When more is not merrier? The case of subscription-based donations

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ABSTRACT

Subscription-based donations are becoming a popular fundraising tool as they are perceived to yield a high donor lifetime value. A common practice of online donation platforms is to provide information on a cause's donor group size as a tool to attract more, and retain current, donors. We use data from a subscription-based donation platform to study the effect of providing information on donor group size, on the retention of current donors. We use a) repeat donations of individual donors and b) an exogenous shock to the platform that shifts the donor group size to identify its impact. We find that higher donor group size encourages churn. In addition, we provide suggestive evidence that the donor group size information can attract new donors. Taken together, we suggest that managers exercise caution when providing information on the size of the donor base, as the net effect on subscriptions can vary with the "life cycle" of the charity's donors.

Keywords: Subscription based donations, donor churn, bystander effects, observational learning

INTRODUCTION

Every year, billions of dollars are raised for charitable donations (Mohan, Govil, and Malpani 2019; NP Trust 2021). Of the different channels for charitable giving, online giving saw the most significant increase in growth of 42% from 2019 to 2021 and accounted for 12% of the total giving (Blackbaud Institute 2021). This growth in online giving is largely attributed to the ease of donating through online channels and to changes in preferences due to a shift in demographics. The move towards online giving has spurred the growth of several online donation platforms, e.g., Donorbox, Double the Donation, Ketto, etc., which provide valuable benefits to nonprofits and donors. For donors, the platforms a) provide a wide variety of causes to donate to, b) reduce the cost of searching for causes and c) improve the trustworthiness of causes through various verification mechanisms. On the other hand, for nonprofits, platforms a) provide market access to a larger donor base, b) allow them to raise funds for multiple causes simultaneously, and c) lower the costs of raising funds (Ozdemir et al. 2009; Sulaeman and Lin 2018).

Another recent shift in the online giving context has been the adoption of subscription-based donation models (MatchPro 2020). A subscription-based donation model is one in which a donor signs up to donate for a cause for either a fixed period or in perpetuity. A predetermined amount is deducted every period (monthly or quarterly) from the donor's account to support the cause. Although most donations are raised using one-time donation events, it has been shown that donors who sign up for subscription-based donations tend to donate more, both in terms of the total amount donated and duration of donations, than donors who donate using a one-time donation. For instance, (Cipollini 2018) shows that donors on a subscription-based cause donate 4.4 times more than in one-time donations.

The focus of this study is on understanding the impact of a popular marketing practice – providing information about a cause's donor group size (how many people are currently donating to a cause) to current and potential donors – on donation behavior to that cause in a subscription-based donation context. There are at least two reasons motivating our interest in this topic. One, despite being widely prevalent, the impact of donor group size on donation behavior is unclear. Some researchers contend that donors will donate to something primarily because others do (the bandwagon[1] effect). Consequently, as the donor group size (popularity) increases, so will donations (Cialdini and Goldstein 2004; Frey and Meier 2004; Reingen 1982). Others argue that donors will donate less in the presence of others (the bystander[2] effect). Specifically, as the donor group size increases, the overall donation amount (due to a decrease in the propensity to donate) will go down (Darley and Latane 1968; Fischer et al. 2011; Panchanathan, Frankenhuis, and Silk 2013).[3]

A second reason for our interest is that a subscription-based context is substantially different from a one-time donation. While donors in both one-time and subscription-based contexts must decide on the cause and amount to donate, donors in subscription-based contexts must make an additional decision on continuing or cancelling the donation in the subsequent periods based on updates received about their donation and cause every month. For instance, in

[1] Bandwagon effects: In our context, it refers to an increase in the probability of donation based on more people donating to a particular cause.
[2] Bystander effects: In our context, it refers to decrease in probability of donation in presence of others because individual donor believes the responsibility is diffused among others.
[3] Some recent research has attempted to resolve this ambiguity, (Mukherjee, Lee, and Burnham 2020). Nevertheless, we believe that a systematic analysis is required to resolve this issue in subscription-based contexts.

our context, the donor platform regularly sends an email update to the donor at the end of each month. The update contains information on the current donor group size besides other things, such as thanking donors for their donations. Donors can consider this information and make an active choice of whether to continue donating or not; this is not the case with one-time donations.

In this study, motivated by the increasing prevalence of subscription-based donations as a fundraising model (Cipollini 2018; Spencer 2021) and the practice of informing[4] current subscribers of the donor group size (Carman 2003; Chatelaine 2022), we ask the following question on donor behavior for causes on subscription-based donation platforms: what is the impact of donor group size on donation behavior of existing subscribers? In other words, we are interested in understanding the relationship between changes in the size of the donor group and retention.[5] Further, we examine differences in the differential impact of donor group size and donation behavior across cause categories and types of donors (heterogeneity). In addition to donor retention, we also provide suggestive evidence on the impact of donor group size on donor acquisition strategies.

Answering the above questions poses substantial challenges. First, assessing the impact of a cause's donor group size information on donors who already subscribe to the cause requires us to disentangle the effects of donor group size from that of cause and donor characteristics. Further, donors are likely to churn naturally over time. One approach to tackle these challenges is to focus on studying donor behavior within a single cause (e.g., educating underprivileged children) or a single type of donor (e.g., Indians vs. non-Indians) but with serious limitations on the generalizability of findings (Meer 2011; Park and Shin 2017; Proulx, Aknin, and Barasch

[4] Apart from email updates, a donation subscriber might check on the cause's updates on the platform.
[5] Our analysis cannot speak to the effect of the presence or absence of the donor group size; only what happens when it gets bigger or smaller.

2023). Another approach is to account for these factors using detailed data across causes and observing individuals over time to control for the effects of causes and donors but obtaining such data is hard.

We worked with one of India's largest subscription-based donation platforms to obtain a unique and rich dataset that addresses the above challenge. The platform (website) works with more than 300 causes[6] across four categories (nutrition, livelihood, education, and healthcare). It has an active monthly donor base of nearly 10,000 (as of Dec 2020) contributors, primarily based out of India, the US, and UK/Australia/Canada. We also have access to detailed individual transaction-level data from the platform's inception in March 2018 (up to September 2020). Our rich dataset allows us to account for distinctions in altruistic behavior across countries that can occur due to differences in donation cultures or association with causes (Kessler and Milkman 2018; Munz, Jung, and Alter 2020). Similarly, as documented in a few studies, our dataset allows us to account for differences in donation behavior based on cause type, for example, livelihood vs. nutrition vs education. (Bennett 2012; Khodakarami, Petersen, and Venkatesan 2015). Finally, we are able to control for time effects (the "hazard" of cancelling) in a flexible fashion.

A second, and even bigger challenge in our context, is identifying the causal effect of changes in the donor group size. After controlling for donor and cause type, we still need to account for unobservables that might be correlated with both cancellations and donor group size. Our identification strategy to address these challenges is to use an exogenous shock (an event) that led to a "sudden and unanticipated" increase (from the perspective of previous subscribers to a cause) in the total number of donors on the platform. This identification strategy is similar to

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[6] Examples of causes include, a) help underprivileged children with their education, b) support cancer patients with chemotherapy sessions.

(Farronato, Fong, and Fradkin 2020; Natan 2021), who used the merger of two platforms that led to a sudden increase in the number of users to address similar endogeneity concerns. In our setting, the event is a collaboration between the focal donation platform and several e-commerce retailers in India. Consumers and employees of e-commerce retailers were informed about the focal donation platform (see Figure A1 in the Appendix for illustration). Post the event, there was a positive "shock" to the number of donors (donor group size) for some causes on the platform due to this platform-level exogenous event[7]. Causes on the platform experienced differing effects of the event, with some causes experiencing an unexpected increase in donor group size while others saw no changes. As the relative increases in donor group sizes across different causes were primarily due to the exogenous event, we can leverage the variation in the donor group size attributable to the event to identify the impact on *previous* donors – those who had already subscribed to the cause prior to the event.

We find counterintuitively that having a larger donor group size increases cancellations when it comes to existing donors (subscribers). We find that if the donor group size increases by 10, it could lead to at least 1 donor cancelling. Further, we find evidence, albeit suggestive, that donor group size is *positively* correlated with the acquisition of new subscribers, a finding consistent with the extant literature (Cialdini and Goldstein 2004; Frey and Meier 2004; Milgram, Bickman, and Berkowitz 1969; Reingen 1982),.

[7] A potential concern would be if the current donor is exposed to the event announcement. There are two issues here. First, the donor might anticipate the increase in donor group size. Given that the percentage increase in donor group size varies widely across causes, we consider this unlikely. Second, the current subscriber's cancellation may be triggered not by the change in donor group size, but because the donors perceive the collaboration between the donation platform and the ecommerce websites as unacceptable. Again, while we consider this unlikely, in the absence of independent evidence that the event increases retention or cancellation, we assume that there is no direct reaction to the promotion event by current donors.

More importantly, our findings suggest that in the case of subscription-based donations, the learnings about bandwagon effects (i.e., a bigger group donor group size may lead to more new donors) apply at the acquisition stage, whereas for existing donors (subscribers), a larger donor group size encourages cancellation, suggesting the presence of bystander effects (in the presence of others, the individual donor feels diffusion of responsibility and therefore does not donate).

We use our rich transaction-level data to understand the differential impact of donor group size across cause categories and donors. Understanding heterogeneity in effects across donors and causes allows the platform to offer targeted marketing (which they currently are not). For instance, directionally, we find the impact of donor group size on cancellations is less for nutrition, livelihood, and healthcare-related causes when compared to causes that focus on education. We also find that donors who are based out of the US, UK, Canada, etc., are less likely to cancel as compared to the Indian donors.

We rule out multiple other possible explanations using data and institutional information; for example, our results on cancellation could potentially be explained by donors switching to other causes on the platform. Specifically, when more people start donating to a cause, a donor might feel that her resources are better utilized elsewhere, which could lead her to switch. Similarly, cancellations could be explained by macroeconomic policy changes. For instance, if donating in/to a country becomes difficult (for example, changes in taxation), donors might become reluctant to continue donating and cancel their subscriptions. We examine and rule out such possibilities to build the case for our findings and explanations.

Our paper makes the following contributions to theory and practice. We are among the first to present research on a fast-growing model in the charity space – subscription-based donations. Our research also examines the effects of “observational learning” (Cai, Chen, and Fang 2009;

DellaVigna, List, and Malmendier 2012; Zhang 2010) on donation subscribers. Our findings show that firms should be careful about using information about donor group size depending on the type of donor (new vs. subscriber). We also add to the donations and charity giving literature by identifying contexts – different types of donors or different stages of the donor-platform relationship – where bystander effects operate (Garcia et al. 2002). Additionally, we extend the findings to different types of donor groups and a wide variety of causes. Managerially, our study has important implications for charities that employ this strategy in a subscription model.

The rest of the paper is organized as follows; in the related literature section, we cover the extant literature on the effects of donor group size on donations. Next, we provide details on the institutional setting and data. The descriptive evidence section provides visualization and correlation-based tests to provide model-free evidence. The identification strategy provides details on the source of exogenous variation and underlying identifying assumptions. The results and discussion section come next. The robustness checks and alternate explanations section offers more support for our findings. Finally, we discuss the implication of our findings for the platform before concluding the paper.

RELATED LITERATURE

The popularity of a product and its effect on demand has been well studied in the extant literature in different contexts. For instance, research has shown that the probability of purchase of a product is higher if its popularity is displayed vs. when it is not, ceteris paribus (Cai et al., 2009; Tucker & Zhang, 2011; Zhang, 2010). The phenomenon where displaying the popularity of a product affects the demand for the product has been studied using various perspectives such as bandwagon effects, herding, information cascading, etc. (Anderson & Holt, 1997; Banerjee, 1992; Bikhchandani et al., 1992). Broadly speaking, all these studies suggest that consumers use popularity as a signal of quality. When it comes to the charitable donation context, research is divided into two broad groups with divergent findings. The first set of studies argues for a positive effect of displaying popularity, i.e., donation is higher for more popular causes (Cialdini and Goldstein 2004; Frey and Meier 2004; Milgram, Bickman, and Berkowitz 1969; Reingen 1982). In particular, when more people donate to a specific cause, the potential donor thinks that donating to that cause is the right thing to do as others are doing it. The second set of studies argues for a negative effect of displaying popularity, i.e., donation is lower for more popular causes (Bonsu and Belk 2003; Darley and Latane 1968; Fisher, Gallino, and Li 2017; Panchanathan, Frankenhuis, and Silk 2013). However, for the negative effect, the explanation stems from bystander effects. In particular, when more people start supporting a cause, there is a reluctance to continue to help, a phenomenon well-established in the prosocial behavior literature(Panchanathan et al., 2013; Bonsu & Belk, 2003). Alternatively, other explanations could be when more people start supporting a cause, the donor might feel a) her resources could be better utilized somewhere else or b) her contribution no longer makes a difference as others are already supporting the beneficiary.

Some recent papers by (Lee et al. 2017; Mukherjee, Lee, and Burnham 2020) have tried to resolve the divergence in findings. These experiment-based studies, find that moderators such as donor similarity and recipient resource scarcity can explain this divergence. That said, the findings from these studies are not generalizable across different donors and causes as they have a constricted subject pool and focus on a limited set of charities (usually just one). Our study, which is in a field setting and not based on a lab experiment, adds to this growing literature on donation behavior by extending the work into a new context: subscription-based donations. Our rich dataset across different causes and donor types allows us to examine heterogeneity in how changes in donor group size influence subscription behavior. For instance, donation behavior could be inherently different for donors from different backgrounds. (Wang, Kirmani, and Li 2021; Winterich and Zhang 2014).

INSTITUTIONAL SETTING AND DATA

We examine subscription-based donations for an online giving platform based in India and targeted at individual donors. The platform specifically caters to individual donors donating to grassroots causes that serve the affected populations directly. Subscription-based donations are 42% more valuable than fundraisers (Cipollini 2018), and the retention rate for subscription-based donors is nearly 90% compared to 23% for one-time donors and 60% for repeat donors (Recurringgiving.com 2019).

The platform started its operations in November 2017 and generates donations of more than USD 5 MM a year. One of the major challenges in the giving/philanthropy sector is the lack of trust among donors regarding the causes they donate to. To address this, the platform has a thorough onboarding process for causes to be listed on its site. The causes are vetted on multiple dimensions, such as their impact, fundraising, awards, audit history, etc. Only the causes that the platform finds authentic are listed. The platform charges a commission on the funds raised to support its operations.

A donor visits the platform and can select from nearly 300 causes that are on the platform. The causes are broadly divided into four categories - education, health, livelihood, and nutrition. Each cause has a unique webpage where the donor can see detailed information about the cause, such as the entity/persons who will benefit, the nature of the benefit, and detailed information about the affiliated nonprofit. In addition to this information, donors can also view the number of people who are donating to the cause. To the best of our knowledge, there was no systematic change in the information that was provided to donors during the period of our study. Donors can only donate in multiples of a minimum value. For example, if the donor wants to provide food for underprivileged kids and it costs at least USD 4 per month per kid, she can donate in multiples of USD 4 to help the corresponding number of kids. Each month, the donor's payment card gets deducted for her donation.

One of the unique features of the platform and something that we leverage is that donors receive a monthly email about the progress and impact of their donation (this is a common practice among many donation platforms (Ward 2021)). This monthly email contains information on the amount of donation that is due for the month, the number of donors supporting the cause, and a thank you note. While most of the content follows a custom template, the platform considers the number of donors supporting the cause as a strategic variable and provides information about this to donors every month. Each month the donor has an option to either continue or cancel the donation. Donors can also choose to donate to multiple causes if they so wish. However, we find this number to be very small in our dataset (less than 5%).

Data Description

Our dataset consists of transaction-level data from the donation platform from March 2018 to September 2020. It consists of nearly 64,000 transactions from 9,627 donors donating to more than 308 causes[8]. Table 1 below provides the summary statistics from this dataset. For each transaction, we observe the date, the amount of donation, the minimum donation amount, the number of beneficiaries, the cause, the category of cause, the donor group size, demographic variables of donors, and additional characteristics of the cause such as awards received, audited,

[8] Not all 308 causes are available for all the time periods. 308 represents the total number of unique causes in the data. We have removed data for 1 cause as it was an outlier.

year of inception, location, etc. One of the key variables of interest is donor cancellations. This variable is constructed based on how the focal firm considers donor cancellations –a donor cancels if she misses two transactions in a row. Another possible way to infer cancellations is due to card/payment errors. In case of card/payment errors, both the focal firm and the payment gateway partner send out an email to the donor to update her card details. However, if there is no response in a month and the donor fails to pay, she is assumed to have canceled her donation. One potential problem with this measure is that it would undercount donors who restarted their donations after a gap of two months or more. We examined the data for such instances and found no evidence of that happening for most of the data. In a few instances, we do notice donors coming back to the platform after a gap of more than a year and donating to a different cause. Given the time gap, we consider these donors as new donors to that later cause.

Table 1: Summary Statistics of variables of interest.

Statistic	N	Mean	StDev	Min	Max
# Cancellations	5,986	0.78	3.40	0	84
# Joiners	5,986	1.60	7.62	0	177
Net Effect	5,986	.82	5.07	-10	155
Donor Group Size	5,986	10.97	33.58	1	670
# Causes	5,986	240.59	73.64	2	308

Note: This table reports the summary statistics using the panel structure of data at the cause month level.

One of the unique aspects of our dataset is that the platform does not do any other marketing to its subscribed donors. This allows us to disentangle the effect of donor group size in our context cleanly, as we are not concerned about other interventions that can potentially confound our results.

First, in our data, we observe that 76% of all the donors have two or more transactions (see Figure A2 in the Appendix); this indicates that a substantial portion of the donors have committed to continuous giving, a pre-requisite for our analysis of cancellations (churners).

Second, the mean number of joiners for a cause in a month year tends to be higher than the mean number of cancellations. Therefore, the net effect seems to be positive. Also, the donor group size averages around 10.97 with a s.d. of 33.58, indicating variations in donor group size across causes.

Furthermore, the mean number of transactions per donor is 6.66 (s.d = 6.89); this translates to nearly 7 transactions per donor in 7 months without any reminder or appeal from the firm other than the monthly update email. Donors not only donate to more than 300 different causes but also donate in varying amounts ranging from Rs 100 (USD 1.21) to Rs 74,925 (USD 908.73). Unlike most existing work that is restricted in both the number of causes and donation amounts, our dataset is rich and allows us to explore heterogeneity across causes. The donor group size across causes varies from being as low as 1 other person (total donors =2) to 671. The distribution of a) donor demographics and b) cause categories are reported in Tables A1 and A2 in the Appendix, respectively. These tables show the heterogeneity of donors and causes in our data.

DESCRIPTIVE EVIDENCE

In this section, we provide model-free evidence to demonstrate the effect of donor group size on cancellations.

Visualizations

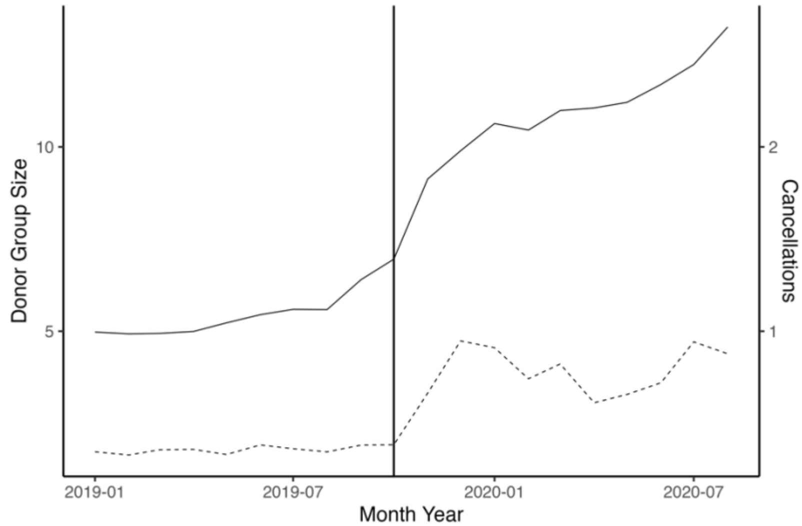

Figure 1: This plot shows the relationship between the number of cancellations and donor group size over time, averaged across causes. The dashed line is cancellations, and the black line is donor group size. The black vertical line represents the event.

Figure 1 shows the relationship between donor group size, cancellations, and time. Specifically, the points represent the average donor group size and cancellations across causes for each month year. The rationale behind this visualization is to present a ‘typical’ cause in a ‘typical’ month, the ‘typical’ donor group size, and cancellations. Donor Group Size for cause ‘c’ at month time ‘t’ is defined as $DGS_{ct} = DGS_{ct-1} - Can_{ct-1} + Join_{ct-1}$, where DGS_{ct-1} is donor group size for cause ’c’ at time ‘t-1’ and Can_{ct-1} ,$Join_{ct-1}$ represent the number of cancellations and new donors (joiners) for cause ‘c’ at time ‘t-1’, respectively. First, note that the value of cancellations is quite low, this is because the data is at cause month-year level, and there are many causes that do not experience any cancellations in any given month. Second, note that cancellations and donor group size both follow almost similar trends before the event. Third, around the event represented by the vertical black line, both cancellations and donor group size experienced a large and unexpected increase, providing some evidence that the event led to a shift both in donor group size and cancellations.

The data patterns, as presented in Figure 1, could be explained by the intrinsic preference of donors for certain causes. In addition, the seasonality of donation cycles could also exhibit such patterns. We conduct a visual "difference in difference" type of analysis that can address such selection and seasonality concerns. Note that our identification is centered around an event (more details in the identification strategy section).

The details of the difference-in-differences analysis are as follows, the causes which experience an increase in donor group size at the time of the event (above the median percentage increase across causes[9]) are labeled as the "increase" group, and the others as the "not increase" group. The data is aggregated at the cause month-year level. We then plot the trends of cancellations of the increase vs. not increase groups, presented in Figure 2. First, note that before the event (represented by the vertical black line in Figure 2), both the increase (dashed line) and not increase (black line) groups show a comparable pattern. Second, typically every year, other than the focal year, the Oct/Nov period is not characterized by a big jump in cancellations indicating the novelty of the event (i.e., subscribers did not expect this to happen). Third, after the event, there is a clear shift in the increase group compared to the not increase group, suggesting that the event had an impact on unexpectedly shifting subscribers for some causes. Collectively, Figures 1 and 2 suggest that an increase in donor group around the event window coincides with there being more cancellations of *existing* subscribers.

[9] We calculate donor group sizes for each cause pre and post event. We then calculate percentage of increase i.e. $\frac{DGS_{Post}-DGS_{Pre}}{DGS_{Pre}} \times 100$. The median percentage increase is calculated.

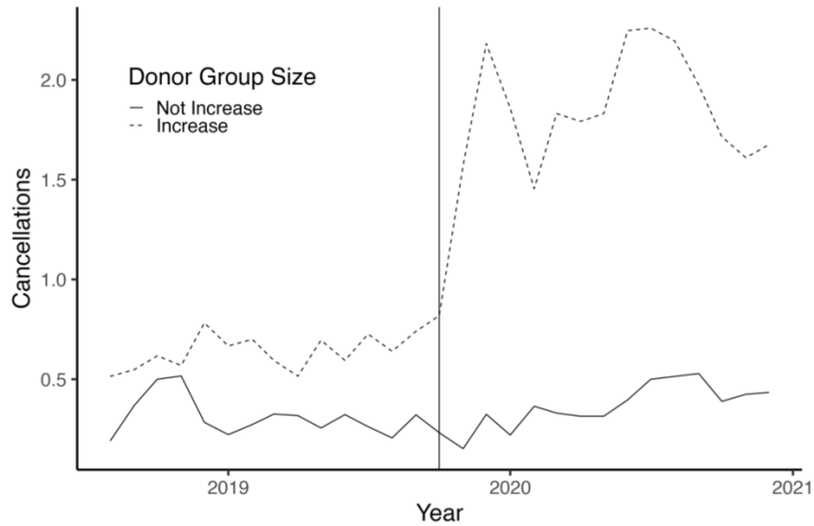

Figure 2: This plot shows the comparison of cancellations across causes that experienced an increase vs those that did not. The vertical black line shows the time of the event (shock). The dashed and black lines represent cancellations across causes that experienced an increase vs. which did not, respectively.

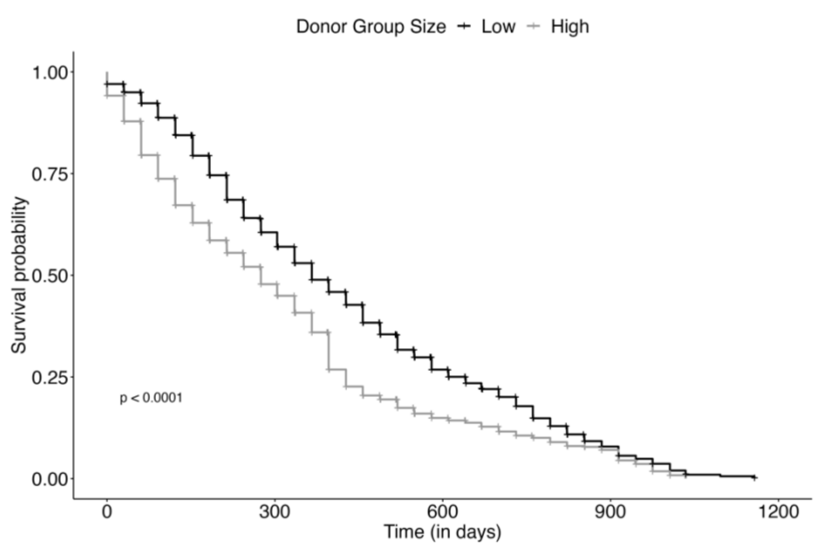

Figure 3: This figure reports the Kaplan Meir survival probabilities (1-Pr (Cancel)) for donors with high and low (median split) donor group size. The p-value from the log-rank test is also reported, indicating the statistical difference between the two groups.

To investigate the individual churn behavior of donors, we plot survival probabilities across donor group sizes. Specifically, we use the Kaplan Meier estimator to model the time to cancel across donor group sizes. Results are reported in Figure 3; donors who are subscribed to causes with particularly high (above the median donor group size) donor group size have lower survival probabilities compared to donors who subscribe to causes with smaller donor group size. Therefore, donors who subscribe to causes with a high donor group size have a higher chance of cancelling their donation subscription. One of the issues that arise when examining individual donation behavior is the right censoring of data that occurs because of the presence of donors in our data span who have not canceled. The Kaplan Meier estimator allows us to account for the right censoring of our data.

We also examine the joiners at an aggregate (cause-time) level using the same exogenous shock/ intervention. We use the same difference-in-difference type setup (as in cancellations) to plot the differences in joiners (new donors) across increase and not increase groups (see Figure 4). We find the increase in donor group size around the time of the event is also associated with an increase in joiners (new donors). This finding on joiners is in line with extant literature on observational learning and prosocial behavior.[10]

In summary, model-free evidence, both at aggregate and at the individual level, seems to suggest that donor group size positively affects cancellations. Also, the increase in donor group size can lead to more new donors (joiners).

[10] Although, we do see an uptick in the previous month and urge caution in interpreting the figure.

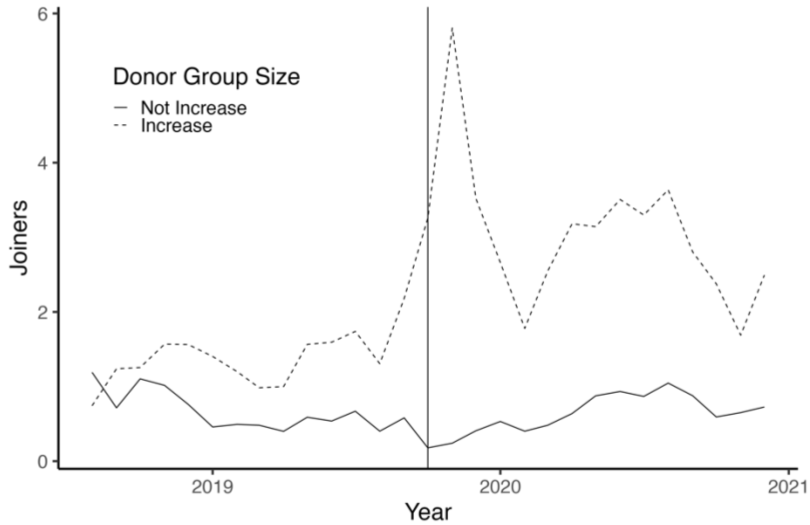

Figure 4: This plot shows the comparison of joiners across causes that experienced an increase vs those that did not. The vertical black line shows the time of the event (shock). The dashed and black lines represent joiners across causes that experienced an increase vs. which did not, respectively.

Correlation-Based Tests

Our visualizations of the data do not account for confounders such as time trends, preferred causes, etc. Next, we use panel regression models[11] with varying model specifications to account for some of these confounders. One of the endogeneity problems we face when running such a regression is that a cause-specific unobservable component may be correlated with the donor group size variable. To address this concern with a (potentially unobserved) omitted variable, we use cause fixed effects. Second, there could be potential time trends due to seasonality in giving behavior. For instance, donors are more likely to give during festivals, financial year closing, etc. (Bartoš 2021; Ekström 2018). We control for this using time-fixed effects. The results from these two specifications for churners are reported in Table 2. We find that in all model specifications, the donor group size is positively correlated with cancellations.

[11] We estimate $Y_{ct} = \beta_1 DGS_{ct} + \delta_t + \alpha_c + \epsilon_{ct}$; where Y_{ct} are the cancellations $and\ DGS_{ct}$ are the donor group size for cause c at time t. δ_t & α_c, represent time and cause fixed effects respectively.

In sum, our model-free evidence has shown that donor group size increases cancellations. While these results provide some preliminary evidence for our research question, it does not account for correlated unobservables. In the next section, we describe the issue, followed by our approach to tackle it.

Table 2: Cancellations and Donor Group Size

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Donor Group Size	0.076^{***}	0.081^{***}	0.076^{***}	0.084^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Time FE	N	N	Y	Y
Cause FE	N	Y	N	Y
Observations	4,814	4,814	4,814	4,814
R^2	0.594	0.672	0.598	0.679
Adjusted R^2	0.594	0.651	0.595	0.656

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The dependent variable is the number of cancellations, standard errors are reported in parenthesis. We run four-panel regression models with different model specifications. In the first two columns, time fixed effects are not included, whereas, in the last two columns, time fixed effects are included. Cause-level control variables are absorbed in the cause-fixed effects.

IDENTIFICATION STRATEGY

Another form of endogeneity not addressed in the earlier analysis is that of correlated unobservables. For illustration, consider Equation (1) where Y_{ct} is the dependent variable that represents the number of cancellations in a cause at time 't'. We are interested in causally establishing the effect of donor group size (DGS_{ct}) on Y_{ct}. However, there could exist unobserved variables (similar characteristics or similar experiences) that could affect both DGS_{ct} and cancellations Y_{ct}.

$$Y_{ct} = \beta_1 DGS_{ct} + \alpha_c + \delta_t + \epsilon_{ct} \qquad (1)$$

One approach to resolve the above endogeneity concern is to identify an exogenous shock that shifts the donor group size for a cause independent of the number of cancellations in the previous period. We do so by using an event that "exogenously" changed the traffic to this platform in a manner uncorrelated with any specific cause on the platform. Specifically, in October 2019, the focal platform collaborated with many Indian firms, which, in turn, encouraged their employees and customers to visit the donation platform and start donating.

Due to this event, there was a sharp uptick in the number of donors for many causes on the platform. Our key identification argument is that the donor group size attributable to the *event* is uncorrelated with the unobservables influencing churners, as this variation comes from the exogenous platform event. The intent of both the platform and the firms was to boost charitable giving and did not focus on any specific cause as such. The event was novel and had not been done earlier by the platform, so there were no expectations on the number of new joiners. While it is possible that certain causes are inherently more attractive, our cause-specific fixed effects help control for such differences. Thus, the event acts as an instrument that shifts our main driver of interest – the donor group size. The correlation between the donor group size attributable to the event and the number of subsequent joiners and cancellations will reflect our effects of interest. A bigger (smaller) increase in donor group size for a specific cause due to the external event could lead to a larger (smaller) number of cancellations.

Our approach here is similar to previous literature (Farronato, Fong, and Fradkin 2020; Natan 2021) that use mergers as an exogenous shock to establish causality. While mergers often lead to changes in both supply and demand aspects, in our context, there was an increase in the number of donors but not in the number of product offerings or minimum donation amount of the available product offerings (see Figure 5). This allows us to better identify the relationship between donor group size and donor behavior without having to worry about supply-side changes. Furthermore, the platform did not make any significant changes (new website design, advertising, etc.) during the event period, nor were there any regulatory policy changes or macroeconomic shocks during the event period. A small portion of our dataset does include the onset of the COVID-19 pandemic, and it is possible that the pandemic could have affected donation behavior. We account for this shift and report the results in the robustness check section.

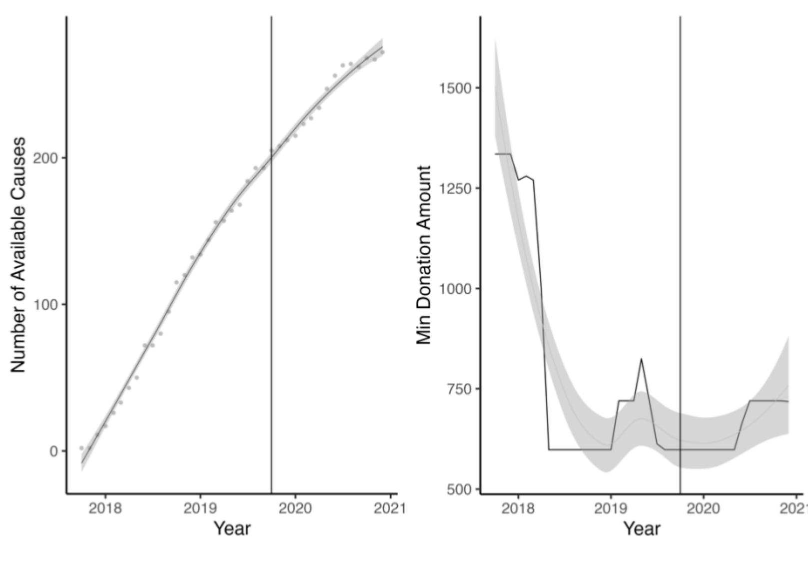

Figure 5: Offerings and Minimum Donation Amount of causes around the event. The left panel shows the number of available causes for donation by month year. The right panel plots the median of the minimum donation amount by month year. The solid vertical black line is the time of the event.

While the event led to an increase in the number of donors to the platform, it would not be sufficient to identify the impact of the donor group if it was consistent with donor expectations of group size in the next period. To demonstrate that this was not the case and that the event led to a change in donor group size that was beyond expectations, we do the following. First, using the data from the periods prior to the event shock, we use an optimized ARIMA model to estimate the evolution of donor group size over time and predict the counterfactual, i.e., the donor group size in the absence of the event shock for the period after. We then compare these predicted donor group sizes with the actual donor group sizes after the event. Our results presented in Figure 6 indicate that there is a substantial change in the donor group size (see black line in Figure 6) compared to what one would expect (see grey line in Figure 6); on average, across all causes, the expected (from past data) donor group size post-shock is 7.2, but we observe it to be 9.2, a 27.8 % increase in donor group size over the expected. The visualization provides model-free evidence for the relevance of the instrument.

Next, to show that the event indeed led to a change in the number of cancellations (our variable of interest), we use a regression discontinuity in time-based (RDiT) approach to demonstrate an interrupted time series for cancellations and donor group size. We follow (Hausman and Rapson 2018) and estimate the equation of the following form.

$$Y_t = f(t) + \beta_1 . \mathbf{1}\{t \geq t_{event}\} + \epsilon_t \qquad (2)$$

Where Y_t are cancellations in period 't'. $f(t)$ is the trend variable that can either be a linear or polynomial of varying degrees. The event represents the shock. Specifically, $\mathbf{1}\{t \geq t_{event}\}$ takes value 1 for the time after the event and 0 otherwise.

The results from this analysis are reported in Table 3, and it shows that the event led to an increase in cancellations after accounting for linear and nonlinear time trends. We also use local (around the event) and full data to show the discontinuity in cancellations at the event.

Finally, to ensure that donors that joined before the shock are similar to donors who joined after the shock, we compare donors on all the observed donor characteristics such as location, gender, donation amounts, choice of cause category, etc. The results for this analysis are in Table A3. We find that donors pre- and post-shock are not systematically different.

Table 3: RDiT results – interruption of cancellations at the event

	Dependent variable:			
	Cancellations			
	(G-Lin)	(G-Poly)	(L-Lin)	(L-Poly)
	(1)	(2)	(3)	(4)
β_1(Event)	0.431^{***}	0.431^{**}	0.391^{**}	0.385^{*}
	(0.164)	(0.169)	(0.198)	(0.202)
Observations	4,814	4,814	1,984	1,984
R^2	0.008	0.008	0.010	0.010
Adjusted R^2	0.008	0.008	0.009	0.009

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: This table reports the results of the RDiT expressed in Equation 2. The dependent variable is cancellations. G- represents that full data is used for estimation, and L- represents the usage of local data (around the event). Lin and Poly represent linear and polynomial functional forms of trend, respectively.

Our goal in this section was to show that the platform-level event could be used as an exogenous shock that shifted the donor group sizes and could be used to identify the relationship between donor group size and cancellations. Our analysis shows that the event changed the donor group sizes across causes and also affected the outcome variable. Further, the changes could not be explained by a) persisting trends in the cancellations and b) strategic changes such as minimum donation amount and the number of available causes around the event. In the next section, we describe our empirical strategy in detail.

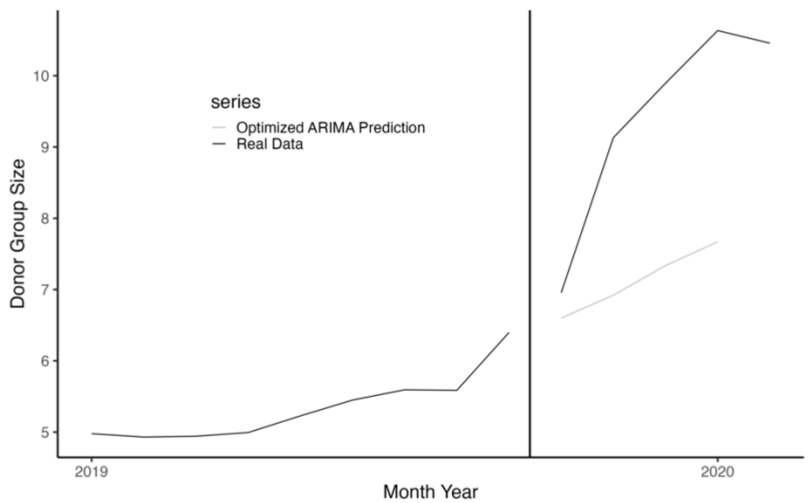

Figure 6: Real vs. Prediction using pre-event data to illustrate shock on donor group size due to event.

EMPIRICAL STRATEGY

First, we perform our analysis on aggregate cause-level data, followed by the analysis of donor-level data. We are interested in estimating the effect of donor group size on cancellations. Our main empirical model employs an instrumental variable approach to causally establish the effect of donor group size on our outcomes of interest. We estimate the equation of the following form.

$$Y_{ct} = \alpha_c + \gamma T_c + \beta_1 DGS_{ct} + \epsilon_{ct} \qquad (3)$$

Where, *c* and *t* represent cause and month year, respectively. Y_{ct} is number of cancellations for a cause *c* in the month year *'t'*, α_c represents cause fixed effects, T_c captures cause specific time trends through γ. Specifically, when a cause is available on the platform T_c takes value 1 and linearly increases until the cause remains on the platform. DGS_{ct} is the donor group size for cause ‘c’ at month time ‘t’. We instrument the donor group size variable with the event shock, and we use a 2SLS approach to resolve the endogeneity problem. The data is aggregated at cause-month level.

Next, we use the rich individual transaction level data to estimate the effect of donor group size on the probability of cancelling a donation subscription across different individual types and cause types. Understanding the heterogeneity in data allows us to generalize and identify boundary conditions for the role of donor group size. We focus on individual differences identified as important by the platform – donor location (US, UK/Australia/Canada, and India), gender, and the donation amount size and cause differences based on the focus of the cause – Nutrition, Healthcare, Livelihood and Education. We use a linear probability model as our empirical specification. Specifically, we estimate the equation of the following form.

$$Cancel_{ijt} = \alpha_j + \beta_1 DGS_{ijt} + \beta_2 T_{ij} + \beta_3 Controls + \epsilon_{ijt} \qquad (4)$$

Where $Cancel_{ijt}$ represents the decision of donor *‘i’* for cause *‘j’* at time *‘t’* to continue or cancel her subscription, it is a dummy which takes the value 1 if the donor decides to cancel and 0 otherwise. α_j are the cause fixed effects. T_{ij} represents a donor-level linear time trend variable and its value increases with each month that a donor remains on the platform. This is used to capture the fact that a donor may be more or less likely to cancel her subscription as her tenure increases (increasing or decreasing hazard). $Controls$ represents the location and gender of the donor. We address the endogeneity problem with the 2SLS approach where we instrument the donor group size with the event shock. We use the protocol suggested by (Goldfarb, Tucker, and Wang 2022) for our instrument variable analysis. Specifically, we report direct effects regression, F statistics, and first stage regression for all our models, which use the 2SLS approach.

RESULTS

Instrumental variables approach with aggregate data

We first report the results of first-stage regression for the 2SLS model (i.e. the regression of donor group size on Event/Instrument) in Table 4. The event results in a positive shift in the donor group size even after controlling for cause fixed and time trend effects. Second, we report our results from the complete 2SLS model (estimates from Equation 3) in Table 5. First, note that the weak instrument test in all model specifications can reject the null, validating the instrument as being relevant (F stat is above 10 and is reported in the last row of Table 4). Second, the coefficient on donor group size (DGS) ranges from .071 to .142 (see Table 5), implying that an increase in donor group size by 10 could lead to .7 to 1.5 subscribers (current donors) cancelling.

Table 4: First stage regression for cancellations and donor group size

	Dependent variable:			
	Donor Group Size			
	(1)	(2)	(3)	(4)
Event	5.771***	2.903***	6.860***	1.061*
	(0.460)	(0.515)	(0.318)	(0.543)
Cause FE	N	N	Y	Y
Time Trend	N	Y	N	Y
Observations	4,814	4,814	4,814	4,814
R^2	0.032	0.059	0.635	0.648
Adjusted R^2	0.032	0.058	0.611	0.625
F stat	159.07	150.38	24.05	27.95

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

Note: This table reports the results from the first stage of 2SLS estimation of Equation (3). The dependent variable is donor group size. The exogenous shock/instrument is the independent variable (Event). Both cause level time trend and fixed effects are added as controls.

Table 5: Cancellations and Donor group size – 2SLS

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Donor Group Size	0.071***	0.110***	0.061***	0.142**
	(0.008)	(0.018)	(0.006)	(0.065)
Cause FE	N	N	Y	Y
Time Trend	N	Y	N	Y
Observations	4,814	4,814	4,814	4,814
R^2	0.016	0.019	0.416	0.419
Adjusted R^2	0.016	0.019	0.377	0.380

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

Note: This table reports the results from the estimation of Equation (3). The dependent variable is the number of cancellations. Donor group size is instrumented with event shock and the 2SLS approach is used for estimation. The first two columns do not have cause level fixed effects but contain cause level control variables. The last two columns have cause level fixed effects and corresponding cause level covariates are absorbed.

Instrumented Linear Probability Model with Donor-level Data

Results for the first stage regressions for Equation (4) are reported in Table 6, note that, in both the models (with and without donor level fixed effects) we get a strong correlation between the event and donor group size along with F stat value (>10) indicating relevance of our event as an instrument. The results for the Equation (4) are presented in Table 7. We report results from linear probability model (LPM, without and with observed heterogeneity), 2SLS linear probability model (IV-LPM with observed heterogeneity) and 2SLS linear probability model (IV-LPM with unobserved heterogeneity). Across all models the donor group size positively impacts cancellation. Second, the coefficient of donor group size in IV-LPM (instrumented linear probability model) is .005 (s.e. =.0003), implying, if the donor group size increases by 10, it can lead to an increase in cancellation probability by 0.05. Third, across various model specifications, the coefficient on Donor Group Size varies between 0.0003 to 0.005, suggesting the robustness of our findings across different model specifications.

Table 6: First Stage Regression for donor level linear probability model

	Dependent variable:	
	Donor Group Size	
	(First Stage LPM with observed heterogeneity)	(First Stage LPM with unobserved heterogeneity)
Event	18.256^{***}	10.554^{***}
	(0.344)	(0.406)
Cause FE	Y	Y
Donor Time Trends	Y	Y
Donor Controls	Y	N
Donor FE	N	Y
Observations	21,145	21,145
R^2	0.750	0.796
Adjusted R^2	0.747	0.784
F stat	320.07	65.21

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

Note: This table reports the results from the first stage of 2SLS estimation of Equation (4). The dependent variable is donor group size. The exogenous shock/instrument is the independent variable (Event). The first column includes cause-fixed effects, donor level time trends, and controls. The second column includes cause-fixed effects and individual (donor) level fixed effects.

Table 7: Churn and Donor Group Size

	Dependent variable:			
	Cancel			
	(LPM-observed heterogeneity)	(LPM-unobserved heterogeneity)	(IV-LPM observed heterogeneity)	(IV-LPM unobserved heterogeneity)
Donor Group Size	0.0003***	0.0003***	0.002***	0.005***
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Cause FE	Y	Y	Y	Y
Donor Time Trends	Y	Y	Y	Y
Donor Controls	Y	N	Y	N
Donor FE	N	N	N	Y
Observations	21,145	21,145	21,145	21,145
R^2	0.022	0.121	0.032	0.129
Adjusted R^2	0.013	0.068	0.023	0.077

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

Note: This table reports the results from estimation of Equation 4. The dependent variable is a binary variable that takes value 1 when a donor cancels her subscription, 0 otherwise. Controls include donor gender and location. Columns 1,2 presents results from the linear probability model (LPM) with observed and with unobserved donor heterogeneity. Columns 3 and 4 present results from the second stage regression of IV-LPM with observed heterogeneity and unobserved heterogeneity respectively. Linear time trend has also been reported.

Heterogeneity

The donation behavior of an individual is dependent on the type of cause (appeal framing) they donate to (Lindauer et al. 2020). For example, the probability to donate for saving a child's life might be higher than the probability to donate to rebuild a community center. We report results that capture the differential (by cause and donor characteristics) impact of donor group size on cancellations in Table 8. We find that, as the donor group size increases, the probability of cancelling goes down in Nutrition, Livelihood, and Healthcare relative to education causes. Our results are broadly in line with the extant literature, in that, there are differential bystander effects based on cause categories (Chekroun and Brauer 2002; Clark and Word 1974; Fischer et al. 2011; Harari, Harari, and White 1985; Schwartz and Gottlieb 1976). Minimum donation amount does not influence the cancellation probabilities. One might expect that budget constraints for average donors could likely lead them to cancel causes that cost them more money with a higher propensity, however, we do not find any such effects. We also do not find evidence for gender differences. That said, our data is not rich enough to separate out drivers of gender differences. The location of the donor does play a role in cancellation probabilities. Specifically, we find that when donor group size increases donors in donors based out of countries such as US, UK, Australia and Canada are even less likely to cancel as compared to donors based out of India. While these differences in findings could potentially be explained by the collectivist and individualistic nature of Indian and Western culture donors (Balcetis, Dunning, and Miller 2008; Casale and Baumann 2015), we are unaware of work that shows the effect of observational learning across different cultures. Overall, we think that further study is required to capture the role of donor demographics on observational learning and its effect on donation behavior.

Table 8: Linear probability model with donor heterogeneity

	Dependent variable:
	Cancel
Donor Group Size	0.003^{***}
	(0.0003)
Donor Gender Male	0.002
	(0.004)
Donor Location UK/Australia/Canada	0.007
	(0.006)
Donor Location US	0.006
	(0.005)

Time Trend	0.000^{***}
	(0.000)
Cause Category Healthcare	0.005
	(0.008)
Cause Category Livelihood	-0.002
	(0.009)
Cause Category Nutrition	-0.0001
	(0.007)
Minimum Donation Amount	0.007
	(0.010)
Donor Group Size × Donor Gender Male	-0.00004
	(0.0001)
Donor Group Size × Donor Location UK/Australia/Canada	-0.0004^{**}
	(0.0002)
Donor Group Size × Donor Location US	-0.001^{***}
	(0.0001)
Donor Group Size × Cause Category Healthcare	-0.002^{***}
	(0.0003)
Donor Group Size × Cause Category Livelihood	-0.0001
	(0.0005)
Donor Group Size × Cause Category Nutrition	-0.001^{***}
	(0.0003)
Donor Group Size × Minimum Donation Amount	-0.0002
	(0.0003)
Constant	-0.031^{***}
	(0.007)
Observations	21,145
R^2	0.019
Adjusted R^2	0.019

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The dependent variable is a binary variable that takes value 1 when a donor cancels her subscription, 0 otherwise. We do not include cause-fixed effects as it absorbs cause-level observables. The base category for Gender is female (female=0,male=1), cause category is education and for donor location is India. We have used the event as an instrument and the results reported are for IV-LPM. Exponential time trend is used in this analysis for a better model fit.

RULING OUT ALTERNATIVE EXPLANATIONS

It is possible that other explanations besides changes in donor group size could lead to our results. In this section, we examine some of these possibilities and rule them out.

Switching Behavior

It is possible that donors might switch to a different cause or stop donating on the platform if a) at the time of the event, more attractive causes become available on the platform b) a new donation platform is launched. In both these cases, donors might stop donating to their current cause and either donate to a different cause on the platform or to the new platform. We do not find any evidence of this. Of all the donors who canceled, we found very few donors who restarted their donations to a different cause on platform[12] within 6 months of cancelling. The donor might also want to switch to a different mode (another platform, offline) of donation. While possible, we think this scenario is unlikely as this platform was the dominant platform for most online forms of donation, and there was no new platform launched at the time of the event. Most importantly, in all these scenarios, the donor has stopped donating to the cause where they experienced an increase in donor group size.

Intrinsic Churn

[12] We track donors by their personal information. If a donor changes her contact information (both email and phone number) when she restarts the donation, we will not be able to track the donor and miss out on such cases.

In any repeat/subscription-based business, some amount of churn is expected. In our context, more cancellations for a cause over time might be part of the natural churn because of a) better outside options b), changes in donor behavior, for instance, the donor may not want to donate anymore, or c), budget constraints. We control for churn using an individual donor time trend variable as a control. This variable linearly increases with each month a donor is a member of the platform. Our results persist even after controlling for churn (see Table 7)

Position Effects

Higher joiners for a cause could be driven by the position of the cause on the donation platform website. In particular, the platform could strategically position a cause based on its fundraising objective. Therefore, the position of a cause could drive both the donor group size and the number of joiners for the cause leading to an omitted variable bias problem. We were informed by the platform that the position of causes on the website was not manipulated or strategically used. Furthermore, the landing page of the website is a recommended page. On the recommended page, there are only 3-4 causes listed, therefore position effects do not play much of a role here. Specifically, causes are listed in a 1x3 or 2x3 matrix, and the user does not need to scroll down (for visualization, see Figure A3 in the Appendix). Moreover, we include cause-level fixed effects in all our model specifications to control for any position effects if present (see Equation 3,4 and Table 5,7).

Policy Changes

Macroeconomic policy changes with regard to donations/charity giving could also potentially affect our results. During the data span used in our analysis (2018-2020), there were two major policy changes that were related to charitable giving - *FCRA amendment bill* (Ministry of Law and Justice, Government of India 2020) and *Donations* Deductibles (Ministry of Law and Justice, Government of India 2017).

FCRA amendment bill (Ministry of Law and Justice, Government of India 2020)- This bill was passed in Lok Sabha (Lower House of the Indian parliament) in September 2020. It affects the grants from foreign sources to Indian nonprofits. Our donation platform and associated nonprofits had obtained all clearances in time, and thus the donation activity was not affected by this regulation.

Donations Deductibles (Ministry of Law and Justice, Government of India 2017). – This reform introduced new tax rules in 2017-18 and stipulates that that donations above Rs 2000 in cash will not be considered for tax deductions. Again, this does not affect our case as all the transactions are made through debit/credit cards, thereby making them eligible for deductions. In summary, these policy changes do not affect our donation platform and thus cannot explain the cancellation behavior of donors.

ROBUSTNESS CHECKS

Our statistical analysis and measurement contain some standard assumptions. In this section, we provide tests that validate our assumptions.

Time Effects

Equation 3 models the effect of donor group size on cancellations using data aggregated at cause/month level, where we observe the number of cancellations and donor group size for each cause for each month year. To account for the time trends, we used a linear time trend variable. However, it is possible that the underlying data pattern follows a nonlinear time trend, and our results are an artifact of this assumption (that the time trends are linear). Therefore, we use multiple variations of time trends, such as exponential, square, and polynomial time trends, and we find that our results hold across all specifications. We report our results in Table 9. We conduct the same analysis for individual-level data (as used in Equation 4), and we report our results in Table 10, in this case, too, our results hold, although the effects are attenuated with higher-order polynomials.

Table 9: 2SLS model with various time trend effects

	Dependent variable:			
	Cancellations			
	(Linear)	(Exponential)	(Square)	(Polynomial)
Donor Group Size	0.142**	0.061***	0.145**	0.045**
	(0.065)	(0.006)	(0.068)	(0.018)
Cause FE	Y	Y	Y	Y
Observations	4,814	4,814	4,814	4,814
R^2	0.419	0.416	0.419	0.420
Adjusted R^2	0.380	0.377	0.381	0.381

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

Note: The dependent variable is number of cancellations. Donor group size is instrumented with event shock, and 2SLS approach is used for estimation. The time trends used are linear, exponential, square, and polynomial of degree 3. Cause level fixed effects are included in all the specifications.

Table 10: Linear probability model with various time trend effects

	Dependent variable:			
	Cancel			
	(Linear)	(Exponential)	(Square)	(Polynomial)
Donor Group Size	0.005***	0.003***	0.005***	0.005***
	(0.0003)	(0.0001)	(0.0003)	(0.0003)
Donor FE	Y	Y	Y	Y
Observations	21,145	21,145	21,145	21,145
R^2	0.129	0.129	0.130	0.130
Adjusted R^2	0.077	0.077	0.078	0.078

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

Note: This table reports the results from estimation of Equation (4). The dependent variable is a binary variable that takes value 1 when a donor cancels her subscription, 0 otherwise. The time trends used are linear, exponential, square, and polynomial of degree 3. Donor level fixed effects are included in all the specifications.

Covid-19 Shock

The COVID-19 crisis has shown to affect the donation behavior of individuals. On one hand, the pandemic shrunk the economies of many countries, leading to shortage to disposable income for donation (Monitor 2020) . On the other hand, there is documented evidence of increased generosity due to catastrophe compassion (Alós-Ferrer, García-Segarra, and Ritschel 2021). To account for this shift, we right truncate our data until March 2020 and report our main results in Table A4 in the Appendix. Our results hold even after accounting for the Covid-19 shock.

Direct Effect of the Instrument (the "Reduced Form" Regression)

We have earlier established how the instrument(event) affects cancellations (Table 3). We establish the direct effect of the instrument for the aggregate and individual-level models (as recommended by (Goldfarb, Tucker, and Wang 2022)). Specifically, we regress cancellations (observations are at cause month level, as in Equation 3) on the instrument for the aggregate model. For the individual level model, we regress Cancel (1 if the donor cancels and 0 if the donor continues) on the instrument. The results are reported in Table 11, and the results indicate a strong effect of the instrument on both the dependent variables.

Table 11: Direct effect of instrument on cancellations and Pr(Cancel)

	Dependent variable:	
	Cancellations	Cancel
	(1)	(2)
Event	0.768^{***}	0.049^{***}
	(0.240)	(0.004)
Time Trends	Y	Y
Cause FE	Y	Y
Donor FE	N	Y
Observations	4,814	21,145
R^2	0.423	0.129
Adjusted R^2	0.381	0.077

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: This table reports the results for direct effects of the instrument on cancellations and Pr(Cancel), i.e. for aggregate and individual level model. Column 1 reports the results of the regression of Cancellations (at cause month level) on Instrument (Event), and Column 2 reports the results of the regression of Cancel (1 if donor cancels and 0 if donor continues) on Instrument (Event).

EFFECT ON THE SUBSCRIPTION DECISION

The extant literature has focused largely on new donors, and it has been shown that an increase in donor group sizes attracts more new donors, largely driven by bandwagon effects (Cialdini and Goldstein 2004; Frey and Meier 2004; Milgram, Bickman, and Berkowitz 1969; Reingen 1982). In this section, we present the results from our analysis that identifies the effects of donor group size on new subscribers (joiners) to the platform. We have already provided descriptive evidence through visualization earlier in the section that shows that the number of new donors increases as donor group size increases. In the analysis of donor group size on new joiners, we use the same identification strategy that we used for cancellations. Specifically, we once again use the event as an exogenous shock to estimate the impact of donor group size on the number of joiners. For the event to work as an instrument for new joiners, we need to assume that unobservables at the time of the event are uncorrelated with post-event unobservables. So, we view our results here as being largely suggestive in nature.

Under these assumptions, we report results from 2SLS in Table 12. We find the coefficient on donor group size to vary from .125 to .748, implying that an increase of 10 in donor group size can lead up to 1 to 7 new donors joining the platform. Our results are consistent with the literature on observational learning that suggests that a cause with more donors provides a signal of higher quality and thereby leads to more new donors subscribing.

Table 12: Joiners and Donor group size – 2SLS

	Dependent variable:			
	Joiners			
	(1)	(2)	(3)	(4)
Donor Group Size	0.125***	0.324***	0.073***	0.748***
	(0.024)	(0.054)	(0.019)	(0.216)
Cause FE	N	N	Y	Y
Time Trend	N	Y	N	Y
Observations	4,814	4,814	4,814	4,814
R^2	0.006	0.007	0.289	0.289
Adjusted R^2	0.005	0.007	0.242	0.242

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

Note: This table reports the results from the estimation of Equation (3). The dependent variable is the number of joiners. Donor group size is instrumented with event shock, and the 2SLS approach is used for estimation. The first two columns do not have time trends, whereas the last two columns include time trend variables. Columns 3 and 4 have cause-level fixed effects.

DISCUSSION

The popularity of a product has been shown to be an important tool for increasing demand (purchase intention). This is especially true in the charitable donation context, where donors are regularly informed of the number of donors for causes. Despite the impact of donor group size on donation behavior being mixed (Bonsu and Belk 2003; Cialdini and Goldstein 2004; Mukherjee, Lee, and Burnham 2020; Panchanathan, Frankenhuis, and Silk 2013), it is used in donation contexts, including subscription-based donation. Unlike donors in traditional donation contexts, donors in subscription-based donation contexts must not only commit to a certain donation but also decide if they want to continue with the subscription each period. Given the increasing importance of subscription-based donations and changes in the donation behavior of donors, we analyze the impact of donor group size on donor behavior.

In this paper, we work with one of India’s largest subscription-based donation platforms to study the effects of cause popularity (donor group size) on donation behavior in the context of subscription-based donation. We use an exogenous shock to the platform as our main identification strategy. We found that overall, donor group size positively impacts donations. Specifically, the higher the donor group size for a cause, more donors start donating to a cause. Surprisingly, the higher the donor group size, more donors also cancel their subscriptions. Our analysis suggests that when donor group sizes for a cause increase by 10 donors, it could attract nearly 3 new donors while losing nearly 1 existing donor. Our findings suggest that in the case of subscription-based donations, displaying donor group size can have both positive and negative effects depending on whether the donor is a new donor or an existing one. Specifically, donor group size could potentially serve as a signal of quality for the joiners, leading to a higher number of joiners while for cancellations, donor group size seems to reduce the propensity to help a person. Furthermore, given that donor retention rates are consistently going down year on year (AFP Global 2020; Hay 2015), the implications of donor group size information on donor cancellations become even more critical.

Examining differences across different donor types and causes, we find that the impact of donor group size is less for nutrition, livelihood and healthcare-related causes when compared to causes that focus on education. We also find that donors based out of the US, UK, Canada etc are less likely to cancel their subscription as compared to the Indian donors.

Our findings suggest that platforms should be judicious about using the donor group size information for marketing. Specifically, platforms should use donor group size information to bring new donors on the platforms, but not to existing donors. The platform can also leverage differential cancellations across locations and cause categories.

While our study uses a very rich dataset that spans different causes and donor types, it has certain limitations in terms of generalizability. For one, donors who contribute to subscription-based donations could be fundamentally different from donors in other contexts. Additionally, our context is online, and therefore donors and causes who prefer the online environment may be different from the offline environment. Future research could potentially address these limitations. Furthermore, researchers could look at the effect of buyer group size and purchase behavior of customers in subscription-based product markets such as magazines, phone plans, etc.

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APPENDIX

Event promotion banner

Text: Want to make someone smile. Generic photo of an individual (s). Link to cause listing page.

Figure A1: The above figure represents a typical event promotion banner that appeared on the website of collaborating firm's webpage.

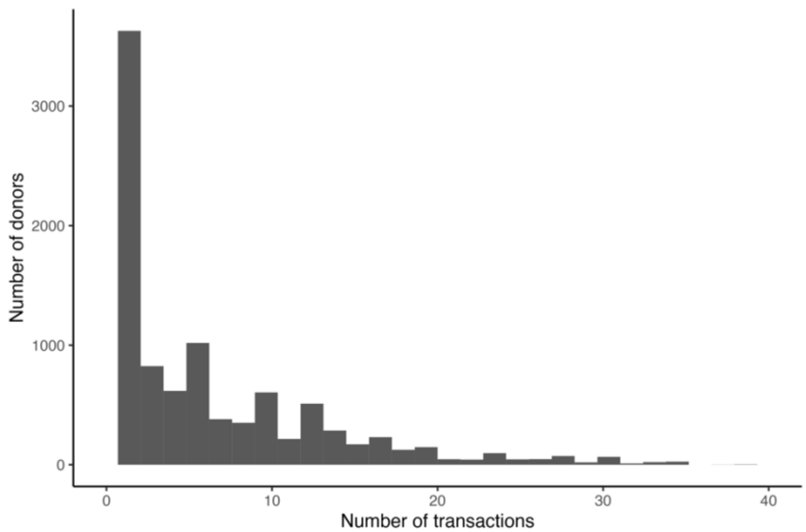

Figure A2: Distribution of the number of transactions

Table A1: Broad distribution of causes by category

Category	**Education**	**Healthcare**	**Livelihood**	**Nutrition**
Count	114	56	77	60
Percentage	37.1	18.2	25	19.5

Table A2: Broad distribution of donors by location

Location	**India**	**US**	**Others**
Count	6614	1964	1043
Percentage	68.7	20.4	10.8

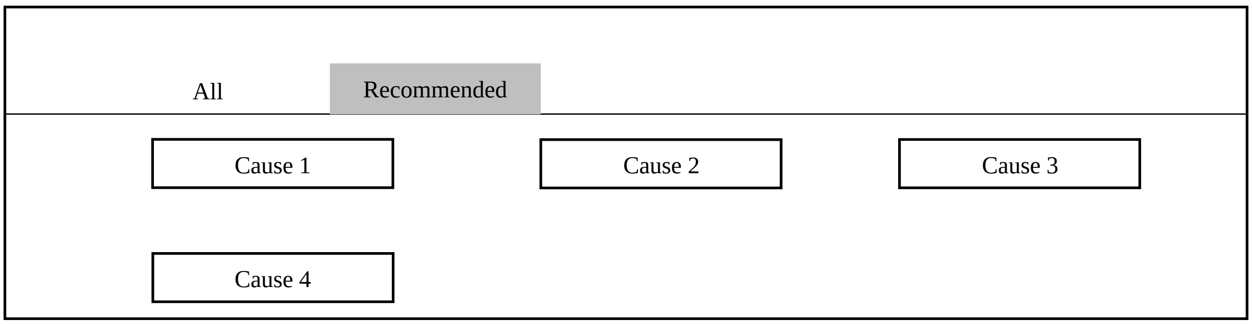

Figure A3: Position effects - This figure illustrates the landing page of the website.

Table A3: Comparing Donor's characteristics pre and post-event

	Dependent variable:
	Donor Join Pre vs Post Event
Healthcare	.073
	(.201)
Livelihood	.045
	(.271)
Nutrition	.133
	(.191)
Education	.130
	(.276)
Other Locations	-.091
	(.201)
US Location	-.193

	(.156)
Male	.086
	(.103)
Log (Min Donation Amt)	-.405
	(.667)
Observations	906
Log Likelihood	-547.761
Akaike Inf. Crit.	1,111.521
	*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the comparison of donor characteristics before and after the event to show that the difference in donation behaviour is stemming from the event shock and not because of a new donor base. The dependent variant takes the value 1 if the donor joined after the event, and 0 otherwise. We find the donors who joined after the event are similar to donors who joined before the event.

Table A4: Cancellations and Donor Group Size – 2SLS – incorporating COVID shock

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Donor Group Size	0.085***	0.137***	0.074***	0.110**
	(0.011)	(0.027)	(0.008)	(0.045)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	3,560	3,560	3,560	3,560
R^2	0.017	0.023	0.351	0.356
Adjusted R^2	0.017	0.022	0.300	0.305

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

Note: This table reports the results from estimation of Equation (3), incorporating COVID shocks. Specifically, we limit the data to before March 2020, the onset of COVID-19. The dependent variable is a number of cancellations. Donor group size is instrumented with event shock and the 2SLS approach is used for estimation. The first two columns do not have cause-level fixed effects but contain cause-level control variables. The last two columns have cause level fixed effects and corresponding cause-level covariates are absorbed.