Fundraising Outcomes and Donation Frictions

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Abstract

Some donation platforms (DPs) 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 DP sometimes diverting the funds to a different cause rather than returning it to the donors. Donors' future participation on such a DP, is therefore contingent on the outcome of the fundraisers they participate in, and how the DP 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 DP. To this end, we use donor- and cause-level data from one of the largest donation platforms and leverage an exogenous shock to the platform 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 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 of the model to examine the efficacy of various churn-reducing tactics. We find a 2.5% increase in retention by using a segment choice architecture, which translates to an extra $ 2.1M in donations.

Keywords: fundraising, donation platforms, churn, ranking algorithms, state dependence, segmented choice architecture

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1 Introduction

More than 88% of medical expenses-related fundraisers fail to reach their goal amount[1]. 16% of fundraisers are not able to raise a single dollar (Lee (2022)). Online donor retention is 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, their churn rates, and future dollar contributions. Playing a key role in determining the nature of this relationship is the donation platform and how it deals with donors experiencing fundraising failures. Consider the following example, a fundraiser is posted on an online crowd-sourcing donation platform[2] and a donor makes a donation to a cause. In a few days, the donor is informed that the fundraiser was not able to raise the amount (failed). 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.

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 donation to some other project on the platform. Specifically, 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 donated for, it would lead to disappointment, however, this disappointment

[1]fundraisers which fail to raise their goal amount will be called failed fundraisers henceforth in the paper

[2]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

may or may not have implications on the donor's future participation. For example, the theory in commitment inertia or warm glow (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. Similarly, there could be arguments such as if the donor feels that had they donated slightly more and that increasing the donation amount would have helped complete the project, they might increase their future participation. Thus, it is not clear which one of these explanations is supported in the field and how donors would behave after a failed fundraising experience. We formalize this tension in the subsequent theoretical motivation section.

For our empirical investigation, we look at data from one of the largest US-based donation platforms which 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%. Next, we leverage a natural intervention to identify the impact of fundraising failure on future donor behavior. In particular, in May of 2015, Stephen Colbert a famous American talk show host funded all the live projects on the platform based out of South Carolina (Brenneman (2015)) which resulted in the donors to these causes not experiencing potential failures they might have otherwise faced. This intervention allows us to create a quasi-experimental setting where we can compare donors who get their project completed unexpectedly due to the intervention to "similar"[3] donors who have a status quo success rate of 70%. Our identification rests on the low to no information dissemination (through news, web search, and internal email data) of the event to donors and potential donors of the DP. Thus the effects we

[3] using propensity score (Rosenbaum and Rubin (1983))) donors based on their first transaction details such as amount, time period, project category, grade, resource category

measure are purely due to project completion and not a combination of celebrity endorsement and project completion. Indeed, our estimates can be viewed as conservative since we compare the 100% success group to the status quo, i.e., the 70% group.

We find that if the donor's first donation experience is 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 but due to their failed fundraising experience reduced their contribution. We complement our findings with heterogeneous effects, specifically, we test if the failed fundraising experience is moderated by donor proximity (local philanthropy (Agrawal et al. (2015), Burtch et al. (2014))), time to donation (goal gradient (Kuppuswamy and Bayus (2017), Cryder et al. (2013))) and 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 my reduced form analysis. Mediation analysis indicates that participants only blame (disappointed[4]) the platform and not themselves or others.

Given that donors find the platform to be the source of their disappointment, we propose potential tactics around the design of the platform to reduce churn. In the current setup, the presentation (rank order display) of projects on the 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.

[4]for being unable to provide the donors a successful donation experience

To quantify the impact of such a design, 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 (outcome: success/fail of the project on the last donation occasion). Apart from the transaction data set obtained from the platform, estimation requires two other critical building blocks - the interarrival time of donors and the ranking algorithm of the platform. We use the comScore dataset to estimate the interarrival time[5]. 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.

To infer the page rank of projects we scrape the data from the platform page for 45 days and use a "Learning to Rank" algorithm (Burges et al. (2005)) to learn how the ranks on the webpage are decided based on the project features (number of donors, category, days to raise, the amount left to raise, etc.) We use institutional information from the firm, and the study by (Vana and Lambrecht (2022)) , that claim that the ranks of the projects are a nonlinear function of these features. Using these 3 sets of data, we estimate our structural model. Since our data are at the donor level, we allow for heterogeneity across donors in the effects of the model parameters which yields a random coefficients logit model that we estimate 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 can lead to the probability to donate again of 12.81%, an increase of 2.5%. Such an increase translates to a$2.1M increase in total donations.

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

[5]Interarrival time denotes the time between two visits by the donor on the DonorsChoose website, the visitation may or may not include the donation event

find evidence against goal gradient. To understand the mechanism behind our findings we conducted a survey and we are able to reject the self-efficacy or social comparison as reasons behind churn, rather, donors only blame the platform for the fundraising failure and therefore churn out. 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 platform design. A platform that is trying to maximize donations in the short term (myopic objective) might ignore the importance of donor retention. Specifically, this paper helps managers quantify the impact of unsuccessful donation experiences and related donor churn. It also proposes a low-cost solution to alleviate related concerns.

The rest of the paper is organized as follows in the Institutional Details section we provide details on the platform. In the data section, we describe the data in detail, followed by reduced form evidence where we construct a simple empirical setting to identify the effect. The role of the model section is to mimic the donor decision process and eventually use counterfactuals to design an alternate choice architecture to churn concerns. In the mechanism section, we conduct a survey to figure out the mechanism behind the effect. Finally, we discuss the implication of this research before concluding the paper.

2 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.

3 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.[6] 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 claim tax deduction of all the 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,

[6] 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)

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.[7] 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 Data

DonorsChoose was generous to share all of its transaction data since the inception of the platform. Specifically, we observe detailed donation transactions from 2001-2021. We filter the data to 2013-2018 because we only have detailed information about donors for this period. In total, there are 4.5 million donation transactions, 2 million unique donors, 1 million projects, and 54 project categories across all states in the US. In our data span, the platform raised nearly $274

[7] 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.

million.

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.

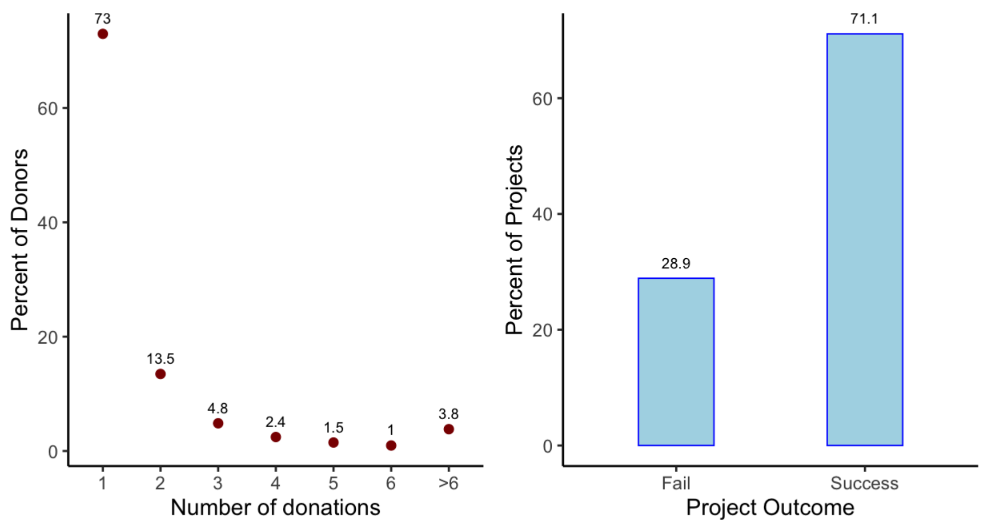

Figure 1: Donor Retention and Project Outcomes

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.

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 Technologies. 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.[8] More than 75% of 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).

5 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.

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

5.1 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.

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

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 amount of subsequent donations on the platform.

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

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 a success, and the log of total future transactions is also negatively correlated with the first donation failure variable. 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	-0.056^{***}	0.028^{***}	-0.013^{**}	0.045^{***}
	(0.006)	(0.004)	(0.001)	(0.005)
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.

5.2 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. 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.

5.3 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 donors who contributed to similar projects that were not completed by Stephen Colbert because the projects were based in another state.

Specifically, we want to estimate the causal effect of experiencing a donation failure, as shown in equation 3. We operationalize the IV approach by constructing a dummy variable $StephenColbert_i$ that takes on a value of 1 for donors that contributed to a project in South Carolina which were live (available on the website for donation) in May 2015[9]. The variable takes on a value of 0 for donors that contributed to projects based in other states. We instrument for

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

FDE_i using $StephenColbert_i$.

$$Churn_{i2} = \beta_0 + \beta_1 FDE_i + \varepsilon_i \tag{3}$$

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 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[10]) 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.[11] 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.

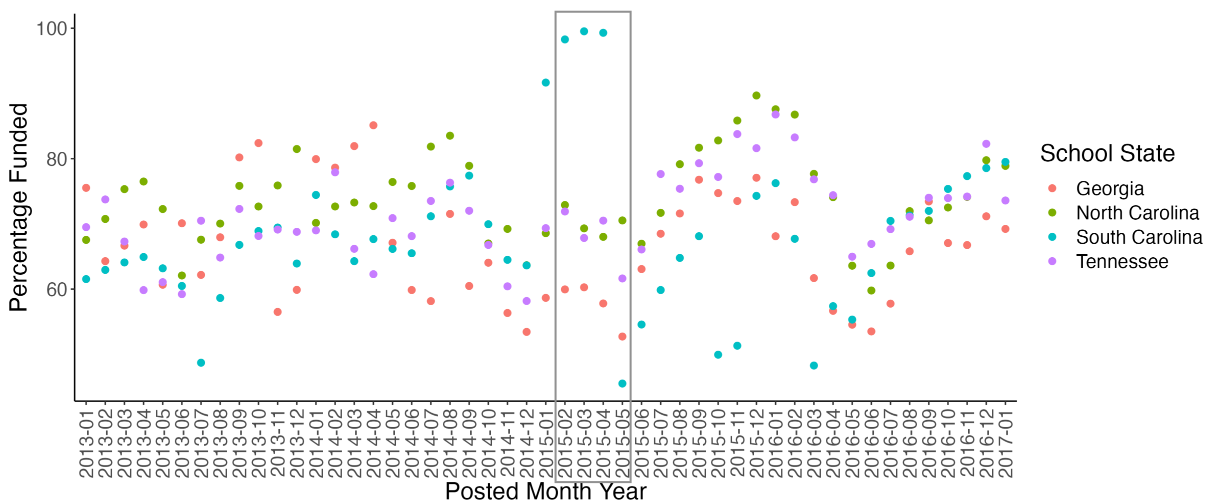

Figure 2: Percent of projects funded by month year of their posting

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

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

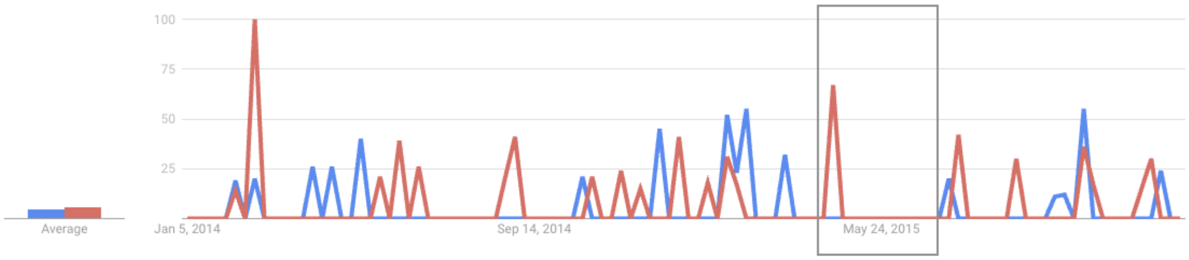

Figure 3: News coverage of Stephen Colbert donation event

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	0.758***	−3.6391***	0.498**	−2.006**
	(0.119)	(0.763)	(0.163)	(0.665)
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 weak instrument tests are included in the last row.

5.4 Propensity Score Matching

Although the instrument helps isolate exogenous variation in the first donation outcome, there could be still 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 a 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.

5.5 Heterogeneity

In this section, we explore heterogeneity in how donors respond to experiencing a first donation failure. To this end, we expand equation 3 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)). 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)). 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 shows that a donor's distance to the recipient school and the donation amount does not appear to moderate the effect of experiencing a donation failure. Interestingly, regarding the timing of a donation, we find that people who donate late are less affected by a fundraising failure than donors who donate early.

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

	Dependent variable:	
	Churn	log(Tot Future Don)
	(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.

6 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.

6.1 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 B)

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.

6.2 Results

6.2.1 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.

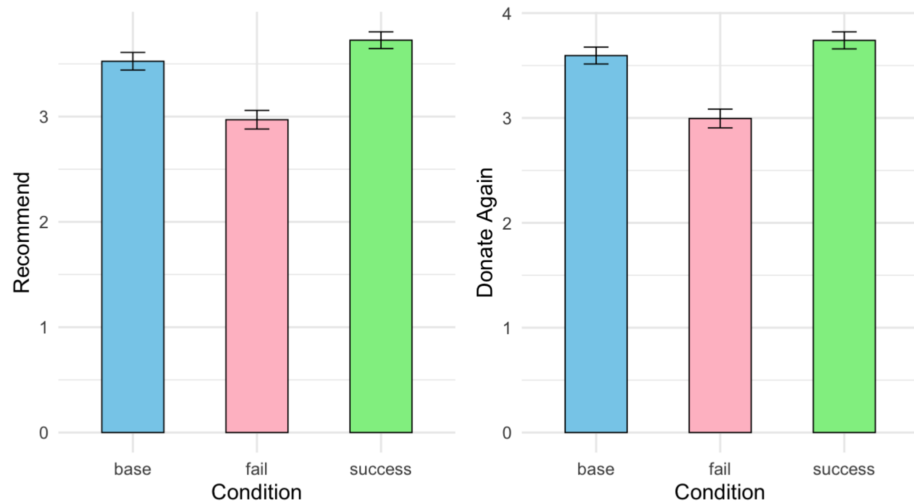

Figure 4: Propensity to recommend (left panel) and donate again (right panel) across different conditions

6.2.2 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 × More	-0.430^{*}	-0.280
	(0.236)	(0.235)
Success × 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.

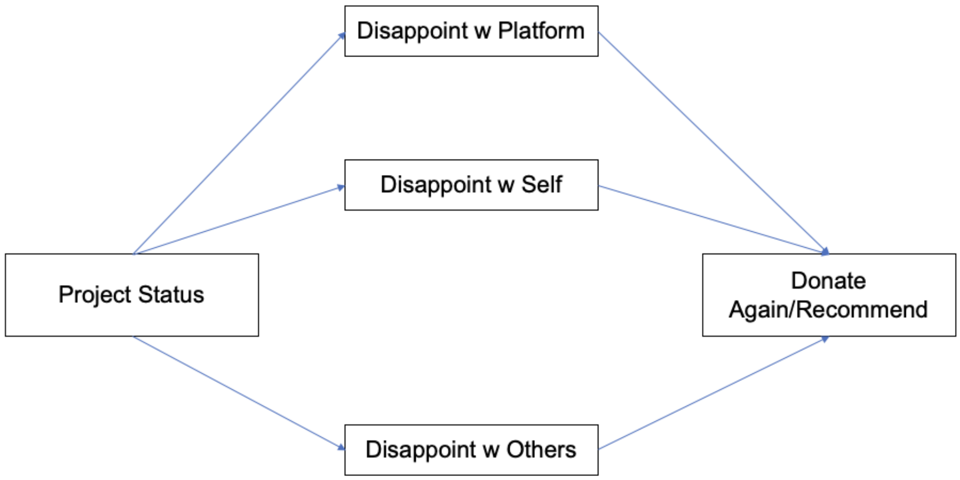

Figure 5: Path diagram: Independent variable (project status), possible mediators and dependent variable

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.

6.3 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.

7 Model

7.1 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 use a segmented choice architecture. Specifically, we propose that the platform should customize the ranking algorithm such that projects which have the highest probability of success are ranked first for first-time donors, thereby increasing the chance that they have a successful first experience. This 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.

7.2 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.

7.3 Model Formulation

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

$$u_{ijt} = \beta_{0i} + \beta_{1i}SD_{it} + \beta_2 Rank_{jt} + \beta_3 PF_{jt} + \varepsilon_{ijt} \tag{4}$$

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 random intercept term (assumed to be normally distributed) 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 the project features such as project cost, days remaining for donation, etc. Lastly, ε_{ijt} are the random shocks for donor i for project j at time t, which are assumed to be type I extreme value. Equation 5 gives the joint likelihood function, which we estimate using simulated maximum likelihood.

$$L(\beta, \sigma|\mathbf{y}, \mathbf{X}) = \prod_{i=1}^{N} \prod_{k=1}^{T_i} \int \left[\prod_{j=1}^{J} \frac{e^{\mathbf{x}_{ij}\beta_j}}{\sum_{k=1}^{J} e^{\mathbf{x}_{ik}\beta_k}} \right] f(\beta) d\beta \tag{5}$$

7.4 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.

7.4.1 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 our partner 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.

Next, we will illustrate the data creation process. Consider a donor 'i' who first donated at the time 't', to get a consideration set, we select the top 10 projects based on the rank score [12] for time 't'. Although there are almost 25000-30,000 projects available, we assume that only the top 10 projects would be in the donor's consideration set. [13]. Next, using the empirical CDF of the intervisit time from comScore data, we draw a random intervisit time, say 30 days. We will then create a stack of rows prior to the first donation, which has the top 10 projects for time t-30 and their corresponding features. For the next transaction after 't', we again draw from the intervisit time distribution, say this time the draw is 20 days, and if the next true transaction has after 20 days from 't', we will again inject a stack of rows with the top 10 projects from 't+20' with no donation and corresponding project features. For all subsequent transactions, we follow the same steps, i.e. drawing an intervisit time and stacking non-donation (visit but no donation) events with the top 10 projects and their features.

Estimating Rank - To estimate the rank of projects each day we scrape the website and use the scraped ranks and project features to train a ranking algorithm. The details of how ranks are created are available in the section 7.5. 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 reduces potential endogeneity due to personalization. The rankings are also not adjusted with the last donation outcomes.

State Dependence Variable - state dependence variable is used to capture the donation out-

[12]This rank score is estimated from the learned ranking algorithm using project features for that day

[13]Top 10 ranked projects have the highest market share. Prior literature and suggestive evidence provide the basis for this assumption

come of the last donation of a donor. We create the state-dependent variable as follows - in case the donor's last transaction is after the project is completed and there is an outcome of the project, then we assume the outcome of the last project as the state for the current period. However, if the project has not materialized then the state variable takes the outcome of last to last project outcome.

Initial Conditions - The starting point/ initial conditions have been shown to have a considerable effect in the state dependence model (Simonov et al. (2020)). In my setting, the initial conditions can be thought of as a donor's prior on project outcome. Results from the survey show that when donors are not provided with any information they assume the project to succeed. Therefore, for initial conditions, we assume the state to be a success.

7.5 Learning To Rank

Effects of position on the webpage and associated click/choice probabilities have been well documented (Ursu (2018), Derakhshan et al. (2022), Ferreira et al. (2022)). Project positions if not accounted for can cause omitted variable bias in models which involve linking project features and choice.

Ranking algorithms are confidential to the platform and we could not get access to the ranking algorithm. However, as documented by (Vana and Lambrecht (2022)), our focal platform project rankings are a nonlinear function of the observed characteristics of the projects.

To this end, we scraped 45 days of data from our partner platform website, although most of our data is scraped for the year 2023. We were also able to scrape a few days in 2015 using a web archival (Wayback Machine) website. With scraping, we get features [14] of the listed projects for each day.

Typical ranking algorithms (Burges et al. (2005), Burges (2010)), have the following structure, $x = (q, d) \longrightarrow$ Scoring Model $\longrightarrow s = f(x)$, where q is the query and d is the document

[14] project category, resource category, project cost, the amount remaining, days remaining, number of people who have already given, etc.

(for example - if you search dog food (query) in Amazon search you get a list of items (documents) Next, we train a learning-to-rank algorithm (LAMBDAMART), where we use 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) is the building block of the LAMBDAMART algorithm. We train the algorithm on the scraped data and use the model to predict the ranking score on the transaction-level data. Using this model, the NDCG metric of 0.91 is achieved.

Therefore, for each project for the time its active (until its fully funded or expired), we know the project features from the existing data and we predict the corresponding ranking score for each project for each day until it is active).

7.6 Identification

Until now, we have assembled all the data pieces required to model the donor decision journey. In the equation 4, β_{0i} represents the baseline utility of donation, this is identified through the outside option, for each occasion. β_{1i}, the coefficient on the state dependence variable, is identified through the exogenous variation in data (*ijt*), there could be bias due to heterogeneous preferences over state dependence, to address this we include random coefficients and assume it to follow a normal distribution. Position effects could cause endogeneity concerns, however, we estimate a pooled coefficient of the rank score (which in principle captures the position effects). The identification comes from natural variations in data. Lastly, the project features could be endogenous as the teachers/platform might design projects which can solicit more donations. We assume the project features to be exogenous due to an institutional feature i.e. most teachers post only 1 project in their lifetime. Hence, we assume that teachers have not learned or acquired enough information to strategically design projects.

7.7 Results

First note, that the intercept ($\mu(\beta_{0i})$) is a large negative number, indicating that a donation event is unlikely. This is an artifact and confirmation of data, specifically, due to multiple non donation but visitation events. Second, the coefficient ($\mu(\beta_{1i})$) on the state-dependence variable is positive with a relatively smaller variance ($\sigma(\beta_{1i}$). This indicates a) if the last donation outcome is a success a donor is more likely to donate in the current period and b) 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 indicates that projects which are shown higher on the listing page have a higher chance of donation. A negative coefficient on project cost indicates that the donor prefers to donate to projects with a lower overall ask amount. Donors are more likely to donate to projects which have a higher number of donors supporting, lastly, days left to raise indicate that donors prefer projects which are not near deadlines and have raised enough donations (amount raised until). The structural estimates are in line with the reduced form in that the last donation outcome (fail) does reduce the future donation probabilities.

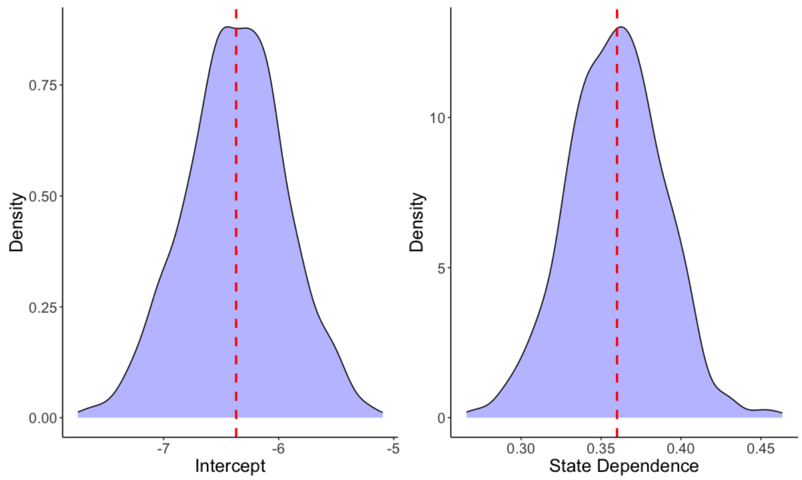

Figure 7: Distribution of intercept (left) and state dependence (right) coefficients

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 Raised Until ($)	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. State Dependence variable and Intercept are assumed to follow a normal distribution and their mean and standard deviations are reported.

7.8 Counterfactuals

One of the ways the platform can induce a higher successful fundraising experience is by updating the project display ranking algorithm on the website. The new ranking algorithm will display the project 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.

7.8.1 Predicting Success

To predict the success probability of a project, we use an eXtreme gradient boosting algorithm (XGBOOST). It is important to realize that the prediction problem is not trivial. Specifically, each day the dynamic components of a project change (for instance, the days remaining, and the amount remaining) and the target variable remains the same within the panel. Furthermore, we want to estimate the success probability for each project for each day it is available on the platform. We report the model performance metrics (ROC curve[15]) in Figure 8 below. The model achieves the AUC[16] metric of 0.945.

7.8.2 Comparing Old vs New Ranking Schemes

To estimate this, we replace the projects considered by donors on their first donation with the project predicted from the success probability algorithm. Next, we calculate the predicted probability using the model estimates and project features. The donor picks the option with the highest indirect utility or predicted probability. We extract the outcome of the selected project from the platform data. For the next period, we assume the state to be the outcome of the last step and generate the probability of making a donation. The counterfactual compares the shift in the probability of donation in the old vs new ranking algorithm. We report the probabilities to donate after the first donation under 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

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

[16]AUC: Area under the curve, 0.5 suggests no discrimination, 1.0 suggests perfect discrimination between classes

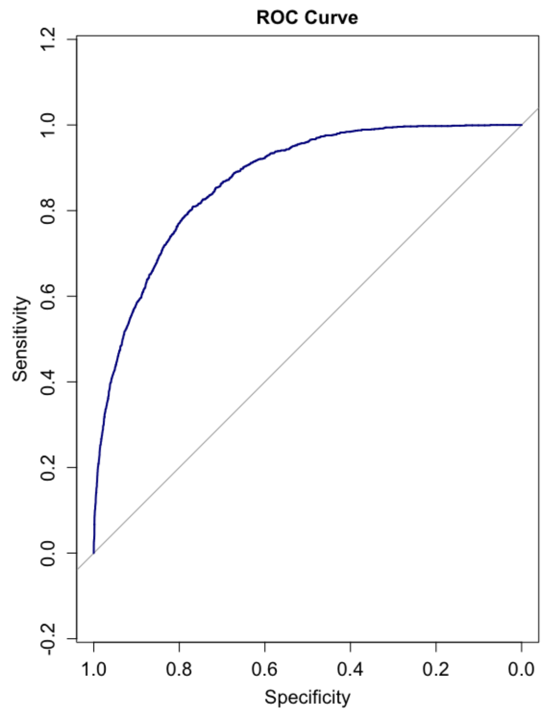

Figure 8: ROC curve for predicting the success vs failed projects

the projects with decreasing order of 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

8 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 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 displayed projects with higher success probability, 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 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.

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Part I

Web Appendix

A 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	3/4/16	1	F
	d1	p3	3/4/16	0	F
	d1	p4	3/4/16	0	F
After	d1	p5	3/4/16	0	NA
	d1	p6	3/4/16	0	NA
	d1	p7	3/4/16	0	NA

B 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.

C 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

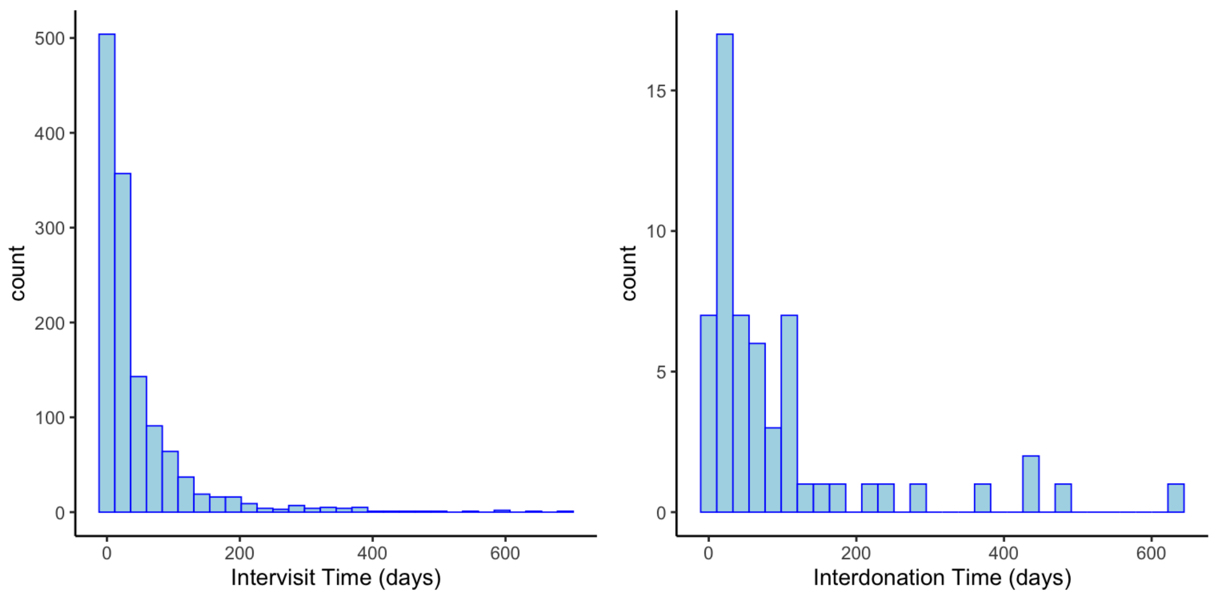


Figure A1: Distribution of Intervisit and Interdonation Time in Days using comScore data

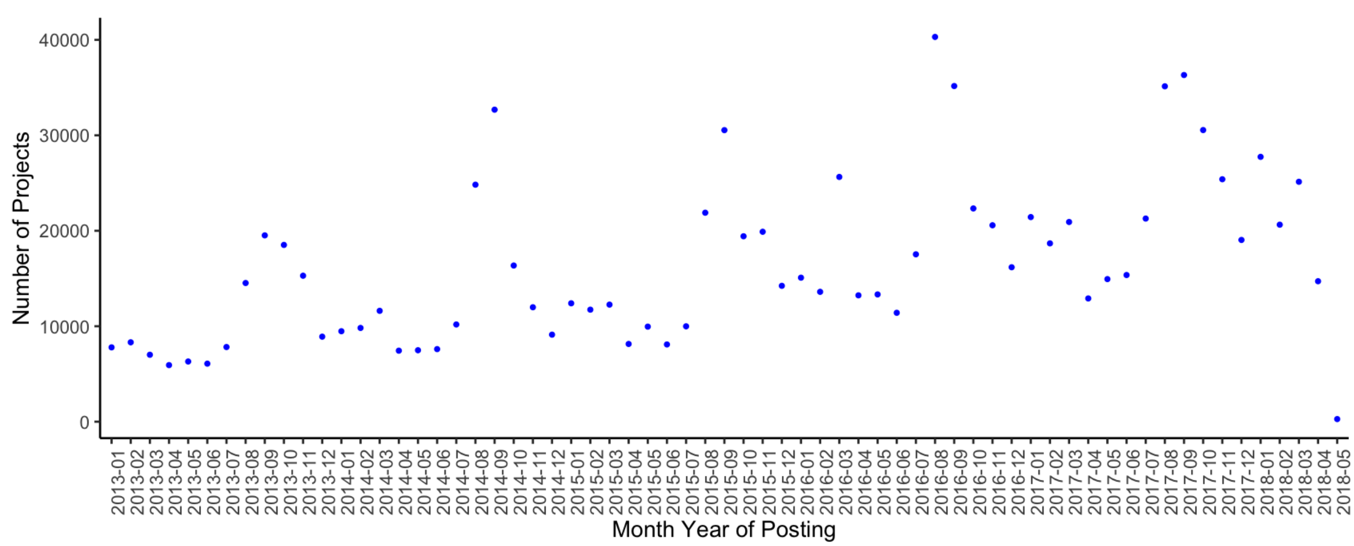


Figure A2: Number of projects posted by month year

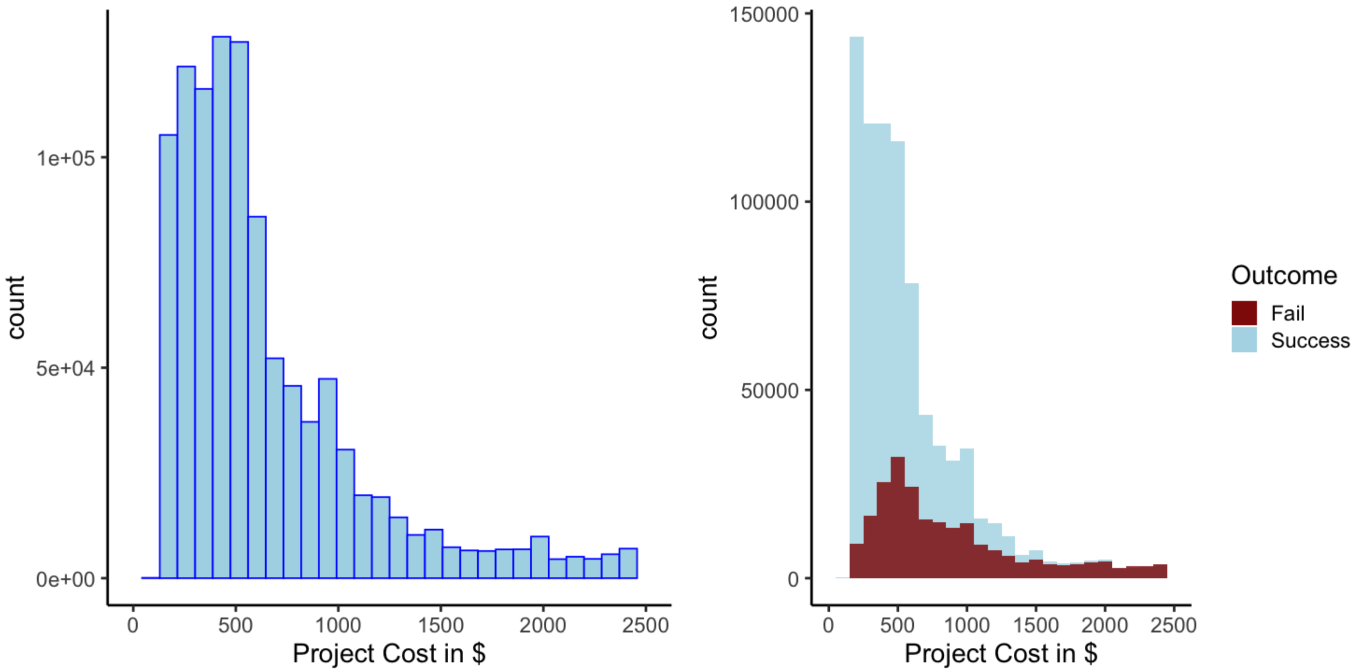


Figure A3: Overall (left panel) project cost (in$) distribution and breakup (right panel) by project outcome

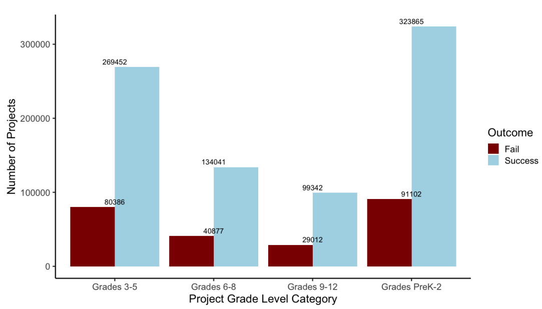


Figure A4: Number of projects - failed vs success - by class grade

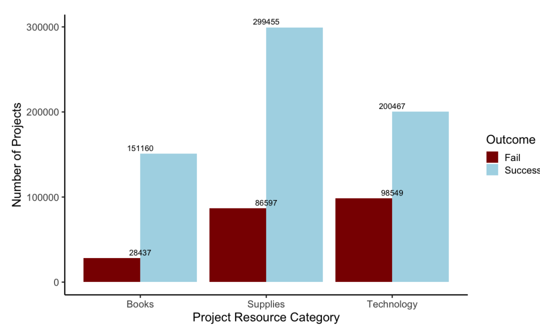


Figure A5: Number of projects - failed vs success - by top resource category

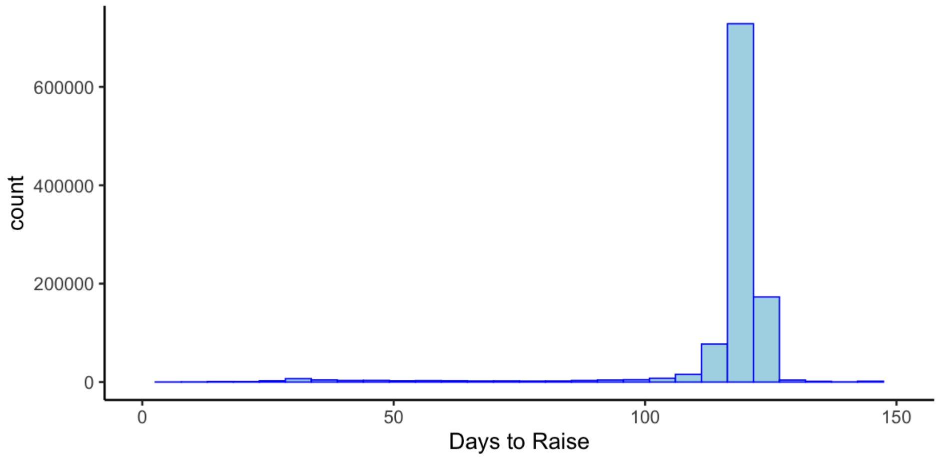


Figure A6: Number of days to raise funds before the project expires

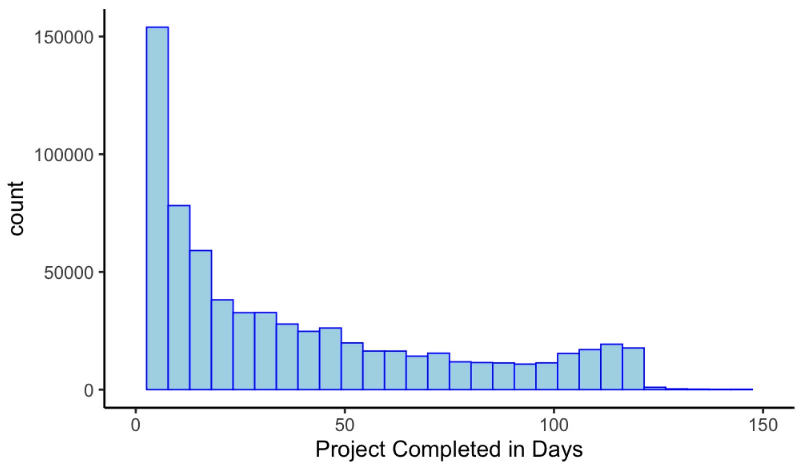


Figure A7: Days needed to raise 100% of project cost

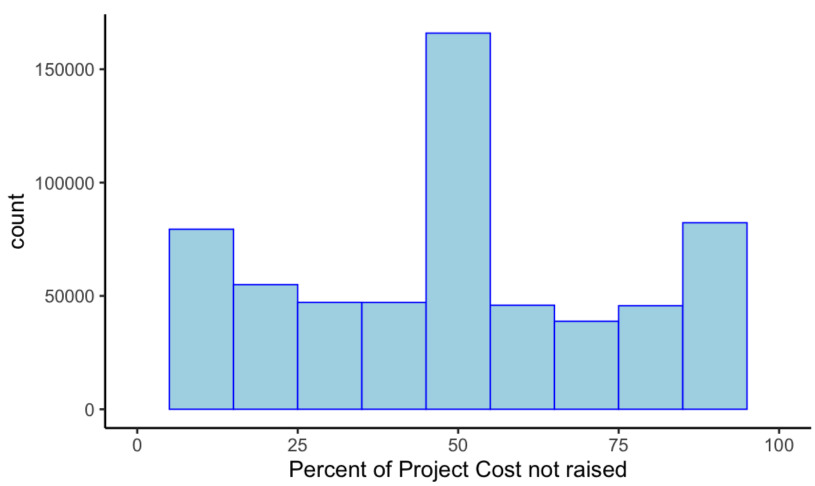


Figure A8: Percentage of project cost not raised for failed projects

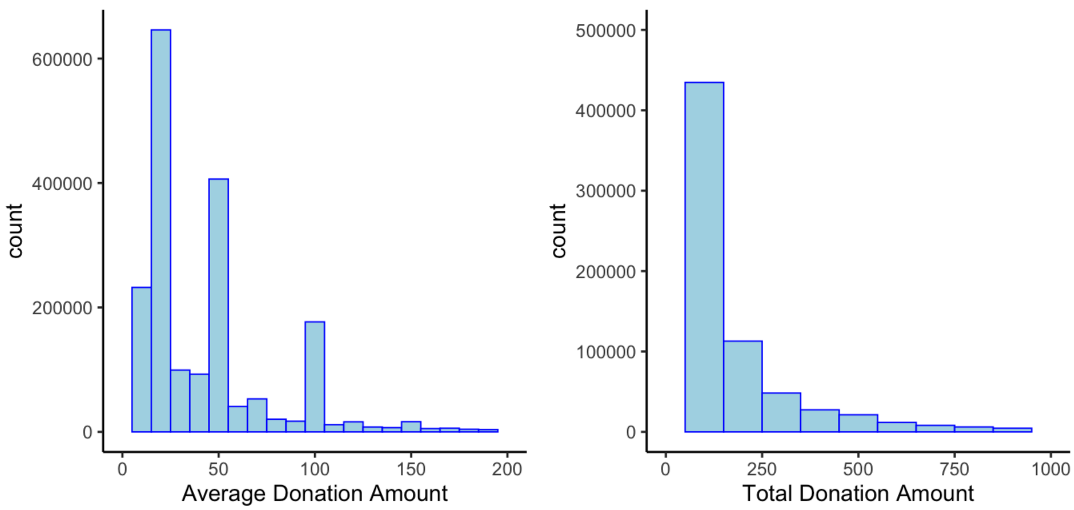


Figure A9: Avg and Total Donation Amounts in USD

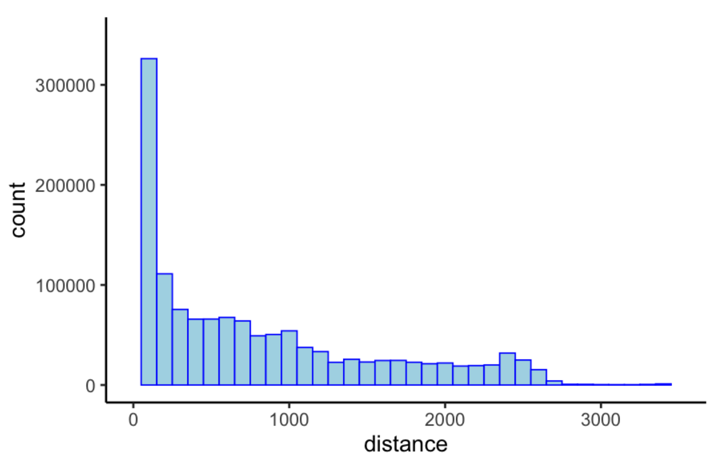


Figure A10: Distance in miles of donors to schools

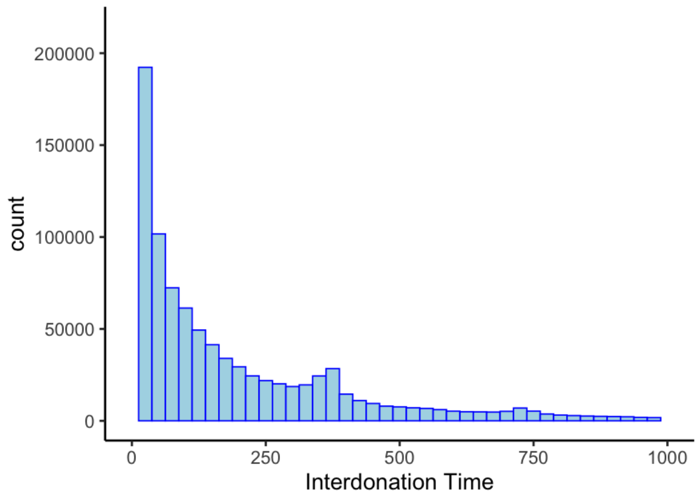


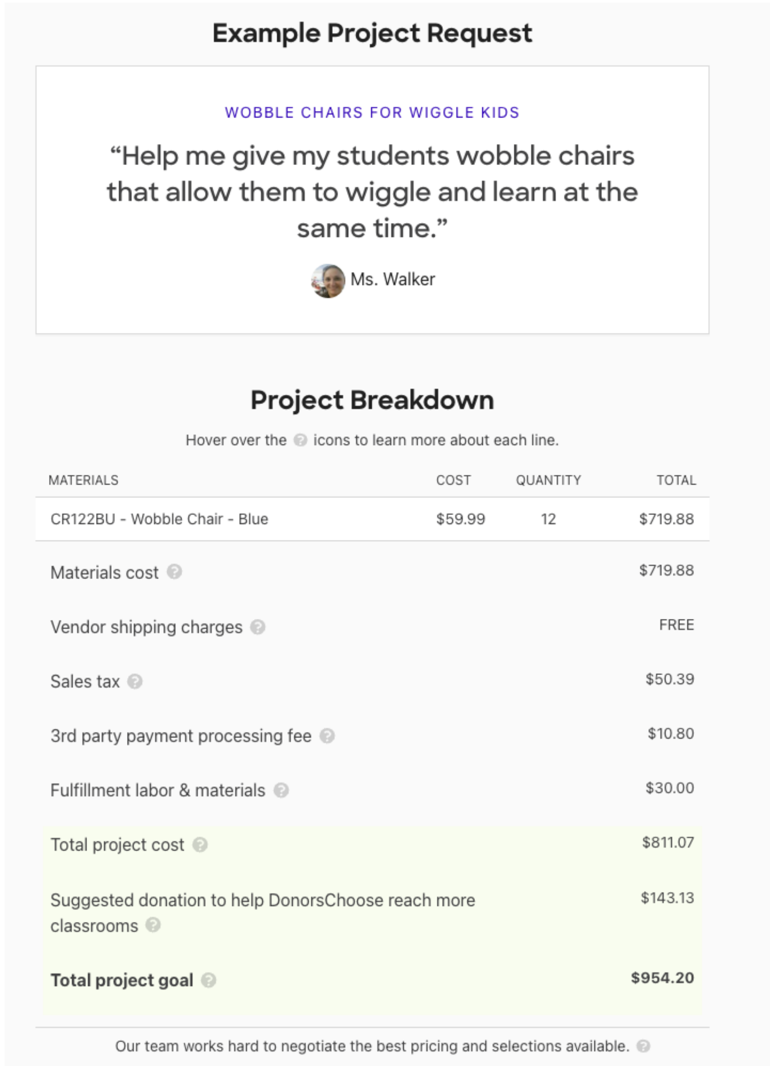
Figure A11: Interdonation Time from the platform data

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

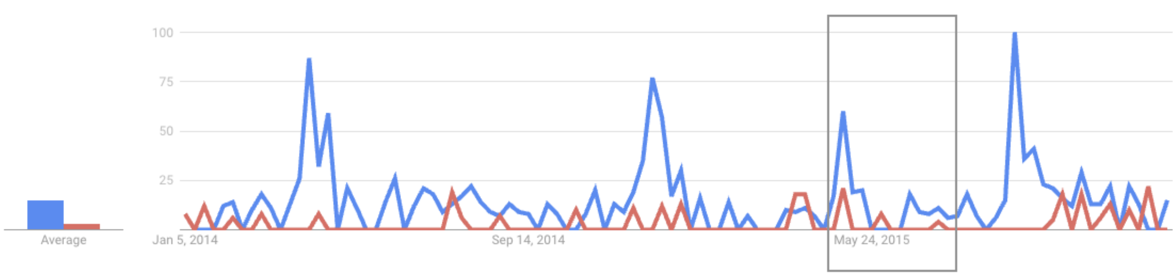


Figure A13: Google Trends comparing Stephen Colbert and DonorsChoose around the event

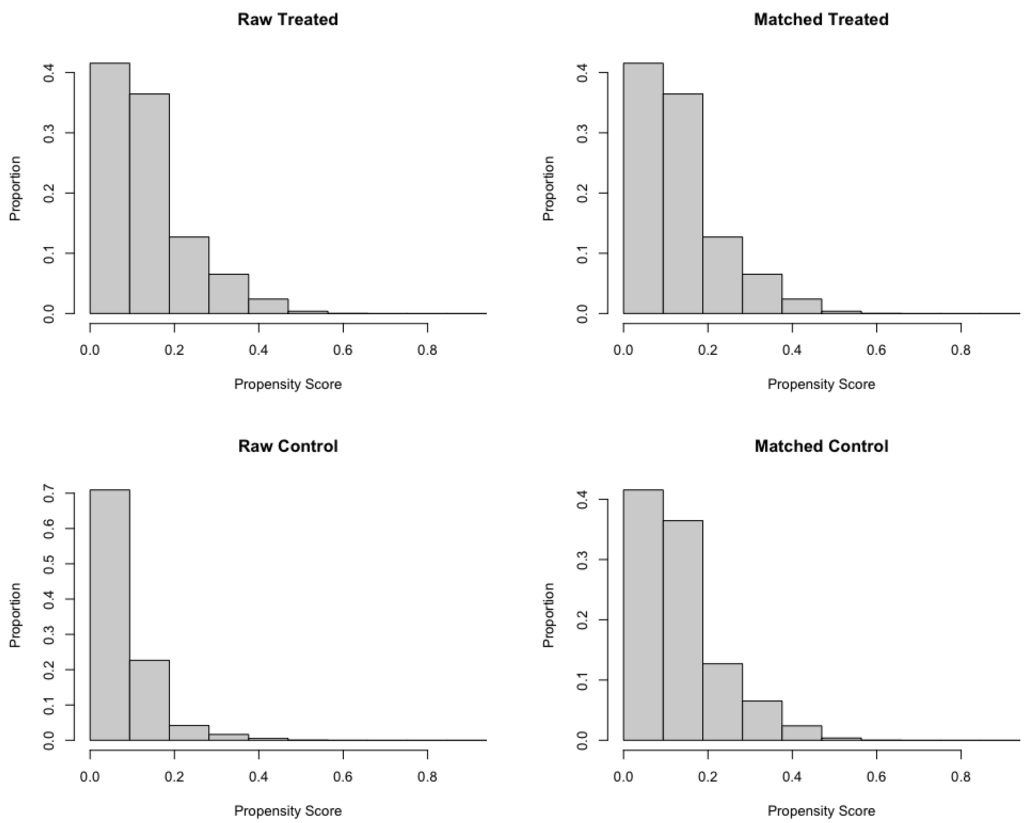


Figure A14: Overall Match (exact) Quality - comparison of propensity score raw and matched groups

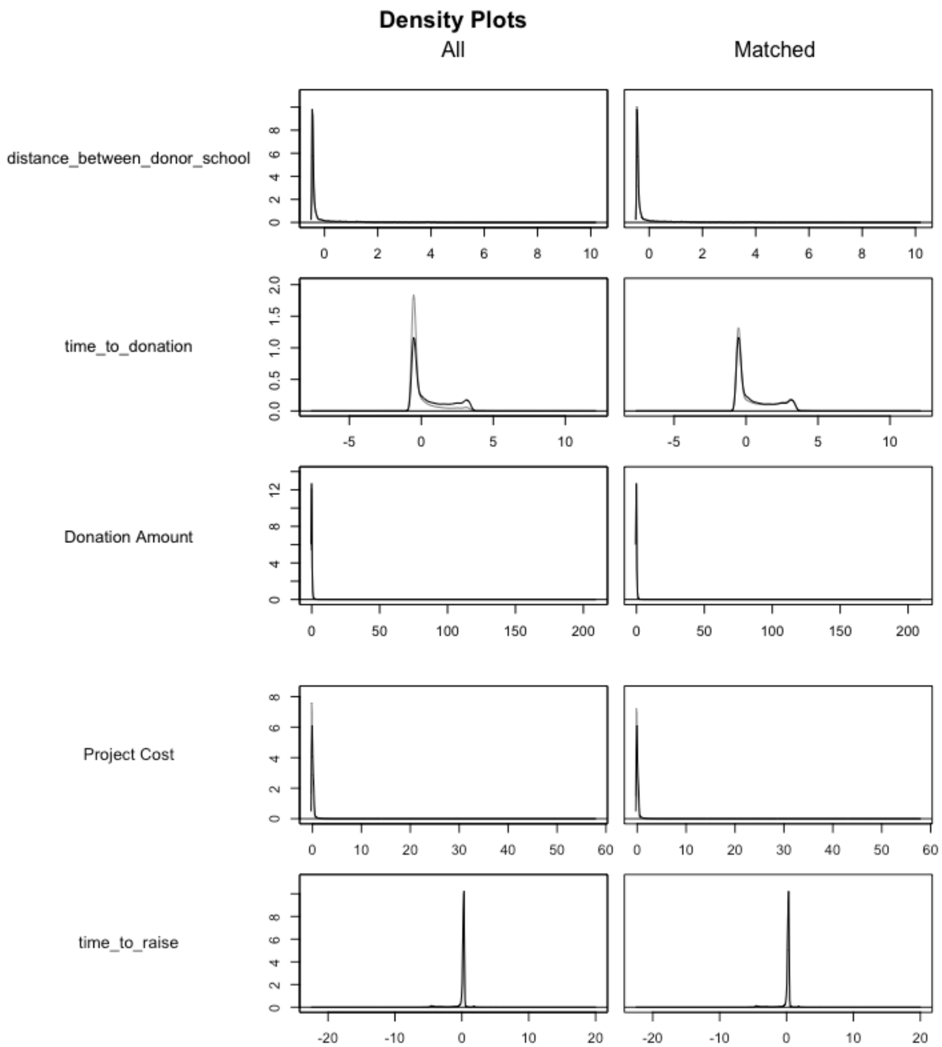


Figure A15: Variable matched on (continuous) - comparison of densities pre and post matching