Fundraising Outcomes and Donation Behavior

Abhishek Rishabh* Anna Tuchman Pradeep Chintagunta

Northwestern–Kellogg Northwestern–Kellogg Chicago–Booth

June 30, 2023

Preliminary and Incomplete. Do not cite without permission.

Click here for the latest version

Abstract

Some donation platforms aim to raise funds for causes with a specified target amount (the goal) and a deadline. In such situations, it is possible that a cause is not fully funded, with the platform sometimes diverting the funds to a different cause rather than returning it to the donors. Donors' future participation on such a platform, is therefore contingent on the outcome of the fundraisers they participate in and how the platform deals with the fundraiser outcome. Theories in social exchange predict that a donor would reduce future participation in the event of a failure, conversely, warm glow would predict no change in future participation. In this paper, we investigate the impact of fundraising experiences on donors' future giving on such a platform. To this end, we use donor- and cause-level data from one of the largest donation platforms and leverage a shock to the platform that exogenously shifted a donor's propensity to experience a fundraising failure. to document that if a donor's first fundraising experience is a failure (with the money diverted to a different cause), then they are 32.8% more likely to not contribute in future (i.e., "churn"). Further, conditional on donating in the future, they reduce their donation amount by 61.9%. To understand the mechanism underlying our findings, we conducted a survey on MTurk and find that donors only blame the platform (supporting the expectation disconfirmation theory) and not themselves or other donors for the failed fundraiser. To obtain further substantive implications of our results, we formulate a structural model of a donor's decision journey and use the estimates

*abhishek.rishabh@kellogg.northwestern.edu is a Golub Capital Social Impact Post Doctoral Fellow in Marketing at Northwestern's Kellogg School of Management. Anna Tuchman is an Associate Professor at Kellogg and Pradeep Chintagunta is a Professor at the Booth School of Business, University of Chicago.

We thank Chethana Achar, Dean Karlan, and Angela Lee for their help and support, Donorschoose.com for providing the data, members of the Golub Capital Lab at Kellogg and participants at brown bag seminars at Northwestern for their insightful comments, and the Kilts Center for Marketing for financial support. IRB approval was provided by Northwestern University (STU00219174).

of the model to examine the efficacy of various churn-reducing tactics. We find a 2.5% increase in retention(translates to an extra $ 2.1M in donations) by using a ranking algorithm for first-time donors that orders projects by their success probabilities.

Keywords: fundraising, donation platforms, churn, ranking algorithms, state dependence

1 Introduction

On many donation platforms, individual fundraisers are posted with a specified target amount (the goal) and a deadline. Some projects manage to raise the goal amount by the deadline, while other projects fall short. Henceforth in this paper, we refer to this latter group as failed fundraisers. Such fundraising failures are common. For example, more than 88% of medical expenses-related fundraisers fail to reach their goal amount. 16% of fundraisers are not able to raise a single dollar (Lee (2022)). Furthermore, online donor retention is low at 23% (Blackbaud 2022), compared to 75% retention in product markets (Statista 2023). In this paper, we explore the relationship between failed fundraiser experiences of donors and their churn rates and future dollar contributions.

Donation platforms play a key role in determining the nature of this relationship, as different platforms have different approaches for how to deal with fundraising failures. Consider the following example. A fundraiser is posted on an online crowd-sourcing donation platform and a donor makes a donation to a cause.[1] In a few days, the donor is informed that the fundraiser was not able to raise the goal amount before the fundraiser's deadline. Donation platforms deal with failure in a variety of ways. Table 1 below presents various strategies and examples of donation platforms. These strategies can influence how donors interact with the platform in the future.

[1]A crowd-sourcing donation platform is a digital service or tool that facilitates the process of giving money to individuals, groups, or organizations. These platforms provide a secure and efficient method for people to donate to causes, charities, or projects.

Table 1: Donation platform strategy

Strategy	Example
Return donations to donors	Indiegogo (2021)
Transfer all donations to beneficiary	GlobalGiving (2021)
Redirect donations to other projects	DonorsChoose (2020)

In this paper, we focus on a platform that redirects the donations of failed fundraisers to other projects on the platform, and we aim to answer the following questions: (i) does a failed fundraising experience affect a donor's future participation (churn and dollar contribution) on the platform; (ii) if so, what is the mechanism underlying the observed effects; and (iii) what actions can the platform take to address any negative consequences for donor retention and future contributions?

Theories in social exchange (Andreoni and Payne 2013) would predict that since the donor did not get what they intended from their donation, it would lead to disappointment; however, this disappointment may or may not have implications for the donor's future participation with the donation platform. For example, the commitment inertia or warm glow theories (Andreoni 1990, Karlan and Wood 2017) would predict that disappointment would have no effect, as the outcome of the project does not affect a donor's future participation. On the other hand, the expectation disconfirmation theory (Oliver 1977, 1980) would predict a reduction in future participation. Finally, one could argue that if the donor feels that increasing their donation amount would have helped complete the project, they might instead increase their future participation. Ex ante, it is not clear which one of these explanations is supported in the field and how donors actually behave after a failed fundraising experience. We formalize this tension in the theoretical motivation section (see Appendix A).

For our empirical investigation, we analyze data from one of the largest US-based donation platforms, DonorsChoose. This platform helps school teachers raise money for their classroom projects. These projects include buying books, stationery, musical instruments, class repairs, etc. The platform provided us with detailed transaction-level data from the DP's inception, i.e., nearly 20 years of data. We first document that 30% of all the projects listed on the platform fail to raise their targeted goal amount in the designated time period. Furthermore, donor attrition after the first donation is 73%, and after two donations is almost 87%. We want to understand how much of this attrition is due to negative reactions to fundraising failures.

With this motivation in mind, we leverage a natural experiment to identify the impact of fundraising failure on future donor behavior. In particular, in May 2015, Stephen Colbert, a famous American talk show host, funded all the live projects on the platform based out of South Carolina (Brenneman 2015). As a result, the donors to these causes did not experience any fundraising failures, while donors to similar causes based out of other states did. This intervention serves as a quasi-experimental setting where we can compare donors who get their project completed due to the intervention to "similar" donors who have a status quo success rate of 70%.In particular, we use the Stephen Colbert intervention as an instrumental variable, and we construct a group of similar donors using propensity score matching where donors are matched based on their first transaction details such as amount donated, time period, and the recipient project's category, grade, and resource category (Rosenbaum and Rubin 1983). Our identification strategy rests on an assumption of low to no information dissemination (through news, web search, and internal email data) about Colbert's involvement to donors and potential donors of the DP. We present data on Google Trends searches that supports this assumption. Thus, the effects we measure are purely due to project completion and not a combination of celebrity endorsement and project completion.

We find that if the donor's first donation experience is a failure, she is 23.6% percentage points more likely to churn, i.e., not donate again (the "extensive margin") and conditional on future donation, such donors reduce their dollar contribution by nearly 62% (the "intensive" margin). The results indicate not only immediate effects (donor churns) but also a lasting effect, where a donor who wanted to donate reduces their contribution because of their failed fundraising experience. We complement our findings with heterogeneous effects, specifically, we test if the failed fundraising experience is moderated by the geographic proximity of the donor to the project (local philanthropy (Agrawal et al. 2015, Burtch et al. 2014)), the time to donation (goal gradient (Kuppuswamy and Bayus 2017, Cryder et al. 2013)) and the donation amount (willingness to give (Jensen et al. 2013)).

Next, we explore the causes underlying our findings. We hypothesize three potential explanations. First, donor churn may be prompted by dissatisfaction with the platform (Anderson and Sullivan 1993). Second, it could be a consequence of disappointment with peers or others (society), leading donors to reevaluate their generosity and subsequently opt out (Festinger 1954). Lastly, the churn could stem from self-disappointment, where donors feel ineffective or incapable of selecting appropriate projects for their donations (Bandura and Wessels 1994). Using a survey conducted on Amazon Mechanical Turk with 600 participants, we first confirm the results from the reduced form analysis— learning of a donation failure leads participants to report a lower likelihood of donating again. Additional mediation analysis indicates that participants only blame or are disappointed in the platform and not themselves or others.

Given that donors find the platform to be the source of their disappointment, we propose potential tactics that the platform could use to reduce churn. Under the status quo, the rank order display of projects on the platform's homepage is not personalized for each donor. We propose that if the platform was able to show donors projects that had a higher probability of success, they would be able to reduce churn rates. Given that altering the rank algorithm for all website visitors would likely have substantial equilibrium effects, we propose that the platform focus on prioritizing high-success probability projects for first-time donors. We focus on first-time donors because prior work has shown that the utility a customer derives from their initial purchase experience can affect their expectations about future purchase occasions (Kim 2020).

To quantify the impact of prioritizing high-success probability projects in the ranking algorithm, we build a structural model in which the utility derived by a donor is a function of the page rank of the project, project features, and a state dependence variable that records whether the donor's previous donation experience ended in a success or failure. Apart from the transaction data set obtained from the platform, we require two other critical building blocks in order to estimate the model – the interarrival time of donors and the ranking algorithm of the platform. We use the comScore dataset to estimate the interarrival time.[2] In particular, to generate potential choice events (visit but no donation), we use the comScore data and then supplement it with the platform's transaction data to recreate a donor's decision journey. This reconstruction of website visits without a donation is critical because our research question focuses on understanding the impact of past fundraising failures on the extensive margin – whether to give.

To infer the page rank of projects, we scrape data from the platform website for 25 days and use a "Learning to Rank" algorithm (Burges et al. (2005)) to learn how the ranks on the webpage are a function of the project features (number of donors, category, days to raise, the amount left to raise, etc.) In training this algorithm, we use institutional information from the firm and Vana and Lambrecht (2022)'s observation that the ranks of the projects are a nonlinear function of project features. Using these three data sets, we estimate our structural model. Since our data are at the donor level, we use a random coefficients logit model that allows for heterogeneity across donors in the effects of the model parameters. We estimate the model using simulated maximum likelihood.

The model estimates reveal that if a donor experiences success, their probability to donate again increases by 12.5%. In the counterfactual analysis, we modify the page rank design such that first-time donors are shown the projects with the highest probabilities of completion. We find that such a redesign leads to a probability to donate again of 12.81%, an increase of 2.5%. Such an increase translates to a $2.1 million increase in total donations.

This paper contributes to both theory and practice. Theoretically, it shows that failed fundraisers have substantial negative effects on future participation on donor platforms and thus supports the predictions from the expectation disconfirmation theory. Furthermore, we estimate heterogeneous effects and find support for theories in local philanthropy and willingness to give; however,

[2]Interarrival time refers to the time between two visits by the donor on the DonorsChoose website. The visitation may or may not include a donation event.

we find evidence against goal gradient. To understand the mechanism behind our findings we conducted a survey and, based on the results, we are able to reject self-efficacy or social comparison as reasons behind churn. Rather, donors only blame the platform for the fundraising failure. Lastly, through the structural model, we are able to highlight the importance of state dependence in the charitable giving context and how better donation experiences (through an updated ranking algorithm) can lead to increased retention. In practice, this paper has implications for understanding the impacts of failed fundraisers and for platform design. Specifically, this paper helps managers quantify the impact of unsuccessful donation experiences and related donor churn. Further, it proposes a low-cost solution to improve donor retention by increasing the probability that a first time donor experiences a successful campaign.

2 Institutional Information

The donation platform we study, DonorsChoose, began its operations in the United States in 2000. It is a crowdfunding platform specifically designed for teachers to raise funds for educational projects and classroom resources.[3] For example, teachers can use it to raise money for repairing classrooms, buying books, and acquiring computing equipment. The platform connects teachers who have specific project needs with donors who are willing to contribute and support those projects. In 2021, the platform received $187 million in funding from contributions and grants (DonorsChoose.com (2022)) and as of 2018 almost 80% of all public schools in the US have had at least one project on the platform (Lambeck (2018)). The donation platform makes money from grants and takes a cut from the donation amount. The platform claims to pass through 95% of all donations, leaving only 5% for overhead and other administrative expenses. Donors can

[3] The platform defines a *teacher* to be a full-time employee of a PreK-12 public school, charter school, or Head Start Center in the 50 states or District of Columbia that is approved and verified by DonorsChoose. Teachers should work directly with students at least 75% of the time. Administrators, paraprofessionals, teacher's aides, substitute teachers, and student teachers are not eligible to post projects on the platform. The school administration is generally not involved in any capacity, with the exception of some school districts that have banned teachers from posting projects on the platform. (Source: https://www.edweek.org/leadership/school-districts-are-banning-teachers-from-using-donorschoose/2019/03)

claim a tax deduction on all donations made on the platform, under the 501(c)(3) tax code.

When a teacher creates a project on the platform, they set a funding goal that represents the total amount of money needed to fully implement their project. The deadline for the project is decided by the platform and is generally around 120-130 days from the date of posting. Donors can browse through the various projects on the platform. For each project, a donor can see information such as the project's need, total goal amount, days remaining until the project deadline, the amount remaining to be raised, school name and location, and a detailed project pitch from the teacher. Donors can choose to donate to one or multiple projects.

If the project is successful, the platform orders the requested items from their verified vendors and the items are delivered to the teacher that posted the project.[4] The project's donors receive a thank-you letter and are informed that the necessary supplies have been secured and delivered.

If a project fails to reach its goal amount within the designated time limit, the platform reaches out to the project's donors to check if they would like to reallocate their donation to a different project. If a donor does not respond within 30 days, their donation amount is redirected to an urgent classroom project of the platform's choice. The platform communicates with donors via email about how their money is used. It is important to note that under no circumstances does the donor receive a refund for their donation. Approximately 30% of all the projects registered on the platform fail to reach their goal amount.

On any given day, there are approximately 25,000-30,000 projects listed on the website. The presentation of the project listings is not customized for each website visitor. We conducted checks by logging into the website using multiple devices (mobile phone vs. laptop), from various locations (within the US and India), and using different browsers (Google, DuckDuckGo, etc.) and confirmed that the project rankings did not change across devices, locations, and browsers.

[4] Materials funded through the platform are meant for the classroom to which the materials are shipped. The teacher that posts the project controls the use of the materials.

3 Data

At a high level, the goal of this project is to ascertain whether project outcomes affect donor retention. Thus, we begin by showing descriptive patterns on these two key metrics of interest – donor retention and project success. The left panel of Figure 1 shows that 73% of all donors donate only once, while 13% of donors have donated 3 or more times to the platform. This is typical of online giving in the US, where online donor retention is about 29% (BlackBaud (2021)). The right panel of Figure 1 shows that almost 29% of projects fail to raise funds.

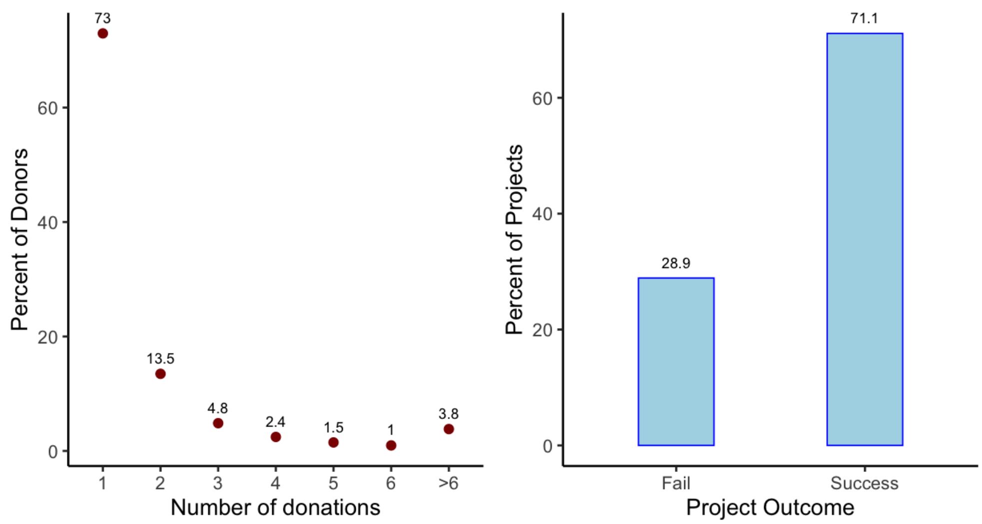


Figure 1: Donor Retention and Project Outcomes

Note: The left panel plots the percent of the platform's two million donors that make a given number of contributions. The right panel plots the percent of the platform's one million projects that succeed vs. fail to raise funds within the project's deadline. Data ranges from 2013-18.

Digging deeper into the data on donors, on average, a donor contributes $56 per donation and a total of $140.40, with an average of 2.2 transactions between 2013-2018. Conditional on donating at least twice, the distribution of inter-donation time (i.e. the time between two donations) is presented in Appendix Figure A11. The median inter-donation time is 78 days. Furthermore, we find that donations are not highly localized; donors do not just donate to their neighborhood schools or even schools in their home state. 35% of donors donate to a project based in another state and more than 50% of donors donate to schools at least 33 miles away (see Appendix Figure

A10). The average donor resides in a neighborhood with a median household income of $51,204 and donates to schools that are located in neighborhoods with a median household income of $49,056.

Turning to the supply side, 333,856 teachers post a project, where the median number of projects posted by a teacher is 1 and the mean is around 2.7. In our analysis, it will be important to account for teachers' experience with the platform, as it could directly impact the project quality and thereby donations. Out of the 1 million projects in the data, more than 75% are for Grades PreK-2 and Grades 3-5, and the resource requests of these projects are largely centered around Books, Supplies, and Technology products. Projects are posted throughout the year, but a relatively higher proportion of projects are posted during the Fall months (see Appendix Figure A2). The median project cost is around $512, the mean project cost is $735, and 95% percent of projects are under $1,995.[5] More than 75% of successful projects are able to raise funds within 60 days of listing (see Appendix Figure A7). Once the project achieves its goal amount, it is removed from the platform. Furthermore, among the projects that fail, more than half are not able to raise even 50% of their ask (see Appendix Figure A8).

4 Reduced Form Evidence

We are interested in understanding the impact of fundraising failures on future donations. Given the high attrition rate of 73% after the first donation (see Figure 1), we focus on the impact of the first donation experience (success/failure) on future donations (churn and dollar value). In this section, we first present raw correlations between a donor's first donation experience and their future donation behavior. Next, we discuss potential endogeneity concerns, describe how we address these endogeneity concerns using quasi-experimental methods, and present the results. Finally, we explore heterogeneity in how donors respond to experiencing a first donation failure.

[5] Appendix Figure A12 shows an example of how a project's itemized costs are presented to donors.

4.1 Correlational Evidence

Do first-time donors that contribute to a project that succeeds return to the platform at a higher rate than first-time donors that contribute to a project that fails? To operationalize this, we estimate equation 1. $Churn_{i2}$ takes a value of 1 if donor i churns after the first donation and 0 if they donate again. FDE_i represents the first donation experience of donor i and takes a value of 1 if the project is a failure and 0 if the project is successful. β_1 captures the correlation between experiencing a first donation failure and subsequently churning from the platform.

$$\underbrace{Churn_{i2}}_{\text{Did donor churn after first transaction?}} = \beta_0 + \beta_1 FDE_i + \varepsilon_i \tag{1}$$

Next, we also estimate the correlation between experiencing a first donation failure and a donor's future donation amount. We compute a donor's future donation amount as the sum of their future donations, $\sum_{t=2}^{T_i} D_{it}$, where i represents the donor index and t is the transaction index for each donor. If the donor never donates again, the variable takes a value of 0. To account for skewness in the data, we take the natural log transformation and add 1. In equation 2, β_1 reflects the correlation between experiencing a first donation failure and the number of subsequent donations on the platform.

$$\log(1 + \underbrace{\sum_{t=2}^{T_i} D_{it}}_{\text{Future Donations}}) = \beta_0 + \beta_1 FDE_i + \varepsilon_i \tag{2}$$

The results from estimating equations 1 and 2 are reported in Table 2. Across multiple model specifications, we find that if the project outcome is a failure, donors are less likely to churn compared to donors who experience success, and the log of total future transactions is also negatively correlated with the first donation failure variable. Specifically, if the first donation experience is a failure, the probability to churn reduces by 1 percentage point (Pr(Churn| FDE=Success)=0.78, Pr(Churn|FDE=Fail)=0.77) and the future dollar contribution increases by 2.8%(=100*exp(0.028)-1). However, these correlations need not reflect a causal relationship due to potential endogeneity arising from unobserved confounders. We will describe the potential sources of endogeneity and solutions to resolve it in the following section.

Table 2: OLS - Churn and Future dollar contribution

	Dependent variable:			
	Churn	log(Tot Future Don + 1)	Churn	log(Tot Future Don + 1)
	(1)	(2)	(3)	(4)
FDE	-0.010^{***}	0.028^{***}	-0.013^{**}	0.045^{***}
	(0.001)	(0.004)	(0.001)	(0.005)
Constant	0.788^{***}	0.806^{***}	–	–
	(0.0003)	(0.001)		
Controls	N	N	Y	Y
Observations	1,684,144	1,684,144	1,101,400	1,101,400
R^2	0.051	0.061	0.052	0.059

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results from estimating equations 1 and 2. Columns 1 and 2 report raw correlations without controls. Columns 3 and 4 add the following control variables: Project Cost, Time to Raise Funds, Distance between Donor and School, and fixed effects for Donor State, School State, Resource Category, and Subject Category. FDE takes a value of 1 if the first donation experience is a failure and 0 if it is a success.

4.2 Identification

The challenge we face is that donors who contribute to projects that end up failing may differ in their baseline propensity to churn relative to donors who contribute to projects that end up succeeding. For example, in the context of equation 1, there may be some unobserved factor - say, generosity - that correlates with a donor's propensity to experience a first donation failure and to churn. If more "generous" donors are more likely to take a risk on a project, they may be more likely to experience a first donation failure, but this generosity may also make the same donor more likely to return to the platform to donate again. Failing to account for heterogeneity in generosity across donors could make it look like experiencing a donation failure actually makes a donor more likely to return.

From an identification perspective, it is helpful to imagine what the ideal dataset would look like and then consider how we can approximate this setting using the observational data we have.

Suppose we could conduct an experiment in which we randomize donors into two groups: a treatment condition in which donors are told that the project they contributed to failed, and a control condition in which donors are told that the project succeeded. This randomization would make the first donation experience variable orthogonal to all other factors that contribute to a donor's churn probability. We could then compare the mean difference in churn across the two groups to learn about the causal effect of donation failure on future churn and donation behavior.

In practice, we are not able to run such an experiment in the field. Instead, we utilize quasi-experimental methods to isolate variation in fundraising outcomes that is arguably orthogonal to other factors that predict a donor's return donation behavior.

4.3 Instrumental Variables Approach

We use an instrumental variables approach that leverages a shock to the platform that exogenously shifted a donor's propensity to experience a fundraising failure. In May 2015, Stephen Colbert, a popular American talk show host, completed all of the available projects based in South Carolina (Brenneman 2015). If a project was live on the donation platform with some remaining amount to be completed and the beneficiary school was based anywhere in South Carolina, Stephen Colbert's philanthropic fund paid its outstanding balance. In total, Colbert donated $800,000 to schools in South Carolina. As a result, the donors who had previously contributed to the projects that were completed by the Stephen Colbert fund experienced a donation success, but in expectation, 30% of these projects would have failed if Colbert had not intervened. Our instrumental variables approach will compare these "treated" donors with similar donors who contributed to similar projects that were not completed by Stephen Colbert because the projects were based in another state or in a different time period.

Specifically, we want to estimate the causal effect of experiencing a donation failure, as shown in equation 1. We operationalize the IV approach by constructing a dummy variable $StephenColbert_i$ that takes on a value of 1 for donors that contributed for the *first time* to a project in South Carolina which was live (available on the website for donation) in May 2015.[6] The variable takes on a value of 0 for donors that contributed to projects based in other states and for other periods (including for South Carolina). We instrument for FDE_i using $StephenColbert_i$.

In order to be a valid instrument, the variable needs to satisfy the requirements of IV relevance (the inclusion restriction) and IV exogeneity (the exclusion restriction). We first provide some visual evidence regarding the relevance of the instrument. Figure 2 plots the month of posting on the x-axis against the percentage of projects that were successfully funded on the y-axis. The data is plotted separately for projects located in South Carolina and its neighboring states. Given that projects are typically live for about three to four months, projects posted in January - April 2015 were active in May 2015 when Colbert made his donation. First, the graph shows that the completion rate jumps up to almost 100% for projects posted in South Carolina in the months leading up to May 2015. Second, this jump is not cyclical – this discontinuous jump happens only once between 2013-2017. Third, we do not find such jumps in neighboring states (North Carolina, Georgia, and Tennessee) around the same time. Taken together, Figure 2 provides strong evidence that Stephen Colbert's donation increased the first donation success probability for donors that contributed to a project based in South Carolina in the months leading up to May 2015. We also provide results from first-stage regressions (see Table A3) and report the coefficients and F stats, the results indicate the Stephen Colbert intervention is a strong instrument.

The IV exclusion restriction requires that the instrument should not effect the outcome variable of interest, $Churn_i$, except through its effect on the endogenous variable, FDE_i. One potential way the Stephen Colbert event could violate the exclusion restriction is if the event garnered attention in the press, which could make DonorsChoose more top of mind for donors or lead them to increase their prior beliefs about the platform's quality. This could lead donors to be more likely to donate to the platform in the future, and this pathway would be separate from the project completion effect. To address this concern, we looked into how much public

[6]This data includes the donors who have donated in earlier months for example, March, but the project was available to donate in May 2015.

exposure Colbert's donation received. We found that there was no explicit communication by the platform about Colbert's involvement. Further, we also collected data on web search (we search for DonorsChoose and Stephen Colbert keywords) and news trends using Google Trends, which we plot in Figures A13 and 3, respectively. We do not find any substantial changes in news coverage (obtained from google trends[7]) of Stephen Colbert or DonorsChoose during the time of the event. Furthermore, Stephen Colbert was off-air during this period: he hosted Colbert Report from Oct 2005 to Dec 2014 on Comedy Central and started hosting Late Night with Stephen Colbert from Oct 2015 onwards.[8] In light of these institutional facts, we argue that the only way Stephen Colbert's donation should affect donors' churn probability is through changing the success probability of the first donation experience.

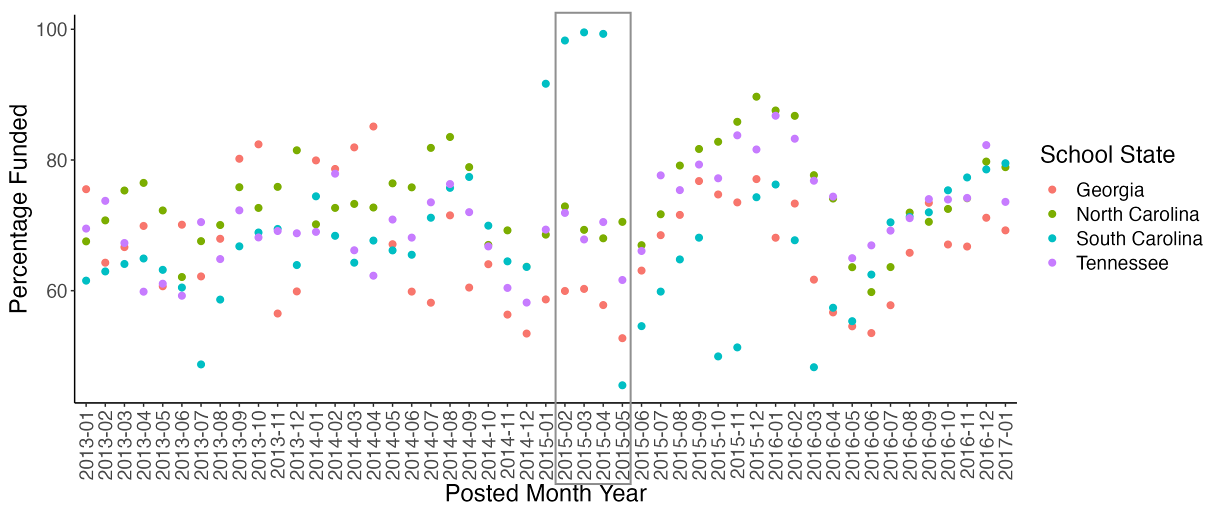


Figure 2: Percent of projects funded by month year of their posting

[7]Google Trends News Search - https://techcrunch.com/2017/11/27/google-trends-now-surfaces-data-from-news-images-youtube-and-shopping-verticals/

[8]Colbert Report - https://www.imdb.com/title/tt0458254/. Late Night with Stephen Colbert - https://www.imdb.com/title/tt3697842/

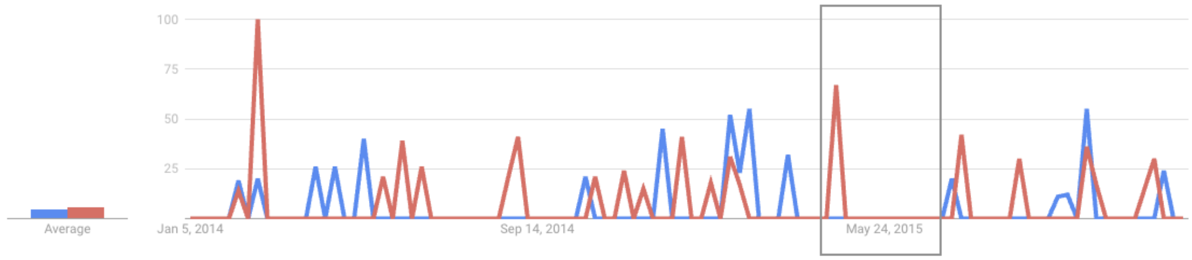


Figure 3: News coverage of Stephen Colbert donation event

Note: The red line denotes news search about Stephen Colbert, blue line denotes news search about DonorsChoose. The box denotes the time around the Stephen Colbert event.

We estimate the IV regression using 2SLS. The results are presented in Table 3. Notably, the coefficients on FDE_i change sign compared to the OLS results presented in Table 2. After isolating exogenous variation in the first donation outcome using the instrument, we find that experiencing a donation failure increases a donor's churn probability and decreases their future donation amount on the platform.

Table 3: Two Stage Least Squares Regressions

	Dependent variable:			
	Churn	log(Tot Future Don + 1)	Churn	log(Tot Future Don + 1)
	(1)	(2)	(3)	(4)
FDE	0.896***	−3.6391***	0.498**	−2.006**
	(0.018)	(0.763)		
Constant	0.669***	−1.2992***	–	–
	(0.189)	(0.075)		
Controls and FE	N	N	Y	Y
Observations	1,684,144	1,684,144	1,101,400	1,101,400
Weak Instrument	Reject	Reject	Reject	Reject

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports 2SLS estimates for equations 1 and 2 where FDE is instrumented with the Stephen Colbert shock. The first two columns do not include control variables. Columns 3 and 4 add the following control variables: Project Cost, Time to Raise Funds, Distance between Donor and School, and fixed effects for Donor State, School State, Resource Category, and Subject Category. FDE takes a value of 1 if the first donation experience is a failure and 0 if it is a success. Results from Wu Hausman's weak instrument tests are included in the last row.

4.4 Propensity Score Matching

Although the instrument helps isolate exogenous variation in the first donation outcome, there could still be some remaining unobserved differences across donors that are correlated with their first donation outcome and their propensity to donate again on the platform. For example, the IV regression picks up the fact that donors to projects outside of South Carolina are more likely to experience failure, but these donors might also have different incomes and preferences over projects that could correlate with the probability of returning to the platform. To address this issue, we layer propensity score matching into the IV regressions. This construction brings us closer to an experimental setting by helping us compare donors that are similar but that experience different project outcomes due to Colbert's intervention. Specifically, donors are matched on their observables, such as donation amount, project category, resource category, donor locations, and project cost for their initial donations. Matching ensures that the donors who get the Stephen Colbert funding (project completion) vs. the ones who do not are similar in all other aspects. It is important to note that exact matching reduces the total number of observations. The quality of the match is reported in Appendix Figures A14 and A15.

After matching, the first donation experience variable is instrumented with the Stephen Colbert shock variable. The results from 2SLS after matching are reported in Table 4. In column (1), the constant reflects the average churn probability for donors that experience a successful first donation – 71$\%$. The coefficient on FDE indicates that experiencing a first donation failure increases the churn probability by 0.236 (s.e.=0.103), implying a churn rate of 94.6$\%$ for this group. Furthermore, column (2) shows that, on average, experiencing a first donation failure decreases a donor's total future donation amount by 61.9$\%$ $(= 100 \times (e^{-0.964} - 1))$.

Table 4: 2SLS after matching

	Dependent variable:	
	Churn	log(Tot Future Don + 1)
	(1)	(2)
FDE	0.236**	−0.964**
	(0.103)	(0.414)
Constant	0.715***	1.115***
	(0.012)	(0.048)
Observations	63,075	63,075
Weak Instrument	Reject	Reject
Note:		*p<0.1; **p<0.05; ***p<0.01

Note: This table reports 2SLS estimates for equations 1 and 2 where FDE is instrumented with the Stephen Colbert shock and donors are matched using propensity score matching. The first two columns do not contain control variables. Columns 3 and 4 add the following control variables: Project Cost, Time to Raise Funds, Distance between Donor and School, and fixed effects for Donor State, School State, Resource Category, and Subject Category. FDE takes a value of 1 if the first donation experience is a failure and 0 if it is a success. Results from Wu Hausman weak instrument tests are included in the last row.

4.5 Heterogeneity

In this section, we explore heterogeneity in how donors respond to experiencing a first donation failure. To this end, we expand our instrumental variables set-up to include interactions between the FDE treatment variable and three observable X variables. In particular, we consider whether the effect of the first donation experience could be moderated by a) the donor's proximity to the school, b) when the donor decides to donate in the lifecycle of the project, or c) the amount of the donor's contribution. A donor's proximity to the school could moderate the effect of a failure on churn if donors who are located close to the recipient school have a pre-existing relationship with the school and are thus less affected by fundraising failures (Burger et al. (2004), Guéguen et al. (2018)), we do not find any significant results and thus cannot reject the hypothesis. Second, whether a donor contributes early vs. late into a project's lifecycle can indicate a commitment to the project and variation in the reliance on observational learning or peer effects (Solomon et al. (2015)). We find that if a donor donates late(days between the donation date and the project posted date), they are less likely to churn in the event of fundraising failure. Finally, we do not find any significant effects of donation amount on the first donation experience. However, it could be argued that people who donate a larger amount would exhibit greater disappointment in the event of failure; we find opposite effects (with low statistical significance).

Table 5: Heterogeneity across donors in the effect of a first donation failure

	Dependent variable:	
	Churn	log(Tot Future Don+1)
	(1)	(2)
FDE	0.241^{*}	-0.963^{*}
	(0.132)	(0.541)
Distance To School	0.015	-0.080
	(0.022)	(0.092)
Time to Donation	0.072^{***}	-0.311^{***}
	(0.014)	(0.056)
Donation Amount	0.009	0.031
	(0.026)	(0.109)
FDE×Distance To School	-0.156	0.769
	(0.188)	(0.771)
FDE×Time to Donation	-0.062^{***}	0.266^{***}
	(0.012)	(0.051)
FDE×Donation Amount	-0.082	0.463
	(0.281)	(1.153)
Constant	0.717^{***}	1.114^{***}
	(0.015)	(0.062)
Observations	63,075	63,075
Weak Instrument	Reject	Reject

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the results from estimating equations 1 and 2, where FDE is instrumented with the Stephen Colbert shock and interacted with Distance to School, Time to Donation, and Donation Amount to capture heterogeneity in FDE. Results from Wu Hausman weak instrument tests are included in the last row.

5 Mechanism

Thus far, we have established that a failed donation experience can substantially affect a donor's future participation with the platform. Naturally, we would like to understand why such an effect exists and whether the negative effect can be counteracted. After a failed fundraising experience, donors might attribute the failure to a) the *platform* —the platform is not efficient enough in raising funds or cannot be trusted in the future (Keiningham et al. (2007), Van Doorn et al. (2010)) b) *society* —the fundraiser failed because others did not donate enough, leading the donor to update their own willingness to give (Mollick (2014), Belleflamme et al. (2014)) or c) the *self* —the donor might feel that it is her own fault because she did not pick the right cause, leading to self-efficacy concerns (Bitner et al. (1990), Weun et al. (2004)).

To understand why donors are more likely to churn if they experience a failed fundraiser compared to a successful one, we conducted a survey. The goal of the survey is to a) provide external validity that complements our analysis of observational data (Gui (2020), Yang and Ding (2020)) and b) uncover the reasons behind donor churn.

5.1 Method

At the beginning of the survey, the participants are informed about a fictitious platform called Giverschoice. Next, donors are asked to choose between two projects that mimic two real projects from the DonorsChoose platform and imagine that they made a donation to that project. Each participant is then randomized into one of six treatment conditions. The conditions are $\{$Outcomes: Success, Failure, Base$\}$ $\times$ $\{$Social Comparison: More, Less$\}$. Success refers to a condition where donors are informed that the project was successful in raising funds. Failure refers to a condition where donors are informed that the project was unsuccessful in raising funds and that their donation is now being diverted to a different project. Participants in the base condition do not receive a message about the status of their project. Including this condition helps us infer what donors assume about a project's status in the absence of explicit information. In addition to the status of the project, donors were also informed if their donation was more or less than the average donation amount of others who gave to the project. After receiving these treatment-specific messages, donors were asked to rate their propensity to a) recommend the platform to others and b) donate again. Donors were also asked to report their feelings about their self, society/others, and the platform (Happy, Satisfied, Ashamed, Disappointed, Angry, Proud). Further details on the survey design are presented in Appendix C)

A total of 600 workers on Amazon MTurk completed the study. The participants were recruited through CloudResearch and only participants from the US with a rating score of over 95% were selected for the study. Four participants failed the random attention checks or duplicate IP address checks and were thus excluded from the analysis.

The demographic details of the participants are as follows: Out of the 600 respondents, 393 (66%) reported having online donation experience. There were 345 males and 251 females. A total of 492 participants claimed to have an income of less than $100,000, and 355 participants were 35 years of age or older.

5.2 Results

5.2.1 Main Effects

Looking first at the main effects, we regress the donate again and recommend the platform dummies on dummies for the $Success$ and $Failure$ outcome conditions, a dummy for the $More$ social comparison condition, and interactions between the outcome condition dummies and the $More$ social comparison dummy. The results are presented in Table 6 and Figure 4.

We find that, compared to baseline, participants in the failure condition are significantly less likely to donate again or recommend the platform ($\beta_{Fail}^{DonateAgain} = -0.397$, $\beta_{Fail}^{Recommend} = -0.378$). Second, average outcomes in the baseline and success conditions lack significant differences, which suggests that in the absence of explicit outcome information, most donors assume that the status quo is that the project would be funded successfully. Third, when participants believe that they have donated more than the average donation amount by others, this positively influences their propensity to donate again and recommend the platform ($\beta^{DonateAgain}_{More} = 0.484$, $\beta^{Recommend}_{More} = 0.521$) relative to when they think they donated less than others. Lastly, we did not find any significant interaction effects.

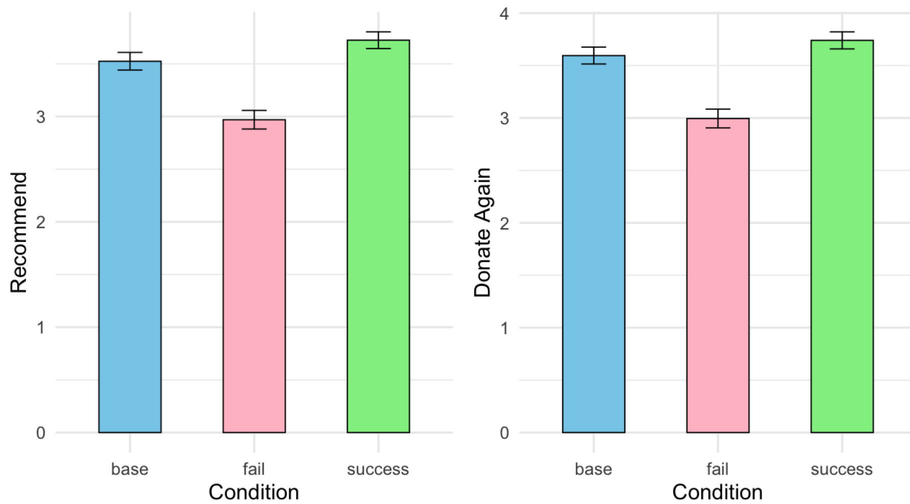


Figure 4: Propensity to recommend (left panel) and donate again (right panel) across different conditions

5.2.2 Mediation Analysis

To investigate the source of churn, we ask participants to report their degree of disappointment with various stakeholders. The path diagram presented in Figure 5 illustrates our independent variable (project status/outcome), mediators (disappointment with various stakeholders) and dependent variable (recommend or donate again). The Project Status variable takes a value of 0 for baseline, -1 for fail, and 1 for success. Disappointment (mediator) with different stakeholders ranges between 1 to 5, with 1 being the least disappointed and 5 being the most disappointed. Results of the mediation analysis are presented in Table 7. The direct effect of Project Status on Donate Again was significant (Estimate = 0.16 SE = 0.06, p $<$ 0.007), indicating a direct pathway from Project Status to Donate Again. Regarding the indirect effects, we found evidence of significant mediation only through the Platform Disappointment mediator. For this mediator,

Table 6: Main Effects: Results from survey

	Dependent variable:	
	DonateAgain	Recommend
	(1)	(2)
Fail	-0.397^{**}	-0.378^{**}
	(0.169)	(0.168)
Success	0.197	0.178
	(0.170)	(0.169)
More	0.484^{***}	0.521^{***}
	(0.169)	(0.168)
Fail $\times$ More	-0.430^{*}	-0.280
	(0.236)	(0.235)
Success $\times$ More	-0.117	0.064
	(0.237)	(0.236)
Constant	4.463^{***}	4.284^{***}
	(1.183)	(1.176)
Observations	596	596
R^2	0.158	0.171
Adjusted R^2	0.111	0.125
Residual Std. Error (df = 564)	1.158	1.152
F Statistic (df = 31; 564)	3.406^{***}	3.744^{***}

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports regressions of the donate again and recommend response variables on outcomes and social comparison treatment dummies and controls. Controls include gender, race, education, and income.

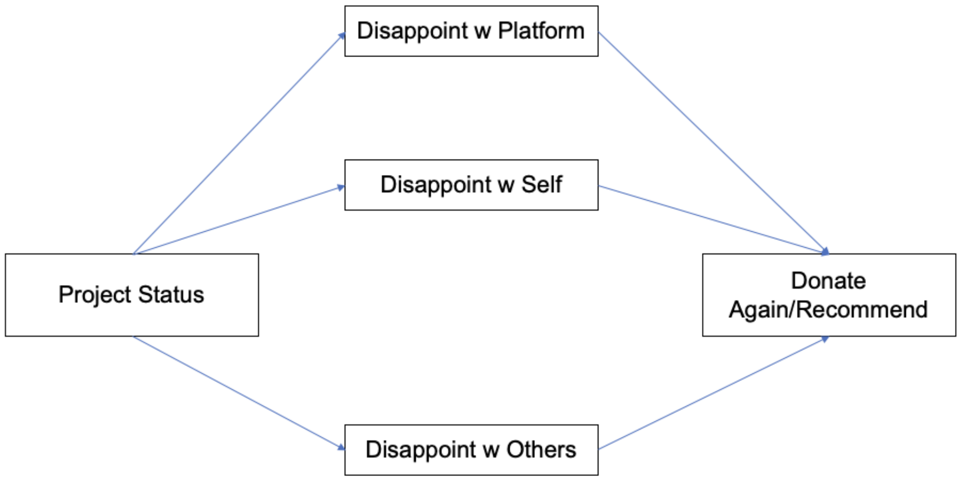


Figure 5: Path diagram: Independent variable (project status), possible mediators and dependent variable

the indirect effect was significant (Estimate = 0.24, SE = 0.03, $p < 0.00$). Self and Others' disappointment mediators turn out to be insignificant. The total effect of Project Status on Donate Again, which combines both direct and indirect effects, was also significant (Estimate = 0.37 SE = 0.06 $p < 0.00$). Similar results are observed in the mediation analysis of the Recommend dependent variable (see Appendix Table A5).

Table 7: Results from mediation analysis with Donate Again as DV

	Estimate	Std. Err.	z	p
	Regression Slopes			
DonateAgain				
Project_Status	0.16	0.06	2.69	0.007
Platform-Disappointment	−0.37	0.03	−10.95	0.000
Yourself-Disappointment	−0.02	0.04	−0.44	0.657
Others-Disappointment	0.11	0.04	2.79	0.005
Platform-Disappointment				
Project_Status	−0.65	0.07	−9.83	0.000
Yourself-Disappointment				
Project_Status	−0.27	0.06	−4.24	0.000
Others-Disappointment				
Project_Status	−0.34	0.06	−5.93	0.000
	Constructed			
Indirect-Platform	0.24	0.03	7.31	0.000
Indirect-Self	0.00	0.01	0.44	0.658
Indirect-Others	−0.04	0.01	−2.52	0.012
Total	0.37	0.06	6.18	0.000
	Fit Indices			
χ^2(df)	460.93(3)			0.000
CFI	0.37			
TLI	−1.10			
RMSEA	0.50			

$^+$Fixed parameter

Note: This table reports the results from mediation analysis. Both direct and indirect effects are reported. Donate again is the dependent variable, project outcome is the independent variable and disappointment with the platform, yourself and others are three mediators.

5.3 Discussion

The direct results indicate that experiencing a project failure reduces a donor's propensity to donate again or recommend the platform to others. This finding is in line with our reduced-form analysis of observational data from the DonorsChoose platform. Furthermore, it is interesting to observe that, when provided with no information (baseline), donors react similar to the success condition in our survey. The results from our mediation analysis rule out the possibility of disappointment with self and others as probable reasons behind donor churn after failed fundraising outcomes. It is clear from the path analysis that the survey participants were disappointed with the platform. These results underscore the importance of interventions done by the platform to alleviate the failed fundraising experiences for donors Next, we turn to such an intervention. But for this purpose, we need a model that can help us evaluate the impact of alternative interventions on a donor's churn rate.

6 Model

6.1 Model goal and motivation

The survey presented in the previous section reveals that experiencing a fundraising failure leads donors to reduce their participation on the platform because they become disappointed with the platform. This leads us to propose a solution whereby the platform can reduce the chance that a donor experiences a failure with their first donation. We propose that the platform customizes its fundraiser ranking algorithm such that projects which have the highest probability of success are ranked first for first-time donors who land at the DonorsChoose website. This would increase the chance that they have a successful first experience which, based on our previous results, suggests a lower churn rate. Our proposal is based on a simple cost-benefit analysis. If the platform can retain an extra 10% of donors after the first donation, the platform can raise an additional 146,000*$50 (average donation amount)=$7.3 million in the span of 5 years. As documented in the reduced form evidence, experiencing a first donation success can significantly reduce the probability of churning.

The goal of the model is to estimate donors' preferences and understand how previous donation outcomes affect future donations. We then construct counterfactuals in which project rankings are changed for first-time donors, and we use the estimated model parameters to predict how donors would respond and quantify the resulting impact on platform profitability.

6.2 Donor Decision Process

Figure 6: Donor decision journey timeline

Consider a donor's decision process as illustrated in Figure 6. Suppose that at time t_1 a donor visits the website, goes over the donation options based on the rank-ordered display, and decides not to donate on the platform. In this visit the donor chose the outside option – not to make a donation. On the next visit in t_2, she views the donation options and decides to donate to one of the options. Before her next visit at t_3, she learns the outcome of her donation — was the project able to raise funds or not. Thus, her donation decision in t_3 is contingent on her last donation outcome. She continues this process and exits the platform after a few donations.

6.3 Model Formulation

We formulate a choice model with this donor decision process in mind.

$$u_{ijt} = \beta_{0i} + \beta_{1i} SD_{it} + \beta_2 Rank_{jt} + \beta_3 PF_{jt} + \varepsilon_{ijt} \tag{3}$$

Let u_{ijt} represent the indirect utility donor i would derive from donating to project j at time t. Upon each visit to the website, the donor selects the project that maximizes her utility, or she chooses not to donate. In the utility formulation, β_{0i} is a donor-specific intercept term (assumed to be normally distributed across donors) that captures the baseline utility from donating to one of the inside goods. SD_{it} reflects the state dependence for donor i at time t and captures the project outcome (success or failure) of the last donation. β_{1i} is a random coefficient that reflects whether the last donation outcome (state dependence) influences a donor's future donation decision. β_2 captures the influence of the rank score of project j at time t, which is how we account for position effects. β_3 captures preferences over project features such as project cost, days remaining until the project expires, etc. Lastly, ε_{ijt} is a random shock to donor i for project j at time t, which is assumed to be distributed type I extreme value. Equation 4 gives the joint likelihood function, which we estimate using simulated maximum likelihood.In the Equation 4, $\delta_{ij(t)t}$, takes value 1 if donor i, selects project j at time t, and 0 otherwise. It is important to note that the consideration sets are different for each day.

$$L(\beta, \sigma|\mathbf{y}, \mathbf{X}) = \prod_{i=1}^{N} \int \prod_{t=1}^{T_i} \prod_{j=1}^{J} \left(\frac{e^{\mathbf{x}_{ij(t)t}\beta}}{\sum_{k=1}^{J} e^{\mathbf{x}_{ik(t)t}\beta}} \right)^{\delta_{ij(t)t}} f(\beta) d\beta \tag{4}$$

6.4 Data for Estimation

In our model of the donor decision process, the key building blocks are website visits, the attributes and display rank of projects, and transactions. In our data from DonorsChoose, we observe data on project attributes and transactions. Below, we describe how we draw on additional data sources to infer and fill in missing data about donors' website arrival rates and the platform's ranking algorithm.

6.4.1 Inferring Intervisit Time from Clickstream Data

Understanding a donor's decision process involves observing donors at all interactions with the platform website (visited but not donated, visited and donated). Unfortunately, we were not able to obtain access to clickstream data from the platform. Instead, we use comScore data from Jan 2019 to Dec 2021 to understand the inter-visit and inter-donation times of donors on the platform. In the comScore dataset, we observe when someone visits the platform and whether or not they make a donation. We identify visits and transactions to the donor platform by searching for DonorsChoose in the domain name field. This process produces a dataset that records 523,930 clicks on the DonorsChoose website coming from 3846 distinct user ids and 4271 machine ids.

We then aggregate the data to the user-day level and find that the average user visits the website on 3 distinct days. The inter-visit time is presented in Appendix Figure A1. Interestingly, we find that more than 98% of donors visit the website before making their first donation (i.e. the sequence of website visitation is *visited but not donated and then visited and donated*). We use this information to construct a modified version of the DonorsChoose dataset that fills in observations for website visits that did not result in a transaction. When filling in observations, we match the moments of the comScore data in terms of intervisit times and the number of interactions with the platform.

6.4.2 Estimating Project Rankings

Position effects are well-documented in the literature, whereby the ranking of a product on a website influences consumers' probability of clicking and choosing that product (Ursu 2018, Derakhshan et al. 2022, Ferreira et al. 2022). Failing to include project rank as a factor affecting choice can lead to biased estimates of preferences over project features since rank is correlated with project attributes.

The ranking algorithm used by DonorsChoose is confidential. However, Vana and Lambrecht (2022) shows that project rankings on DonorsChoose are a nonlinear function of the observed characteristics of the projects. Thus, we devise the following approach to estimate the daily rank of projects. First, we scrape the website and record data on project features and project ranks (12 April 2023 to 6 May 2023). Then we use the scraped ranks and project features to train a learning-to-rank algorithm, LAMBDAMART (Burges et al. (2005)). We then use the model to predict the ranking score of each project on each day that the project is active (until it is fully funded or expired). We provide additional detail on the rank estimation in Appendix D. The key identifying feature of the setup is that the rank order display is not personalized. In particular, the rank order of the project displayed is the same for everyone. This institutional setup makes it possible for us to estimate rankings using the method detailed above. A key assumption we make in our analysis is that the ranking algorithm has not changed over time, and thus the model we estimate on our recently scraped data can be used to estimate historical rankings. We base our assumption on a) the ranking algorithm is not yet personalized by location, device etc. b) we are also conducting tests where we collect old page ranking data from WayBack machine and testing if the underlying project feature to rank mapping is the same.

6.4.3 Additional Details on Data Construction

In this section we illustrate the data creation process. Consider a donor i who first visited the platform at time t. We assume that each donor's consideration set is comprised of the top 10 projects for time t based on the rank score. As described above, the daily rank score is estimated from the learned ranking algorithm using daily data on project features. Although there are almost 25,000-30,000 projects available at any given time, for now we assume that only the top 10 projects would be in the donor's consideration set.[9] Next, using the empirical CDF of the intervisit time from the comScore data, we draw a random intervisit time, say 30 days, and assume that the donor visited the platform that many days before their first observed transaction. To implement this website visit without a purchase, we create a stack of rows prior to the first donation, which has the top 10 projects for time $t-30$ and their corresponding features. We record the donor's choice in that period as choosing the outside option, since we know no transaction was made. For the next website visit after t, we again draw from the intervisit time distribution. Suppose this time the draw is 20 days. If the next true transaction occurs more than 20 days after t, we again inject a stack of rows with the top 10 projects from day $t + 20$ and record that the donor chose the outside option not to donate. If a transaction is observed within the $t + 20$ intervisit period, we do not need to inject an unobserved visit into the dataset. We follow the same steps for all subsequent periods, i.e. drawing an intervisit time and stacking visit but no donation events with the top 10 projects and their features. The data ends 30 days after the last

[9] The algorithm achieves a NDCG metric of 0.91 in the test data, indicating, given project features the algorithm can predict the ranks quite accurately.

observed donation. The last event is again coded as visitation but no donation[10].

State Dependence Variable - the state dependence variable is included in the model to allow for the possibility that a donor's prior donation outcome can affect their propensity to donate again in the future. We create the state-dependence variable as follows - on a given website visit, if the outcome of the project that the donor previously gave to is known - i.e. the project was successfully funded or it expired without getting funded - then we set state dependence in the current period equal to the outcome of that last project. However, if the donor's previously donated project is still open, then the state variable takes the outcome of the last project that the donor contributed to that has a known outcome - either success or failure in getting fundedDubé et al. (2010).

Initial Conditions - What do new donors that do not have prior experience with the platform assume? Assumptions about initial conditions have been shown to have a considerable effect in state dependence models (Simonov et al. (2020)). In our setting, the initial condition can be thought of as a donor's prior on project outcomes. Results from our mTurk survey show that when donors are not provided with any information about the success or failure of previous donations, they seem to default to assuming the recipient project succeeded. Therefore, for initial conditions, we assume the state to be a success. We also check the sensitivity of our results to this assumption

6.5 Identification

With the data needed to estimate the model in hand, we briefly discuss model identification before presenting the estimation results. In equation 3, β_{0i} represents the baseline utility of donation. The mean and variance of this random coefficient is identified by the extensive margin - how often do website visitors choose the outside option versus donating to one of the inside goods, and

[10] For example if a donor has made only one transaction, where she consider only 10 options in each occasion. In our data she will have 30 rows, first 10 rows will correspond to visitation but no donation (donation variable (Y) column has all zeros, whereas project features variable (X) column will have values of project features), next 10 rows will have one 1 and 9 zeros (corresponding to donation to one option but considered 10 options) and last 10 rows will again have 10 zeros

how does that vary across donors? Prior work has shown that in order to properly identify state dependence, it is important to account for a rich distribution of unobserved heterogeneity. β_{1i}, the coefficient on the state dependence variable, is pinned down by differences in the conditional probability of donating in the current period given success or failure in the previous donation experience.[11] Donors could be heterogeneous in how they respond to prior donation failures. To address this, we model the parameter on state dependence as a random coefficient that follows a normal distribution. Position effects are captured by the coefficient on project rank score, and identification of this parameter comes from correlations between observed choices and ranks in the data. The typical endogeneity concern with project rank stems from concerns that more popular projects are also ranked higher, and thus failing to account for "popularity" could lead to biased effects of rank. We include a large number of project features in our model, and thus the coefficient on rank is identified under the maintained assumption that there are not any unobserved project features that are used to rank projects and that also affect the project's likelihood of being chosen. Finally, the coefficients on project features are identified under the assumption that these features are not endogenous - that is, we assume that there are not any unobserved project features that correlate with the observed features and that affect a project's propensity to receive donations. Given that most teachers only post a single project on the platform, we think it is unlikely that teachers would have the opportunity to learn how to strategically design projects.

6.6 Results

We estimate Equation 4 using simulated maximum likelihood using 25 draws to approximate the integral and present the results in Table 8 and Figure 7. First, the mean of the intercept, $\mu(\beta_{0i})$, is a large negative number, indicating that a donation event is unlikely. This is expected given that we constructed the data to align with the relatively high prevalence of visits without donations that we observe in the comScore data. Second, the random coefficient $\beta_{1i})$ on the state-dependence

[11] Going forward, we plan to use a control function approach that leverages the Stephen Colbert shock as an instrumental variable that exogenously shifts the prior donation success probability.

variable has a positive mean with a relatively small variance ($\sigma(\beta_{1i})$. The positive mean indicates that donors are less likely to give in the current period if their last donation outcome was a failure. This is in line with the reduced form results where we found that experiencing a donation failure reduces the future donation probabilities. In terms of the magnitude, all else equal, if the last donation outcome is a success it can increase the probability to donate again by nearly 50%. It is important to note that this number is an average across all donation events (for example: first to second, fifth to sixth, etc.). A large positive coefficient on rank score (highest rank score implies first position on the webpage, lowest rank score implies last position on the webpage) indicates that projects which are shown higher on the listing page have a higher chance of receiving a donation. A negative coefficient on project cost indicates that donors prefer to donate to projects with a lower overall ask amount. Donors are also more likely to donate to projects that have already received support from a higher number of donors, they prefer projects which are not near deadlines, and projects that have already raised more money.

Table 8: Summary of Model Results

	Estimate	Std. Error
Rank Score	0.88	0.18
Project Cost	-0.001	0.00
Donors Until	0.04	0.00
Days Left to Raise	0.035	0.00
Amount Already Raised ($)	0.01	0.00
$\mu(\beta_{1i})$	0.36	0.13
$\sigma(\beta_{1i})$	0.03	0.17
$\mu(\beta_{0i})$	-6.37	0.21
$\sigma(\beta_{0i})$	0.44	0.05
Observations	69441	
Num Donors	1000	
Halton Draws	25	
LL	-3054	

Note: This table reports the results from simulated maximum likelihood estimation of equation 4. Column 1 and 2 report estimates and their corresponding std errors. The coefficient on state dependence and the intercept are assumed to follow a normal distribution. The estimation is done using RChoice package in R. Sarrias (2016)

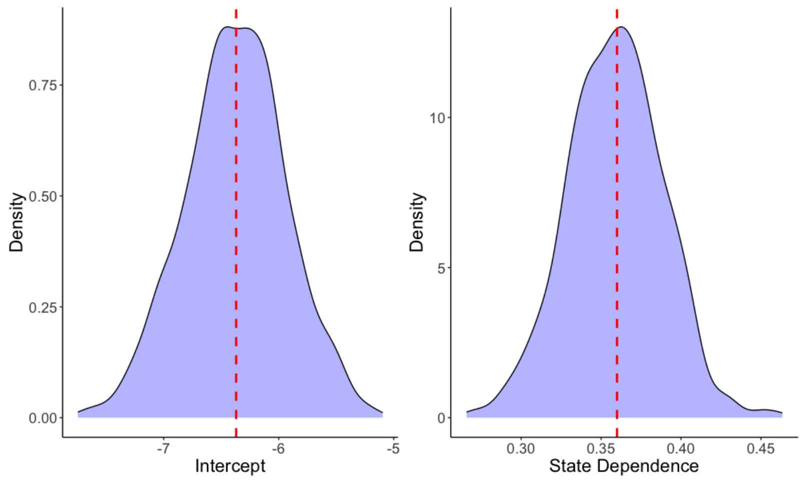


Figure 7: Distribution of intercept (left) and state dependence (right) coefficients

6.7 Counterfactuals

One of the ways the platform can induce a more successful fundraising experience is by updating the project display ranking algorithm on the website. We propose a new ranking algorithm that would display the projects to first-time donors based on the decreasing order of probability of success. The underlying idea is if the first-time donors are first shown the projects with the highest success probability, they will most likely choose one of the displayed options and are more likely to experience a successful donation experience.

6.7.1 Predicting Success

To predict the success probability of a project, we use an eXtreme gradient boosting algorithm (XGBOOST). It is important to emphasize that the prediction problem is not trivial. From the data we know that if a project failed or succeeded (1/0), however, each day some feature of the project changes, for example, days remaining, amount to be raised, number of donors until that day etc. and some features of the projects are fixed such as category, project cost etc. Therefore, for each project the target variable is constant (succeed or fail) however, the dynamic components change in the project feature space. Using the model we want to estimate the success probability for each project for each day it is available on the platform. We report model performance metrics (an ROC curve) in Figure 8.[12] The model achieves the AUC metric of 0.945.[13]

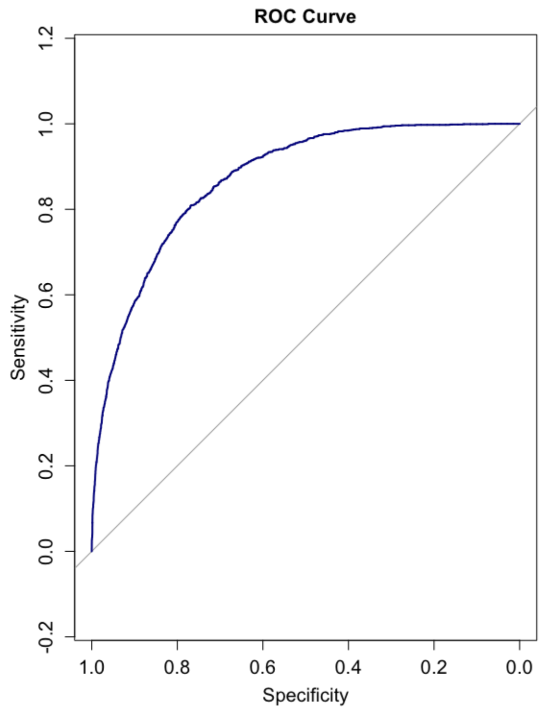


Figure 8: ROC curve for predicting the success vs failure of projects

6.7.2 Comparing Old vs New Ranking Schemes

To estimate this, we first calculate the success probability for each project on each day using the model estimates and project features. Then we replace the ten projects in the consideration set of first-time donors with the ten projects that the algorithm predicts have the highest success probability on that day. We then assume the donor would choose the option that gives them the highest indirect utility. This represents the donor's counterfactual choice that would be made under the alternative ranking algorithm. We extract the outcome of the selected project from the platform data. For the next period, we set the donor's state to be the outcome of the last step and compute the probability that the donor would make a donation. In this way, the counterfactual compares

[12] The ROC curve plots the True Positive Rate (TPR) or sensitivity, against the False Positive Rate (FPR), or 1 - specificity, at various threshold settings.

[13] An AUC (Area under the curve) of 0.5 suggests no discrimination, while an AUC of 1.0 suggests perfect discrimination between classes.

the shift in the probability of donating again under the old vs new ranking algorithm. We report the probabilities to donate after the first donation under the new vs old ranking algorithms in Table 9. The probability to donate again increases by 2.5% over the old ranking algorithm. This increase is only attributable to the change in ranking algorithm. It is important to note that, even though the new algorithm displays the projects with decreasing order of model-predicted success probabilities, not all first-time donor experiences are successful.

Table 9: Old vs New Ranking - Probability to Donate Again

	Old Ranking	New Ranking	Change (%)
Prob Donate Again	0.125	0.128	2.5

7 Conclusion

Donation platforms organize multiple fundraisers on their websites, and many of these fundraisers are unable to achieve the fundraising goal. This paper shows that failed fundraising experiences can significantly increase churn and decrease the overall dollar contribution of donors. Furthermore, our analysis resolves the contrasting predictions of different theories in the charitable giving literature. Second, this paper explores the mechanism behind reduced participation using a survey and finds that participants are disappointed with the platform (supporting expectation disconfirmation theory) and not with themselves or other donors for the fundraising failure. Third, this paper models the donor decision process using a structural model to estimate the impact of fundraising outcomes on future donations. Using the model parameters, a segmented choice architecture is proposed to show that if first-time donors are exposed to projects with higher success probabilities, overall donations on the platform can increase.

The limitations of the paper are first the absence of information about the ranking algorithm and clickstream data of donors. Although we tried to supplement the data with assumptions, methods, and other datasets, the deviations from the real data could impact model estimates.

Another limitation is driven by the time unit of analysis, all the models in the paper use a day as the most granular unit; however, the website's project rankings may change more frequently and thus our approach might introduce some aggregation bias. Future studies can alleviate these concerns with better data and experiments with the platform.

We also think this paper sparks opportunities for future work. We study how donors respond to a fundraising failure on a single platform that has a policy to re-distribute the funds raised by projects that do not meet their target goal amounts. As mentioned previously, other donation platforms use different approaches to deal with fundraisers that miss their targets, either returning the money to the donor or giving what money has been raised to the project owner. We think it would be very interesting to look at whether donors also respond negatively to fundraising failures when these other mechanisms are used. In particular, if the money still goes to the project owner, then the donor may not see the inability to meet the goal as a fundraising failure.

References

Agrawal, A., Catalini, C., and Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy*, 24(2):253–274.

Anderson, E. W. and Sullivan, M. W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing science*, 12(2):125–143.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *The economic journal*, 100(401):464–477.

Andreoni, J. and Payne, A. A. (2013). Charitable giving. In *Handbook of public economics*, volume 5, pages 1–50. Elsevier.

Bandura, A. and Wessels, S. (1994). *Self-efficacy*, volume 4. na.

Belleflamme, P., Lambert, T., and Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of business venturing*, 29(5):585–609.

Bitner, M. J., Booms, B. H., and Tetreault, M. S. (1990). The service encounter: diagnosing favorable and unfavorable incidents. *Journal of marketing*, 54(1):71–84.

BlackBaud (2021). Online giving trends. https://institute.blackbaud.com/charitable-giving-report/online-giving-trends/. [Accessed 02-Jun-2023].

Blackbaud, I. (2022). Online giving trends.

Brenneman, R. (2015). Stephen colbert helps fund every donorschoose project in south carolina- edweek.org. https://www.edweek.org/teaching-learning/stephen-colbert-helps-fund-every-donorschoose-project-in-south-carolina/2015/05. [Accessed 04-Jun-2023].

Burger, J. M., Messian, N., Patel, S., Del Prado, A., and Anderson, C. (2004). What a coincidence! the effects of incidental similarity on compliance. *Personality and Social Psychology Bulletin*, 30(1):35–43.

Burges, C., Shaked, T., Renshaw, E., Lazier, A., Deeds, M., Hamilton, N., and Hullender, G. (2005). Learning to rank using gradient descent. In *Proceedings of the 22nd international conference on Machine learning*, pages 89–96.

Burtch, G., Ghose, A., and Wattal, S. (2014). Cultural differences and geography as determinants of online prosocial lending. *Mis Quarterly*, 38(3):773–794.

Cryder, C. E., Loewenstein, G., and Seltman, H. (2013). Goal gradient in helping behavior. *Journal of Experimental Social Psychology*, 49(6):1078–1083.

Derakhshan, M., Golrezaei, N., Manshadi, V., and Mirrokni, V. (2022). Product ranking on online platforms. *Management Science*, 68(6):4024–4041.

DonorsChoose (2020). What happens to donations when a project isn't funded? Accessed: 2023-06-07.

DonorsChoose.com (2022). Financials — DonorsChoose — donorschoose.org. https://www.donorschoose.org/about/finance.html. [Accessed 31-May-2023].

Dubé, J.-P., Hitsch, G. J., and Rossi, P. E. (2010). State dependence and alternative explanations for consumer inertia. *The RAND Journal of Economics*, 41(3):417–445.

Ferreira, K. J., Parthasarathy, S., and Sekar, S. (2022). Learning to rank an assortment of products. *Management Science*, 68(3):1828–1848.

Festinger, L. (1954). A theory of social comparison processes. *Human relations*, 7(2):117–140.

GlobalGiving (2021). Can i change my fundraiser's goal? Accessed: 2023-06-07.

Guéguen, N., Lamy, L., and Fischer-Lokou, J. (2018). Does the sense of the geographic proximity of a requester influence donation? three evaluations in field studies. *Journal of Human Behavior in the Social Environment*, 28(2):193–203.

Gui, G. (2020). Combining observational and experimental data using first-stage covariates. *arXiv preprint arXiv:2010.05117*.

Indiegogo (2021). Choose your funding type: Can i keep my money? Accessed: 2023-06-07.

Jensen, J. D., King, A. J., and Carcioppolo, N. (2013). Driving toward a goal and the goal-gradient hypothesis: The impact of goal proximity on compliance rate, donation size, and fatigue. *Journal of Applied Social Psychology*, 43(9):1881–1895.

Karlan, D. and Wood, D. H. (2017). The effect of effectiveness: Donor response to aid effectiveness in a direct mail fundraising experiment. *Journal of Behavioral and Experimental Economics*, 66:1–8.

Keiningham, T. L., Cooil, B., Andreassen, T. W., and Aksoy, L. (2007). A longitudinal examination of net promoter and firm revenue growth. *Journal of Marketing*, 71(3):39–51.

Kim, Y. (2020). *Customer retention under imperfect information*. PhD thesis, The University of Chicago.

Kuppuswamy, V. and Bayus, B. L. (2017). Does my contribution to your crowdfunding project matter? *Journal of business venturing*, 32(1):72–89.

Lambeck, L. C. (2018). DonorsChoose.org celebrates funding of 1 million educational projects — ctpost.com. https://www.ctpost.com/local/article/DonorsChoose-org-celebrates-funding-of-1-million-12522460.php. [Accessed 31-May-2023].

Lee, B. Y. (2022). Most gofundme campaigns for medical bills fail, less than 12% reach goals.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of business venturing*, 29(1):1–16.

Oliver, R. L. (1977). Effect of expectation and disconfirmation on postexposure product evaluations: An alternative interpretation. *Journal of applied psychology*, 62(4):480.

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of marketing research*, 17(4):460–469.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Sarrias, M. (2016). Discrete choice models with random parameters in r: The rchoice package. *Journal of Statistical Software*, 74:1–31.

Simonov, A., Dubé, J.-P., Hitsch, G., and Rossi, P. (2020). State-dependent demand estimation with initial conditions correction. *Journal of Marketing Research*, 57(5):789–809.

Solomon, J., Ma, W., and Wash, R. (2015). Don't wait! how timing affects coordination of crowdfunding donations. In *Proceedings of the 18th acm conference on computer supported cooperative work & social computing*, pages 547–556.

Statista (2023). Customer retention rate by industry worldwide as of 2nd half 2022. Accessed: 2023-06-07.

Ursu, R. M. (2018). The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions. *Marketing Science*, 37(4):530–552.

Van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., and Verhoef, P. C. (2010). Customer engagement behavior: Theoretical foundations and research directions. *Journal of service research*, 13(3):253–266.

Vana, P. and Lambrecht, A. (2022). The role of ranking algorithms in crowdfunding. *Available at SSRN 4132785*.

Weun, S., Beatty, S. E., and Jones, M. A. (2004). The impact of service failure severity on service recovery evaluations andpost-recovery relationships. *Journal of services marketing*.

Yang, S. and Ding, P. (2020). Combining multiple observational data sources to estimate causal effects. *Journal of the American Statistical Association*, 115(531):1540–1554.

Part I

Web Appendix

A Theoretical Motivation

Consider two types of donors A (warm glow/commitment inertia) and B (expectation disconfirmation theory) and their population is α and $1-\alpha$, respectively. Assume that both donors donate \$X (a random variable), characterized by a cumulative distribution function, $F(.)$. Assume the funding goal (project cost) is 'c'. The project will be completed if $\alpha X + (1-\alpha)X \geq c$. Therefore, $Pr(Success)$=$P(X \geq c)$=$1 - F(c)$. From the definition of donors A and B we know that A will not get affected by $Pr(Success)$, however, donor B gets affected. Therefore,

$$\#Donations_2 = \alpha + (1-\alpha) \times Pr(Success)$$

$$\#Donations_1 = 1$$

It is straightforward to see that $\alpha + (1-\alpha)Pr(Success) \leq 1$ or $\alpha + (1-\alpha)(1-F(c)) \leq 1$, therefore, to ensure no churn, either all the donors should be of type A (donors who are not affected by donation outcome) or the projects should be successful.

Now consider the amount of donation. Assume that if the project is not able to raise ϕ fraction of its funding goal then the donor will get highly disappointed and would never donate again, however, if the project raises more than ϕ fraction then the donor might be motivated to complete the future projects and increase their donation by ψ. Therefore, the total donations raised in period 2 is $\alpha X + (1-\alpha)X^{new})$

$$X^{new} = \begin{cases} X, & \text{w.p } 1 - F(c) \\ 0, & \text{w.p } F(\phi c) \\ \psi X, & \text{w.p } F(c) - F(\phi c) \end{cases}$$

Expected donation raised in period 2 is given by, $E[\$Raised_2] = \alpha X + (1-\alpha)(X(1-F(c)) + \psi X(F(c) - F(\phi c))$. Now, comparing donations in period 1 and 2.

$$E[\$Raised_2] \geq E[\$Raised_1]$$
$$\implies \alpha X + (1-\alpha)(X(1-F(c)) + \psi X(F(c) - F(\phi c))) \geq X$$
$$\implies \psi \geq \frac{F(c)}{F(c) - F(\phi c)}$$

Therefore, there exists a scenario where even under project failure, the net donation raised in the next period could be more than the first.

Overall, the churn and future donation amounts depend on the donor motivations(α, ϕ,), project success/failures (F(.),c), and donor behavior post-project outcomes (ψ). Therefore, a careful empirical analysis is required to understand the impact of failed vs successful project outcomes on future donation behavior.

B Data Translation

Table A1: Raw Transaction Data Structure

Donor Id	Project Id	Date	Donate	Outcome
d1	p1	3/3/16	1	S
d1	p21	19/05/16	1	F

Table A2: Data structure after incorporating consideration sets and complete donor journey

	Donor Id	Project Id	Date	Donate	Outcome
Before	d1	p10	3/2/16	0	NA
	d1	p11	3/2/16	0	NA
	d1	p12	3/2/16	0	NA
First Transaction	d1	p1	3/3/16	1	S
	d1	p16	3/3/16	0	S
	d1	p17	3/3/16	0	S
In between Transaction	d1	p21	3/4/16	0	NA
	d1	p22	3/4/16	0	NA
	d1	p23	3/4/16	0	NA
Second Transaction	d1	p2	19/5/16	1	F
	d1	p3	19/5/16	0	F
	d1	p4	19/5/16	0	F
After	d1	p5	19/6/16	0	NA
	d1	p6	19/6/16	0	NA
	d1	p7	19/6/16	0	NA

C Survey Details

600 participants were recruited from Amazon Mechanical Turk. We used the cloud research platform to screen the survey participants on their response score etc.

Cover Story: Please imagine that you receive an invitation to make a donation on GiversChoice, a website where teachers from different school districts can seek support by posting a description of what they are looking for and how much it would cost. GiversChoice was founded in the year 2000 to help teachers enhance the learning experience of students across the nation (US). The projects that the teachers post cover a wide range, from book supplies to classroom repairs. Teachers have 100 days to secure the requested funds. For projects that are successfully funded, GiversChoice will procure the supplies and deliver them to the teachers. 70% of all the projects that are posted on the platform get successfully funded. Donors coming to the website can choose which teacher project they would like to support. On the next screen, you will see the project descriptions of two different projects. Please review them carefully.

The participants were then randomized into 6 treatment arms. Specifically, success, failure, and baseline $\times$ more or less than avg donation of others.

We focused on this design because our thesis was that donors attribute fundraising failures on others (other people in the society were not generous enough)

Next based on the treatment arm assignment the donors are shown the following prompts

Base: Let's say you have made a donation to the project. Several days have passed, and you receive an email from GiversChoice, thanking you for your donation. You also learned that the amount that you donated was less/ more than the average donation amount of other donors.

Success: Let's say you have made a donation to the project. Several days have passed, and you receive an email from GiversChoice thanking you for your donation and that the project you made a donation to reached its goal. The money that you have donated has been directed to the project and the supplies have been disbursed to the beneficiaries. You also learned that the amount that you donated was less/more than the average donation amount of other donors.

Failure: Let's say you have made a donation to the project. Several days have passed, and you receive an email from GiversChoice thanking you for your donation and that the project you made a donation to did not reach its goal. The money that you have donated has been directed to another project posted by a different teacher on the GiversChoice website, and the supplies have been secured and delivered to the teacher. You also learned that the amount that you donated was less/more than the average donation amount of other donors.
In all conditions following questions are asked.

Please tell us how you feel about the donation platform, GiversChoice.
(Scale: 1-5)
(Happy, Satisfied, Ashamed, Disappointed, Angry, Proud)
Please tell us how you feel about other donors on the donation platform.
(Scale: 1-5)
(Happy, Satisfied, Ashamed, Disappointed, Angry, Proud)
Please tell us how you feel about yourself making the donation.
(Scale: 1-5)
(Happy, Satisfied, Ashamed, Disappointed, Angry, Proud)
How likely would you be to donate again on this platform?
How likely would you be to recommend GiversChoice to others as a donation platform?
Demographic questions.

D Learning the Ranking Algorithm

The DonorsChoose website ranks projects using an algorithm that takes observable project features as inputs. We reverse-engineer the daily ranks of the projects in our dataset by i) scraping data from the website on project features and project ranks, ii) training a rank model algorithm, and iii) using the estimated algorithm to predict the daily ranks for the projects in the data.

First, we scraped 25 days of data from the DonorsChoose website. Although most of our data is scraped from the year 2023, we were also able to scrape a few days of data from 2015 using the web archival Wayback Machine. With scraping, we get the ranks and features of the listed projects for each day. Project features include project category, resource category, project cost, the amount remaining, days remaining, and the number of people who have already given, among other variables. Next, we train a learning-to-rank algorithm called LAMBDAMART using the daily scraped rank of projects and their corresponding features as the training set. Gradient boosting methods with loss function as NDCG (normalized discounted cumulative gain) form the building block of the LAMBDAMART algorithm. Using this model, the NDCG metric of 0.91 is achieved. Finally, we use the trained model and the observed project features to predict the daily rank score for each project in the main dataset while the project was active (i.e. until the project was funded or expired).

E Additional Tables and Figures

Table A3: First Stage Regressions

	Dependent variable:	
	First Donation Experience (FDE)	
	(w/o controls)	(w controls)
Stephen Colbert Donation	-0.080^{***}	-0.096^{***}
	(0.009)	(0.005)
Observations	1,684,144	1,240,362
R^2	0.00005	0.002
Adjusted R^2	0.00005	0.002
Residual Std. Error	0.298 (df = 1684142)	0.285 (df = 1240357)
F Statistic	80.649^{***} (df = 1; 1684142)	489.924^{***} (df = 4; 1240357)

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the first stage regression results from instrument variable estimation, column 1 denotes regression of FDE (1 if project fails, 0 if success) on Stephen Colbert Donation Event, column 2 denotes regression of FDE on Stephen Colbert Donation along with controls such as Project Cost, Time to Raise Funds, Distance between Donor and School, and fixed effects for Donor State, School State, Resource Category, and Subject Category

Table A4: Number of donations and Mean Success Rate

	Dependent variable:	
	Mean Success	log(Mean Success + 1)
	(1)	(2)
#Donations	0.0001^{***}	0.0002^{***}
	(0.00002)	(0.00001)
Observations	1,990,586	1,990,586
R^2	0.00001	0.0001
Adjusted R^2	0.00001	0.0001

*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the relationship between number of transactions and mean success, indicating, how increasing number of donations influences selection of successful projects by a donor

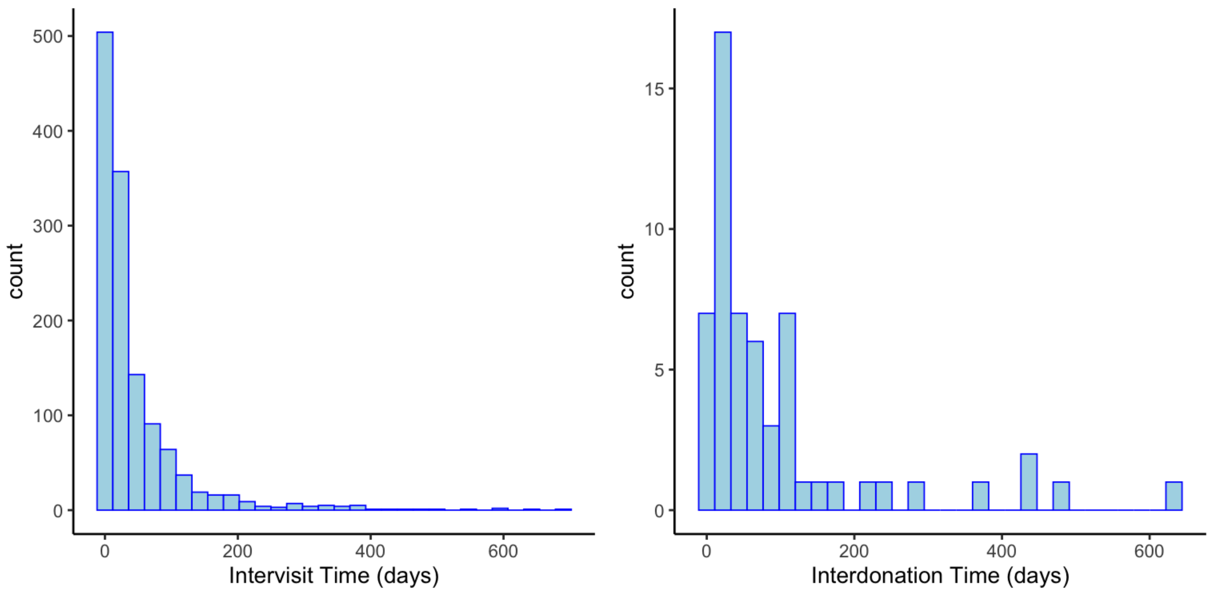


Figure A1: Distribution of Intervisit and Interdonation Time in Days using comScore data

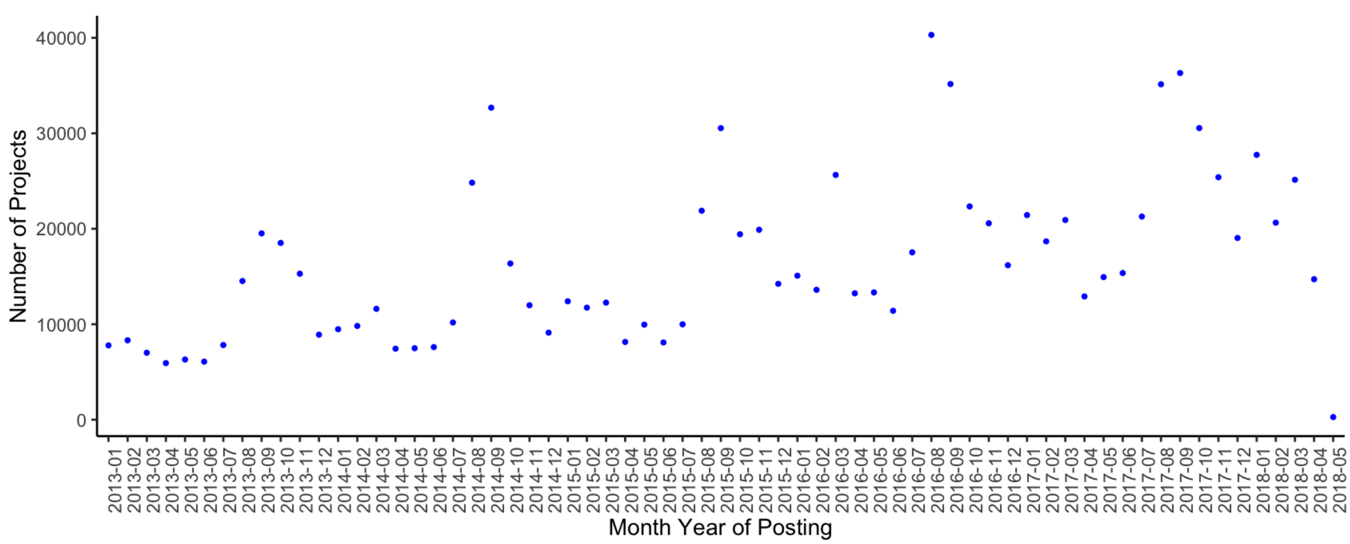


Figure A2: Number of projects posted by month year

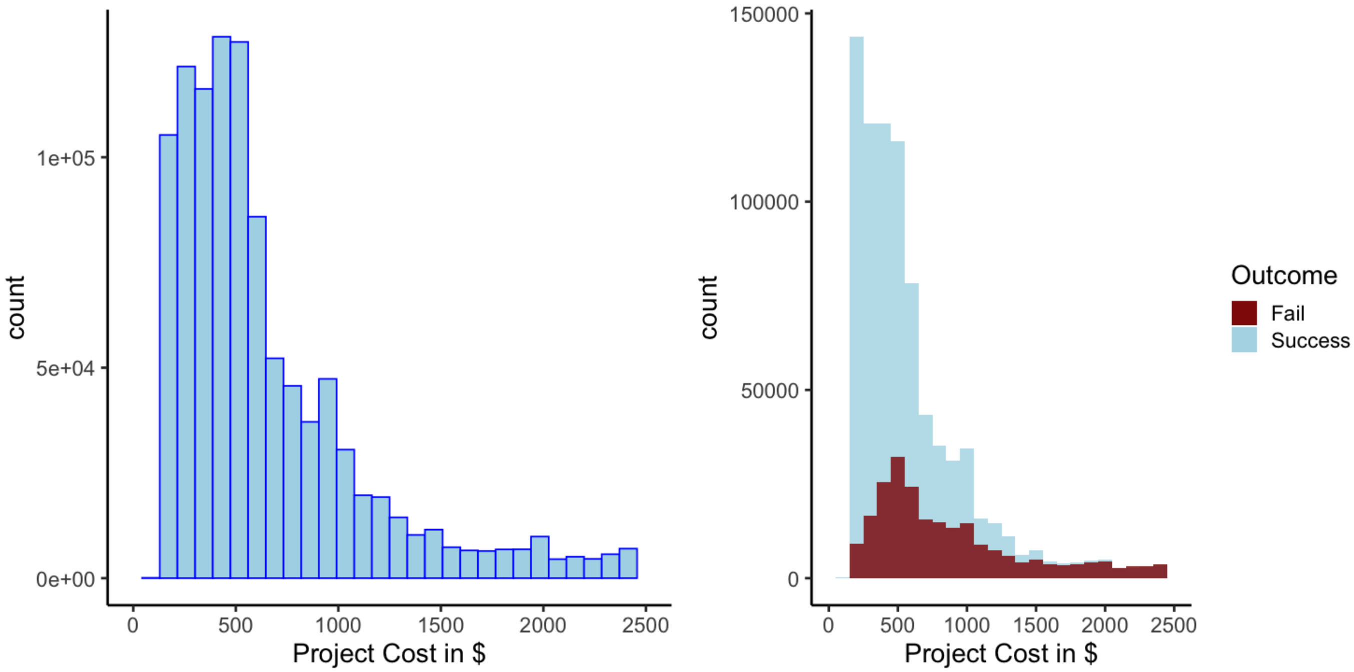


Figure A3: Overall (left panel) project cost (in$) distribution and breakup (right panel) by project outcome

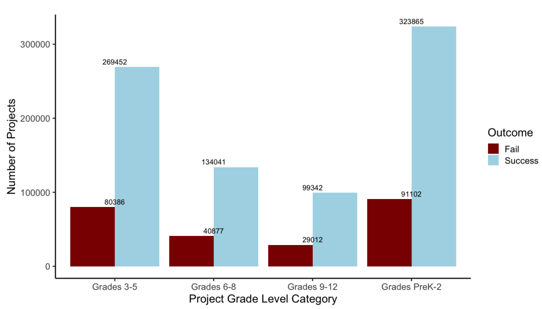


Figure A4: Number of projects - failed vs success - by class grade

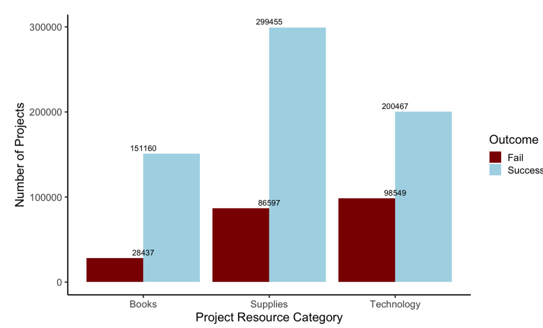


Figure A5: Number of projects - failed vs success - by top resource category

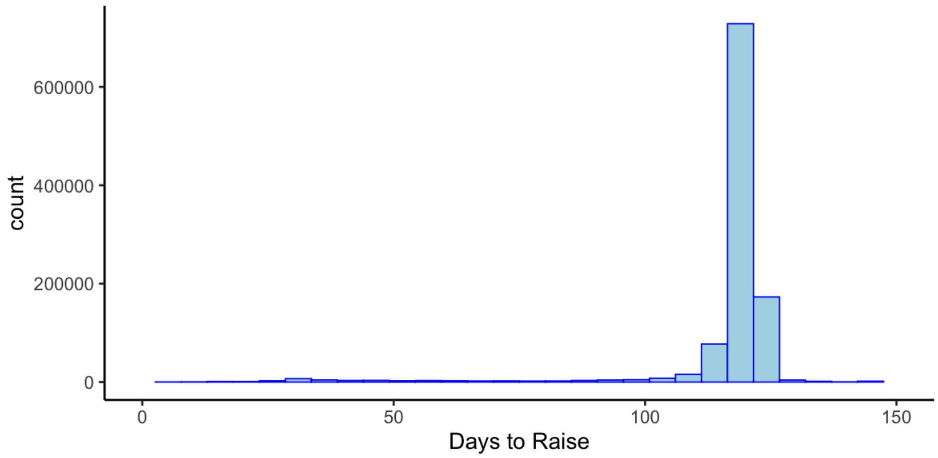


Figure A6: Number of days to raise funds before the project expires

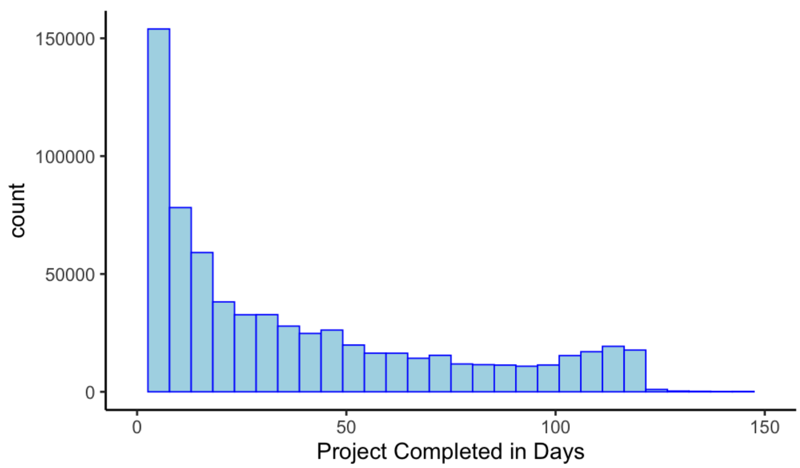


Figure A7: Days needed to raise 100% of project cost

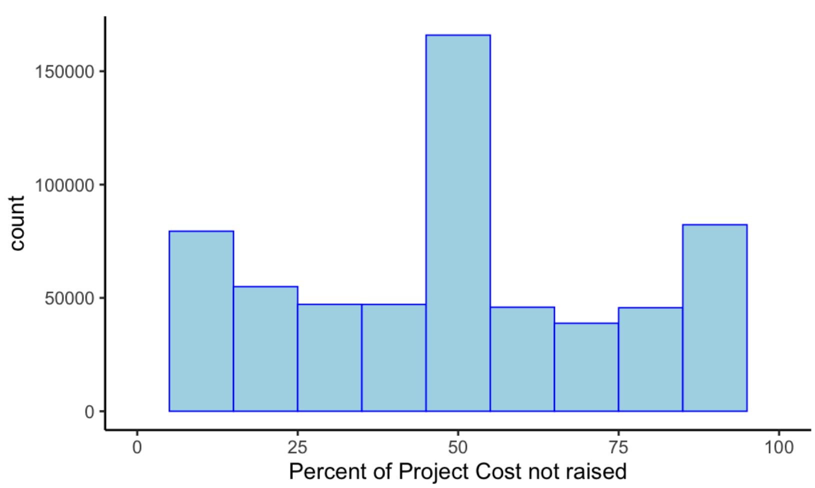


Figure A8: Percentage of project cost not raised for failed projects

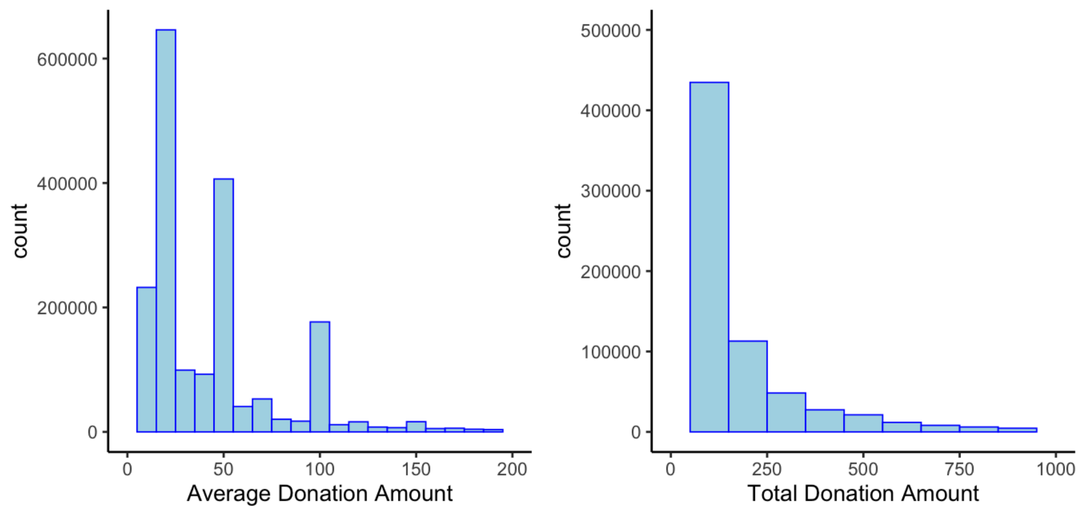


Figure A9: Avg and Total Donation Amounts in USD

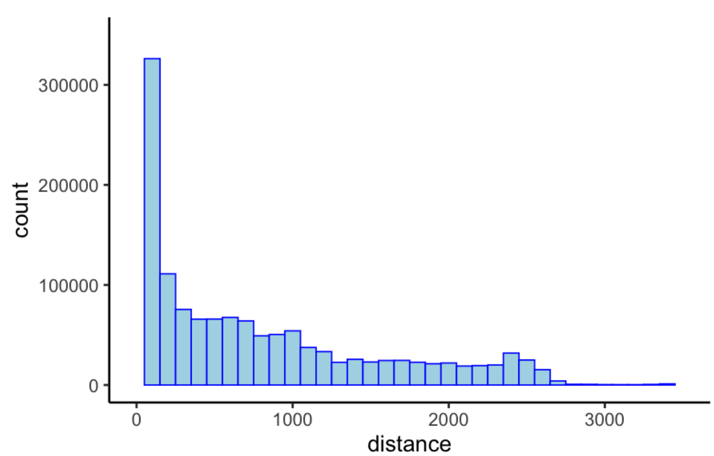


Figure A10: Distance in miles of donors to schools

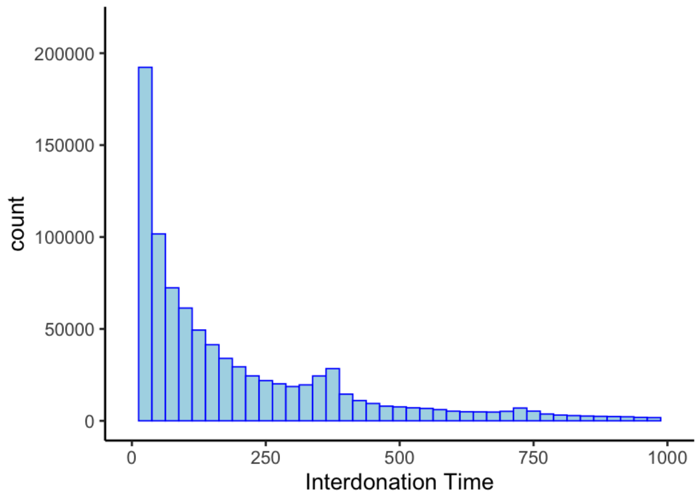


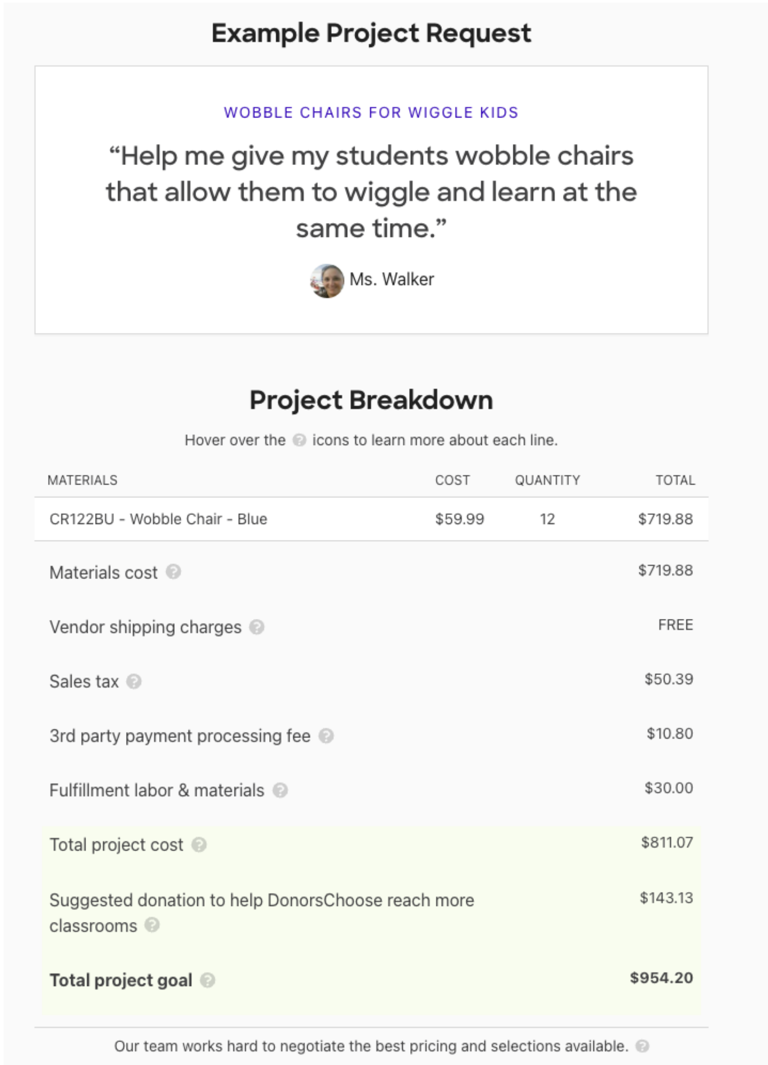
Figure A11: Interdonation Time from the platform data

Table A5: Results from mediation analysis with recommend as DV

	Estimate	Std. Err.	z	p
		Regression Slopes		
Recommend				
Project_Status	0.16	0.06	2.69	0.007
Platform-Disappointment	−0.38	0.03	−11.03	0.000
Self-Disappointment	−0.01	0.04	−0.16	0.876
Others-Disappointment	0.09	0.04	2.32	0.020
Platform-Disappointment				
Project_Status	−0.65	0.07	−9.83	0.000
Self-Disappointment				
Project_Status	−0.27	0.06	−4.24	0.000
Others-Disappointment				
Project_Status	−0.34	0.06	−5.93	0.000
		Constructed		
Indirect-Platform	0.24	0.03	7.34	0.000
Indirect-Self	0.00	0.01	0.16	0.876
Indirect-Others	−0.03	0.01	−2.16	0.031
Total	0.38	0.06	6.27	0.000
		Fit Indices		
χ^2(df)	460.93(3)			0.000
CFI	0.37			
TLI	−1.09			
RMSEA	0.50			

$^+$Fixed parameter

Note: This table reports the results from mediation analysis. Both direct and indirect effects are reported. Recommend is the dependent variable, project outcome is the independent variable and disappointment with the platform, yourself, and others are three mediators.



Example Project Request

WOBBLE CHAIRS FOR WIGGLE KIDS

“Help me give my students wobble chairs that allow them to wiggle and learn at the same time.”

Ms. Walker

Project Breakdown

Hover over the icons to learn more about each line.

MATERIALS	COST	QUANTITY	TOTAL
CR122BU - Wobble Chair - Blue	$59.99	12	$719.88
Materials cost			$719.88
Vendor shipping charges			FREE
Sales tax			$50.39
3rd party payment processing fee			$10.80
Fulfillment labor & materials			$30.00
Total project cost			$811.07
Suggested donation to help DonorsChoose reach more classrooms			$143.13
Total project goal			**$954.20**

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

Figure A12: Project Cost Breakdown

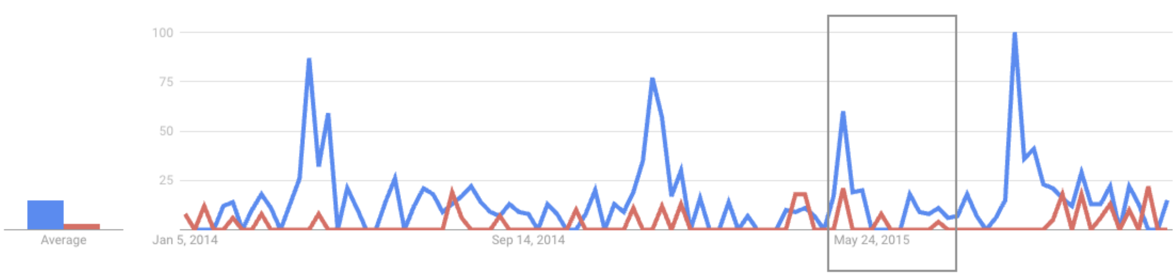


Figure A13: Google Trends comparing Stephen Colbert and DonorsChoose around the event

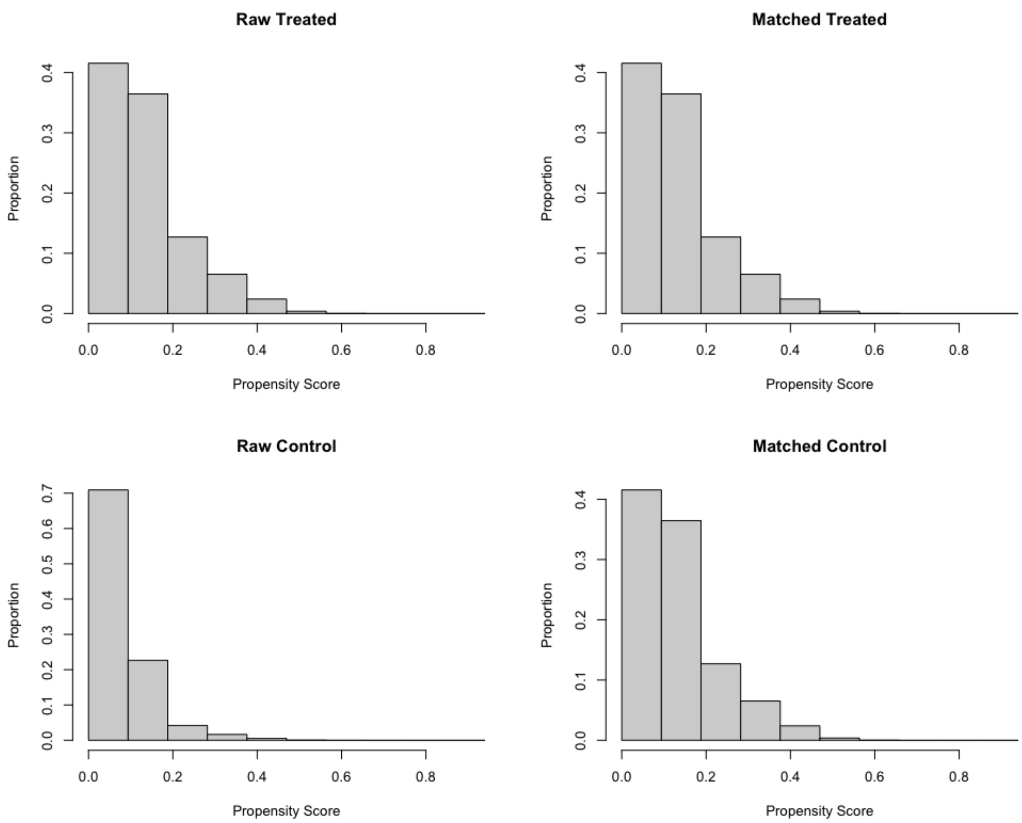


Figure A14: Overall Match (exact) Quality - comparison of propensity score raw and matched groups

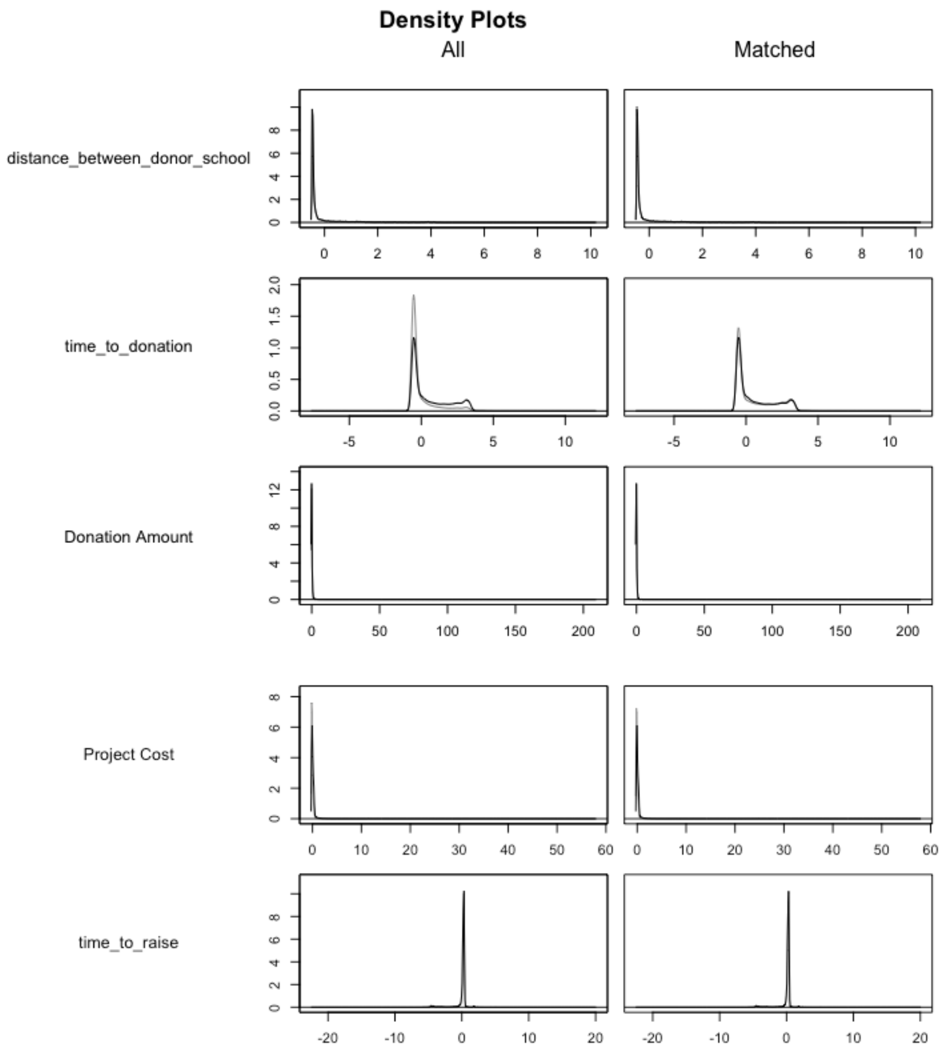


Figure A15: Variable matched on (continuous) - comparison of densities pre and post matching