How Do Late Donors Respond to Early Donors in Crowdfunding?

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Abstract

The application of crowdfunding to philanthropy has not yet been studied extensively. We focus on the sequential nature of giving on crowdfunding platforms. On the one hand, this feature exacerbates donors' incentives to free-ride. On the other hand, sequential giving provides an opportunity for leadership-giving by early donors. In particular, late donors' conditional cooperation due to moral obligation, reciprocity, social pressure, social norm-compliance, inequality aversion, or self-image concerns can lead to a positive response to early donations by downstream donors. Moreover, early donors can signal their information about the quality of the public good to downstream donors, which can induce a similar positive response. We use data from a prominent crowdfunding platform to estimate early donations' effect on later donations. We find evidence that supports altruism and free-riding being the main drivers of donor behavior in crowdfunding platforms.

JEL Classifications: H00, H41, D64, I22

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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 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 (2021a) 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. Most existing studies use 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. However, to date, few empirical studies of large data sets have been conducted in this area.

We study how late donors respond to early donors and time 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 donor arrives, they can infer the probability of public good provision (project being funded) based on cumulative past giving and time left to the project deadline. We find that in this setting, giving is decreasing in past contributions and increasing in time. These results indicate that late donors free-ride on both past donations and expected future donations. This evidence supports altruism and free-riding 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 free-riding. 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, which is the "classic free-riding" result consistent with Varian (1994). 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 incentives. We also show

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

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. We refer to this propensity to free-ride on potential upcoming donations as "forward free-riding." The result is that all else equal, giving is increasing in time.

We argue that while altruism leads to classic and forward free-riding, 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 could, in turn, alleviate free-riding behavior. Other-regarding preferences can also influence giving behavior. Specifically, social motives that take into consideration the relative size of a donation to others' donations, induce a sort of reciprocal behavior that alleviates free-riding. In the context of crowdfunding, a given donor does not directly observe every individual contribution. Nonetheless, each donor can infer the average past gift size based on their observation of past cumulative giving and the time elapsed from when the project was posted. In short, higher cumulative giving during a shorter time from project posting (more time left to expiration) implies a higher average past gift, which would 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).

To examine whether altruism is the main driver of donor behavior, we empirically test for free-riding in a rich crowdfunding database from DonorsChoose.org.[2]We estimate the effects of cumulative past donations and time 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 free-riding 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. In fact, 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 strong evidence in support of free-riding. In particular, we estimate a statistically significant negative impact of total accumulated past donations on donation size, which is consistent with classic free-riding, i.e., donors' free-riding on the total of earlier donations. 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). In addition, we find that donation size responds positively to the time passed from the project posting date, which is consistent with forward free-riding. 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, resource type, and number of donations by a donor. However, in the absence of the first donations, evidence of classic free-riding diminishes, suggesting that while later donors are much smaller than the initial donation, there is no evidence of further diminishing of donation size as past donations grow. The last finding suggests that altruism weakens as donations accumulate (Ottoni-Wilhelm et al., 2017).

Our database contains a large number of fundraising projects that can be observed and compared, which makes 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. One important characteristic of crowdfunding is sequential giving, where each donor observes the sum of past contributions, which provides a setting to test classic free-riding. Another important aspect of most crowdfunding platforms, including DonorsChoose.org, is threshold giving, which means: a) projects will be funded only if contributions reach a given threshold (the amount asked by the fundraiser), and b) projects stay on the website for a limited time (up to four months in the case of DonorsChoose.org).

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 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

[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)).

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 contribute to the literature on online charitable fundraising campaigns to understand more about the operational and fundraising side of crowdfunding and its impact 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.

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

[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.

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 n periods, such that period t starts at time $\frac{(t-1)T}{n}$ and ends at time $\frac{tT}{n}$. 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 n. Let g_t represent the contribution in time period $t \in \{1, 2, 3, ..., n\}$.[6] The public good will be provided if the sum of all donations $G = \sum_{t=0}^{n} g_t$ is no less than a threshold G_0, and each donor i's utility will be:

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

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.

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

2.2 Last Donor's Contribution

Consider donor i that arrives in the last time period n, and let $g_{-i} = \sum_{t=1}^{n-1} g_t$ 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 their valuation of the public good is higher than the utility cost of covering the gap until the provision threshold G_0.

2.3 Classic Free-Riding

Consider donor i that arrives in the time period $n-1$, and let $g_{-i} = \sum_{t=1}^{n-2} g_t$ 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, they will contribute $G_0 - g_{-j}$ if Inequality (2) holds for them, the probability of which depends on the distribution of donor types. Let's denote the latter probability as follows:

$$p_n(g_{-j}) = Prob(V_j \geq v_j(w_j) - v_j(w_j - G_0 + g_{-j})) \tag{3}$$

Since $g_{-j} = g_{-i} + g_i$, donor i's expected utility in period $n-1$ will be:

$$E_{n-1}(u_i(g_{-i}, g_i)) = \begin{cases} v_i(w_i) + \nu p_n(g_{-i} + g_i)[V_i - v_i(w_i) + v_i(w_i - g_i)] \text{ if } g_i < G_0 - g_{-i} \\ v_i(w_i - g_i) + V_i \text{ if } g_i \geq G_0 - g_{-i} \end{cases} \tag{4}$$

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 $g^*_{n-1}(g_{-i})$ that satisfies the following first order condition:

$$\frac{p'_n(g_{-i} + g^*_{n-1}(g_{-i}))}{p_n(g_{-i} + g^*_{n-1}(g_{-i}))} = \frac{v'_i(w_i - g^*_{n-1}(g_{-i}))}{V_i - v_i(w_i) + v_i(w_i - g^*_{n-1}(g_{-i}))} \tag{5}$$

$g^*_{n-1}(g_{-i})$ 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. The expected utility of giving $g^*_{n-1}(g_{-i})$ is $v_i(w_i) + \nu p_n(g_{-i} + g^*_{n-1}(g_{-i}))[V_i - v_i(w_i) + v_i(w_i - g^*_{n-1}(g_{-i}))]$.

[7] The other case is trivial.

[8] The other case is trivial.

Hence, donor j donates $G_0 - g_{-i}$ that is the whole contribution gap needed to provide the public good if and only if the following holds:

$$v_i(w_i - G_0 + g_{-i}) + V_i \geq v_i(w_i) + \nu p_n(g_{-i} + g^*_{n-1}(g_{-i}))[V_i - v_i(w_i) + v_i(w_i - g^*_{n-1}(g_{-i}))]$$

Otherwise, she optimizes her giving at $g^*_{n-1}(g_{-i})$ where the provision probability and the net benefit are equally sensitive to the marginal gift. Since $v()$ is an increasing and concave function, it follows that the right-hand-side of Equation (5) is increasing in $g^*_{n-1}(g_{-i})$. Thus, the following proposition holds regarding g^*_j:

Proposition 1 *If and only if* $\frac{p'_n()}{p_n()}$ *is non-increasing in its argument, i.e.,* $ln(p_n())$ *is a concave function,* $g^*_{n-1}(g_{-i})$ *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 (Classic Free-Riding) *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 $ln(p_n())$ is strictly convex or the altruistic donor utility model does not fully capture donors' preferences.

However, the full picture of donor i's behavior is not limited to interior solutions ($g^*_{n-1}(g_{-i})$), and includes the cases where her optimal choice is the corner solution where she contributes $G_0 - g_{-i}$. Interestingly, while $g^*_{n-1}(g_{-i})$ is decreasing in g_{-i}, donor i becomes more likely to switch to a corner solution as g_{-i} grows. The reason is that as g_{-i} increases, $g_{-j} = g_{-i} + g^*_{n-1}(g_{-i})$ converges to G_0. Therefore, there is not much left for the last donor j to contribute. Thus, $p_n(g_{-j})$ converges to 1, and donor i's expected utility of donating $g^*_{n-1}(g_{-i})$ converges to $(1-\nu)v_i(w_i) + \nu[V_i + v_i(w_i - g^*_{n-1}(g_{-i}))]$. However, the utility of donating $G_0 - g_{-j}$ converges to $V_i + v_i(w_i - g^*_{n-1}(g_{-i}))$ 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). The following proposition formalizes this argument:

Proposition 2 *There exists* $g^0_{i,n-1}$ *such that for any* $g_{-i} \geq g^0_{i,n-1}$, *donor* i *will contribute* $G_0 - g_{-i}$.

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 (Full Provision and Classics Free-Riding) *The probability of a donor giving the full amount left to the provision threshold is increasing in the sum of past donations.*

2.4 Forward Free-Riding

Consider donor i that arrives in the time period $n-2$, and let $g_{-i} = \sum_{t=1}^{n-3} g_t$ represent past donations. Furthermore, as before, we focus on the case where $g_{-i} < G_0$.[9] 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:

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

where $p_{n-1}()$ is the expected probability of public good provision on or after period $n-1$ as a function of cumulative contributions, conditional on a final donor's arrival:

$$p_{n-1}(g_{-j}) = Prob(g_{-j} \geq g^0_{j,n-1}) + \nu E_{g_{-j} < g^0_{j,n-1}} \left(p_n(g_{-j} + g^*_{n-1}(g_{-j}))\right) + (1-\nu)p_n(g_{-j}) \tag{7}$$

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 $g^*_{n-2}(g_{-i})$ that satisfies the following first order condition:

$$\frac{p'_{n-1}(g_{-i} + g^*_{n-2}(g_{-i}))}{p_{n-1}(g_{-i} + g^*_{n-2}(g_{-i}))} = \frac{v'_i(w_i - g^*_{n-2}(g_{-i}))}{V_i - v_i(w_i) + v_i(w_i - g^*_{n-2}(g_{-i}))} \tag{8}$$

Analogous to a the case analyzed in Subsection 2.3, the right-hand-side of Equation (8) is increasing in $g^*_{n-2}(g_{-i})$, 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 $n-2$. Therefore, at first glance, the behavior of donor i looks very similar in periods $n-1$ and $n-2$. 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:

$$p_{n-1}(g_{-i} + g_i) > p_n(g_{-i} + g_i) \tag{9}$$

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. Moreover, since both probabilities $p_n()$ and $p_{n-1}()$ converge to 1 as their argument (total contributions) approaches G_0, Inequality (9) implies:

$$p'_{n-1}(g_{-i} + g_i) < p'_n(g_{-i} + g_i) \tag{10}$$

As a result, comparing Equations (5) and (8) reveals that for a given level of past donations, $g^*_{n-2}(g_{-i}) < g^*_{n-1}(g_{-i})$, which is formalized in the following proposition:

[9] The other case is trivial.

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

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 (Forward Free-Riding) *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 $n-2$ analogously. Thus, there exists $g^0_{i,n-2}$ such that for any $g_{-i} \geq g^0_{i,n-2}$, donor i prefers contributing $G_0 - g_{-i}$ to giving $g^*_{n-2}(g_{-i})$, i.e., $u_i(g_{-i}, G_0 - g_{-i}) > E_{n-2}(u_i(g_{-i}, g^*_{n-2}(g_{-i})))$. However, it can be established that $g^0_{i,n-2} > g^0_{i,n-1}$. The logic is as follows. Consider $g_{-i} \geq g^0_{i,n-2}$. From Equation (9), $p_n(g_{-i} + g^*_{n-1}(g_{-i})) < p_{n-1}(g_{-i} + g^*_{n-1}(g_{-i}))$. Therefore, $E_{n-1}(u_i(g_{-i}, g^*_{n-1}(g_{-i}))) < E_{n-2}(u_i(g_{-i}, g^*_{n-1}(g_{-i}))) < E_{n-2}(u_i(g_{-i}, g^*_{n-2}(g_{-i}))) < u_i(g_{-i}, G_0 - g_{-i})$ which implies that if donor i prefers the corner solution in period $n-2$, they must prefer it in period $n-1$ for the same level of past contributions. This result can be summarized in the following proposition:

Proposition 4 *The full provision threshold* $g^0_{i,t}$ *is decreasing in* t*, i.e.,* $g^0_{i,n-2} > g^0_{i,n-1}$

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

Hypothesis 4 (Full Provision and Forward Free-Riding) *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, which is why we have labeled this behavior "forward free-riding."

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 predictions of free-riding. Therefore, the rejection of any of the 4 free-riding hypotheses stated in the previous sections would imply that donors' giving behavior is not, at least primarily, governed by 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_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_t^* would become increasing in g_{-i}.

Lastly, strategic "quality signaling" has also been established as a determinant of giving behaviour when donors' giving is observable by subsequent donors. (Vesterlund, 2003; Andreoni, 2006; Krasteva and Saboury, 2021b) 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 is interpreted as a signal of quality and leads to more giving. Thus, g_t^* could become increasing in g_{-i}.

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 free-riding) 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.[10] 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,[11] 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,[12] 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.

As described in Section 2, donors who contribute nothing or contribute enough to reach the requested amount and complete a project (corner solutions) are not sensitive to marginal variations in past giving or time left to the project end date. Moreover, corner solutions do

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

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

[12]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).

not reveal a donor's actual willingness to give since the observed contribution is truncated. Therefore, we focus on interior solution cases where a donor gives a positive amount but not enough to complete the fundraising. In other words, we want a sample of individuals with smooth behavior who reveal their true preferences. Such donors may have other ties to a project, like their familiarity with the school, teacher, or the project. All these cases prevent us from observing smooth behavior. If anything, the donation may be decreasing but mechanically, not due to the strategic behavior. Therefore, we have decided to drop donation observations that the amount contributed is greater or equal to the amount left to the threshold target (about 17.7% of the sample).[13] That leaves us with 12,128,801 donation-date observations (hereafter, our preferred sample).

3.2 Empirical Strategy

Equation (11) represents our baseline empirical model to estimate the effect of time to project expiration and accumulated donation on a donor's contribution:

$$y_{ipd} = \alpha_{my} + \beta_1(t_{pd}) + \beta_2(g_{-ipd}) + \beta_3(g_{-ipd} \times t_{pd}) + \beta_4 Donor_{-ipd} + \epsilon_{ipd} \tag{11}$$

where i and p are indexed for donor and project, and d is the donation date (as day-month-year). y_{ipd} is the outcome of interests, which can be the donation size by donor i to a project p in a particulate date d (g_{ipd}). We are also interested in the probability of a corner solution or whether a donor contributed the remaining amount to complete a project. In that case, the outcome variable is $I(corner)_{ipd}$, which takes a value of one if a contributed donation made a project fully funded.

g_{ipd} is the donation size relative to the amount requested by the fundraiser (i.e., the public good provision threshold),

$$g_{ipd} = \left(\frac{Amount\ donated_{ipd}}{Amount\ requested_p}\right) \times 100 \tag{12}$$

and g_{-ipd} is the total amount donated just before time d relative to the amount requested by the fundraiser (hereafter, relative donations up to t).

$$g_{-ipd} = \left(\frac{Cumulative\ past\ donations_{ipd}}{Amount\ requested_p}\right) \times 100 \tag{13}$$

We also use detailed information on the timing of postings and donations to calculate the expiration date and the number of days passed from the posting date.[14]. Then, we use Equation (14) to calculate t_{pd}, which represents the percentage of the posting period passed from the time

[13]For each donation observation, we find the completion amount at t as the amount requested minus the amount contributed up to time t. Then, we flag those observations as the corner solution observations if the amount contributed at time t is greater or equal to the completion amount.

[14]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.

of posting a project (hereafter, relative time).

$$t_{pd} = \left(\frac{donation\ date_{pd} - project\ posted\ date_p}{expiration\ date_p - project\ post\ date_p} \right) \times 100 \tag{14}$$

Our 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. Note that DonorsChoose.org does not reveal information on the exact donation amount contributed by previous donors to new donors. Late donors will only observe the accumulated past donations, elapsed time, and the number of donors who contributed so far.

Our empirical design is based on the across-project variation. We claim that within a project, the relative time and relative donation are not independent of each other. If anything, these two measures will change at the same time and have opposite effects. Additionally, in our model, we consider a normalized measure for donation amounts and elapsed time. Hence, the appropriate approach is to investigate how donors behave across projects. We argue that there is a random variation in the relative past donations and share of time needed to reach full funding. Hence, they have to make a comparison between posted projects based on the information they receive as browsing this platform. Lastly, we do not have information on donors' characteristics besides having a unique identifier. We do not also include donor-fixed effects in our model due to considering the between-project variation and the majority of donors to be one-time donors.[15]

Our goal is to determine the relative importance of free-riding and other motives (such as conditional cooperation) on giving behavior in crowdfunding by estimating the model in Equation (11). Although 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.

One 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 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

[15]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 6).

left to reach their funding target. Our first-page likelihood index takes a value of 1 if a project satisfies all these criteria representing the urgency of a project. 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.[16]

Hence, we can rewrite our baseline model as follows:

$$\begin{aligned} y_{ipd} = \alpha_{my} + \beta_1(t_{pd}) + \beta_2(g_{-ipd}) + \beta_3(g_{-ipd} \times t_{pd}) \\ + \beta_4 Donor_{-ipd} + \delta I(first - page)_{pd} + \epsilon_{ipd} \end{aligned} \tag{15}$$

where "first-page" is our first-page likelihood index taking the value of 1 if a project includes all the mentioned criteria to be posted on the first page of the platform. In other words, the first-page index takes into account the urgency of a project. δ is the associated coefficient.

Another 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 provides an opportunity for teachers to spread the word and jumpstart pre-funding through the "Friends & Family Pre-Funding" option that allows fundraising before the DonorsChoose.org team reviews a project. All pre-funding contributions are applied to the project once it is officially on the website.[17] 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.[18]

Lastly, not observing non-donors in our dataset, i.e., those who might have visited the website but made no contribution, could be seen as a concern regarding our results. In other words, our results are only based on donors with nonzero contributions. However, it is highly unlikely that there are many (if any) zero-donors. After all, one would only visit and search DonorsChoose.org if they have already made the decision to contribute, and their only question should be how much and to which project. Put differently, it is hard to imagine individuals who randomly drop by DonorsChoose.org and just browse without any prior intention to donate.

4 Results

In this section, we present the empirical results on how late donors respond to previous donations and time in crowdfunding. First, we show the relationship between giving and cumulative past donations up to t using a binscatter plot (Figure 1). This figure shows a nonlinear relationship between current and past donations.[19] It provides evidence of classic free-riding and confirms our proposed Hypothesis 1.

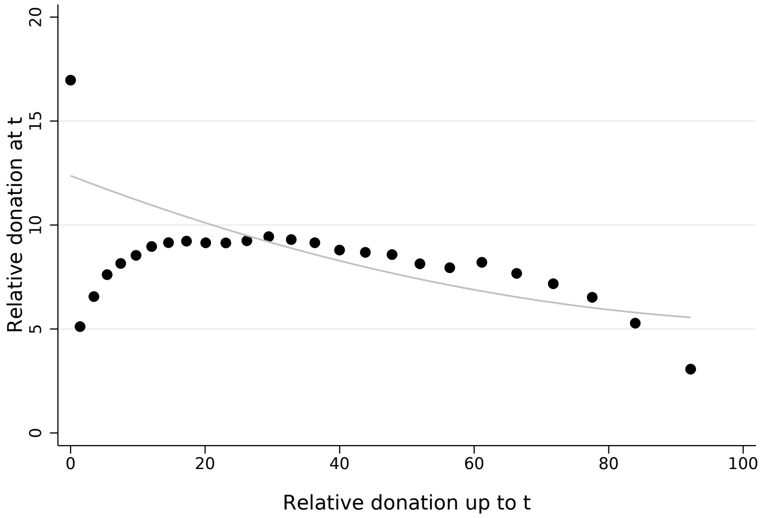
[16] Overall, about 81.37% of donation-date observations are made to projects from low-income schools.

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

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

[19] After excluding the first donations to any projects, the relationship between the accumulated donations and current giving is more transparent (A2).

Figure 1: Relative donation at time t (g_i) by relative donation up to time t (g_{-i})



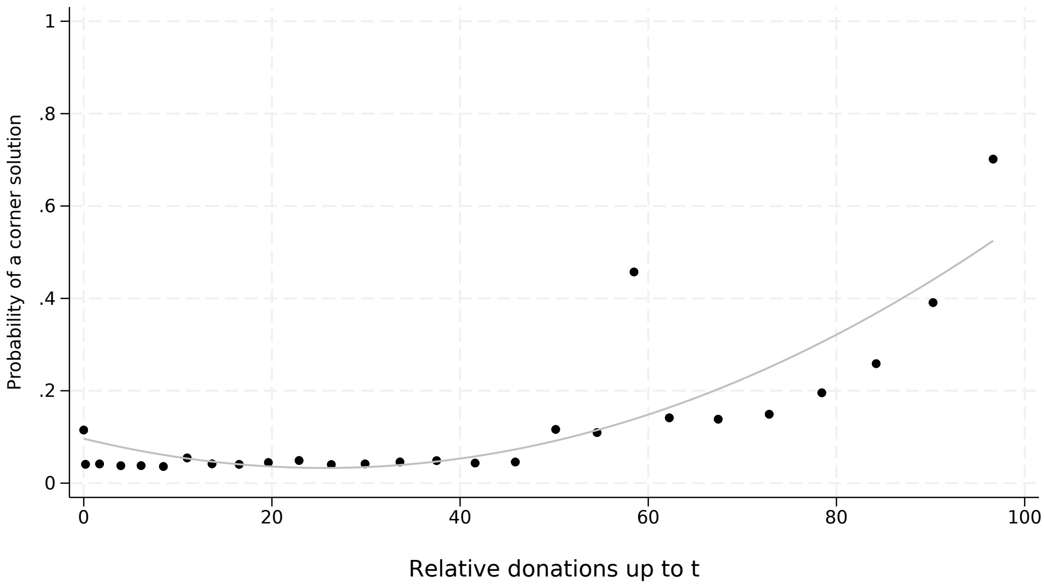
Note: This figure shows the relationship between collected donations and current giving for our preferred sample.

Then, we explore the relationship between the proportion of donations that reached the threshold (probability of a corner solution) and the relative donations up to t. Figure 2 presents evidence of Hypothesis 2 and confirms that the probability of a donor contributing the full amount left (a corner solution) is increasing in the sum of pas donations. We further investigate this by looking at the probability of a corner solution occurring by the relative donation up to t at any given relative time (Figure A3), confirming our Hypothesis 2.

In addition, we show the relationship between a project getting fully funded and the sum of relative donations ($g_{-i} + g_i$) at any given time in Figure A4. It presents evidence of the shape of the probability function introduced in Equation 3 and supports the concavity assumption mentioned in Proposition 2.

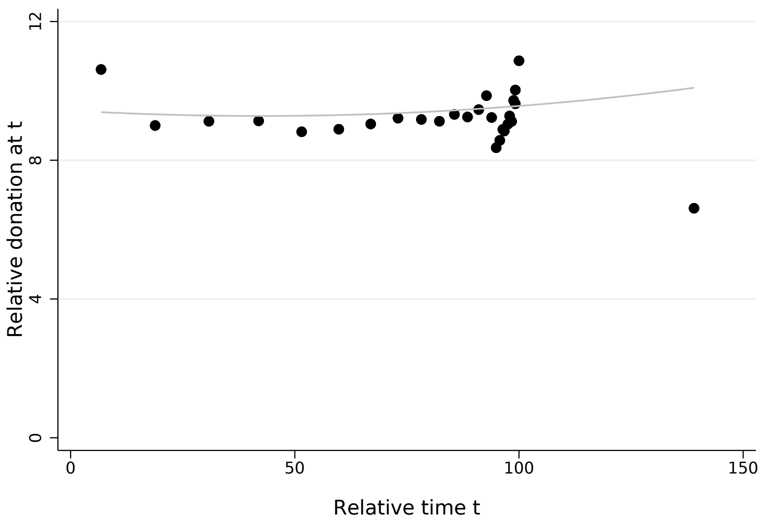
We present the relationship between the percent days passed from the posted date (relative time) and current giving at time t in Figure 3. This figure provides evidence of forward free-riding and confirms our Hypothesis 3.

Figure 2: Probability of a corner solution by relative donation up to t (g_{-i})



Note: This figure shows the relationship between the probability of a corner solution occurring and the sum of past donations up to time t. We use all the observations in our sample that the past giving has not exceeded the threshold.

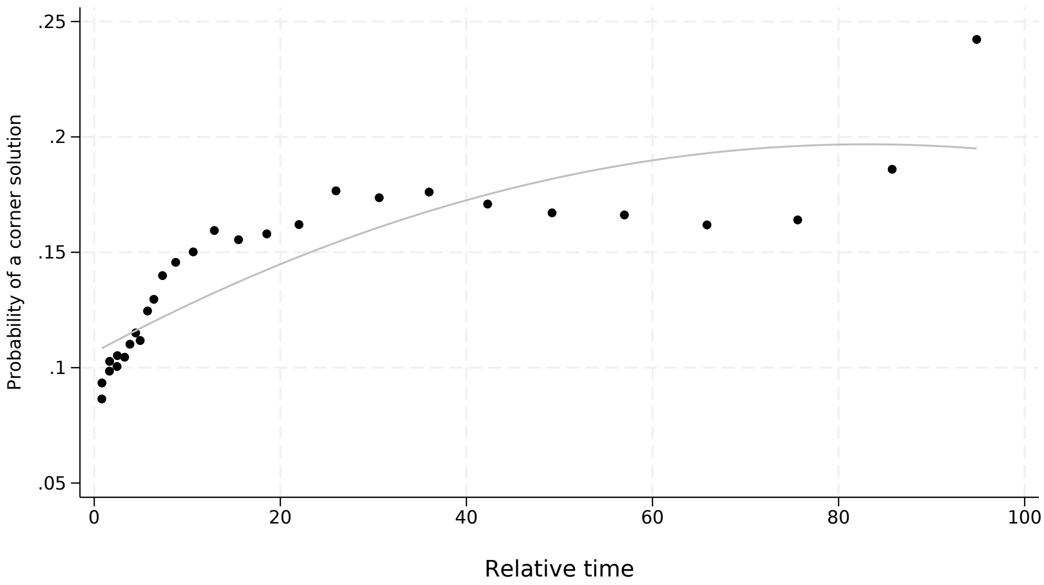
Figure 3: Relative donation at time t (g_i) by relative time t



Note: This figure shows the relationship between the percent days passed from the posted date (relative time) and current giving for our preferred sample.

Similarly, we investigate the relationship between the probability of a donor contributing the full amount left (probability of a corner solution) and the relative time. Figure 4 shows that the probability of a corner solution occurring is increasing in relative time, which confirms Hypothesis 4.

Figure 4: Probability of a corner solution by relative time



Note: This figure shows the relationship between the probability of a corner solution occurring and the percent days passed from the posted date (relative time). We use all the observations in our sample that the past giving has not exceeded the threshold. We also exclude those donations contributed before the official posted date.

We estimate Equations 11 to find the impact of both relative time and past donations on contributions using our preferred sample (excluding corner solution observations). The results are presented in Table 2. Column 1 contains the main result and shows that as the time passed from the posting date increases by one percentage point, the amount contributed decreases by about 0.03 percentage points relative to the project provision threshold. Furthermore, a one percentage point increase in past contributions leads to a reduction of 0.05 percentage points in giving at time t relative to the threshold. Relative donations at time t will be decreasing with the number of donors previously contributing to a project by about 0.07 percentage points. These findings demonstrate that a donor has fewer incentives to give with longer time left to the campaign's expiration or with larger past donations up to the time they visit the website, which is consistent with our theoretical analysis of classic and forward free-riding in Sections 2.3 and 2.4.

We show the results controlling for the possibility that a project is listed on the first page in Column 2, using Equation 15. The results are robust after controlling for project urgency; we still find evidence of classic and forward free-riding similar to Column 1. The coefficient for the first page (as an index for the urgency of a project) shows a positive effect (about 0.8 percentage points on average). Although donors seem to respond differently to those urgent projects, their impact does not reject the free-riding hypothesis. As mentioned before, overall, less than 0.08% of the sample satisfies all the three criteria to be on the first page. [20]

Table 2: The impact of relative time and past donations on contributions - preferred sample

	Relative donations at t (g_i)	
	(1)	(2)
Relative time	0.0270***	0.0268***
	(0.0004)	(0.0004)
Relative donations up to t (g_{-i})	-0.0520***	-0.0520***
	(0.0020)	(0.0020)
Number of donors up to t	-0.0742***	-0.0742***
	(0.0093)	(0.0093)
(Relative time) × (Relative donations up to t)	-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 impact of time left and past donations on giving by estimating Equation 11 (Column 1) for our preferred sample (dropping corner solution observations). All the columns include donation-month-year fixed effects. We estimate Equation 15 in Column 2, controlling for the first page criteria for our preferred sample. Standard errors are in parentheses and clustered at the project level.

In Table 3, we present a set of results estimating how relative time and past donations impact the probability of a corner solution. It shows that the likelihood of a donor contributing the remaining difference to complete a project is increasing in the past donations and the number of days remaining. A one percentage point increase in relative accumulated donations increases the probability of a corner solution by 0.0045, and a one percentage point increase in the time passed (from the posting date) increases the likelihood of the corner solution by 0.0005.

[20] In Table A1, we show the results from estimating Equation 11 using all the observations in our final sample (including corner solution observations).

Table 3: The impact of relative time and past donations on probability of a corner solution - final sample

	Probability of a corner solution at t	
	(1)	(2)
Relative time	0.0005***	0.0004***
	(0.0000)	(0.0000)
Relative donations up to t (g_{-i})	0.0045***	0.0045***
	(0.0000)	(0.0000)
Number of donors up to t	-0.0024***	-0.0024***
	(0.0003)	(0.0003)
(Relative time) $\times$ (Relative donations up to t)	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 impact of time left and past donations on whether a contribution leads to a corner solution, by estimating Equation 11 (Column 1). The outcome variable takes a value of one if a donor's contribution made a project fully funded. All the columns include donation-month-year fixed effects. We estimate Equation 15 in Column 2, controlling for the first page criteria for our preferred sample. Our sample includes all the observations, including corner solutions, but excludes those projects that received only one contribution in total. Standard errors are in parentheses and clustered at the project level.

As discussed in Section 3, we are interested in observing strategic behavior from donors. Hence, the donors who have some ties with the project, school, or familiarity with a teacher may not reveal smooth behavior.[21] robustness check, we exclude the first donation contributed to a project to prevent any behavior caused by other incentives. Table 4 presents the results of estimating Equation 15 using our preferred sample and excluding the first donations received by a project. Our results still show evidence of forward free-riding. However, we do not find evidence of classic free-riding (Table 4 Column 1). Our results suggest that the first donation may play an important role in later contributions. In the absence of the first donations, other motives like warm glow, conditional cooperation, and signaling (as mentioned in section 2.5) minimize the impact of classic free-riding.

[21] As noted in Section 3.1, pre-funding cases exist but they are less than 0.09%; hence, their impact should be negligible.

Table 4: The impact of relative time and past donations on contributions - excluding the first donations

	Relative donations at t (g_i) (1)	Probability of a corner solution at t (2)
Relative time	0.0418***	0.0008***
	(0.0005)	(0.0000)
Relative donations up to t (g_{-i})	0.0051**	0.0049***
	(0.0019)	(0.0000)
Number of donors up to t	-0.0727***	-0.0023***
	(0.0090)	(0.0003)
(Relative time) $\times$ (Relative donations up to t)	-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 impact of time left and past donations on donations (Column 1) and whether a contribution leads to a corner solution (Column 2) by estimating Equation 15, excluding the first donation contributed to a project. Column 1 uses our preferred sample (dropping corner solution observations), while in Column 2, we include all the observations, including corner solutions, but exclude those projects that received only one contribution in total. All the columns include donation-month-year fixed effects. Standard errors are in parentheses and clustered at the project level.

5 Robustness

In this section, we investigate issues that may threaten our identification strategy. In our setup, we consider the across-project variation. Hence, one concern could be whether the results hold after controlling for all the observable characteristics of a project. To do so, we additionally control for the requested amount and estimate Equation 15. The results are shown in Table 5. We find that additionally controlling for the project target goal will not affect our results and we still observe both classic and forward free-riding.

Table 5: The impact of relative time and past donations on donations and the probability of a corner solution - controlling for the requested amount

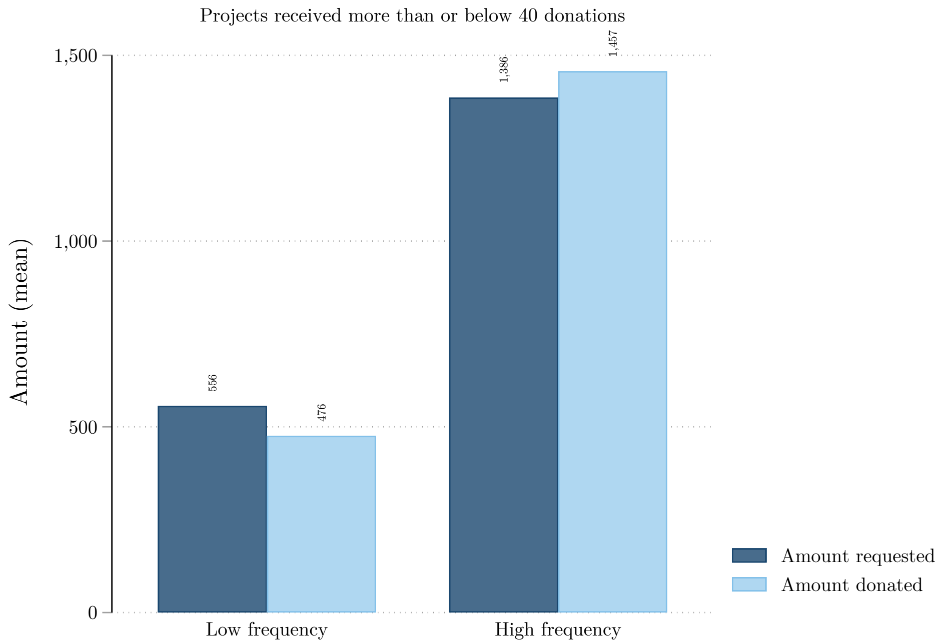
	Relative donations at t (g_i)	Probability of a corner solution at t
	(1)	(2)
Relative time	0.0270***	0.0004***
	(0.0004)	(0.0000)
Relative donations up to t (g_{-i})	-0.0526***	0.0045***
	(0.0020)	(0.0000)
Number of donors up to t	-0.0710***	-0.0024***
	(0.0093)	(0.0003)
(Relative time) × (Relative donations up to t)	-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 impact of time left and past donations on donations (Column 1) and whether a contribution leads to a corner solution (Column 2) by estimating Equation 15. We additionally control for the project requested amount. Column 1 uses our preferred sample (dropping corner solution observations), while in Column 2, we include all the observations, including corner solutions, but exclude those projects that received only one contribution in total. All the columns include donation-month-year fixed effects. Standard errors are in parentheses and clustered at the project level.

In our sample, on average, projects received about 19 donations. However, we also observe that some projects received relatively large numbers of donations. Figure 5 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 in the first place. On average, the requested amount for those projects is about 1,400 USD, which is relatively twice the average requested amount in our final sample (Table 1). This 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. 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 providing evidence of classic and forward free-riding.

Figure 5: Projects with high and low frequencies of contributions



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

Another concern to our identification is a donor who donates to a project multiple times. Donors can be strategic in visiting and contributing to a project multiple times. The incentives behind this behavior can be a concern for our identification. Figure 6 presents the number of donations contributed to a project by a single donor. It shows that in 86.42% of projects, donors contributed only once. Multiple contributions to a project by a donor occurred in rare circumstances. We properly investigated this case by limiting our sample to those donors who contributed to a project only once. Our results are robust to the sample of donors with a single donation to a project (Table 7).

In the DonorsChoose.org platform, teachers ask for different resources for their classroom projects, from art, technology, supplies, etc. It is also interesting to see whether donors behave differently depending on the type of projects requested by teachers. For this matter, we combine projects into four different categories based on teachers' requests and whether they are related to enrichment, classroom supplies, technology, or other needs. Table A2 shows the results for each category. We find consistent results and evidence of classic and forward free-riding across those categories.

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 can have more familiarity with the school or stronger preferences to give to the classroom projects in their geographic locations. To examine whether local or non-local donors behave differently, we look at donations from the same state as the school or from different states. Table A3 shows the results based on the geographic locations of the contributions, and our findings are robust to this consideration.

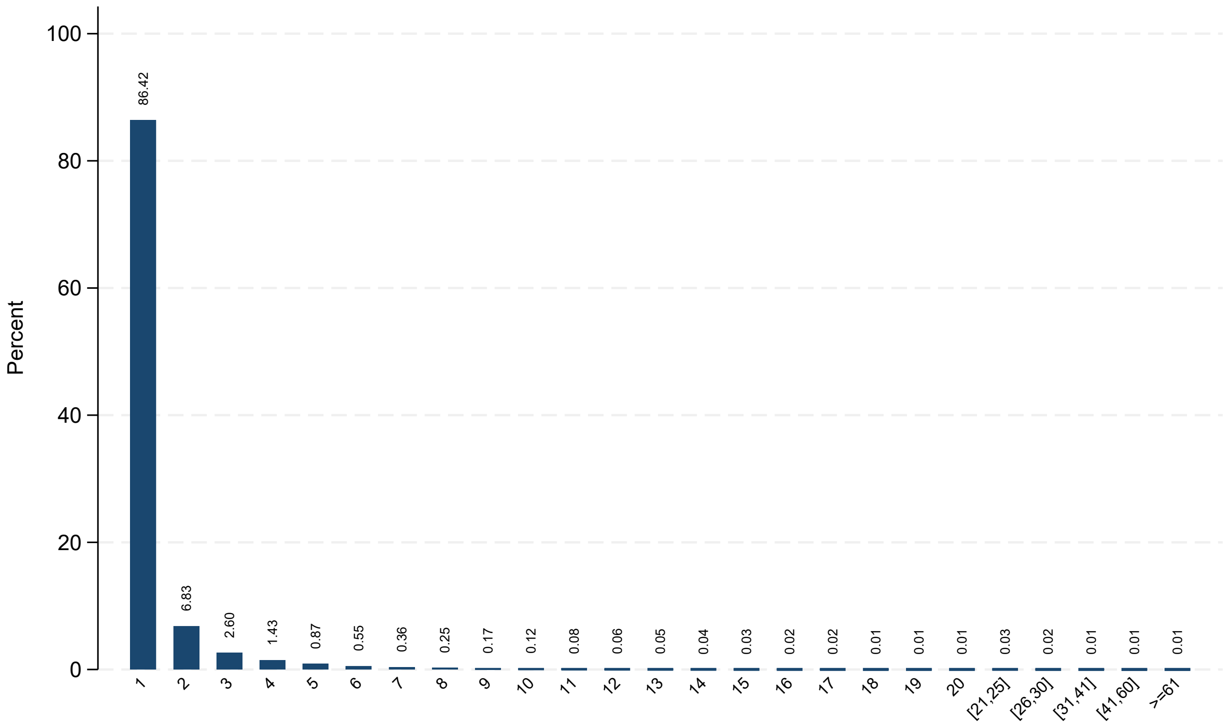
Table 6: The impact of relative time and past donations on contributions - excluding projects with higher frequencies of contributions

	Relative donations at t (g_i)	Probability of a corner solution at t
	(1)	(2)
Relative time	0.0268***	0.0004***
	(0.0004)	(0.0000)
Relative donations up to t (g_{-i})	-0.0520***	0.0045***
	(0.0020)	(0.0000)
Number of donors up to t	-0.0742***	-0.0023***
	(0.0093)	(0.0003)
(Relative time) × (Relative donations up to t)	-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 impact of time left and past donations on donations (Column 1) and whether a contribution leads to a corner solution (Column 2) by estimating Equation 15, excluding those projects with more than 40 contributions (defined as higher frequencies). Column 1 uses our preferred sample (dropping corner solution observations), while in Column 2, we include all the observations, including corner solutions, but exclude those projects that received only one contribution in total. All the columns include donation-month-year fixed effects. Standard errors are in parentheses and clustered at the project level.

Figure 6: Number of contributions 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 relative time and past donations on contributions - excluding donors with multiple contributions to a project

	Relative donations at t (g_i)	Probability of a corner solution at t
	(1)	(2)
Relative time	0.0287***	0.0007***
	(0.0005)	(0.0000)
Relative donations up to t (g_{-i})	-0.0697***	0.0048***
	(0.0022)	(0.0001)
Number of donors up to t	-0.1013***	-0.0036***
	(0.0126)	(0.0004)
(Relative time) × (Relative donations up to t)	-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 impact of time left and past donations on donations (Column 1) and whether a contribution leads to a corner solution (Column 2) by estimating Equation 15, excluding those donors with multiple contributions to a project. Column 1 uses our preferred sample (dropping corner solution observations), while in Column 2, we include all the observations, including corner solutions, but exclude those projects that received only one contribution in total. All the columns include donation-month-year fixed effects. Standard errors are in parentheses and clustered at the project level.

6 Conclusion

In this paper, we focus on donor behavior in crowdfunding platforms. We use data from DonorsChoose.org to estimate the impact of cumulative past donations and time to expiration on donation size. We find that donors reduce their contribution size in response to an increase in both variables, which is consistent with free-riding behavior stemming from altruistic motives. Our results are robust to adding various controls and specifications. However, we find out that excluding the first donations diminishes the impact of classic free-riding in favor of other motives.

We should emphasize that the prominence of free-riding behavior and the partial crowd-out effect of past donations do not indicate the absence of other motives for giving. In fact, our simple theoretical analysis demonstrates that the net effect observed is a result of interaction between various giving motives, and the direction of the effects simply points to the strongest driver of giving. Our results suggest that in the context of crowd-funding platforms, altruism (donors' focus on public good provision) is the dominant force. However, the literature on this topic is rather recent, and there is a need for further investigation of this research question.

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A Appendix

Figure A1: Sample of DonorsChoose.org Requested Project

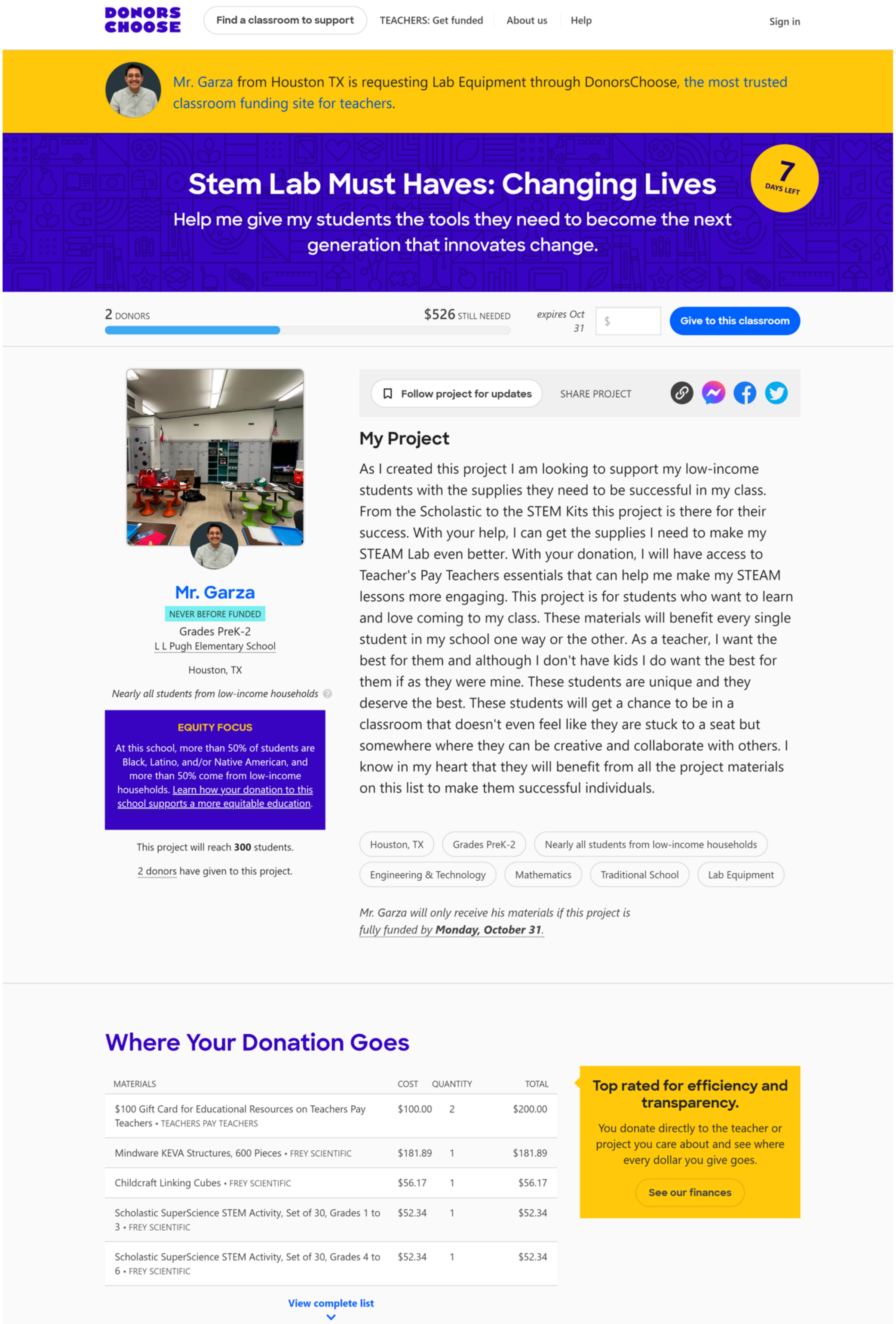
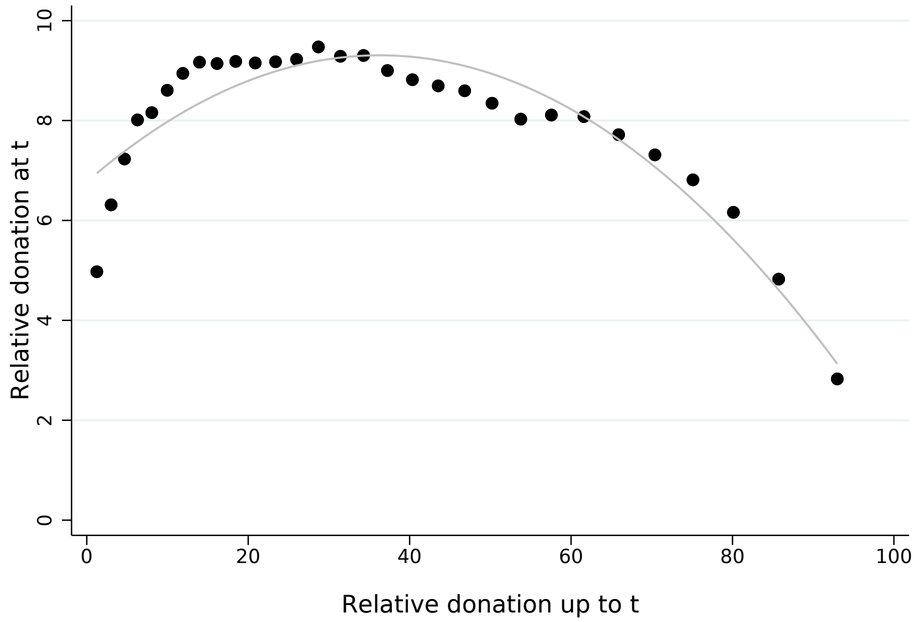
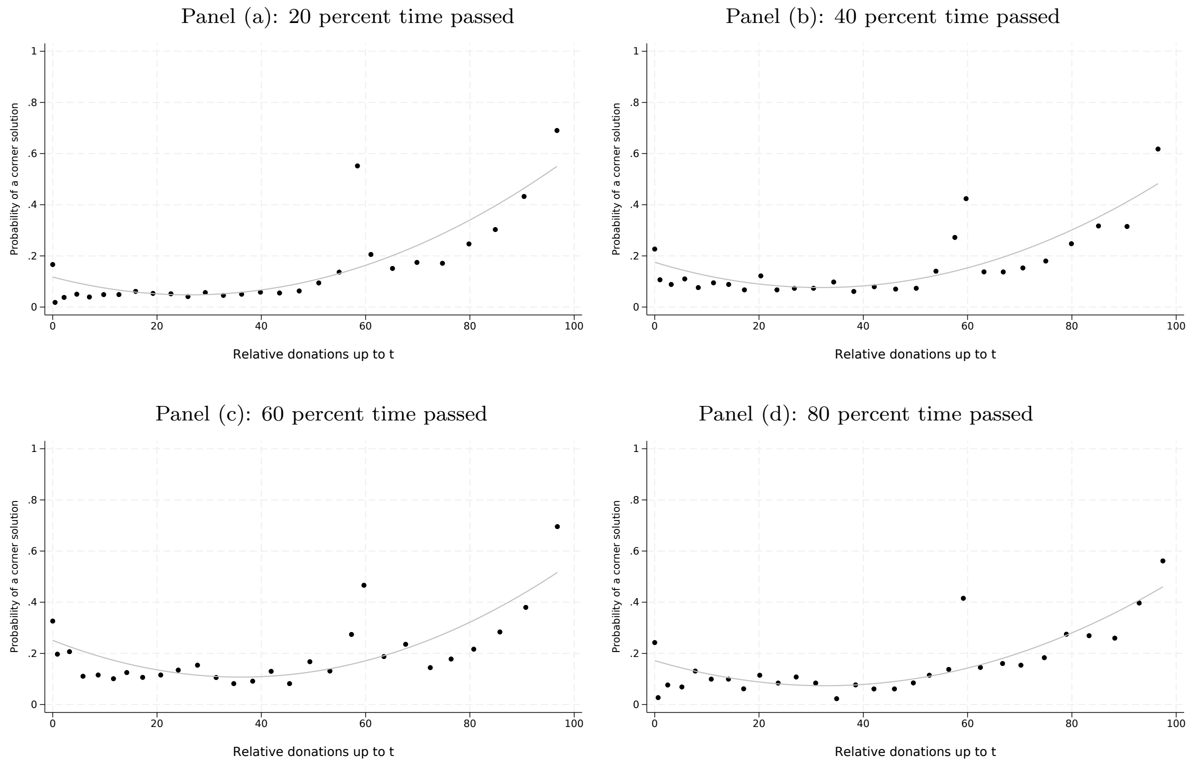


Figure A2: Relative donation at time t (g_i) by relative donation up to time t (g_{-i})



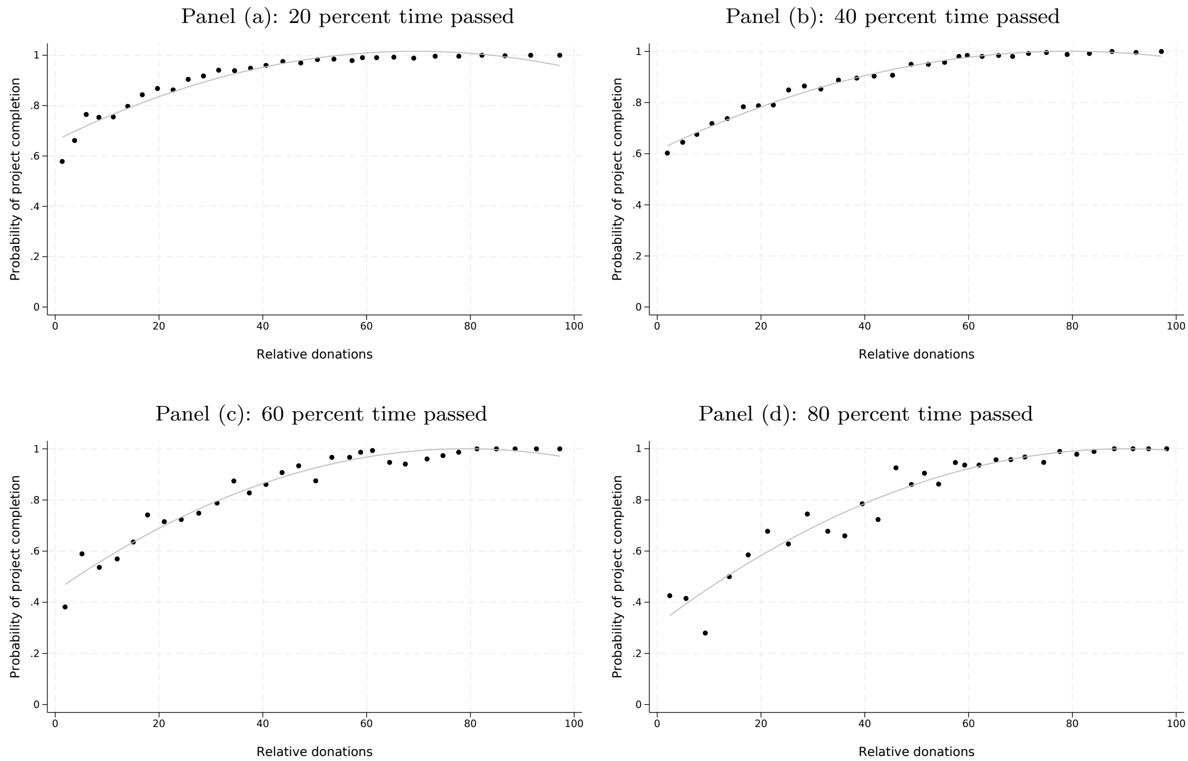
Note: This figure shows the relationship between collected donations and current giving for our preferred sample, excluding the first donations to the projects.

Figure A3: Probability of a corner solution by relative donation up to time t (g_{-i})



Note: This figure shows the relationship between the probability of a corner solution occurring and the sum of past donations up to time t at any given time. We use all the observations in our sample that the past giving has not exceeded the threshold.

Figure A4: Probability of project completion by the sum of relative donations $(g_{-i} + g_i)$



Note: This figure shows the relationship between the probability of a project being fully funded and the sum of donations at any given time. We use all the observations in our sample that the past giving has not exceeded the threshold.

Table A1: The impact of relative time and past donations on contributions - final sample

	Relative donations at t (g_i)	
	(1)	(2)
Relative time	0.1473***	0.1471***
	(0.0062)	(0.0063)
Relative donations up to t (g_{-i})	-0.0481***	-0.0481***
	(0.0040)	(0.0040)
Number of donors up to t	-0.1265***	-0.1265***
	(0.0163)	(0.0163)
(Relative time) × (Relative donations up to t)	-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 impact of time left and past donations on giving by estimating Equation 11 (Column 1) for our final sample (dropping corner solution observations). All the columns include donation-month-year fixed effects. We estimate Equation 15 in Column 2, controlling for the first page criteria for our preferred sample. Standard errors are in parentheses and clustered at the project level.

Table A2: The impact of relative time and past donations on contributions by project resource types

	Relative donations at t (g_i)				Probability of a corner solution at t			
Resource Type	Enrichment	Supplies	Technology	Others	Enrichment	Supplies	Technology	Others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Relative time	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)
Relative donations up to t (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)
(Relative time) × (Relative donations up to t)	-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 impact of time left and past donations on donations (Columns 1-4) and whether a contribution leads to a corner solution (Columns 5-8) by estimating Equation 15, by resource types requested by teachers. Columns 1-4 use our preferred sample (dropping corner solution observations), while in Columns 5-8, we include all the observations, including corner solutions, but exclude those projects that received only one contribution in total. All the columns include donation-month-year fixed effects. Standard errors are in parentheses and clustered at the project level.

Table A3: The impact of relative time and past donations on contributions by geographic location

	Relative donations at t (g_i)		Probability of a corner solution	
	Same state	Different state	Same state	Different state
	(1)	(2)	(3)	(4)
Relative time	0.0297***	0.0004***	0.0400***	0.0008***
	(0.0006)	(0.0001)	(0.0007)	(0.0000)
Relative donations up to t (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)
(Relative time) × (Relative donations up to t)	-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 impact of time left and past donations on donations (Columns 1-2) and whether a contribution leads to a corner solution (Columns 3-4) by estimating Equation 15, based on donation geographic locations. Columns 1-2 use our preferred sample (dropping corner solution observations), while in Columns 3-4, we include all the observations, including corner solutions, but exclude those projects that received only one contribution in total. Columns 1 and 3 show donations coming from the same state as the school, while columns 2 and 4 show out-of-state donations. All the columns include donation-month-year fixed effects. Standard errors are in parentheses and clustered at the project level.