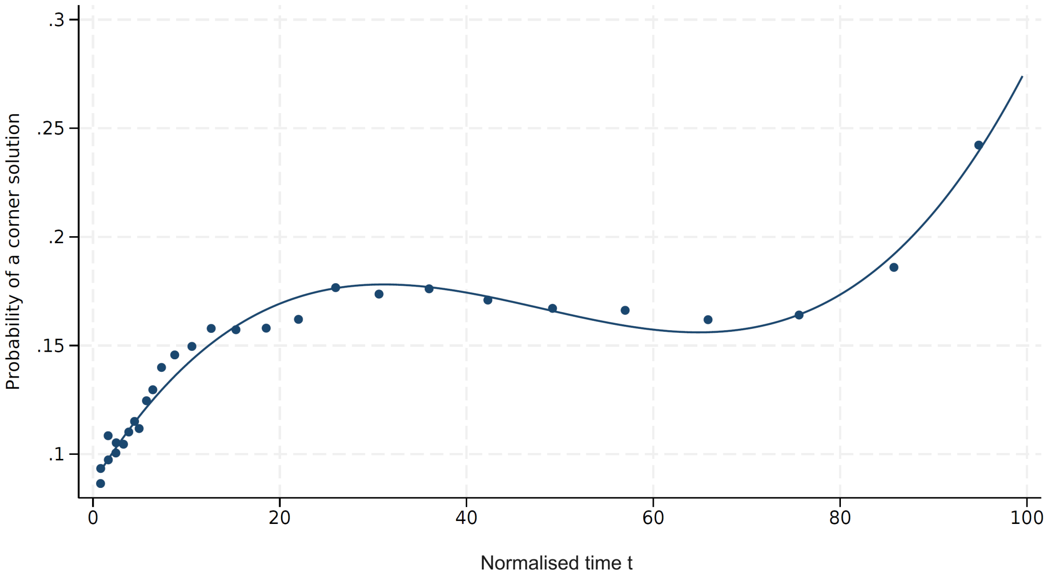
Figure 4: Normalised donation (g_i) by normalised time (t)



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 altruism-based crowd-out.[26] 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.

[26] 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 an altruism-based 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

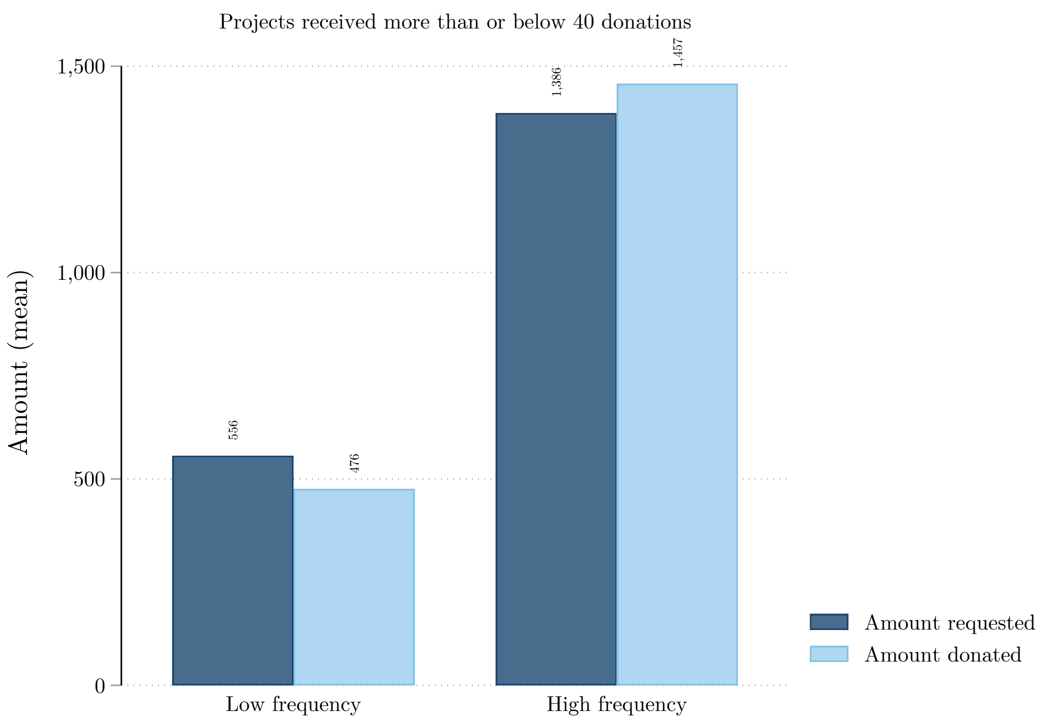
$*p < 0.1 **p < 0.05 ***p < 0.01$.

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) × (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

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

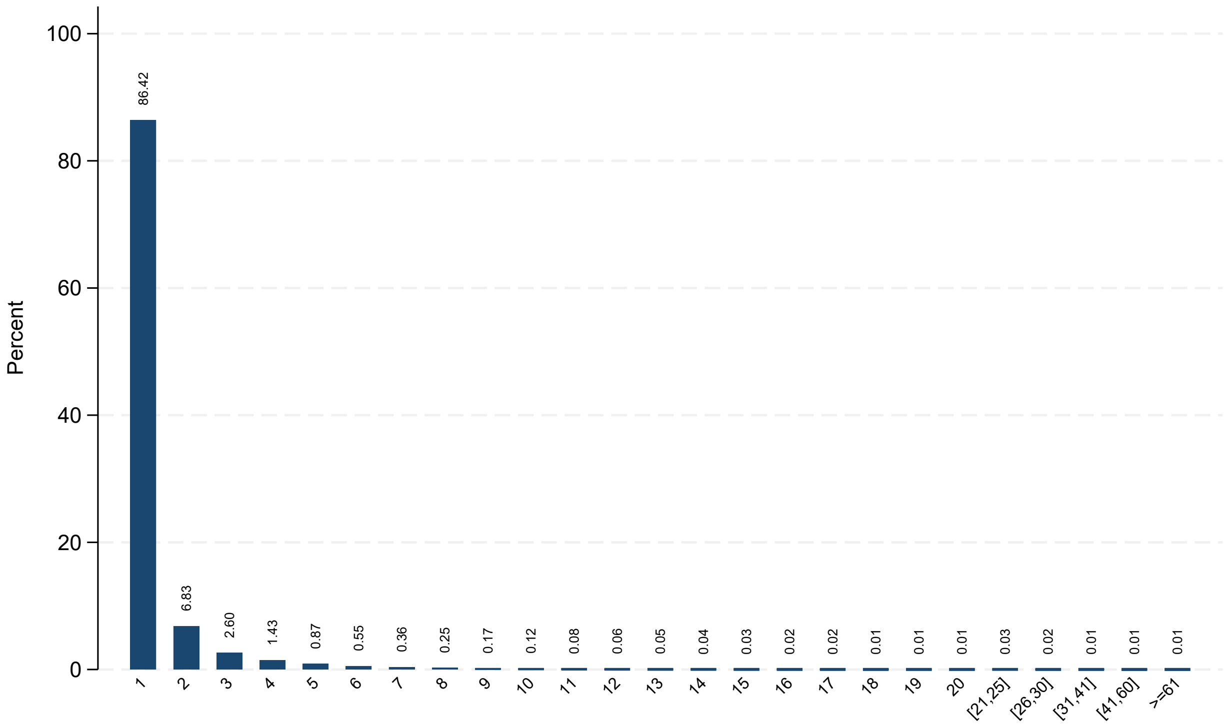
This table presents the estimation of Equation 15 (Column 1) for our preferred sample and Equation 16 (Column 2) for our final sample, excluding those projects with more than 40 contributions (defined as higher frequencies). Standard errors are in parentheses and clustered at the project level. All the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

In this paper, we demonstrate a forward-looking form of crowding-out in charitable giving in a crowdfunding platform. We show that the anticipation of future donations weakens donors' giving incentives. We use a rich crowdfunding database from DonorsChoose.org to empirically test for this crowd-out hypothesis and examine whether altruism is the main driver of donor behavior. We find that giving decreases with past contributions and increases as more time passes, which is consistent with crowd-out behavior driven by altruistic motives. 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.

We should emphasize that the prominence of crowd-out does not indicate the absence of other motives for giving. Rather, the observed effects are the result of interaction between various giving motives, and the direction of the effects simply points to the strongest motive. In fact, previous studies have shown that altruism and other motives (particularly warm-glow) can coexist (Andreoni et al., 2008). Of course, the literature on this topic is rather recent, and there is a need for further investigation of this question.

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A Appendix

Figure A1: Sample of DonorsChoose.org Requested Project

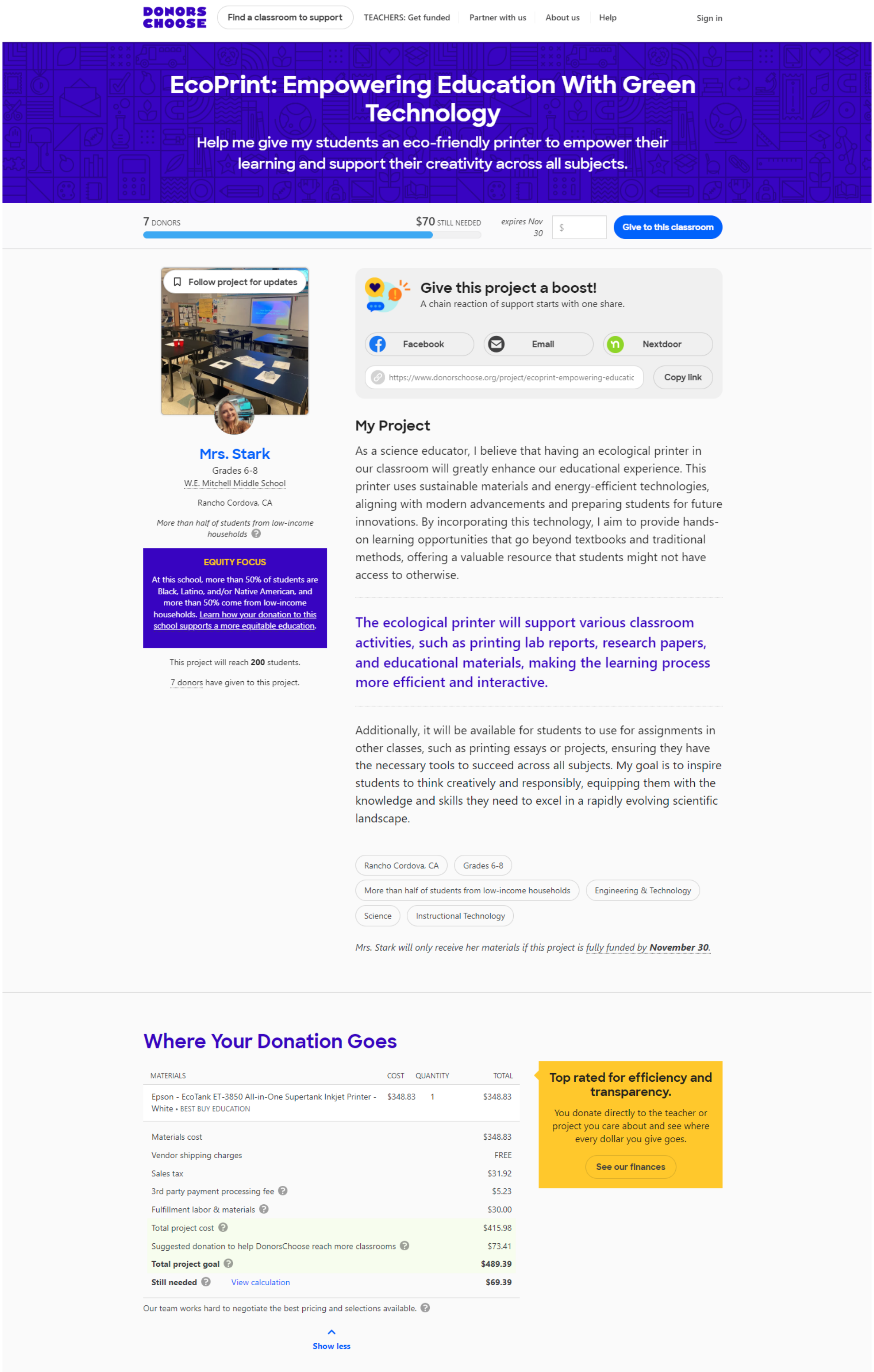
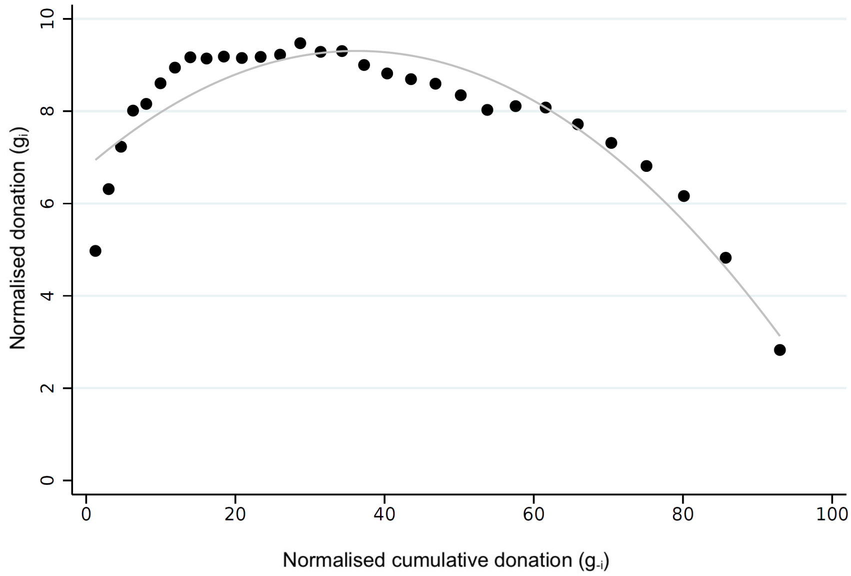
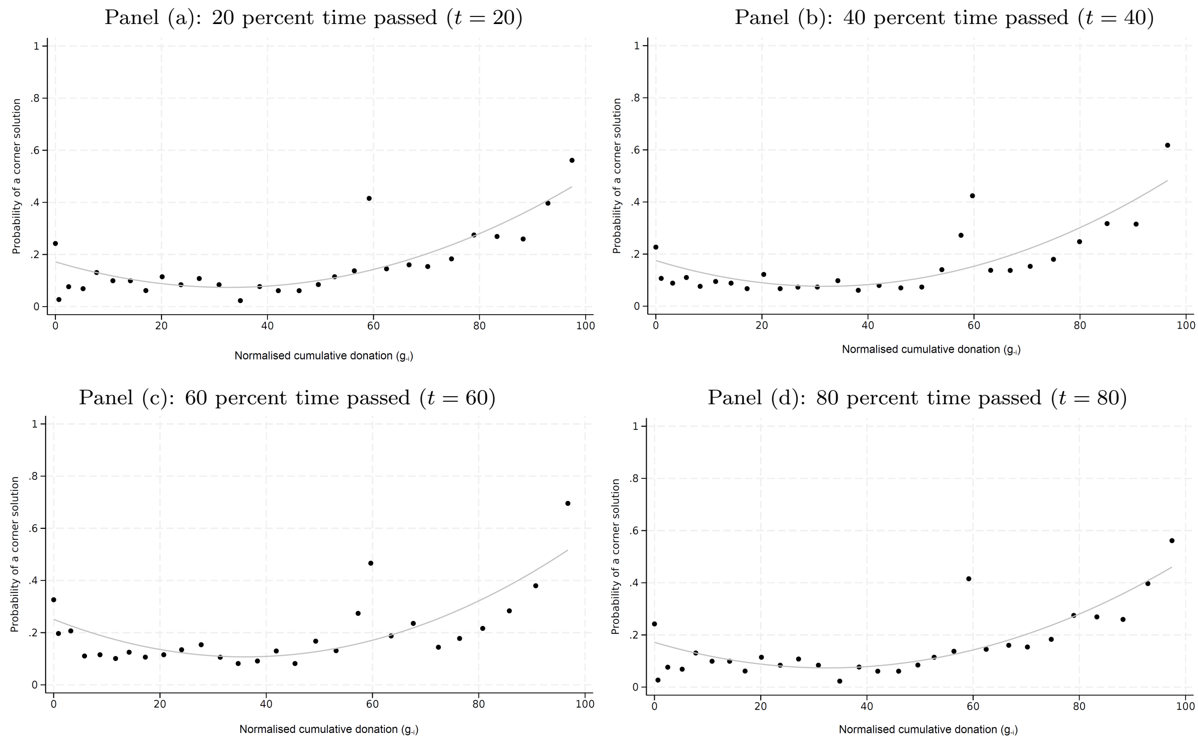


Figure A2: Normalised donation (g_i) by normalised cumulative donation (g_{-i})



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) × (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.