Fundraising Outcomes and Donation Frictions

Abhishek Rishabh*

Kellogg, Northwestern

June 22, 2023

Click here for the latest version

Abstract

Donation platforms (DPs) are two-sided platforms between beneficiaries/nonprofits and donors. DPs list fundraisers with a certain goal amount and deadline (ex: Raise $1000 for cancer care in 30 days). Donors' future participation on the DP, is contingent on the outcome of the fundraiser and how the DPs deal with the fundraiser outcome. Theories in social exchange predict that a donor would reduce future participation in the event of a failure, conversely, commitment inertia would predict no change in future participation. In this paper, I investigate the impact of fundraising experiences on donors' future giving. To this end, I collaborated with one of the largest donation platforms and use donation level data along with an exogenous shock to the platform to document that if a donor's first fundraising experience is a failure, then they are 32.8% more likely to churn and conditional on future donations they reduce their donation amount by 37.8%. Next, I propose a segmented choice architecture to alleviate the churn associated with failed fundraising experiences. I build a structural model which models a donor's decision journey and using the estimates of the model I test the efficacy of my proposed architecture. I find a 2.5% increase in retention, which translates to an extra $ 2.1M in donations. Last, I use a survey to uncover the mechanism behind my findings.

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

*abhishek.rishabh@kellogg.northwestern.edu. I am a Golub Capital Social Impact Post Doc Fellow in Marketing at Kellogg School of Management. I thank Pradeep Chintagunta, Anna Tuchman, and Dean Karlan for their mentorship on this paper. I am grateful to Donorschoose.com for providing data for this research. I would also like to thank the members of Golub Capital Lab at Kellogg, Northwestern and participants at brown bag seminars of Northwestern University for their insightful comments. IRB approval was provided by Northwestern University (STU00219174).

1 Introduction

More than 88% of medical expenses-related fundraisers fail to reach their goal amount[1], and 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))), implying, 77% of donors never donate again. In this paper, I explore the connection between failed fundraiser experience of donors and their churn and future dollar contribution. An important agent between this connection is the donation platform and how it deals with the fundraising failure experiences. For illustration consider the following example, a fundraiser is posted on an online crowd-sourcing donation platform[2] and a donor makes a donation. In a few days, she is informed that the fundraiser was not able to raise the amount (failed). Now the platform can do one of the following a) return her money (ex: Indiegogo (2021)) b) direct the total raised money to the beneficiary (ex: GlobalGiving (2021)) c) redirect the money to something else (ex: DonorsChoose (2020)). These are some strategies practiced by major donation platforms, which could then influence a donor's future participation on the platform.

In this paper, I focus on a platform that redirects the donation to some other project on the platform. Specifically, I aim to answer, does a failed fundraising experience affects a donor's future participation (churn and dollar contribution) on the platform. What drives the results? And, how can the platform address the related concerns?

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 may or may not have implications on the donor's future participation. For example, the theory in commitment inertia or warm glow (Andreoni (1990);

[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

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 extra donation would have finished the project, they might increase future participation. Thus, it is not clear which one of these explanations holds true and how would donors behave after a failed fundraising experience. I formalize this theoretical dilemma in the theoretical motivation section.

To study this phenomenon, I collaborated with one of the largest US-based donation platforms which helps school teachers raise money for their classroom projects such as buying books, stationery, musical instrument, class repair, etc. The platform was generous to provide detailed transaction-level data from its inception, nearly 20 years of data. I first document that the problem of fundraising failure is present on the focal platform, 30% of all the projects listed fail to raise their goal amount. Furthermore, donor attrition after the first donation is 73%, and after two donations is almost 87%. Second, I construct an empirical setting where I compare donors who are similar in everything else (observed) except a natural intervention, this construction helps me create a quasi-experimental design for a proper comparison in means of churn and dollar contribution. Specifically, I match (using propensity score (Rosenbaum and Rubin (1983))) donors based on their first transaction details such as amount, time period, project category, grade, resource category, location of donor and school, etc. Next, for identification, I use an exogenous shock on the platform. 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)). This institutional intervention helps me create a quasi-experimental setting where I can compare donors who get their project completed suddenly due to intervention to donors who have a status quo success rate of 70%. I use low to no information dissemination (through news, web search, and internal email data) to ensure instrument validity. Specifically, the effects are purely due to *project completion* and not a combination of *celebrity endorsement* and *project completion*.

My estimates can be an underestimation of the phenomenon (since I compare the 100% success group to the status quo - which is 70% group), I find that if the donor's first donation experience is failure she is 23.6% percentage points more likely to churn (extensive margin) and conditional on future donation (intensive margin), the donors reduce their dollar contribution by nearly 38%. 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. I complement my findings with heterogeneous effects, specifically, I 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, I delve into exploring its underlying causes. I hypothesize three potential explanations. First, donor churn may be prompted by dissatisfaction with the platform itself Anderson and Sullivan (1993). Second, it could be a consequence of disillusionment with peers or others, 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 I first confirm the results from my reduced form analysis. Mediation analysis indicates that participants only blame the platform and not themselves or others.

Given that donors find the platform to be the source of disappointment, I propose a modified/segment choice architecture. In the current setup, the presentation (rank order display) of projects on the homepage is not personalized by donors and I propose that if the platform somehow on average the first-time donation experience to success compared to status it would not lose out as many donors.

To achieve this I build a structural model in which the utility derived by a donor is a function of the rank of the project, project features, and state dependence variable (outcome: success/fail of the project in the last donation occasion). My model is not estimable just using the platform dataset as it only contains donation-level information. Apart from the transaction data set, the two other critical building blocks are inter-arrival time for donors and the ranking algorithm. I use the proprietary comScore dataset to estimate the interarrival[3] time for donors. In particular, to generate choice events (visit but no donation), I use the comScore data and then supplement it with platform transaction data to create a full donor decision journey.

To infer the rank of projects I scrape the data from the platform page for 45 days and use a "Learning to Rank" algorithm 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.) I use the institutional information from the firm and a paper that claim that the ranks of the projects are a nonlinear function of the features. With all the components available now, I can estimate the previously described structural model. Given the random nature of the coefficients, I use simulated maximum likelihood to estimate the model.

The model estimates reveal that if a donor experiences a success their probability to donate again increases by 12.5%. In the counterfactual analysis, I use the segmented choice architecture where the first-time donors are first shown the projects with the highest probability of completion. I find that just this minimal intervention can lead to the probability to donate again to 12.81% an increase of 2.5% , which translates to a $2.1M increase in total donations.

[3]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

This paper contributes to theory and practice. Theoretically, it establishes that the failed fundraisers could have substantial effects on future participation on the platform and therefore bolster the predictions from expectation disconfirmation theories. A segment choice architecture that is rooted in personalization is proposed to alleviate the churn attributable to failed fundraising experiences.

The rest of the paper is organized as follows in the Institutional Details section I provide details on the platform. In the data section, I describe the data in detail, followed by reduced form evidence where I 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, I conduct a survey to figure out the mechanism behind the effect. Finally, I 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 I 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 or the projects should be successful.

Now consider the amount of donation. Also assume that if the project is not able to raise 50% of its funding goal then the donor will get highly disappointed and would never donate again, however, if the project raises more than 50% then the donor might be motivated to complete the future project and increase their donation by ψ. Therefore, the total donations raised in period 2 is $\alpha X + (1-\alpha)X^{new})$

$$X^{new} = \begin{cases} X, & \text{w.p } 1 - F(c) \\ 0, & \text{w.p } F(c/2) \\ \psi X, & \text{w.p } F(c) - F(c/2) \end{cases}$$

Donation raised in period 2 is given by, $E[\$Raised_2] = \alpha X + (1-\alpha)(X(1-F(c)) + \psi X(F(c) - F(c/2)).$

Under what conditions will the total raised amount in period 2 can be more than in period 1?

Comparing it period 1 amount. $E[\$Raised_2] \geq E[\$Raised_1] \implies \psi \geq \frac{F(c)}{F(c)-F(c/2)}$

For illustration, if I assume $F' = f \sim U(0,1)$ then $\psi \geq 2$.

This implies, if failure is by a small amount (less than 50% of project cost) and the donor compensates by more than doubling the donation in future transactions, there could be a possibility of raising more donations even under failure conditions.

Overall, the churn and future donation amounts depend on the donor motivations(α), project success/failures (p, 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

Our partner donation platform began its operations in the United States in 2002. It is a crowdfunding platform specifically designed for teachers and schools to raise funds for educational projects and classroom resources. 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 the calendar year, 2021, the platform received USD 187M 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)).

When a teacher[4] creates a project on the platform, they set a funding goal that represents the total amount of money needed to fully implement their project [5]. The deadline of the project is decided by the platform and is generally around 120-130 days from the date of posting. Donors can then 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, 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.

Website –On any given day, there are approximately 25,000-30,000 projects listed on the website. The projects are not geotagged, meaning that the project listings are not customized for each website visitor. I conducted checks by logging into the website using multiple devices (mobile vs. laptop), from various locations (within the US and India), and using different browsers (Google, DuckDuckGo, etc.).

[4] *Definition of a teacher*: Should 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; Should work directly with students at least 75% of the time; and Not an administrator, paraprofessional, teacher's aide, substitute teacher, or student teacher.

[5] For example - Help my students understand math better by buying mental math books. Funding goal - USD 1,000, Deadline - Apr 25, 2017

If a project is unable to reach its goal amount within the designated time limit, the platform reaches out to the donor to check if they would like to donate to a different project. If the donor does not respond within 30 days, the donation amount is redirected to an urgent classroom project in need of support. 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. Furthermore, as required by the platform, if a project reaches its goal, the donor receives a thank-you letter and is informed that the necessary supplies have been secured and delivered. Approximately 30% of all the projects registered on the platform are unable to reach their goal amount. Teachers do not receive the money directly, the platform works with various vendors to procure and deliver the items to the schools and teachers[6]. 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 overheads and other administrative expenses. Donors can claim tax deduction of all the donations made on the platform, under the 501(c)(3) tax code.

4 Data

Our partner donation platform was generous to share all the data since the inception of the platform. Specifically, the data contains detailed donation transactions from 2002-2021. I filter our data from 2013-2018 because I have detailed information about donors only for this period. In total, I have nearly observations, 4.5 M transactions, 2M unique donors, 1M projects, 54 project categories, across all states in the US. In our data span, the platform raised nearly USD 274 M.

As shown in Figure 1 left panel, 73% of all donors (nearly, 1.45 M) donate only once.

[6]*Ownership*– Materials funded through the platform are meant for the classroom to which the materials are shipped. Teacher who request for the material controls the use of the materials.

13% (nearly, 260k) 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)). Second, note that (Figure 1 right panel), almost 29% of all the available projects tend to fail raise funds. On average, a donor contributes USD 56 per donation and a total of USD 140.4, with 2.2 transactions over their lifetime. The distribution inter-donation time i.e. time between two donations is presented in Figure 18. The median inter-donation time is 78 days. The median donation amount for the first-time donation is USD 30. Out of 4.5 M transactions, 8.6% transactions are associated with failed projects.

35% of donors donate out of their state and more than 50% of donors donate to schools at least 33 miles away, indicating the donations are not localized, specifically, donors are just not donating to their neighborhood schools or concentrated towards their home state. Donors are based out of neighborhoods with a median household income of $51,204 and donate to schools that are located in neighborhoods with a median household income of $49,056.

In the data span, there are 333,856 teachers, the median projects posted by each teacher is 1 and the mean is around 2.7. It is important to account for teachers' experience with the platform as it could directly impact the project quality and thereby donations.

Out of 1M projects in the dataset, more than 75% of projects are for Grades PreK-2 and Grades 3-5, the resource requests of these projects are centered around Books, Supplies, and Technologies. Projects are posted all across the year but there are some patterns in posting, specifically, a relatively higher proportion of projects are posted during the Fall month (Aug-Sep). The median project cost is around USD 512, the mean project cost is USD 735 and 95% percent of projects are under USD 1995. An example of project breakup cost is presented in Figure 19. More than 75% of the projects are able to raise funds within 60 days of listing see Figure 14 in Appendix 8. Furthermore, the projects which fail more than 50% projects are not able to raise more than 50% of their ask see Figure 15. Once the project achieves its goal amount, it is removed from the platform, I find less than 0.1% projects to have donations of more than 100% of the project cost amount.

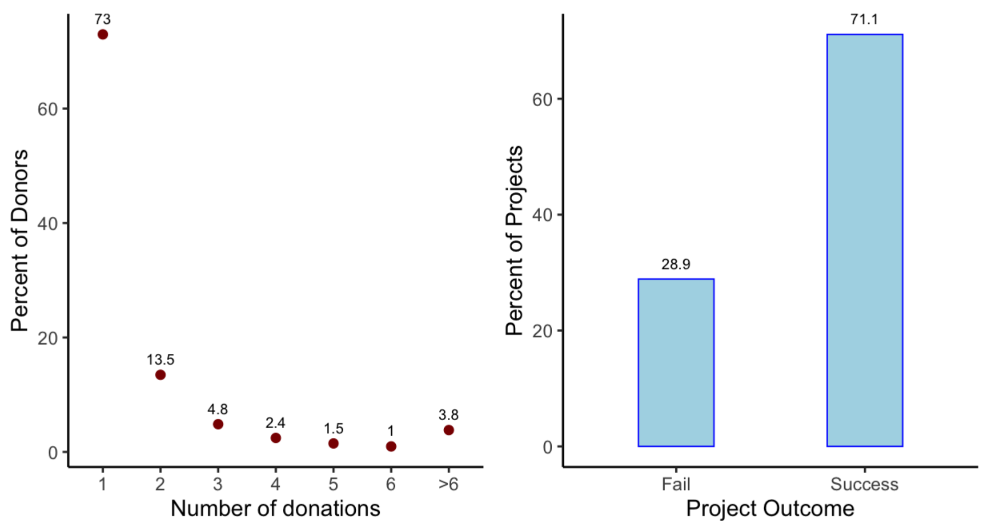


Figure 1: Left Panel: Donor Retention, Right Panel: Percent Failed and Successful Projects

4.1 Data Borders

We observe each donor and their corresponding donation transaction. Since our data starts from 2013 it could be that, when we observe a donor's first transaction, it might be incorrect, since they would have made transactions prior to 2013. To decide if a donor is a first-time donor or a have transacted with the platform earlier than 2013, we use our main dataset which contains donation transactions from the inception of the platform, and based on their IDs we flag first-time vs repeat donors.

5 Reduced Form Evidence

I am interested in understanding the impact of failed fundraising experiences on future donations. Given the attrition associated with the first donation (see Figure 1, I will focus on the first donation experience. In particular, the impact of the first donation experience (success/fail) on future donations (churn and dollar value). The ideal way to identify this problem could be a randomized controlled trial. Specifically, we randomize potential donors into two groups and in the treatment condition, the project to which donors donate - fails, whereas in the control condition, the project succeeds. The mean difference in churn and future donation is compared across two groups. However, in the absence of such a setting, I approach our identification in two broad approaches, data-based and survey-based. Details of the data-based approach are in the following section. The survey-based approach is detailed in the section 7.

5.1 Correlation Based Tests

To quantify the impact of a failed experience. I construct the following empirical setting. Consider donors A and B who donate to projects P1 and P2, respectively. Project P1 succeeds however project P2 fails. First, I compare the differences in churn. To operationalize this, I construct equation 1. $Churn_{i2}$ takes the value 1 if the donor 'i' churns and 0 if not after the first donation, FDE_i represents the first donation experience of donor 'i', and takes value 1 in case of failure and 0 when the project is successful. ε_i represents noise. β_1 captures the difference in the probability to churn of donors who have their project donation outcome as fail vs success.

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

(1)

Second, consider future donation amount, to operationalize, I sum up all the future donations and construct $\sum_{t=2}^{T_i} D_{it}$, 'i' represents the donor index and 't' is the transaction index, it goes from second transaction to the last transaction for each donor. If the donor never donates again, the variable takes value 0. Definitions of FDE_i and ε_i remain the same.β_1 captures the difference in the future donation amount (in dollar terms) if the first project is fail vs success.

$$\underbrace{\sum_{t=2}^{T_i} D_{it}}_{\text{Total Future Donations}} = \beta_1 FDE_i + \varepsilon_i$$

(2)

The results from the estimation of equations 1 and 2 are reported in Table 1. Across multiple model specifications, I find that if the project outcome is a failure, donors are less likely to churn compared to donors and the log of total future transactions also goes down if the first experience is a failure. These estimates are not reliable as their could be potential endogeneity concerns. I will describe the source of endogeneity and potential solutions to resolve it in the following section.

Table 1: 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 estimation of equations 1 and 2, columns 1 and 2 report results without controls. Columns 3 and 4 have control variables included - Project Cost, Donor State, School State, Resource Category, Subject Category, Time to Raise funds, and Distance between donors and school. FDE takes the value 1 if the first donation experience is a fail and 0 if success.

5.2 Instrument

The problem with correlation-based tests could be the endogeneity of FDE. Individual donor characteristics could influence both the choice of cause (and therefore success and failure of cause) and future participation. For illustration, extending the above example if Donor A and B are inherently different, it could influence both the first donation experience (through picking more/less successful project and the propensity to churn/ participate. To address this challenge, I use an event on the platform as an instrument. In May of 2015, Stephen Colbert, a popular American talk show host, completed all the available projects based of South Carolina (Brenneman (2015)). For instance, if a project was live on the donation platform and the beneficiary school was based anywhere in South Carolina with some remaining amount to be completed, the remaining amount will be added to the project from Stephen Colbert's fund. In total $800,000 were donated to schools in South Carolina. for the donors who have donated to the projects which were completed by Stephen Colbert fund would all get successful, although they had a prior of 30% project failure. Therefore the donors who donated to projects based out of South Carolina in May 2015 were completed by the Stephen

Colbert fund-treatment group whereas donors who donated to projects but have the status quo failure rates can be thought of as the control group. comparison of churn and future participation can yield the difference between 100% success vs 70% success (status quo) groups and is an underestimation since the true comparison should be between 100% and 0% groups to estimate the effect of failures and success in donor churn and participation.

5.3 Relevance and Exclusion

To ensure the relevance of the instrument I first provide some visual evidence, specifically note that in Figure 2, the project completion (represented using light green colored dots) jumps up to almost 100%, second, this jump is not cyclical, in the data period i.e. 2013-2018, this happens only once. Third, I compare the success rates to border states (North Carolina, Georgia, and Tennessee) of South Carolina, we do not find such jumps in border states around the same time.

The Stephen Colbert event could lead to contamination, specifically, the donors might change their future behavior due to Stephen Colbert and not just because of the project completion effect. To address, this I got some institutional information that donors – there was no explicit communication by the platform. I also collected data on web search and news trends using Google Trends and have reported in Figure 20 and 3 respectively. I don't find any substantial differences in the news coverage during the time of the event. Furthermore, Stephen Colbert was off-air during this period, specifically, 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. Hence, I argue that the only way the Stephen Colbert affects the churn is through changing the first donation experience and I rule out instrument contamination as well as threat to exogeneity assumption through data patterns and institutional information.

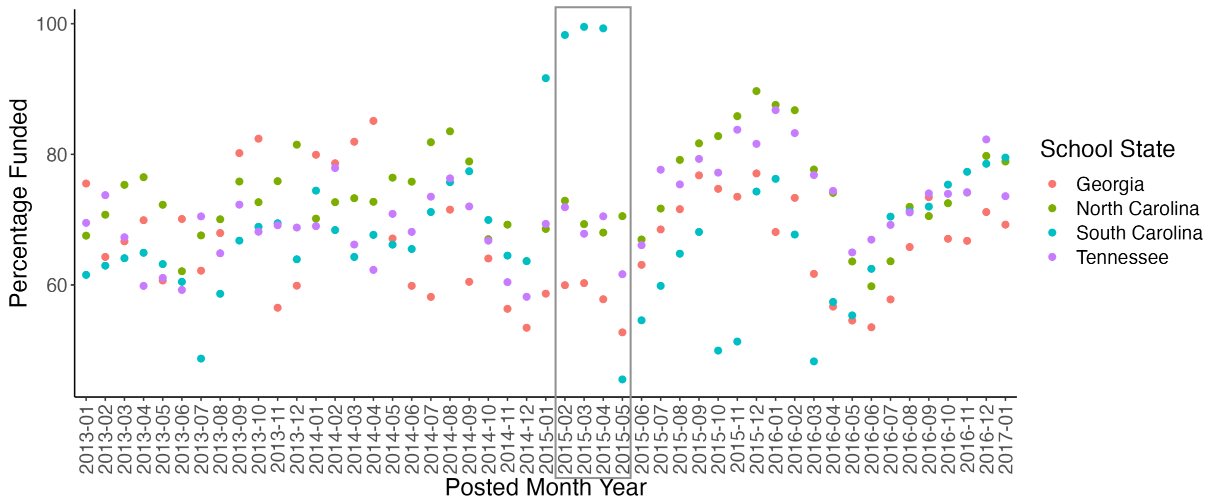


Figure 2: Percent of projects funded by month year of their posting

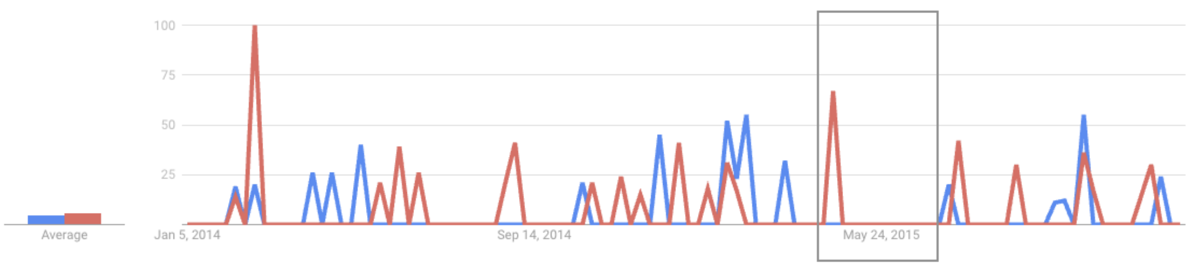


Figure 3: News coverage of Stephen Colbert donation event

Table 2: Two Stage Least Squares

	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 the FDE is instrumented with Stephen Colbert shock. The first two columns do not contain control variables whereas the last two columns include controls such as Project Cost, Donor State, School State, Resource Category, Subject Category, Time to Raise funds, and Distance between donors and school. Results from Wu Hausman - weak instrument tests are included in the last row.

5.4 Selection

The instrument allows me to create this group of donors who experience different donation experiences. However, there could be still some differences in donors in these two groups. To address this issue, I use propensity score matching. PSM allows me to compare donors who are comparable but they somehow experience different project outcomes. This construction brings us closest to an experimental setting. Specifically, donors are matched on their observables such as donation amount, project category, resource category, school and donor locations, and project cost. Matching ensures that the donors who get the Stephen Colbert vs the ones who dont are similar in all other aspects. It is important to note that, matching contracts the observations as I need to consider donors who donated for the first time before the event (May 2015). Quality of match is reported in Figure 21 and the associated comparison between groups is reported in Figure 22. Post matching, the first donation experience variable is instrumented with the Stephen Colbert shock variable the results from 2SLS are reported in Table 3. Note that, the churn for the group that experiences the first donation experience as failure is 0.236 (s.e.=0.103) over the baseline, i.e. success group. Implying, conditional on the first transaction being successful the probability to churn is 71% (observed in raw data too), however, if the first transaction is a failure it ramps up the probability to churn to 94.6%.

Table 3: 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 the FDE is instrumented with Stephen Colbert shock and donors are matched using propensity score matching. The first two columns do not contain control variables whereas the last two columns include controls such as Project Cost, Donor State, School State, Resource Category, Subject Category, Time to Raise funds, and Distance between donors and school. Results from Wu Hausman - weak instrument tests are included in the last row.

5.5 Heterogeneity

The effect of the first donation experience could be moderated by when the donors decide to donate, the amount of donation, or the proximity to the school. For instance, proximity to school measure could alleviate the churn due to a donors relationship with the school, and therefore, donors who are located close to school would be less affected by fundraising failures (Burger et al. (2004); Guéguen et al. (2018)). I do find similar effects although with low statistical insignificance see 4. Similarly, when a donor decides (early vs late) to donate can indicate commitment to the project and less weightage on observational learning or peer effects (Solomon et al. (2015)). Interestingly, I find a reverse effect, in that, people who donate late are less effected by the fundraising failure than donors who donate early. Lastly, the donation amount could indicate lower donation amount sensitivity, and thus the donor does not get too affected by the redirection of funds to some other project (failure condition) (Koschate-Fischer et al. (2012)). To this end, I do find evidence in line albeit mild.

Table 4: Heterogeneity in effect of first donation experience

	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***	$-$0.311***
	(0.014)	(0.056)
Donation Amount	0.009	0.031
	(0.026)	(0.109)
FDE$\times$Distance To School	$-$0.156	0.769
	(0.188)	(0.771)
FDE$\times$Time to Donation	$-$0.062***	0.266***
	(0.012)	(0.051)
FDE$\times$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 equations 1 and 2 but the 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.

6 Model

6.1 Model goal and motivation

Until now, I have established that the first failed donation experience can substantially affect future participation. The next obvious thing to investigate is why such an effect exists/happens. To get into the mechanism I conduct a survey, the details are available in section 7. The conclusion from the survey is that the donors attribute their reduced participation to disappointment with the platform and not to others or themselves. This leads me to propose a solution where the platform can reduce the first experience as a failure. I propose a segmented choice architecture. Specifically, I propose that the platform should present first-time donors with the projects which have the highest probability of succeeding and thereby give them a successful first-time experience. My proposal is based on a simple cost-benefit analysis. A naive estimate would be if after the first donation instead of losing 1.46 M (see Figure 1) donors platform loses only 0.9*1.46 M donors (due to the new ranking algorithm), and each of those donors donates only one more time, then the platform can raise at least 0.146M*$50 (average donation amount)=$7.3M in the span of 5 years.

The goal of the model is to understand how past donation outcome affects future donations and thereby construct counterfactuals to improve overall fundraising on the platform.

6.2 Donor Decision Process

Note that, I only have donation transaction level data, and we aim at modeling the donor decision process. In the next paragraph, I will describe the donation decision process (thereby the data-generating process).

A donor visits the website (t-30), goes over the donation options based on the rank-ordered display, and decides to not donate on the platform. This visit is made to understand how the platform works or an outside option is chosen. On the next visit (t), she decides to go over the donation options and decide to donate to one of the options, before her next visit, she gets to know the outcome of her donation (was the project able to raise funds or not), her subsequent donation (t+20) is contingent on her last donation outcome. She continues this process and exits the platform after a few donations. The underlying assumption in this setup is that there was visitation but no donation before the first donation. I use comScore data to validate this assumption (details available in section 6.4), more than 98% of donors visit the platform before making their first donation.

In this model, the key building blocks are – intervisit time, ranks of projects displayed, and transactions, of which, I only have transaction data.

Estimating Rank - To estimate the rank of projects each day I 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 6.3. 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. Specifically, different potential donors do not see different sets of options thereby causing selection concerns. The rankings are also not adjusted with the last donation outcomes.

Intervisit Time - To understand the arrival times of donors on the platform, I use the comScore dataset. The details of how the dataset is created are available in section 6.4. Using the comScore dataset, I can observe when someone visits the platform and the corresponding donation (visited but not donated vs visited and donated), and therefore provide information about intervisit and inter-donation time. My goal is to create a modified transaction dataset that matches the moments of comScore data, in terms of intervisit times and number of interactions with the platform.

Next, I will illustrate the data creation process. Consider a donor 'i' who first donated at time 't', to get a consideration set I select the top 10 projects based on the rank score [7] for time 't'. Although there are almost 25-30,000 project available, I assume that only the top 10 projects would be in the donor's consideration set. [8]. Next, using the empirical CDF of the intervisit time from comScore data, I draw a random intervisit time, say 30 days. I 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', I 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', I 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, I 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.

State Dependence Variable - state dependence variable is used to capture the donation outcome of the last donation of a donor. We create the state dependent variable as follows - in case 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 materialised 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,

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

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

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, I assume the state to be a success.

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

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

U_{ijt} represents the utility for donor 'i' for project 'j' at time 't'. The donor selects the project which maximizes her utility. β_{0i} is a random intercept term (assumed to be normally distributed), this captures the utility from the outside option. SD_{it} is the state dependence for donor i at time t, this captures the project outcome (success/fail) of the last donation. β_{1i} is the random coefficient to capture different motivations (as explained in the theoretical model) of donors, specifically, if the last donation outcome (state dependence) influences a donor's future donation decision. β_2 captures the influence of rank score of a project 'j' at time 't', this is to 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. Equation 4 is the joint likelihood function and is estimated through simulated maximum likelihood.

6.3 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 I 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, I scraped 45 days of data from our partner platform website, although most of our data is scraped for the year 2023. I was also able to scrape a few days in 2015 using a web archival (Wayback Machine) website. With scraping, I get features [9] 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 (for example - if you search dog food (query) in Amazon search you get a list of items (documents) Next, I train a learning-to-rank algorithm (LAMBDAMART), where I use the daily scraped rank of projects and their corresponding features as the training set. Gradient boosting methods with loss function as NDCG (normalised discounted cumulative gain) is the building block of the LAMBDAMART algorithm. I train the algorithm on the scraped data and use the model to predict the ranking score on the transaction-level data.

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

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

6.4 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). I did not get access to clickstream from our partner platform, therefore, I use Comscore data[10] [11]. In the final dataset, I have 523,930 observations, indicating the number of clicks, this includes 3846 distinct user ids and 4271 machine ids. Each user can visit the website multiple times on the same day. Aggregating data at the day level, yields, 11,380 rows, indicating that each user on average visits on nearly 3 (=11380/3846) different days. The inter-visit time is presented in Figure 8. The median intervisitation across users is 19 days. Furthermore, more than 98% of donors have visited the website before donation (i.e. the sequence of website visitation is visited but not donated and then visited and donated), this observation supports our assumption behind the model structure.

6.5 Identification

Until now, I have assembled all the data pieces required to model the donor decision journey. In the equation 3, 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 I include random coefficients and assume it to follow a normal distribution. Position effects could cause endogeneity concerns, however, I estimate a pooled coefficient of 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. I assume the project features to exogenous due to an institutional feature i.e. most teachers

[10] Data is from Jan 2019 to Dec 2021

[11] In the comScore dataset, I search where the domain name contains the name of our partner platform

post only 1 project in their lifetime. Hence, I assume that teachers have not learned or acquired enough information to strategically design projects.

6.6 Results

First note, that the intercept 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 state dependence variable is positive with a relatively smaller variance. 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.

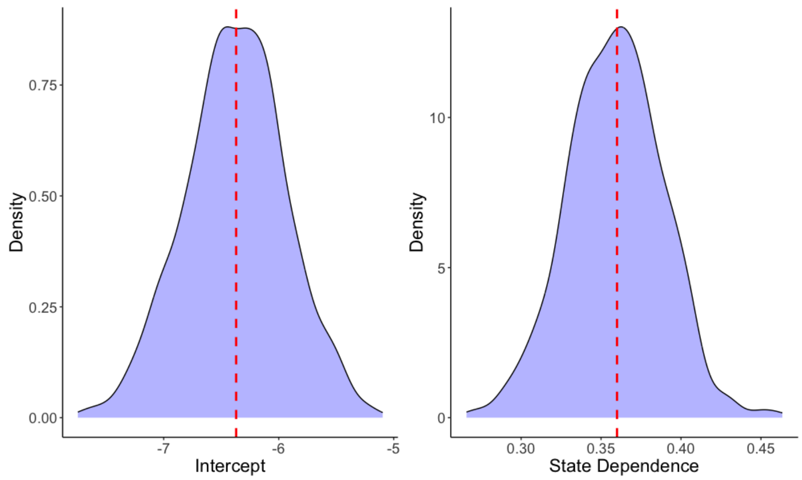


Figure 4: Distribution of intercept (left) and state dependence (right) coefficients

Table 5: 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
$\mu(SD)$	0.36	0.13
$\sigma(SD)$	0.03	0.17
$\mu(Int)$	-6.37	0.21
$\sigma(Int)$	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.

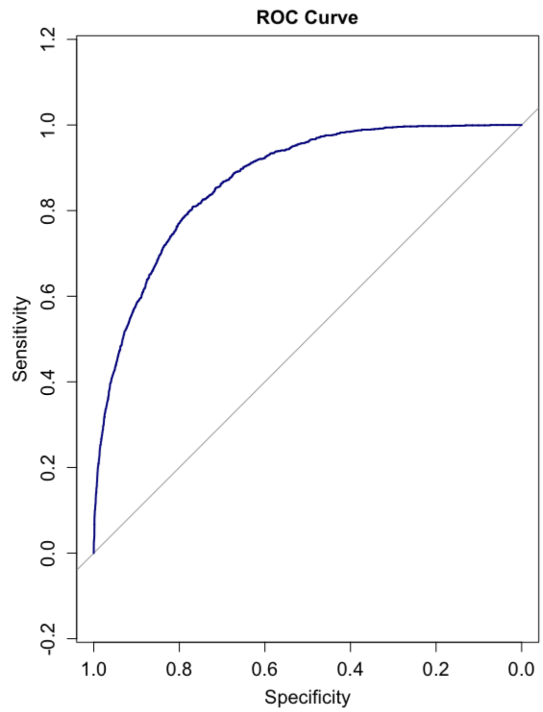


Figure 5: ROC curve for predicting the success vs failed projects

6.7 Counterfactuals

6.7.1 Predicting Success

To predict the success probability of a project, I 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, I want success probability for each project for each day it is available on the platform. I report the model performance metrics (ROC curve[12]) in Figure 5 below. The model achieves the AUC[13] metric of 0.945.

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

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

6.7.2 Comparing Old vs New Ranking Schemes

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.

To estimate this, I replace the projects considered by donors on their first donation with the project predicted from the success probability algorithm. Next, I calculate the predicted probability using the model estimates and project features. The donor picks the option with the highest indirect utility or predicted probability. I extract the outcome of the selected project from the platform data. For the next period, I 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. I report the probabilities to donate after the first donation under new vs old ranking algorithms in Table 6.

Table 6: Old vs New Ranking - Probability to Donate Again

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

7 Mechanism

To understand why donors are more likely to churn if they experience a failed fundraiser compared to a successful one, I conduct a survey. The goal of the survey is to a) provide external validity to our data-based approach (Gui (2020); Yang and Ding (2020)) and b) find the reasons behind donor churn. Donors after a failed fundraising experience might attribute the failure to a) *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 willingness to give (Mollick (2014); Belleflamme et al. (2014)) c) *self* —the donor might feel that it is her at fault as she did not pick the right cause - leading to self-efficacy concerns (Bitner et al. (1990); Weun et al. (2004)).

7.1 Method

A total of 600 workers on MTurk completed the study. The participants were recruited through CloudResearch (cloudresearch.com) based on their ratings. 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.

The demographic details of the participants are as follows: Out of the 600 respondents, 393 claimed to have online donation experience. There were 346 males and 251 females. A total of 492 participants claimed to have an income of less than $100,000. Additionally, 355 participants were 35 years of age or older.

At the beginning of the survey, the participants are informed about the Giverschoice platform (details in the appendix section **??**). Next, donors are asked to choose among two projects which mimic two projects from the platform. Donors are then asked to imagine that they gave to one of the projects and then are presented with 1 of 6 treatment conditions. The conditions are $\{\text{Outcomes} : \text{Success, Failure, Base}\} \times \{\text{Comparison} : \text{More, Less}\}$. 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. 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. Conditional on their treatment, donors were asked to rate their propensity to a) recommend the platform to others b) donate again c) Feelings about self, society/others, and the platform (Happy, Satisfied, Ashamed, Disappointed, Angry, Proud).

7.2 Results

7.2.1 Main Effects

I find that, first, compared to baseline, people are less likely to donate again or recommend ($\beta_{Fail}^{DonateAgain} = -0.397, \beta_{Fail}^{Recommend} = -0.378$) the platform in the failure condition. Second, baseline and success conditions are not different enough (lack significant differences). Third, when participants know that they have donated more than the average donation amount by others, this positively influences their propensity to donate again and recommend the platform ($\beta_{More}^{DonateAgain} = 0.484, \beta_{More}^{Recommend} = 0.521$). Lastly, I don't find any significant interaction effects.

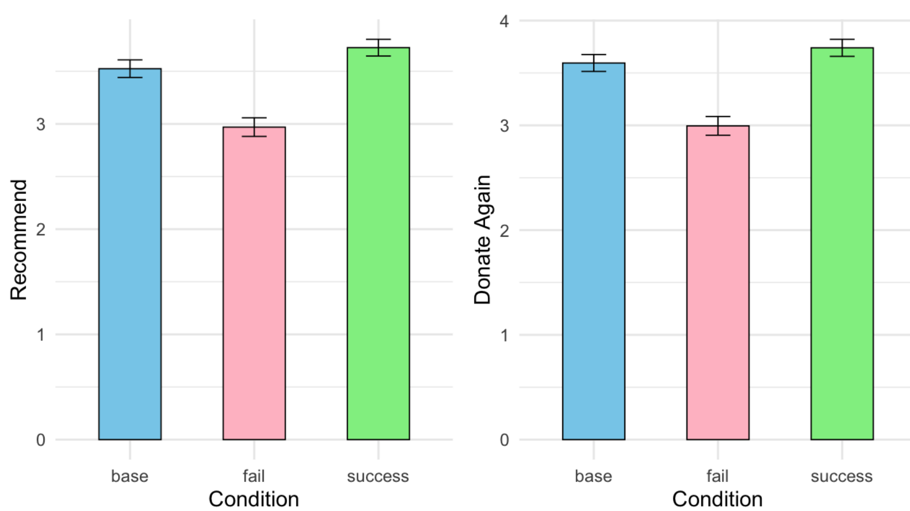


Figure 6: Propensity to recommend (left panel) and donate again (right panel) across different conditions

Table 7: 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 the regression of donate again and recommend dependent/response variables on outcomes, comparison, and controls. Controls include Gender, race, education and income.

7.2.2 Mediation Analysis

To investigate, the source of churn, I ask participants to report their degree of disappointment with various stakeholders. The path diagram is presented in Figure 7 illustrates our independent variable (project status/outcome), mediators (disappointment with various stakeholders and dependent variable (recommend or donate again). Project Status variable takes value 0 for baseline, -1 for fail, and 1 for success. Disappointment (mediator) with different stakeholders ranges between 1 to 5, 1 being the least disappointed and 5 being the most disappointed. 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, I found evidence of significant mediation only through the platform disappointment mediator. For Mediator1, 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 recommend dependent variable.

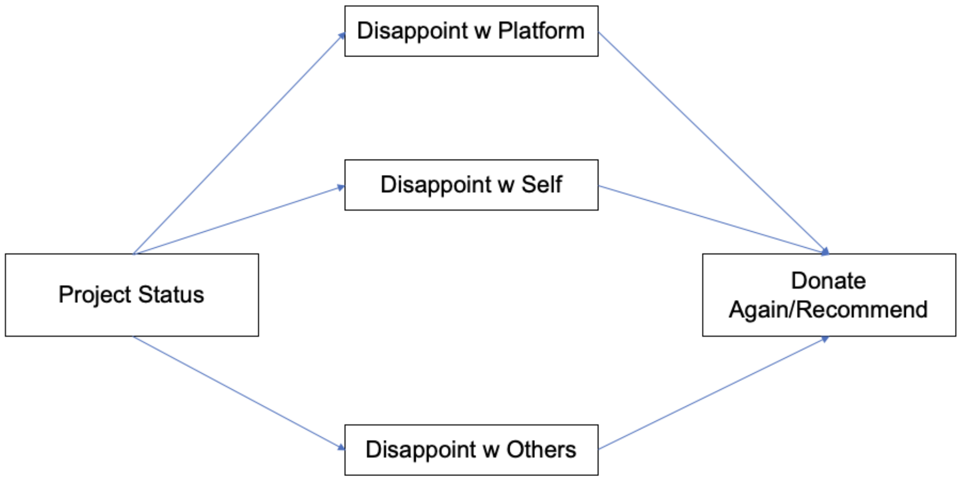


Figure 7: Path diagram: Independent variable (project status), possible mediators and dependent variable

Table 8: 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.

7.3 Discussion

The direct results indicate that project outcome, especially, in the case of failure, reduces a donor's propensity to donate again or recommend the platform to others. This finding is in line with our reduced form evidence. Furthermore, it is surprising to find that donors, when provided with no information (baseline), react similar to the success condition. The results from mediation analysis, rule out the possibility of disappointment with self and others as probable reasons behind donor churn after failed fundraising outcome. It is clear from the path analysis, that the survey participants, were disappointed with the platform. Although our study limits to exactly what disappointment is attributed to, however, these results underscore the importance of interventions done by the platform to alleviate the failed fundraising experiences for donors.

8 Conclusion

Donation platforms organize multiple fundraisers on their websites and many of these fundraisers are unable to achieve the fundraising goal, these fundraising outcomes can lead to donation frictions. This paper shows that failed fundraising experiences can significantly impact churn and overall dollar contribution by donors. Furthermore, it settles the contrasting predictions by theories in charitable giving, resolving the dilemma both at intensive and extensive margins. 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 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 segment 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 I 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 rankings and project change more frequently and thus might introduce certain aggregation bias. Future studies can alleviate these concerns with better data and experiments with the platform.

Appendix: Data Translation

Table 9: 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 10: 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

Appendix: Survey Details

600 participants were recruited from Amazon Mechanical Turk. I 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.

I 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.

Appendix: Tables and Figures

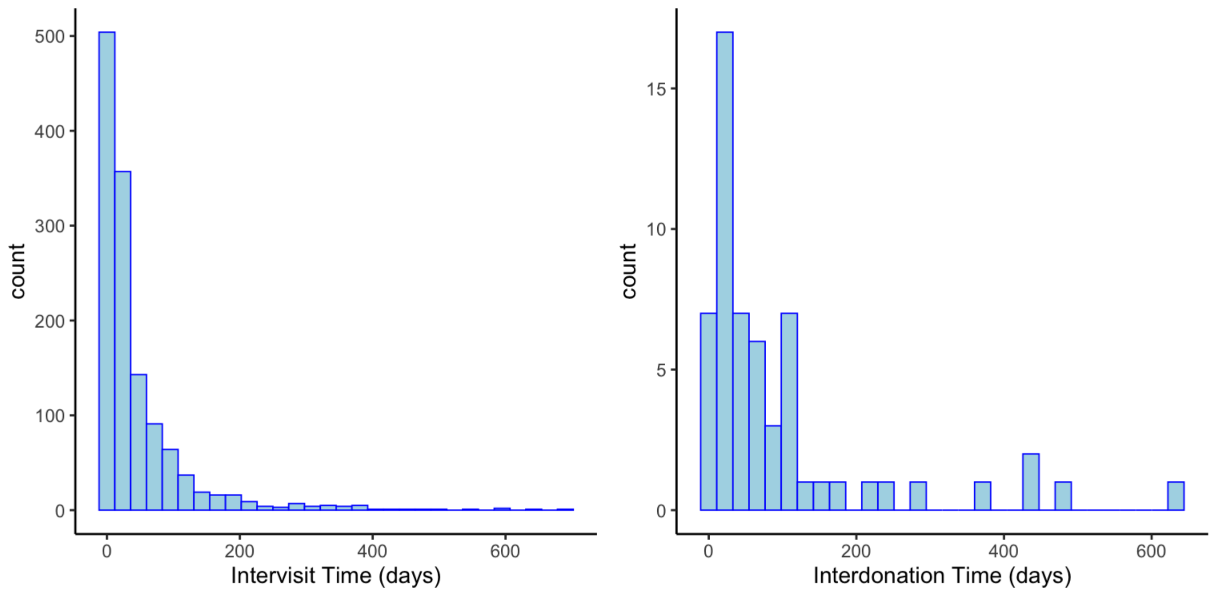


Figure 8: Distribution of Intervisit and Interdonation Time in Days using comScore data

Table 11: 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

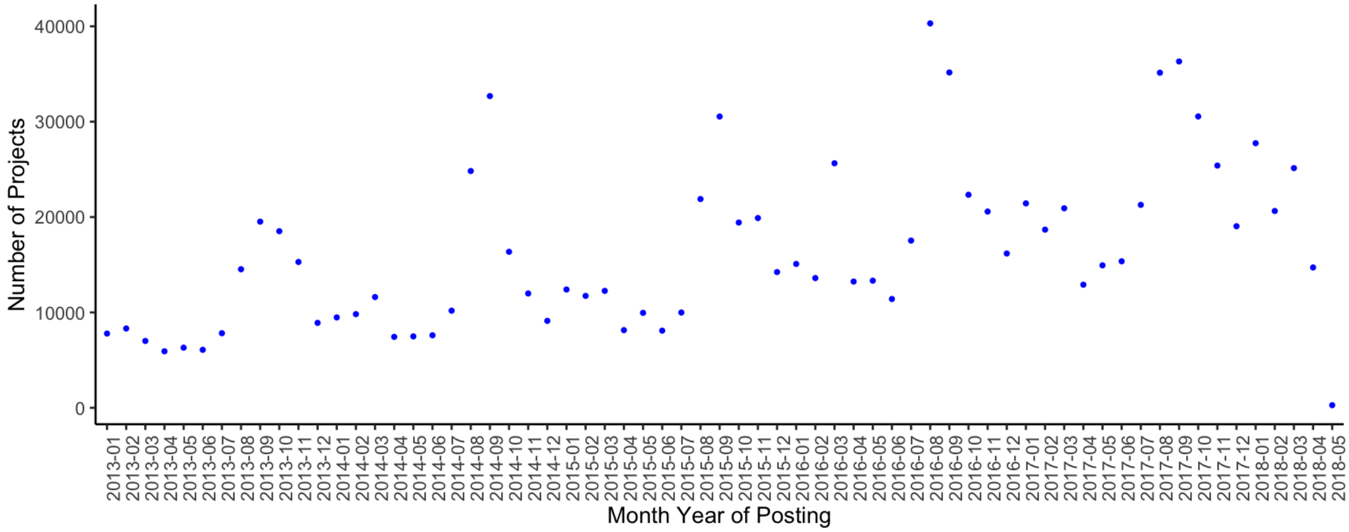


Figure 9: Number of projects posted by month year

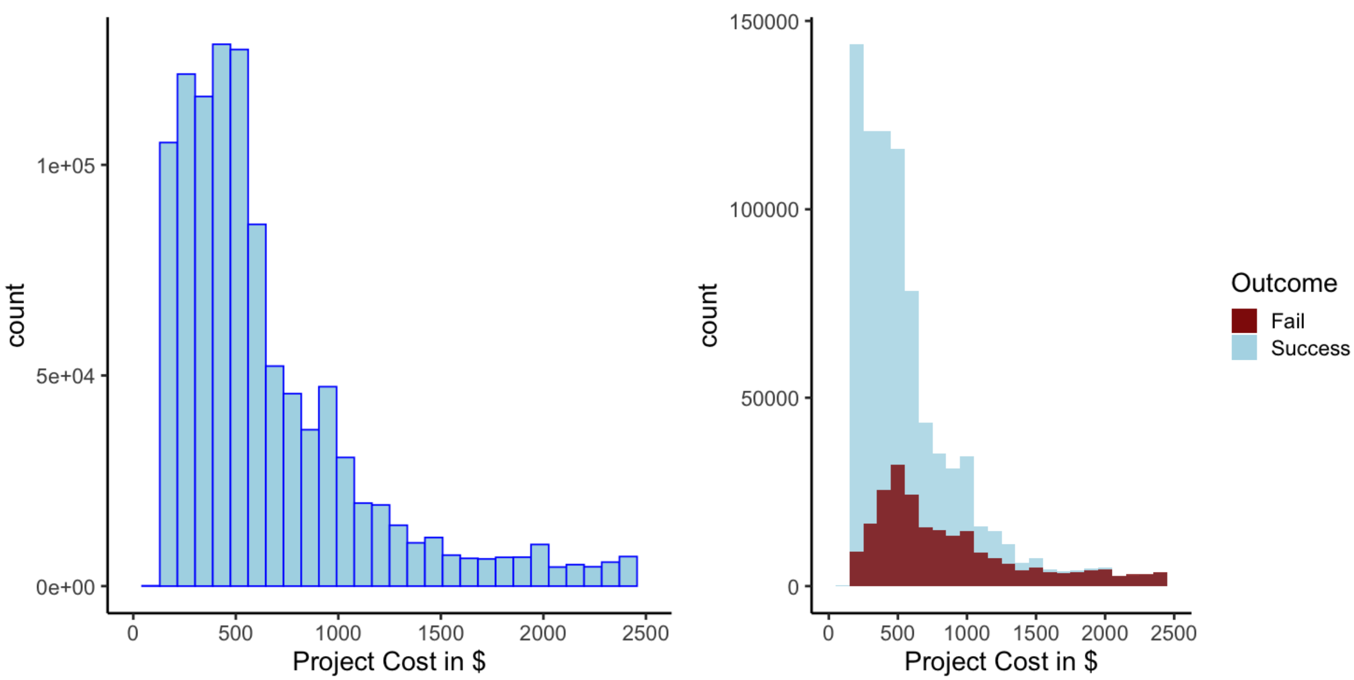


Figure 10: Overall (left panel) project cost (in$) distribution and breakup (right panel) by project outcome

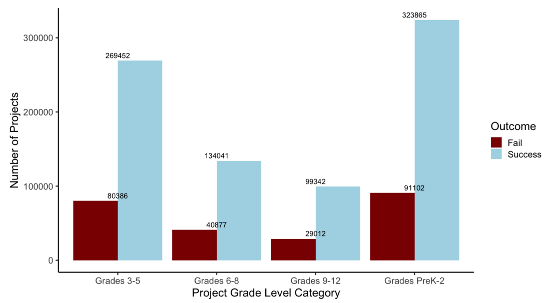


Figure 11: Number of projects - failed vs success - by class grade

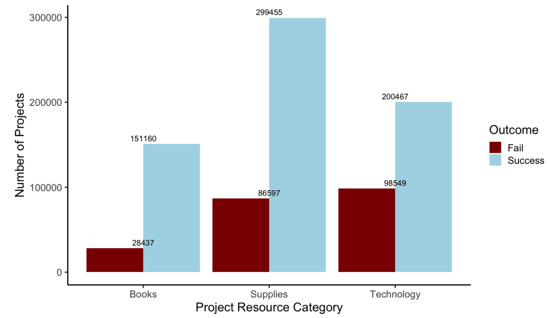


Figure 12: Number of projects - failed vs success - by top resource category

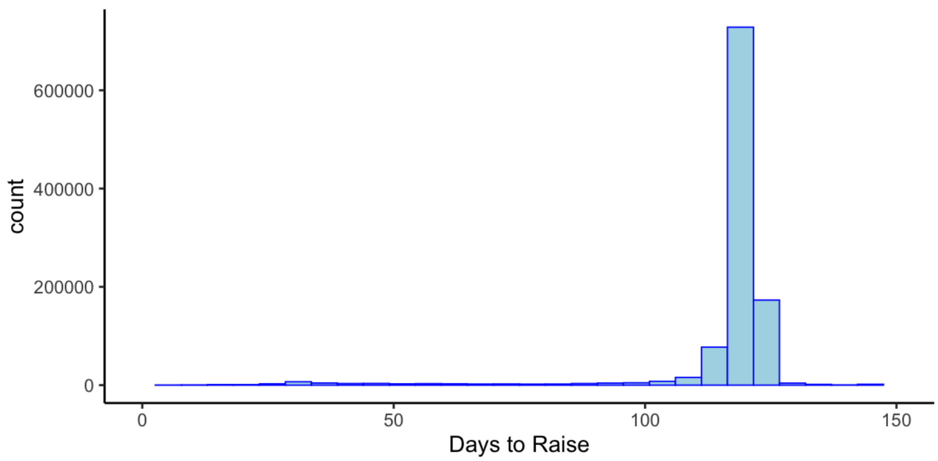


Figure 13: Number of days to raise funds before the project expires

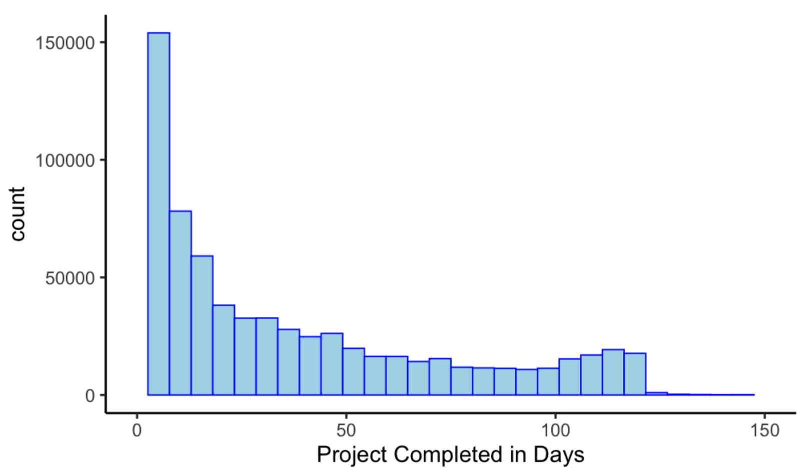


Figure 14: Days needed to raise 100% of project cost

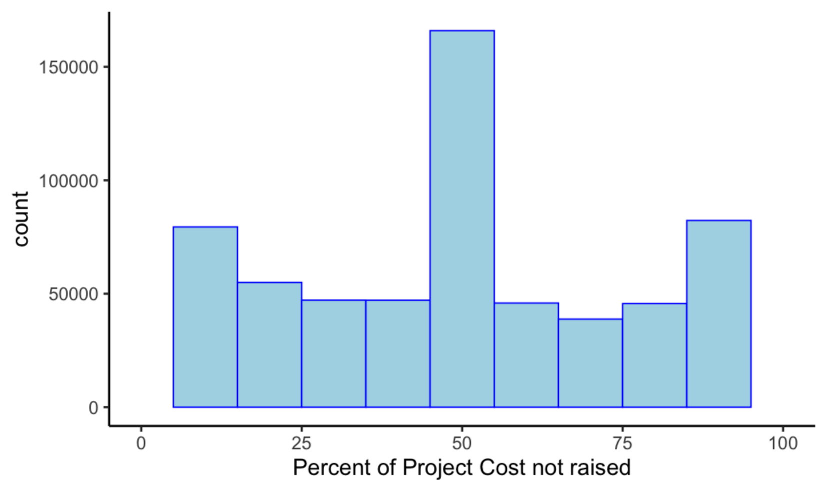


Figure 15: Percentage of project cost not raised for failed projects

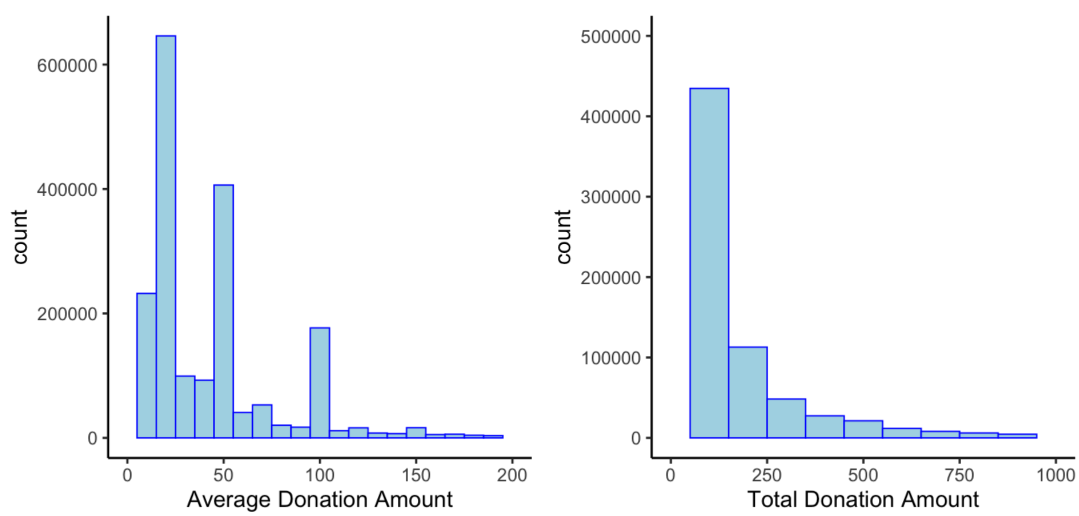


Figure 16: Avg and Total Donation Amounts in USD

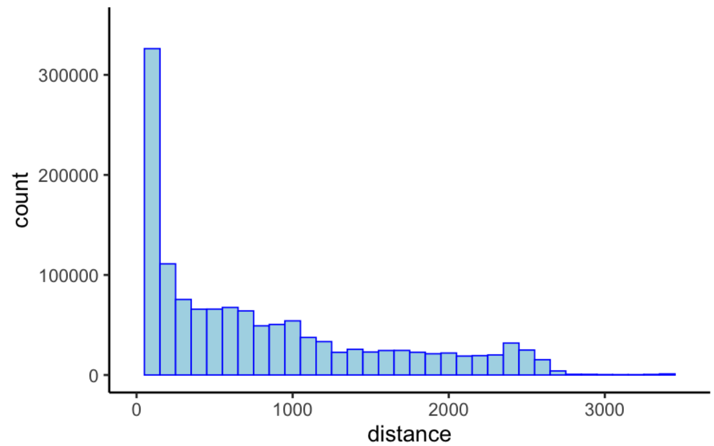


Figure 17: Distance in miles of donors to schools

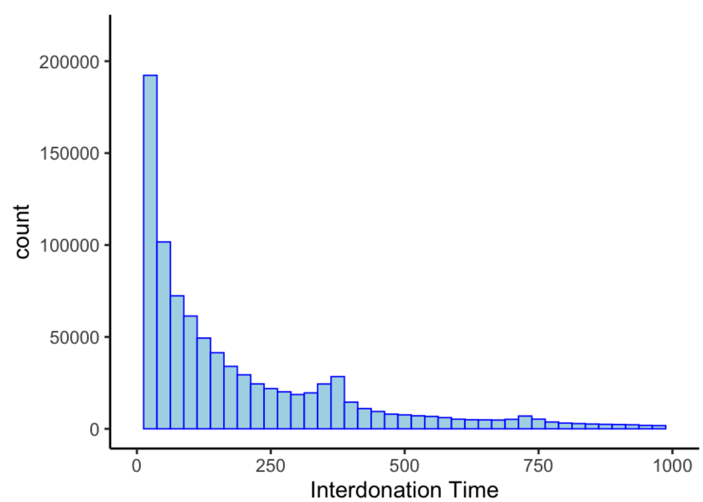
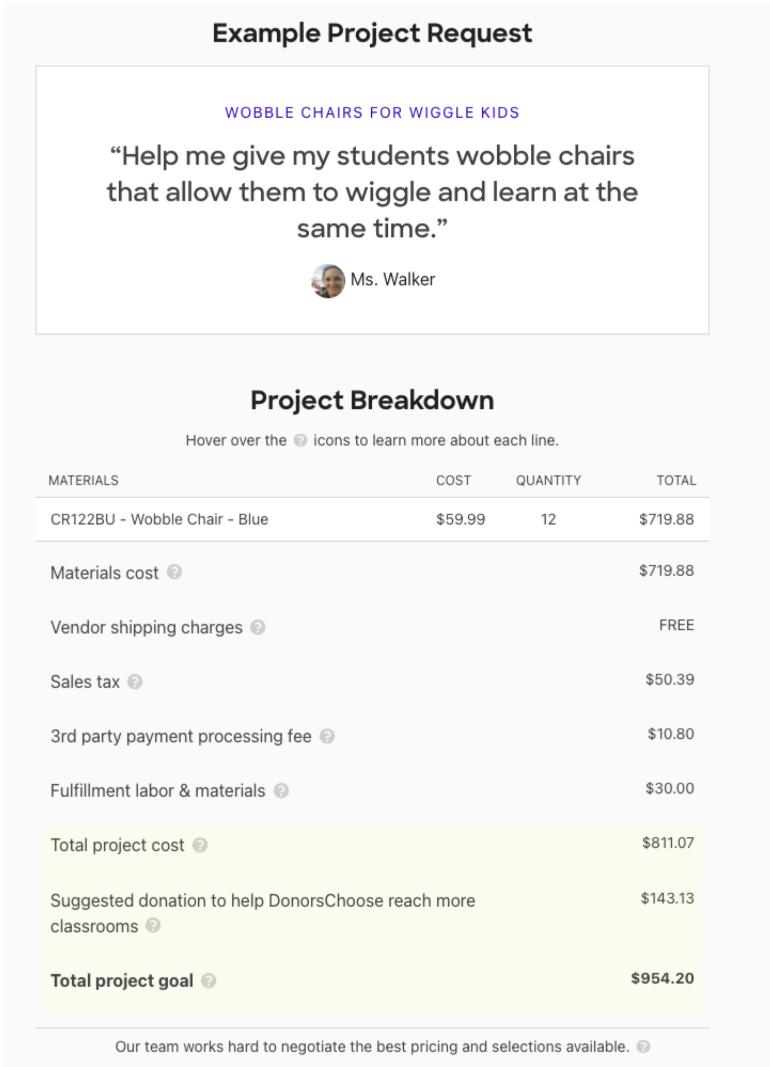


Figure 18: Interdonation Time from the platform data



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 19: Project Cost Breakup

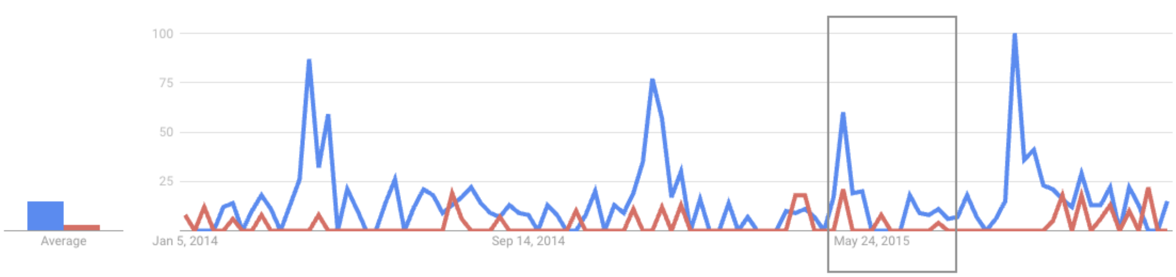


Figure 20: Google Trends comparing Stephen Colbert and DonorsChoose around the event

Table 12: 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.

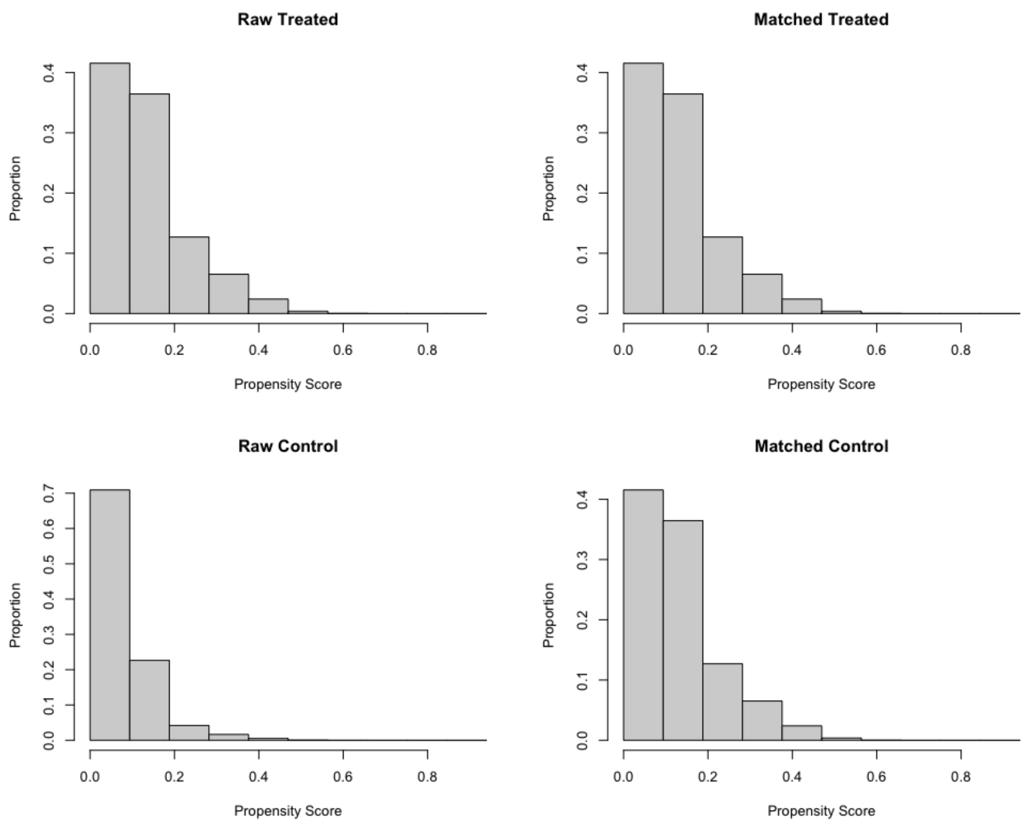


Figure 21: Overall Match (exact) Quality - comparison of propensity score raw and matched groups

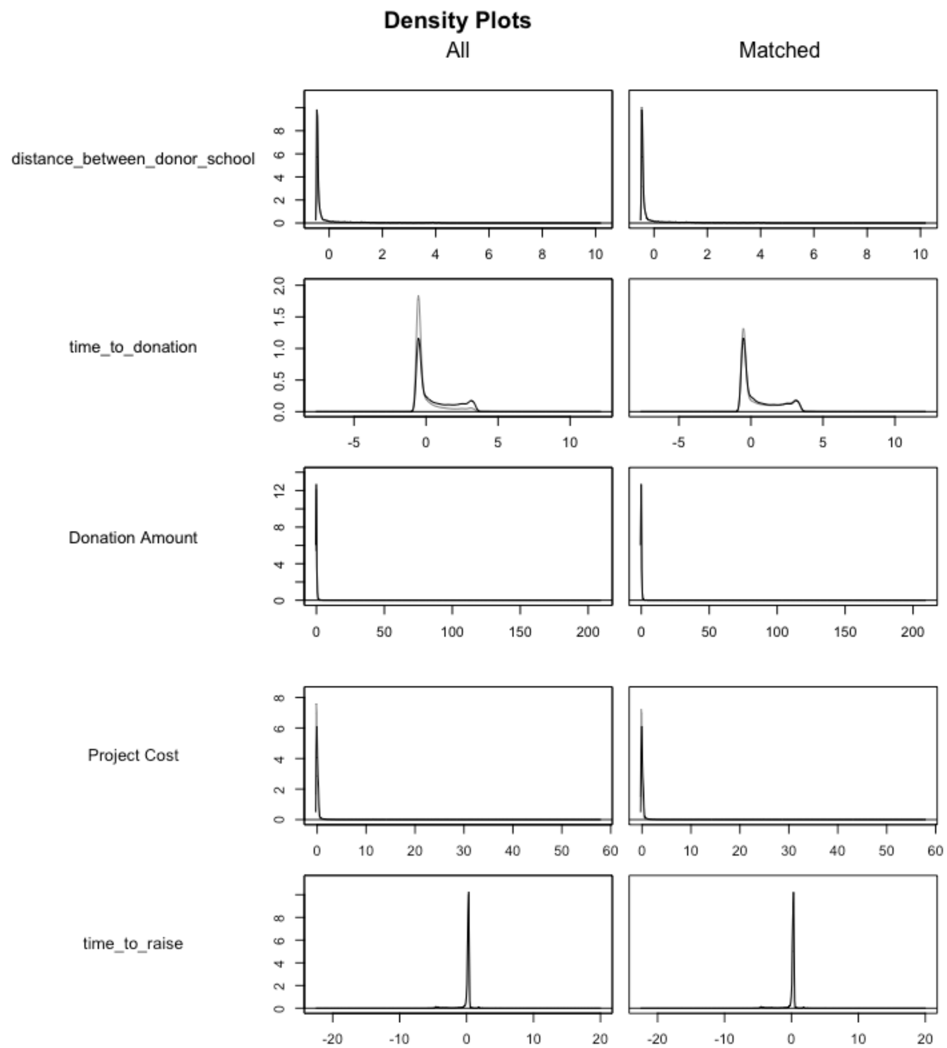


Figure 22: Variable matched on (continuous) - comparison of densities pre and post matching

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 - blackbaud institute — institute.blackbaud.com. 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.

Burges, C. J. (2010). From ranknet to lambdarank to lambdamart: An overview. *Learning*, 11(23-581):81.

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].

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.

Koschate-Fischer, N., Stefan, I. V., and Hoyer, W. D. (2012). Willingness to pay for cause-related marketing: The impact of donation amount and moderating effects. *Journal of marketing research*, 49(6):910–927.

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.

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.