Popular or Crowded: 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 display, for each cause (e.g., cancer treatment or education provision), the donor group size (number of people donating to that cause). We use data from a subscription-based donation platform to study the effect of displaying donor group size on new donors and 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 on the two donor groups. We find that displaying the number of donors can act as a double-edged sword — encouraging new donors (a "bandwagon" effect) while discouraging existing donors (a "bystander" effect) from subscribing. We suggest the managers be careful about displaying the number of donors as the net effect on subscriptions can vary with the "life cycle" of the charity and its donors. Specifically, managers can leverage this information when new donors signup but should not disclose this information to current and active donors.

Keywords: Subscription-based donations, bystander effect, bandwagon effects, donations, donor group size, popularity, crowding out

INTRODUCTION

Billions of dollars are raised for charitable donations every year (Mohan et al., 2019; NP Trust, 2021). With increasing ease of donation through online channels, online donations have increased 21% YoY(Blackbaud Institute, 2021). This growth has led to the formation of many online donation platforms such as Donorbox, Double the Donation, GiveIndia, Ketto. Donation platforms provide a two-sided market for donors and nonprofits. The benefit for donors is a wide variety of causes to choose from, verified nonprofits and lower search costs. The benefits for nonprofits are access to a broad donor base, the ability to raise funds for multiple causes simultaneously, and lower cost to raise funds (Ozdemir et al., 2009). Donation platforms use one-time donation events and subscription-based donations as primary modes of raising donations. Although most donations are raised using one-time donation events, there is a shift towards a subscription-based donation model (MatchPro, 2020).

A subscription-based donation model is where a donor signs up for donating to a cause. A set amount is deducted every period (monthly or quarterly) from the donor's account to support the cause. It has been documented that when donors signup for subscription-based donations, they tend to donate more (amount and duration) than a one-time donation; a survey shows that donors on subscription-based donate 4.4 times more than one-time donation (Classy, 2018).

One of the common strategies used by the donation platforms is to display the number of donors donating to a cause (donor group size). The extant literature seems to be divided on the effects of donor group size on donation. Specifically, on the one hand, papers argue that, as in the product markets, there will be bandwagon[1] effects at play, and therefore, as the donor group size (popularity) increases, so will the donations (Cialdini & Goldstein, 2004; Frey & Meier, 2004; Reingen, 1982). However, on the other hand, there is a strand of literature that argues for the bystander[2] effects at play, specifically, as the donor group size would increase, the probability of donation would go down (Darley & Latane, 1968; Fischer et al., 2011; Panchanathan et al., 2013). Furthermore, the decision process of donors in one-time donation is different from subscription-based donations. Specifically, in subscription-based donations, donors have to decide on a) which cause(s) to donate, b) the amount to donate, c) continue or cancel the donation in the subsequent periods d) donors receive an update on their donation (progress and impact) every month. However, in the case of one-time donations, donors mainly decide on the cause and donation amount.

Therefore, given a) shift towards subscription-based donation in practice, b) unclear answers from the extant literature, and c) different underlying donor's decision process compared to one-time donations warrants an investigation into understanding the effects of donor group size on donations in the subscription-based donation context.

This paper answers the following research questions in the subscription-based donation context.

1. Does a higher donor group size leads to more new donors?
2. Does higher donor group size leads to more current donors cancelling their donation subscription?

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[1] Bandwagon effects – people tend to adopt something primarily because others adopt it. 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 – the propensity to help someone decreases in presence of others. In our context, it refers to decrease in probability of donation (help) if others are already donating to a particular cause.

3. Should a donation platform provide information (display) donor group size information?
4. Do the above findings persist for different cause categories and different types of donors?

We work with one of India's largest subscription-based donation platforms to answer the above questions. The platform (website) started its operations in 2017, provides a gamut of nearly 300 causes[3] across four categories (nutrition, livelihood, education, and healthcare) for donors to choose from. Each cause has its webpage where donors can get more information about the cause, including how many donors are donating to the cause then (donor group size). The minimum donation amount can vary from Rs 100 (USD 1.35[4]) per month to Rs 11,500 (USD 155) per month. The platform donor base of nearly 10,000 (as of Dec 2020) monthly active donors, primarily based out of India, North America, and Western Europe. We have transaction-level data from the platform's inception to Dec 2020. Furthermore, we have information on major strategic decisions by the platform from its inception. Our data is unique compared to the extant literature in that a) we have transaction-level data for subscription-based donations, b) a wide variety of causes c) a wide variety of donors. Therefore, with this data, we can not only comment on the impact of donor group size on donations in the subscription-based donation context, but our results are also more generalisable due to a variety of causes and donors.

We are interested in a) effect of donor group size on new donors b) the effect of donor group size on current donors. Both these relationships can be biased due to multiple types of endogeneities. Next, we explain why these relationships can be biased. Consider the first

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

[4] Exchange rates as of Nov 2021.

relationship, the effect of donor group size (X_1) on new donors (Y_1). As discussed earlier, higher the donor group size, more new donors would join ($Y_1 \leftarrow X_1$). However, as more new donors join, it would lead to higher donor group size as these new donors will become the part of donor group ($X_1 \leftarrow Y_1$), leading to a typical endogeneity concern arising from reverse causality. Now, consider the second relationship, the effect of donor group size (X_2) on current donors (Y_2). As discussed earlier, one strand of literature argues that higher donor group size would lead to lower donation probabilities or higher cancellations ($Y_2 \leftarrow X_2$). However, if a donor cancels, it would lead to a lower donor group size ($X_2 \leftarrow Y_2$). Again, this leads to the trap of reverse causality. Furthermore, some unobserved factors could affect both X and Y together; for example, certain types of causes (saving a child's life vs providing books for the underprivileged) would be more appealing than others.

To address the endogeneity issues in both the relationships (joiners vs DGS and cancellations vs DGS), we use an exogenous shock (the event) as the source of variation for identification. The event was a collaboration between the focal donation platform and many eCommerce retailers in India. In this collaboration[5], consumers and employees of the retailers were informed about the focal donation platform. Post the event; there was an 'unexpected' increase in the number of donors (donor group size) for some causes on the donation platform. Therefore, this shock serves as a random intervention. Furthermore, the causes which experienced an unexpected increase[6] in donor group size are labelled as treated causes and others as untreated causes or the control group. Next, we explain how our setup helps us to causally establish the effect of donor group size on joiners and cancellations.

[5] Donation platform was advertised on the retailers' websites in the form of landing page banners. However, the donation wasn't tied to any offer on the retailer's website. Furthermore, employees and volunteers of the donation platform organised information sessions for the employees of the collaborating retailers.

[6] We use multiple definitions of increase. See Robustness Checks section for the definitions.

First, consider the relationship between joiners and donor group size. The donors, who joined the platform (the treated causes) just after the event, experienced an unusually larger donor group than the control group. Therefore, the event serves as a random intervention. For further illustration, consider a toy example, consider two exactly similar causes. The number of joiners & donor group size are observed for each cause every month. Suppose for one of the causes, there is a sudden increase (shock) in donor group size and post the shock; there is a sudden change in joiners; this increase can be attributed only to the sudden rise in donor group size. The counterfactual is present in the control group. Post the event, the control group didn't experience a sudden increase in joiners because it didn't experience an increase in donor group size.

Second, consider the relationship between cancellations and donor group size. In this case, the donors who were donating to a cause just before the shock, for them, the shock was an unexpected event, i.e., the sudden increase in the donor group size for the treated causes. Therefore, if the cancellations for the treated causes increases compared to the control, that increase can be attributed to the event (sudden increase in donor group size).

Therefore, using the event as the source of exogenous variation, we can causally estimate the impact of donor group size on the number of joiners (new donors) and the number of cancellations of the existing donors.

We use a difference in difference type model on the monthly aggregated data. In the DID set-up, the event serves as the intervention; the causes which experience an increase in the donor group size are labelled as the treatment group and the others as the control group.

We complement the DID method with an instrumental variable approach to build confidence in our results. We instrument the endogenous donor group size variable with the even shock and use a 2SLS approach to estimate our results.

Lastly, we use transaction-level data to estimate the effects of donor group size on the probability of cancelling a donation subscription. We focus only on cancellations in the transaction level analysis because cancellations warrant more investigation because of relatively less focus in literature, and we don't observe choice data for joiners (join/not join). We use a dynamic logit model for estimation; however, as discussed earlier, this model too suffers from a reverse causality problem. Therefore, we instrument the endogenous donor group size variable with event shock. We further complement the dynamic logit model with survival analysis; we use the Cox proportional hazard model with time-varying covariates.

Across all models, we find that donor group size positively affects the joiners (new donors). This finding conforms with the extant product literature on displaying popularity as demand boosting tool. In the charitable donation context, this finding confirms the bandwagon effects. Surprisingly, we find that as more donors start donating to a cause, it hurts the probability of continuing donation for the current donors. This finding is counterintuitive from both the product and at least one strand of charitable donation literature. Therefore, in the case of subscription-based donations, donor group size can have both positive and negative effects, albeit for different types (new vs current) of donors. Specifically, the donor group size serves as a signal of quality for the new donors, leading to a higher number of new donors. In the case of cancellations, the bystander effect seems to be the plausible explanation. Specifically, as widely documented in the prosocial behaviour literature, the propensity to help a person reduces in the presence of others. Therefore, in our context, when the donor group size increases for a cause, the probability of continuing donation for an existing donor reduces.

We rule out multiple other possible explanations using data and institutional information; for example, our results on cancellation can simply be explained by switching. Specifically, when more people start donating to a cause, a donor might feel that her resources are better utilised elsewhere, leading her to either donate to a more 'needy' cause on the current platform (intra) or switch to a different donation platform (inter). We rule out the intra platform switching based on evidence from the data (we don't find donors who cancel their donation to start donating to some other cause on the platform). Similarly, we rule out the inter-platform switching based on the high market share and a wide variety of causes present on the focal donation platform. Furthermore, we rule other possible explanations to build the case for our findings and explanations.

To test the robustness of the results of the models, we test for parallel trends, the persistence of effects post the shock, heterogeneous treatment effects, different definitions of increase and instrument validity through placebo regressions. Our results remain unchanged, and we find the direction of estimates to be intact.

We contribute to the literature in charitable donations in three distinct ways 1) We establish the impact of displaying donor group size in the context of subscription-based donations. Specifically, we find that, in the subscription-based donations context, information on donor group size helps get new donors, but this information also hurts the probability of current donors to continue donations. The net effect is a positive effect on donation when the donor group size is small (gain in new donors > loss in current donors) followed by zero effect (gain in new donors = loss in current donors) when donor group size is high. To the best of our knowledge, ours is the first paper to establish the effects of donor group size in the subscription-based donation context. 2) We bring clarity in the extant divergent literature on the effects of donor group size on donations. We do show that both (positive and negative) sides of the effect and the corresponding explanations are correct, albeit for different types of donors or in different stages of the donor-platform relationship) 3) Our findings are generalisable in that our results hold across different types of donor groups and a wide variety of causes. Extant literature has based its findings on a single cause category with a constricted donor pool, and it has been documented that donation behaviour varies by type of cause and donor (Andreoni, 2007; Liu et al., 2017, Y.-K. Lee & Chang, 2007; Wiepking & Bekkers, 2012).

The rest of the paper is organised as follow; in the related literature section, we cover the extant literature on the effects of donor group size on donations. Specifically, we discuss papers with divergent findings. We also discuss papers that attempt at providing reconciliation on these divergent findings. Furthermore, we discuss the contribution of our paper to the extant literature. Next, we provide details on the institutional setting and data. The descriptive evidence section provides visualisation and correlation-based tests to provide model-free evidence. Identification strategy provides details on our source of exogenous variation and underlying identifying assumptions. The results and discussion section provides details on the results. The robustness checks and alternate explanations section offers more support for our findings. Eventually, 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. Specifically, 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). Researchers use various terms for the phenomenon under different settings 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. Extant research seems to be divided into two broad groups with divergent findings in the charitable donation context. 1) Positive effect- donation is higher for more popular causes(Cialdini & Goldstein, 2004; Frey & Meier, 2004; Milgram et al., 1969; Reingen, 1982) 2) Negative effect – donation is lower for more popular causes

(Bonsu & Belk, 2003; Darley & Latane, 1968; Fisher et al., 2017; Panchanathan et al., 2013). The theoretical explanation behind the positive effect is the appropriate social norm. 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. However, for the negative effect, the explanation stems from bystander effects. In particular, when more people start supporting a cause, there is a reluctance towards continuing help, a phenomenon well established in the prosocial behaviour 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 utilised somewhere else or b) her contribution no longer makes a difference as others are already supporting the beneficiary. Therefore, it is unclear if donor group size affects donation behaviour positively or negatively, creating a dilemma.

Recent papers by (S. Y. Lee et al., 2017; Mukherjee et al., 2020) attempts to resolve this dilemma through a series of experiments and find donor similarity and recipient resource scarcity as essential moderators for these divergent results. The limitation of these studies can be broadly classified into two categories a) inference based on one-time donation data b) lack of generalizability of results, stemming from the constricted subject pool and no variation in the type of charities. We attempt to address all these issues in this paper. Next, we expand on each of these limitations and how they can affect the inference and generalizability of findings.

One-time donation data

Papers that deal with positive or negative effects or which attempt at resolving the dilemma use one-time donation data. For instance, in (Mukherjee et al., 2020), participants must donate *once* for earthquake victims. Findings from one-time donations can’t be applied in the subscription-based donation setting because of donors’ different underlying decision processes. In particular, in subscription-based donation, there are the extra elements of a) deciding to continue or cancel the donation every month b) donor receives update on the progress/goal of the cause every month. Therefore, the effects of donor group size could be amplified in the subscription-based donation setting as the donors are more actively engaged with the cause. Furthermore, with one-time donation data, it is difficult to capture within donor differences or to understand the donor lifecycle (how donation behaviour of the same donor changes over time).

Variation in donors and causes

A standard critique on the generalizability of findings with donation behaviour is the inherently different altruistic behaviour of donors from different countries. For example, in our context, donors from India might be less generous compared to American donors because of inherently different donation culture (Ashraf & Bandiera, 2017; News, 2019). Inversely, Indian donors might feel close to the cause as the recipients are Indians and, therefore, donate more (Kessler & Milkman, 2018; Munz et al., 2020). However, to the best of our knowledge, there are no papers that consider this variation in altruistic behaviour. In our dataset, the donors are not only based in India but also from relatively more generous regions such as the US and Europe. Furthermore, findings in the extant literature are based on one cause (education or healthcare etc.). However, as documented in a few papers, the donation behaviour of individuals can be very different for different causes (Bennett, 2012; Khodakarami et al., 2015). Therefore, for generalised findings, it is useful to test the results across heterogenous donor groups (varied inherent altruism) and a variety of causes.

Contribution

We contribute to the extant literature by a) extending the donation literature to subscription-based donations context, b) resolving a dilemma in extant theory, and c) evaluating the impact of a commonly used strategy by donation platforms/ charities, i.e. providing donor group size information to current and potential donors.

Theory on the effects of donor group size on donation behaviour is divergent. One strand of literature argues for the bandwagon effect (positive), and the other strand argues for the bystander effects (negative), thus creating a dilemma. In this paper, we resolve this dilemma (positive or negative effect), albeit in a subscription-based donation context. We show that displaying donor group size information can affect the donation positively and negatively, although at different points on the donor's donation life cycle.

Our results are useful for managers in that it provides a balanced view on how others' prosocial behaviour information can affect the donation behaviour of potential and current donors. Managers can use this information to better design their platform and interact with the donors. Specifically, managers should use donor group size information to attract new donors. However, they should be careful about providing donor group size information to current donors as it might discourage their donations.

INSTITUTIONAL SETTING AND DATA

Institutional Setting

This paper deals with charitable donations. Specifically, retail donors donating[7] (not organisational or CSR activities) to individual/group of recipients (not organisations). Charitable donations are nearly USD 470 Bn in the US (GivingUSA, 2021). Ease of payment through online channels has led to the creation of many online donation platforms such as Donorbox, Double the Donation, GiveIndia, Ketto. Donation platforms serve as two-sided markets (nonprofits and donors). Donors prefer donation platforms because of ease of

[7] Retail donor refers to individual donors who donate to one or multiple causes/beneficiaries, and the size of donation (value) is generally small, unlike corporate donations.

donation, access to a wide variety of causes and lower search costs, whereas the nonprofits enjoy access to a large donor base and low cost of raising funds (or else they would need to set up and maintain a website/app etc.). One-time and subscription-based donations are two primary modes of donations collection used by the platforms. Subscription-based donations have shown to generate higher revenues and tap into a committed and loyal donor base. Subscription-based donations turn out to be 4.4 times more valuable than one-time donations and 42% more valuable than fundraisers (Classy, 2018). Moreover, the retention rate among subscription-based donors is nearly 90% compared to 23% for one-time donors and 60% for repeat donors (Recurringgiving.com, 2019). Furthermore, donors signup for subscription-based donations because it provides them with a lower cost of giving, fewer donation asks, and a higher engagement (Appfrontier.com, 2020).

We work with a subscription-based donation platform[8] based out of India for this paper. This platform is one of the biggest subscription-based donation platforms in India. The platform started in 2017 and generates donations of more than USD 5 Mn a year. Next, we explain how the subscription donation process works.

A donor visits the platform and can select from nearly 300 causes, divided into four broad categories (education, health, livelihood, and nutrition). Each cause has its webpage where the donor can see detailed information about the cause (who will benefit and for what, information about the affiliated nonprofit etc.). Donors can view how many people are donating to the cause then. She can only donate in multiples of a minimum value. For example, if she wants to provide food for underprivileged kids and it costs at least USD 4 per month, she can donate in multiples of USD 4, which can help one or multiple beneficiaries. Each month the donor’s payment card gets deducted with the amount of her donation. One of

[8] Name undisclosed due to non-disclosure agreement.

the unique features of the platform is that the donors receive a monthly email about the progress and impact of their donation. In particular, the monthly email contains information on, amount of donation for the month, the number of donors supporting the cause in that month and a thank you note. Each month the donor has an option to either continue or cancel the donation. Each donor can choose to donate to multiple causes too, however, we find this number to be very small (less than 5%).

We also document all the major policy changes during the data span used in our analysis (2017-2020), to ensure that our results are not an artefact of any policy change. In this span there were two major policy changes a) FCRA amendment bill 2020[9] b) Donations Deductibles[10] (ClearTax, 2021). Both these policy changes don't affect our analysis and findings.

Data Description

We use transaction level data from the donation platform. The data ranges from Oct 2017(firm start date) to Dec 2020. It consists of nearly 64000 transaction of 9627 donors across 308 causes. Table 1 below represents the summary statistics of the data. For each transaction we observe date, amount of donation, minimum donation amount, number of beneficiaries, cause, meta category of cause, donor group size, demographic variables of donors and some characteristic variables of the cause. A donor is assumed to drop out(cancel) if she misses two transactions in a row[11].

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[9] This bill was passed in Lok Sabha (Lower House of the Indian parliament) in Sep 2020. It affects the grants from foreign sources to Indian non-profits. Our donation platform and associated non-profits had obtained all clearances in time and thus the donation activity wasn't affected by this regulation.

[10] New tax rules introduced in 2017-18 suggests that donation above Rs 2000 in cash will not considered for tax deductions. Again, this doesn't affect our case as all the transaction are made through debit/credit cards thereby making them eligible for deductions.

[11] In case of card/payment errors, both the focal firm and the payment gateway partner sends out an email to the donor to update her card details. However, if there is no response in a month and the donors fails to pay, she is assumed to cancel her donation. We find no evidence of donor restarting donation to the same cause after 2 months. However, there are a few instances where a donor comes back to the platform after a year or so start donating to a different cause.

Table 1: Summary Statistics of variables of interest.

Variable	Mean	St. Dev.	Min	Max
Donor Group Size	114.6	172.56	1	670
Min Donation Amt	1,016.40	1,030.65	100	11,655
Total Donation	1,546.40	2,406.64	100	1,48,000
Number of Transactions	6.66	6.89	1	111
Number of Causes		308		
Number of Donors		9627		
Number of Observations		64080		

Note: The summary statistics are calculated using the panel structure of data. Number of donors and causes are reported as of Dec 2020. Donation amounts are reported in INR.

Subscription-based donations leading to repeat donation without appeal is one of the unique points about our dataset, in contrast, most other papers use one-time donation data per donor[12]. First, observe that although there are a few (24%) donors which stop donating after the first transaction (see Figure A1 in the Appendix), the mean number of transactions per donor is 6.66 (s.d = 6.89), this translates to nearly 7 transactions per donor in a span of 7 months without any reminder or appeal from the firm. Second, donors have not only more than 300 causes to choose from but also a wide range of donation amounts (varying from Rs 100 (USD 1.3) to Rs 148,00 (USD 2000). This variation both on type of cause and donation amount helps us to make generalized inference[13]. Donor group size varies from as low as 1 other person donating to 670. The mean donor group size is 114.6 (s.d=172.6), this variation is the core of our analysis, representing the popularity of causes. The broad distribution of a) donor demographics b) cause category are reported in Table A1 and A2 in the appendix respectively.

[12] (Kim et al., 2021) does have multiple donations per user however, a) the next donation comes after an appeal from the nonprofit b) low annual mean gift frequency (<1)

[13] This makes our setting different. Specifically in extant literature the variety both in causes and amount is relatively less, primarily due to experiment design and subsequent choice overload constraints.

DESCRIPTIVE EVIDENCE

In this section, we provide model-free evidence to demonstrate the effect of donor group size on new donors (joiners) and cancellations.

Visualizations

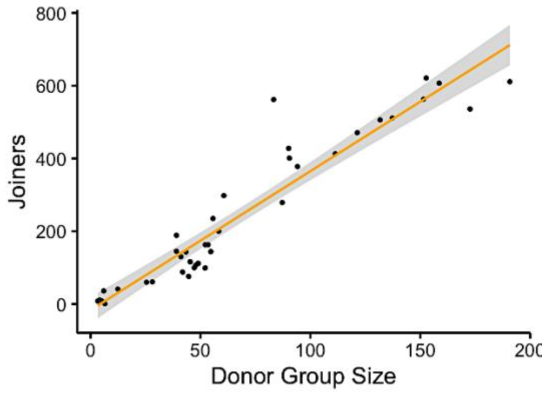

Fig 1 a

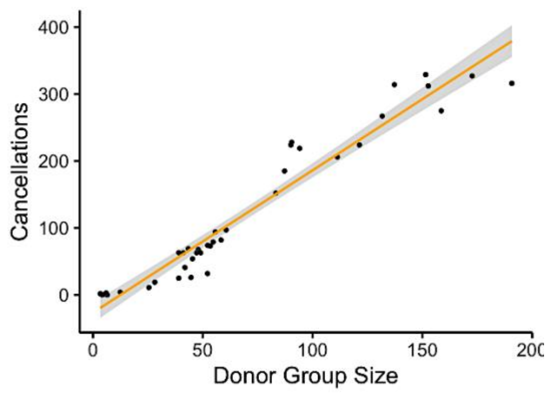

Fig 1 b

Figure 1: The left panel (a) shows the relationship of joiners and donor group size. The right panel (b) shows the relationship between cancellations and donor group size.

Consider Figure 1a and 1b, as donor group size increases, both the joiners and cancellations increase. To ensure that our observation (positive correlation between donor group size and joiners & cancellations) isn't a category-specific phenomenon we plot the same relationship by cause category. Our results presented in Figure A2 (Appendix) show that a positive correlation exists across all-cause categories. Similarly, we cut the data by donor demographics (see Figure A3), minimum donation amount and donor group size, we find that the observation persists across all the data cuts. This ensures that our observation is not moderated by any of the obvious and observed variables. Furthermore, we plot the evolution of cancellations and joiners with donor group size (see Figure A4 in the Appendix), to ensure that the correlation between our variables of interest persists overtime.

To illustrate the net impact (joiners – cancellations) of donor group size on donations we plot Figure 2. It shows that as the donor group size increases, the positive impact of displaying donor group size diminishes. Specifically, as the donor group size increases both joiners and cancellations increase, however, the cancellations increase more compared to joiners, thereby diminishing the benefits from displaying donor group size.

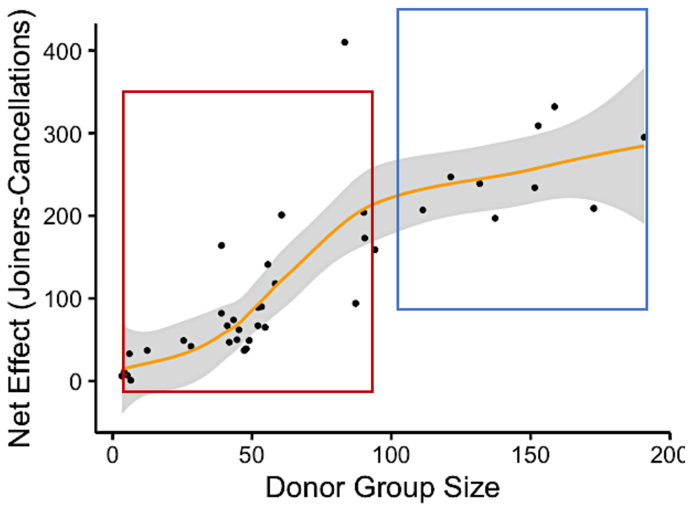

Figure 2: This figure represents relationship between net effect (joiners-cancellations) with donor group size. Transition from red to blue box represents the diminishing marginal benefits of displaying donor group size.

Correlation-based tests

To build further confidence in our preliminary observations we run some correlation-based tests. We use panel regression models[14] with varying model specifications. We use cause fixed effects to account for omitted variable bias (preferred/appealing causes). Furthermore, we use time trends to account for platform level push (growth strategies) over

[14] We estimate $Y_{ct} = \beta_1 DGS_{ct} + T + \alpha_c + \epsilon_{jt}$; where Y_{jt} can be joiners or cancellations, DGS_{ct} is the donor group size for cause c at time t. T represents time trend. c is cause and t represents month year indicator.

time and cyclical giving behaviour of donors (List, 2011). Results for joiners and cancellations are reported in Tables 2 and 3 respectively. We find that in all model specifications, the donor group size is positively correlated with joiners and cancellations.

Using visualizations and correlation-based tests, we produce preliminary evidence for our research question. We find that donor group size positively impacts the new joiners (joiners), however, surprisingly, it also positively affects cancellations. It is important to note that, the results from these tests are not reliable because of simultaneity which is explained in detail in the next section.

Table 2: Joiners vs Donor Group Size

	Dependent variable:			
	Joiners			
	(1)	(2)	(3)	(4)
Donor Group Size	0.167^{***}	0.248^{***}	0.167^{***}	0.259^{***}
	(0.004)	(0.008)	(0.004)	(0.009)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2,556	2,556	2,556	2,556
R^2	0.436	0.551	0.437	0.554

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

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

Table 3: Cancellations vs Donor Group Size

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Donor Group Size	0.080^{***}	0.108^{***}	0.080^{***}	0.110^{***}
	(0.001)	(0.002)	(0.001)	(0.002)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2,556	2,556	2,556	2,556
R^2	0.770	0.833	0.770	0.835

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

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 cause fixed effects are not included, whereas in the last two columns cause fixed effects are included. Cause level control variables are absorbed in the cause fixed effects.

IDENTIFICATION STRATEGY

Correlation-based tests presented above suffer from another form of endogeneity i.e., reverse causality. For illustration, consider Eqn (1). $\mathrm{Y_{ct}}$ is the dependent variable which can either be the number of joiners in a cause at time 't' or it can number of cancellations in a cause at time 't'. We are interested in causally establishing the effect of donor group size (DGS_{ct}) on $\mathrm{Y_{ct}}$. As the donor group size changes, it will change the $\mathrm{Y_{ct}}$, based on extant literature, however, if $\mathrm{Y_{ct}}$ changes it will lead to a different donor group size in the subsequent period[15]. Therefore, both these relationships together create the reverse causality problem.

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

To resolve the above endogeneity concerns we use an exogenous shock to the platform. First, we will provide information on the shock and why it is exogenous. Second, we demonstrate the true randomness of the shock.

In October 2019, the focal platform collaborated with many Indian firms to bring their employees and customers on the donation platform. Due to this event, there was a sharp uptick in the number of donors for many causes on the platform. Figure 3 depicts this event and a corresponding increase in donors. In the extant literature(Farronato et al., 2020; Natan, 2021) mergers have been used as an exogenous shock to estimate the causal effect. In our context, this event is equivalent to a merger, however, in mergers, the increase is not only to

[15] For example, if cancellations increase on increase in donor group size, it will lead to a lower donor group size in the subsequent periods.

the customer base but also to the product offerings. Interestingly, in our context, due to the event there was an increase in the number of donors but not in the number of product offerings.

To elaborate further consider a toy example. Consider two causes A and B, assume for cause A there was an increase in donor group size after the event whereas for cause B there was no increase in donor group size. The event comes as a shock to the donors who were donating to cause A because these donors didn't anticipate the donor group size to suddenly increase, and therefore any change relative to the control group can be attributed only to the sudden increase in donor group size.

Next, to demonstrate the impact of exogenous shock, we use the evolution of donor group size with time and use it to predict the counterfactual, i.e. in the absence of the event shock what would have been the donor group size and compare it to the real data. Using pre-event data we use optimized ARIMA to predict the donor group size after the event. Our results present in Figure 3 indicate that there is a substantial change in the donor group size (see green line in the Figure 3) compared to what one would expect (see red line in the Figure 3). To ensure that the shock wasn't only in a particular, we plot the shock by category (see Figure A5) and we find that although the intensity of the event shock varies by category, it is present in all the cause categories.

Furthermore, to ensure that donors which join before the shock are similar to donors who join after the shock, we compare donors on all the observed donor characteristics such as location, gender, donation amounts, choice of cause category etc. Results for this analysis are reported in Table A3. We find that donors pre and post-shock aren't systematically different. Therefore, the donor behaviour pre and post-shock are comparable.

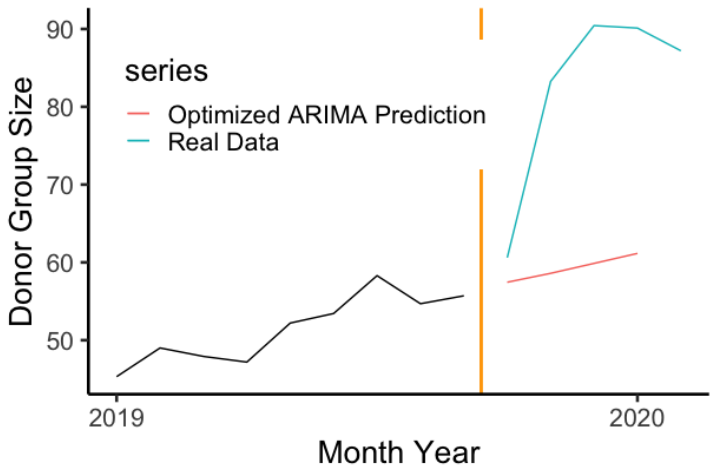

Figure 3: Real vs Prediction using pre-event data to illustrate shock on donor group due to event.

EMPIRICAL STRATEGY

We are interested in estimating the effect of donor group size on a) the number of joiners and b) cancellations. Our main empirical model employs a DID (difference in difference) panel estimator.

To deploy the DID estimator we first present the data as an experiment. Specifically, we use the event shock as an intervention. The causes which experience an increase in donor group size are labelled as treatment group and the others as control group. The data is aggregated at cause month year level. We estimate the equation of the following form.

$$Y_{ct} = \alpha_j + T + \beta_1 Increase_c + \beta_2 Event_t + \beta_3 Increase_c \times Event_t + \epsilon_{ct} \quad (2)$$

Where, c and t represent cause and month year respectively. Y_{ct} can be either number of joiners or number of cancellations for a cause j in the month year ‘t’, T represents the time trend effects and Trt_c is a dummy which takes value 1 if a cause (c) experiences an increase in DGS after the event or 0 otherwise. $Event_t$ is a dummy variable which takes value 1 on or after (Oct 2019) the event and 0 before the event. We are interested in β_3 which represents the difference in difference coefficient.

Next, to build confidence in our inference we use the same data setup however, employ 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.

$$Y_{ct} = \alpha_c + T + \beta_1 DGS_{ct} + \epsilon_{ct} \ (3)$$

Where, c and t represent cause and month year respectively. Y_{ct} can be either number of joiners or number of cancellations for a cause c in the month year 't', T represents the time trend[16] and DGS_{ct} is the donor group size. We have earlier illustrated that, this equation suffers from reverse causality problem. We instrument the donor group size variable with the event shock and we use a 2SLS approach to resolve the reserve causality problem.

Lastly, we use individual transaction level data to estimate the effect of donor group size on probability of cancelling a donation subscription. We put focus on cancellation in individual level data analysis for two reasons a) lack of joiners choice data (join/not join data) and b) relative silence in the literature about the negative effects of donor group size information. We use a dynamic logit model. Specifically, we estimate the equation of the following form.

$$Cancel_{ijt} = f(\alpha_j + \delta_t + \beta_1 DGS_{ijt} + \beta_2 T_{ij} + \beta_4 Controls) + \epsilon_{ijt} \ (4)$$

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 value 1 if donor decides to cancel and 0 otherwise. α_j and δ_t are the cause and time fixed effects respectively.T_{ij} represents donor level time trend variable which takes linearly increasing value with each month a donor remains on the platform. T_{ij} captures the probability of churning, specifically a donor is more likely to cancel subscription as her tenure increases. f can either be a linear or a logit

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[16] We don't time fixed effect here because time effects (at least one) makes the instrument not viable because one of time fixed effects coincides with the event shock which is used as an instrument.

function. As demonstrated earlier, this model setup also suffers from reverse causality. We address the endogeneity problem with the 2SLS approach where we instrument the donor group size with the event shock.

To build further confidence in our results, we use the same transaction-level data setup but we deploy a survival analysis approach. In particular, we estimate a Cox regression with time varying covariates.

In summary, we use a multi method approach with varying data granularity (aggregated vs individual) to ensure that our results persists and our not driven by a particular model setup.

RESULTS

The difference in difference model

Before presenting the formal results of the DID model. We report the DID visualization in Figure 4. Note that, for both the outcomes of interest i.e. joiners and cancellations we find the treatment and control group to move in sync before the even shock. However, after the shock the difference between two groups increase and persists over time.

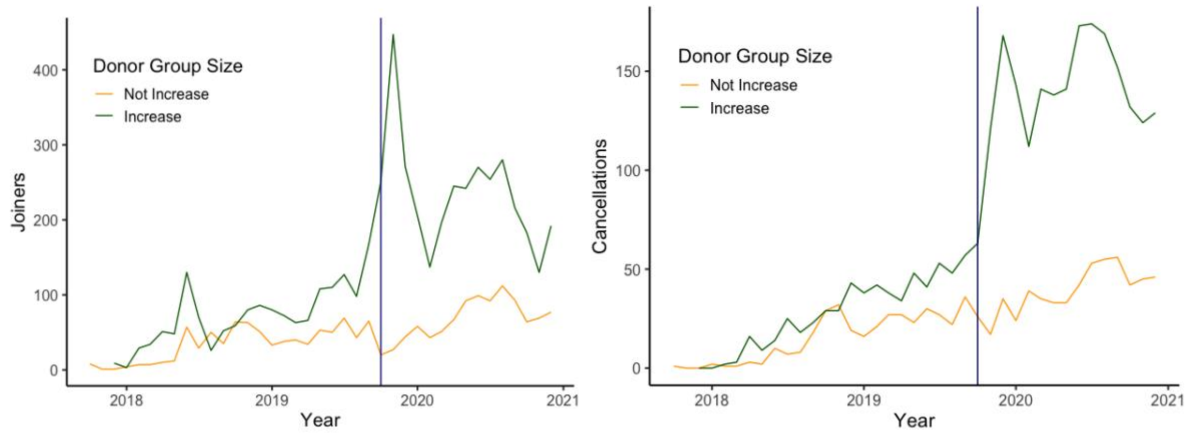

Figure 4: DID - The left panel (a) shows the comparison of joiners across causes which experienced an increase vs which didn't. The right panel (b) shows the comparison of joiners across causes which experienced an increase vs which didn't.

We report the results of our DID analysis (estimates from Eqn (2)) on joiners and cancellations in Table 4 and 5 respectively (Complete results reported in Table A4 and A5 in the appendix). Consider, Table 4 for joiners. The DID coefficient (β_3) in Eqn (2) turns out to be positive. This indicates causes which experience an increase in donor group size gets more joiners compared to causes that didn't. In particular, after the shock, the treated causes got nearly 1.7 (see column 4 in Table 4) more new donors compared to the control group. Similarly, consider Table 5 representing the results for cancellation (estimates of Eqn (2)), in this case too, the treated causes experienced nearly 1.3 more cancellations compared to the control group causes.

Table 4: Joiners vs Donor Group Size (DID - Inc vs Not Inc)

	Dependent variable:			
	Joiners			
	(1)	(2)	(3)	(4)
Increase x Event	1.301***	1.316***	1.727***	1.727***
	(0.348)	(0.348)	(0.278)	(0.278)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5,059	5,059	5,059	5,059
R^2	0.024	0.024	0.440	0.440

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

Note: This table reports the results from DID regression, expressed by Eq 2. It compares the difference in joiners of causes which experienced an increase in donor group size with the ones which didn't experience an increase. Standard errors are reported in parenthesis. We exclude and include cause fixed in the first two and last two columns respectively.

Table 5: Cancellations vs Donor Group Size (DID - Inc vs Not Inc)

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Increase x Event	1.043***	1.033***	1.334***	1.312***
	(0.188)	(0.188)	(0.140)	(0.140)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5,059	5,059	5,059	5,059

R^2	0.032	0.033	0.517	0.519

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

Note: This table reports the results from DID regression, expressed by Eq 2. It compares the difference in cancellations of causes which experienced an increase in donor group size with the ones which didn't experience an increase.

Instrument Variable Approach

We report our results for instrument variable approach (estimates from Eqn(3)) in Table 6 and 7 for joiners and cancellations respectively. Consider, Table 6 for joiners. The coefficient for donor group size varies from 0.146 to 0.392. This translates to, if the donor group size increase by 10, it could attract nearly 1.5 to 4 new donors for a particular cause. Furthermore, the true value would be closer to 4, because the model with full specification (column 4) would be more trustworthy[17]. Given the size of effect, it is not much of a surprise, that many donation platform display donor group size to attract new donors. Next, consider Table 7 for cancellations. In this case the coefficient of interest caries from 0.083 to 0.114, implying, an increase in donor group size by 10 would lead to 0.8 to 1.1 cancellations.

Table 6: Joiners vs Donor group size – 2SLS

	Dependent variable:			
	Joiners			
	(1)	(2)	(3)	(4)
Donor Group Size	0.230^{***}	0.392^{*}	0.146^{***}	0.382^{**}
	(0.043)	(0.220)	(0.035)	(0.184)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2,556	2,556	2,556	2,556
R^2	0.373	-0.352	0.521	0.514

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

Note: This table reports the results from estimation of Eqn (3). The dependent variable is number of joiners. Donor group size is instrumented with event shock and 2SLS approach is used for estimation. The first two columns don't 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.

[17] Column 4 reports the results of two-way fixed effects. In this we control for cause level effects and time trend which parses out the effect of donor group size better compared to other model specifications.

Table 7: Cancellations vs Donor group size – 2SLS

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Donor Group Size	0.096***	0.114***	0.083***	0.107***
	(0.010)	(0.042)	(0.008)	(0.039)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2,556	2,556	2,556	2,556
R^2	0.737	0.629	0.820	0.835

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

Note: This table reports the results from estimation of Eqn (3). The dependent variable is number of cancellations. Donor group size is instrumented with event shock and 2SLS approach is used for estimation. The first two columns don't 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.

Individual-level models

We report the estimates of Eqn (4) in Table 8 (see Table A6 in the appendix for complete results). Recall, for this analysis, we use only the donors who were donating before the event shock (haven't cancelled their subscription). We find that, if the donor group size increases by 10 the probability of cancellation increases by 0.04[18] (see column 4 in Table 8). Two of our control variables, namely, donation amount and donor location provides sanity check of our results. Donation amount estimates imply, higher the donation amount, higher is the cancellation probability. Similarly, Indian donors might be less altruistic due to culture and income compared to their American and European counterparts. We find our results consistent with these predictions.

[18] These estimates are from the linear probability model. We report the results from logit model in the Appendix.

To build further confidence in our results, we deploy the survival analysis approach with time varying covariates. First, we report the visualization from a simple survival model (see Figure A6 in the Appendix) with a median split on donor group. The visualization indicates that for higher donor group the survival probability is lower or the cancellation rate is higher. We empirically, test this with a) log-rank test, to compare survival probabilities between two groups b) cox proportional hazard model with time-varying covariates with multiple model specifications (see Table A7) . We find the results from empirical tests to be consistent with the visualization. In particular, the coefficient on donor group size (in both w/o and with covariate models) is positive, indicating a higher probability of cancellation.

In summary, the results from dynamic probability models and survival analysis indicate conform and are in line with our findings from aggregate models. Specifically, the probability to continue donation reduces when the donor group size increase.

Table 8: Dynamic linear probability model

	Dependent variable:			
	Cancel			
	(1)	(2)	(3)	(4)
Donor Group Size	0.004***	0.006***	0.002*	0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Time Trend	N	N	Y	Y
Cause FE	N	Y	N	Y
Observations	7,368	7,368	7,368	7,368
Weak Instrument	40.41 (< 2e-16)	69.86 (< 2e-16)	7.39 (0.006)	16.339 (0.0005)
Wu-Hausman	95.88 (< 2e-16)	111.98 (< 2e-16)	5.87 (0.015)	8.917 (0.002)

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

Note: This table reports the results from estimation of Eqn 4. The dependent variable is a binary variable that takes value 1 when a donor cancels her subscription, 0 otherwise. Female is the baseline for gender. Location is classified into 3 categories. – India (base), US and Others (mostly – UK, Canada, Australia, UAE etc.). Single Beneficiary (only one recipient of donation) is the baseline for # no of beneficiary segment.

RULING OUT ALTERNATE EXPLANATIONS

In this section, we provide multiple alternative explanations for our findings, and we rule out these explanations based on the data and institutional setting.

Switching Behaviour

An explanation for the increase in cancellations with donor group size could be the switching of donors. Specifically, when more donors (higher donor group size) start supporting a cause, the focal donor might feel that her resources can be better utilized elsewhere. This could lead to two types of switching a) Intra-platform switching b) Inter-platform switching.

Intra-platform switching refers to donors switching to a different cause on the platform. We don't find any evidence of this. Of all the donors who cancelled, we found very few donors who restarted their donations to a different cause on the platform[19] within 6 months of cancelling. Therefore, we can rule out intra-platform switching.

Inter-platform switching refers to switching to a different donation platform. Although this can't be observed, we argue that this is implausible because the focal donation platform has a disproportionately high market share. Alternatively, it could be argued that donors might not find the 'right cause' (fit) to donate to on the focal platform, however, this is unlikely, because compared to competitors the focal donation platform has a much higher variety of causes. Furthermore, donors might have to bear switching costs. Therefore, inter-platform switching is also unlikely.

Lastly, the donor might want to switch to a different mode (offline, one-time donation event) of donation or stop donating. In both these scenarios, the donor has stopped donating

[19] 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.

using subscription-based donation. In summary, our claim, that change in donor group size affects the underlying altruistic behaviour holds and the change in cancellations due to donor group size is not a mere diversion of resources.

Minimum Donation Amount

The minimum donation amount refers is the minimum monthly amount to be paid for supporting a cause. Causes with lower minimum donations might experience higher joiners (more people can afford lower donation amounts). Similarly, cancellations would be lower for lower minimum donation amount as compared to higher minimum donation amount because of budget/expenditure constraints of donors.

We control for minimum donation amounts by using it as a control variable in the models where we don’t have cause fixed effects and using fixed effects. Moreover, we plot (see Figure A7) joiners vs donor group size and cancellation vs donor group size by minimum donation quartile split. We find relationships to hold in both high and low minimum donation amount cases.

Act of Churning

Churning is a part of subscription-based/ repeat transaction businesses, and more cancellations for a cause overtime might be a simple act of churning because of a) better outside options b) donor doesn’t want to donate anymore or c) budget constraints. We control for churning by using the individual donor time trend variable as a control. This variable linearly increases with each month the donor is a member of the platform. For robustness, we also use tenure (how long the donor is member of platform). Our results persist even after controlling for churning.

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 for each category of cause is a recommended page. On the recommended page, there are only 3-4 causes listed, therefore position effects don't play much of a role here. Specifically, causes are listed in 1x3 or 2x3 matrix and the user doesn't need to scroll down (for visualization see Figure A8 in the Appendix). Moreover, we include cause level fixed effects in all our model specifications to control for any position effects if present.

ROBUSTNESS CHECKS

Parallel Trends Assumption

Our main empirical strategy uses a widely accepted DID approach. Parallel trends assumption is the critical assumption for DID model identification. To test for the parallel trends in our context, we follow (Angrist & Krueger, 1999). We conduct a pre trend test with varying pre trend windows, namely, 3, 6 and 9 pre periods. Specifically, we estimate equation (5) below.

$$Y_{ct} = \alpha_c + \mu_c T + \Omega_c T \times I_{\{Treatment\}} + \epsilon_{ct} \quad (5)$$

Where c and t are cause and time subscripts respectively. α_c are the cause fixed effects, μ_t is the common trend parameter and Ω_c represents the deviation of the treatment group from the common trend. T is the time trend variable and $I_{\{Treatment\}}$ is an indicator variable which takes value 1 for all the treated (Increase) causes and 0 for all the untreated (Not Increase) causes. Y_{ct} can be the number of joiners or cancellations by cause and time. Results are reported in Table 9 below. The parameter of interest, Ω_c for both cancellations and joiners turns out to be insignificant for all the pre trend window sizes, supporting our assumption of parallel trends.

Table 9: Pre Trend Test

	Pre Trend Window Size					
	9 months		6 months		3 months	
	# Cancel	# Joiners	# Cancel	# Joiners	# Cancel	# Joiners
	(1)	(2)	(3)	(4)	(5)	(6)
Trend	0.004	-0.023	-0.014	-0.016	-0.016	-0.094
	(0.012)	(0.020)	(0.019)	(0.035)	(0.033)	(0.065)
Trend × Treatment	0.002	0.028	0.043	0.077	0.039	0.032
	(0.016)	(0.028)	(0.026)	(0.049)	(0.046)	(0.093)
Cause F.E.	Y	Y	Y	Y	Y	Y
Observations	1,365	1,365	977	977	679	679
R^2	0.735	0.772	0.760	0.751	0.825	0.799
Adjusted R^2	0.694	0.737	0.704	0.693	0.760	0.725
Residual Std. Error	0.736 (df = 1180)	1.246 (df = 1180)	0.685 (df = 792)	1.267 (df = 792)	0.659 (df = 494)	1.318 (df = 494)

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

Note: This table reports the results from the estimation of equation 5. First two columns are estimates for the 9-month (Jan 2019 to Sep 2019) pre-event window for joiners and cancellations respectively. Similarly, the middle two columns are for the 6-month (April to Sep 2019) pre-event window and the last two columns are for the 3-month (July to Sep 2019) pre-event window. Standard errors are presented in parenthesis ().

Next, to further confirm parallel trends and persistence of the effects of interest. We estimate the interaction of time indicator variables with the treatment group (Autor et al., 2003). Specifically, we estimate the interactions of the month indicator variable with the treatment indicator, the base level is 5 months or before the treatment. The results are presented in Figure 5. Note that, for both cancellations and joiners the estimates before the event turn out to be no different from 0. Furthermore, at and after the event the effect seems to persist for a long time (even 5 months after the shock).

Therefore, from both the approaches we confirm that the parallel trends assumption holds.

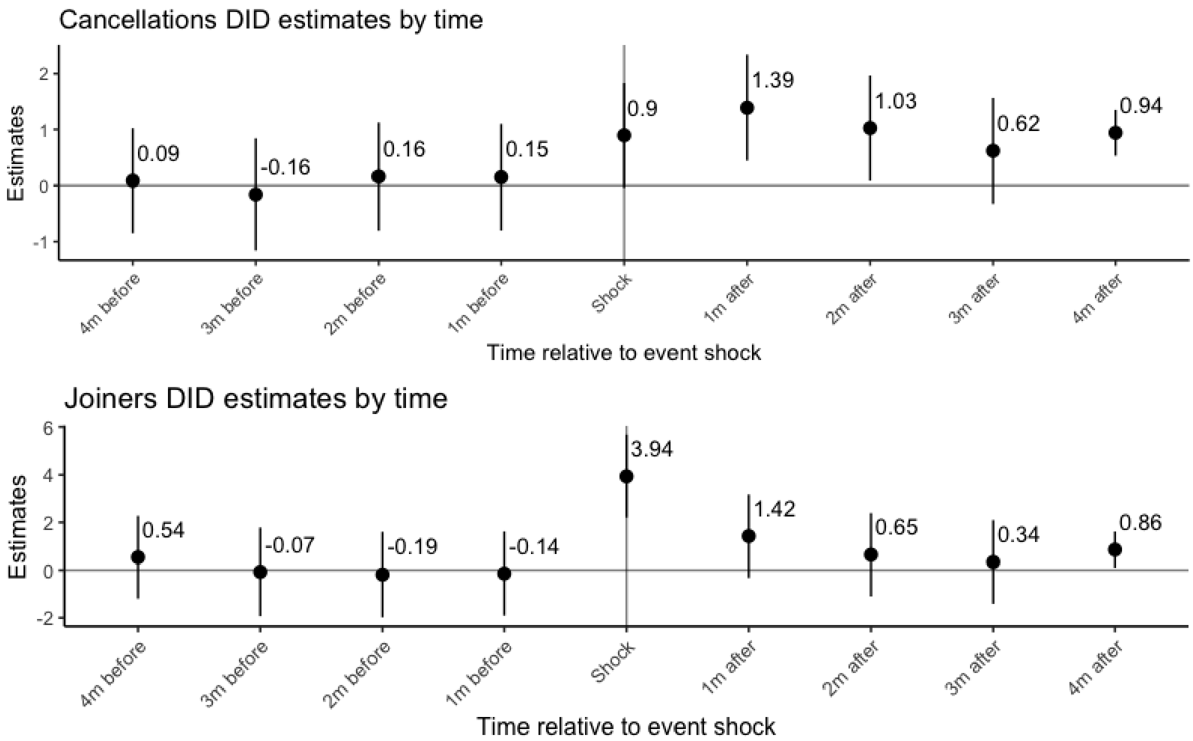

Figure 5: Pre and Post Event Estimate Trend. The top and bottom panels report the DID estimates overtime for cancellations and joiners respectively.

Instrument Validity

To test the validity of our instrument (event shock) we do multiple placebo tests. We do this to show that the variation explained by our instrument is due to the event shock and not due to some spurious correlations. To show that, our instrument (event shock) is relevant and the conditional differences between the treated and untreated causes are due to the event and not a persisting difference, we use placebo regressions. We operationalize this by creating a placebo dummy variable which turns on one month prior to the real event. Specifically, the true event shock takes value 1 on or after Oct 2019 and 0 before it, whereas the placebo dummy takes value 1 on or after Sep 2019 and 0 before it. We find the coefficient corresponding to placebo & treatment group, interaction to be insignificant, however, the true event interaction with the treatment group turns out to be significant. The results for the placebo regressions are reported in Table A8. The first two columns are results for cancellations as the dependent variable. Specifically, the first column reports results without placebo dummy and column 2 reports results with placebo dummy. Note, that the coefficient of interaction between placebo and treatment group is insignificant. Similarly, the last two columns (Columns 3 and 4) report the results of joiners as the dependent variable. In this case, the placebo, treatment group interaction is insignificant.

Different Definitions of Increase

Our core empirical strategy utilizes a diff-in-diff panel estimator. We use the word 'increase' and 'not increase' to address treatment and control groups. To ensure that our results are not an artefact of a particular definition of increase we use multiple definitions of increase such as pure increase, median increase, and unexpected increase. Next, we elaborate on the definitions of increase.

Pure Increase: $Donor\ Group\ Size_{Post} > Donor\ Group\ Size_{Pre}$.The treated group variable takes value 1 for causes which have higher donor group size, post event and 0 otherwise.

Median Increase: We calculate percentage increase for each cause and if the percentage increase in donor group size for cause is higher than the median of percentage increase in all the causes, we label the treated variable group as 1 and 0 otherwise.

Unexpected Increase: For each cause, we predict the donor group size post the event using only pre-event data (using linear regression). If the donor group size after the event is higher than the predicted donor group size, then it is considered as increase (takes value 1) else not increase.

We run our difference in difference model for both joiners and cancellations. Our results reported in Table 10 indicate that donor group size positively effects number of joiners and cancellations across all the definitions of increase.

Table 10: DID estimates by different definitions of increase

	Dependent variable:					
	# Joiners	# Cancel	# Joiners	# Cancel	# Joiners	# Cancel
	(1)	(2)	(3)	(4)	(5)	(6)
PureIncrease × Event	1.976***	1.379***				
	(0.263)	(0.132)				
MedianIncrease × Event			1.997***	1.337***		
			(0.264)	(0.132)		
UnexpectedIncrease × Event					1.603***	1.087***
					(0.262)	(0.131)
Time Trend	Y	Y	Y	Y	Y	Y
Cause F.E.	Y	Y	Y	Y	Y	Y
Observations	5,014	5,014	5,014	5,014	5,014	5,014
R^2	0.442	0.522	0.442	0.521	0.440	0.518
Adjusted R^2	0.420	0.503	0.420	0.502	0.417	0.499
Residual Std. Error (df = 4822)	4.431	2.218	4.430	2.220	4.439	2.227
F Statistic (df = 191; 4822)	19.982***	27.545***	19.990***	27.467***	19.806***	27.103***

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

Note: This table reports the results from DID regression, expressed by Eq 3, across different definitions of Increase. First two columns represent the interaction effects (DID) on joiners and cancellations respectively, when the increase is pure increase. Similarly, the middle two columns represent the estimates for median increase and the last two columns represent unexpected increase. Details on all the definitions of increase is available in different definitions of increase section. All the models have two-way fixed effects included.

Heterogeneity

Donation behaviour of individual is dependent on the type of cause (appeal framing) they donate to (Lindauer et al., 2020). For example, probability to donate for saving a child's life might be higher than probability to donate to rebuild a community center. To illustrate the heterogeneity of the effect of donor group size we evaluate treatment effects across cause category. Our results in Figure 6 show that relative to education, the impact (for both joiners and cancellations) of donor group size is more for Nutrition and Livelihood related causes. However, the donor group size has less of an effect on healthcare related causes compared to Education. Implying, that the treatment effects persist across categories, albeit at different intensity.

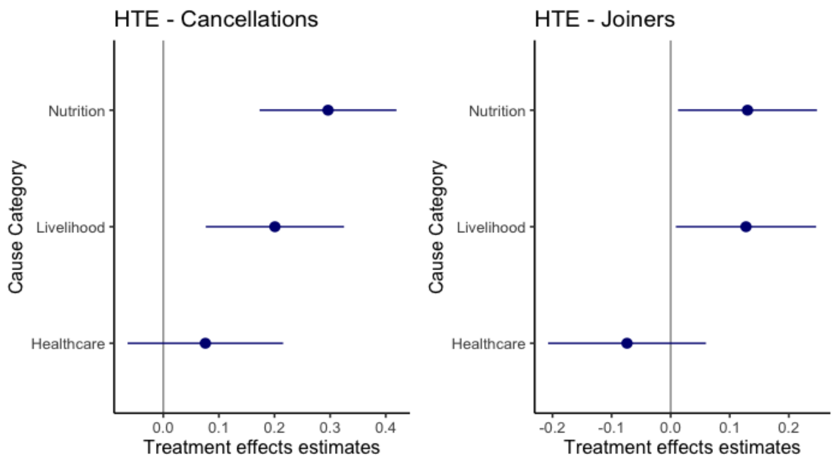

Figure 6: Heterogeneous Treatment Effects by cause category. Left and Right Panel report the DID estimates by cause category on cancellations and joiners respectively, relative to Education (base). The confidence band is at a 90% interval.

DISCUSSION

The goal of this paper is to investigate the effect of donor group size on donation behaviour in a subscription-based donation context. We are interested in studying this question because a) in practice there is a shift towards adopting subscription-based donations and displaying donor group size is believed to improve donations b) the extant literature seems to be divided on the direction of effect and c) the extant research is based on one-time donation data, therefore, the findings might not be relevant in the subscription case.

We found that overall, the donor group size positively impacts the donations. Specifically, higher the donor group size for a cause, more donors start donating to a cause. However, higher the donor group size, more donors cancel their subscription. Our analysis suggests that if the donor group size for a cause increase by 10 donors, it get could attract nearly 2 new donors, however, it might also lose nearly 1 existing donor.

We add to the extant literature in three broad ways 1) we are one of the first studies in the subscription-based donation context and we evaluate the impact of a commonly used strategy i.e., displaying donor group size on donation behaviour 2) we provide resolution to the apparently divergent findings in the extant literature albeit in the subscription-based donation context. Specifically, we show that donor group size can have both positive and negative effects on donation behaviour albeit at different points in the donor lifecycle. 3) Our data has a high variety of donors and causes. In particular, the extant literature has based its findings on constricted pool of subjects and causes. Therefore, our findings are more generalizable compared to the previous studies.

Limitations of our studies come from its setup, in that, our findings can't be generalized for every donor. For instance, donors in our context, self-select themselves into subscription-based donations, therefore, these donors could be systematically different from one-time donors. Furthermore, our findings couldn't be generalized to offline donations because the altruistic behaviour of people who donate online could be different from people who donate offline stemming from in-person interactions in offline donation settings.

Future research could possibly conduct a randomized control trial to establish the effect of donor group size on donation behaviour to improve confidence in the results. Moreover, the same question can be studied in the offline donation context, as offline donation has elements of physical interaction of donor with a) other donors b) beneficiaries and c) platform. Furthermore, researchers could look at the effect of buyer group size and purchase behaviour of customers in subscription-based product markets such as magazines, phone plans etc.

Based on our analysis, we suggest donation platforms be careful about the use of donor group size information. Specifically, donation platforms should provide information on the donor group size to the potential donors who might join the platform, however, the same information can cause the current donors to churn not only from the cause but also from the platform.

CONCLUSION

Displaying the popularity of a product has been shown to be an important tool to increase demand (purchase intention). In the charitable donation context, some papers show that higher the donor group size (popularity) of a cause higher is the probability of donation. Recently, subscription-based donations have emerged as an important tool for fundraising because of their higher donor lifetime value. In this paper, we work with one of India's largest subscription-based donation platforms. Specifically, we study the effects of cause popularity (donor group size) on donation behaviour in the context of subscription-based donation. We use an exogenous shock to the platform as our main identification strategy. We find that causes with higher donor group size attract more new donors to donate to a cause. This is documented as a bandwagon effect both in product and charitable donation literature. Surprisingly, we find that causes with higher donor group size also experience higher cancellation rates for current donors. This phenomenon is documented as a bystander effect in the extant literature. We contribute to the literature by estimating the positive and negative effects of displaying donor group size for subscription-based donation platforms. Furthermore, we bring together the divergent findings in the extant literature and show that in fact, both strands of literature are correct albeit for different donor types (joiners vs cancellations). Our findings can be useful for donation-based platforms, in that, we suggest platforms be judicious about when to use the donor group size information. Specifically, platforms should use donor group size information to bring new donors on the platforms, however, sharing the donor group size information with existing donors could be harmful due increase probability of cancellations.

REFERENCES

Anderson, L., & Holt, C. (1997). Information Cascades in the Laboratory. *American Economic Review*, *87*(5), 847–862.

Andreoni, J. (2007). Giving gifts to groups: How altruism depends on the number of recipients. *Journal of Public Economics*, *91*(9), 1731–1749. https://doi.org/10.1016/j.jpubeco.2007.06.002

Angrist, J. D., & Krueger, A. B. (1999). Empirical strategies in labor economics. In *Handbook of Labor Economics* (Vols. 3, Part A, pp. 1277–1366). Elsevier. https://ideas.repec.org/h/eee/labchp/3-23.html

Appfrontier.com. (2020, June 17). The Nonprofit's Playbook to Recurring Donations. *AppFrontier*. https://www.appfrontier.com/blog/recurring-donations-for-nonprofits/

Ashraf, N., & Bandiera, O. (2017). Altruistic Capital. *American Economic Review*, *107*(5), 70–75. https://doi.org/10.1257/aer.p20171097

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration*. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Banerjee, A. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817.

Bennett, R. (2012). What Else Should I Support? An Empirical Study of Multiple Cause Donation Behavior. *Journal of Nonprofit & Public Sector Marketing*, *24*(1), 1–25. https://doi.org/10.1080/10495142.2011.594666

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, *100*(5), 992–1026. https://doi.org/10.1086/261849

Blackbaud Institute. (2021). *Online Giving Trends*. Blackbaud Institute. https://institute.blackbaud.com/charitable-giving-report/online-giving-trends/

Bonsu, S. K., & Belk, R. W. (2003). Do Not Go Cheaply into That Good Night: Death-Ritual Consumption in Asante, Ghana. *Journal of Consumer Research*, *30*(1), 41–55. https://doi.org/10.1086/374699

Cai, H., Chen, Y., & Fang, H. (2009). Observational Learning: Evidence from a Randomized Natural Field Experiment. *American Economic Review*, *99*(3), 864–882. https://doi.org/10.1257/aer.99.3.864

Cialdini, R. B., & Goldstein, N. J. (2004). Social Influence: Compliance and Conformity. *Annual Review of Psychology*, *55*(1), 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015

Classy. (2018). *The State of Modern Philanthropy 2018 | Classy*. https://learn.classy.org/state-of-modern-philanthropy-2018?sfdc_cid=7012R000000qjebQAA

ClearTax. (2021). *Donations Eligible Under Section 80G and 80GGA*. https://cleartax.in/s/donation-under-section-80g-and-80gga

Darley, J. M., & Latane, B. (1968). Bystander intervention in emergencies: Diffusion of responsibility. *Journal of Personality and Social Psychology*, *8*(4, Pt.1), 377–383. https://doi.org/10.1037/h0025589

Farronato, C., Fong, J., & Fradkin, A. (2020). *Dog Eat Dog: Measuring Network Effects Using a Digital Platform Merger* (SSRN Scholarly Paper ID 3727123). Social Science Research Network. https://doi.org/10.2139/ssrn.3727123

Fischer, P., Krueger, J. I., Greitemeyer, T., Vogrincic, C., Kastenmüller, A., Frey, D., Heene, M., Wicher, M., & Kainbacher, M. (2011). The bystander-effect: A meta-analytic review on bystander intervention in dangerous and non-dangerous emergencies. *Psychological Bulletin*, *137*(4), 517–537. https://doi.org/10.1037/a0023304

Fisher, M., Gallino, S., & Li, J. (2017). Competition-Based Dynamic Pricing in Online Retailing: A Methodology Validated with Field Experiments. *Management Science*, *64*(6), 2496–2514. https://doi.org/10.1287/mnsc.2017.2753

Frey, B. S., & Meier, S. (2004). Social Comparisons and Pro-social Behavior: Testing “Conditional Cooperation” in a Field Experiment. *American Economic Review*, *94*(5), 1717–1722. https://doi.org/10.1257/0002828043052187

GivingUSA. (2021, July 29). *80+ Charitable Giving Statistics & Demographics (2021)*. Define Financial. https://www.definefinancial.com/blog/charitable-giving-statistics/

Kessler, J. B., & Milkman, K. L. (2018). Identity in Charitable Giving. *Management Science*, *64*(2), 845–859. https://doi.org/10.1287/mnsc.2016.2582

Khodakarami, F., Petersen, J. A., & Venkatesan, R. (2015). Developing Donor Relationships: The Role of the Breadth of Giving. *Journal of Marketing*, *79*(4), 77–93. https://doi.org/10.1509/jm.14.0351

Kim, S., Gupta, S., & Lee, C. (2021). *Managing Members, Donors, and Member-Donors for Effective Non-profit Fundraising* (SSRN Scholarly Paper ID 3788459). Social Science Research Network. https://papers.ssrn.com/abstract=3788459

Lee, S. Y., Jung, S., Oh, S., & Park, S. H. (2017). Others’ participation rate influences an individual’s charitable behavior: Others’ similarity as a moderator. *Social Behaviour and Personality: An International Journal*, *45*(10), 1607–1618. https://doi.org/10.2224/sbp.6583

Lee, Y.-K., & Chang, C.-T. (2007). WHO GIVES WHAT TO CHARITY? CHARACTERISTICS AFFECTING DONATION BEHAVIOR. *Social Behaviour and Personality: An International Journal*, *35*(9), 1173–1180. https://doi.org/10.2224/sbp.2007.35.9.1173

Lindauer, M., Mayorga, M., Greene, J., Slovic, P., Västfjäll, D., & Singer, P. (2020). *Comparing the Effect of Rational and Emotional Appeals on Donation Behavior*. https://doi.org/10.31234/osf.io/5wjuv

List, J. A. (2011). The Market for Charitable Giving. *Journal of Economic Perspectives*, *25*(2), 157–180. https://doi.org/10.1257/jep.25.2.157

Liu, L., Suh, A., & Wagner, C. (2017, January 4). *Donation Behaviour in Online Micro Charities: An Investigation of Charitable Crowdfunding Projects*. https://doi.org/10.24251/HICSS.2017.100

MatchPro. (2020, November 17). The Top Nonprofit Fundraising Statistics You Should Know. *360MatchPro*. https://360matchpro.com/fundraising-statistics/

Milgram, S., Bickman, L., & Berkowitz, L. (1969). Note on the drawing power of crowds of different size. *Journal of Personality and Social Psychology*, *13*(2), 79–82. https://doi.org/10.1037/h0028070

Mohan, A., Govil, S., & Malpani, O. (2019). *Everyday Giving in India Report*. 52.

Mukherjee, A., Lee, S. Y., & Burnham, T. (2020). The effect of others' participation on charitable behavior: Moderating role of recipient resource scarcity. *Journal of Business Research*, *120*, 213–228. https://doi.org/10.1016/j.jbusres.2020.08.016

Munz, K. P., Jung, M. H., & Alter, A. L. (2020). Name Similarity Encourages Generosity: A Field Experiment in Email Personalization. *Marketing Science*, mksc.2019.1220. https://doi.org/10.1287/mksc.2019.1220

Natan, O. R. (2021). *Choice Frictions in Large Assortments* [The University of Chicago]. https://doi.org/10.6082/uchicago.2977

News, U. (2019). *Which Countries Are the Most Generous?* US News & World Report. //www.usnews.com/news/best-countries/articles/2019-12-20/the-worlds-most-generous-countries

NP Trust. (2021). *Charitable Giving Statistics*. NPTrust. https://www.nptrust.org/philanthropic-resources/charitable-giving-statistics/

Ozdemir, Z. D., Altinkemer, K., De, P., & Ozcelik, Y. (2009). *An Internet-Enabled Donor-to-Nonprofit (D2N) Marketplace*. https://doi.org/10.2139/ssrn.1415386

Panchanathan, K., Frankenhuis, W. E., & Silk, J. (2013). The bystander effect in an N-person dictator game. *Organizational Behaviour and Human Decision Processes*, *120*(2), 285–297. https://doi.org/10.1016/j.obhdp.2012.06.008

Recurringgiving.com. (2019). *The Nonprofit Recurring Giving Benchmark Study | NextAfter.com*. https://recurringgiving.com/

Reingen, P. H. (1982). Test of a list procedure for inducing compliance with a request to donate money. *Journal of Applied Psychology*, *67*(1), 110–118. https://doi.org/10.1037/0021-9010.67.1.110

Tucker, C., & Zhang, J. (2011). How Does Popularity Information Affect Choices? A Field Experiment. *Management Science*, *57*(5), 828–842. https://doi.org/10.1287/mnsc.1110.1312

Wiepking, P., & Bekkers, R. (2012). Who gives? A literature review of predictors of charitable giving. Part Two: Gender, family composition and income. *Voluntary Sector Review*, *3*(2), 217–245. https://doi.org/10.1332/204080512X649379

Zhang, J. (2010). The Sound of Silence: Observational Learning in the U.S. Kidney Market. *Marketing Science*, *29*(2), 315–335. https://doi.org/10.1287/mksc.1090.0500

APPENDIX

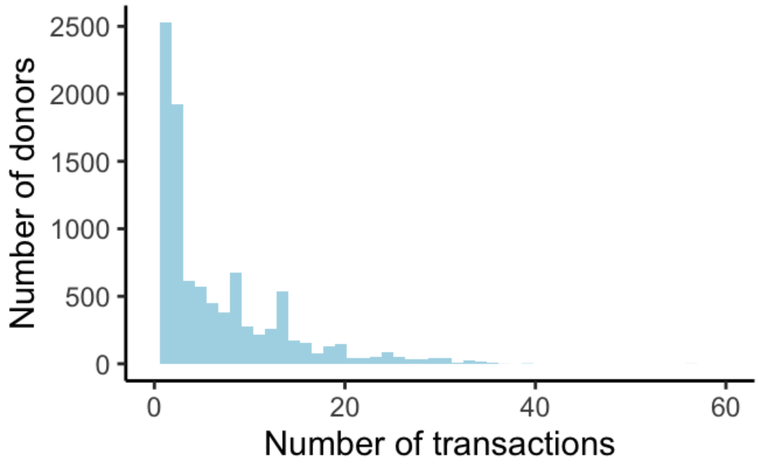

Figure A1: Distribution of the number of transactions

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

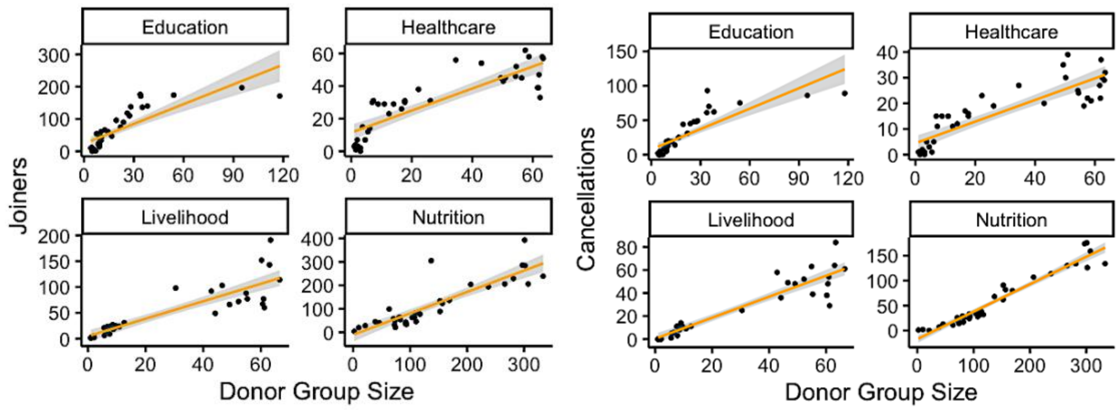

Figure A2: The left panel (a) shows the relationship of joiners and donor group size by category. The right panel (b) shows the relationship between cancellations and donor group size by category.

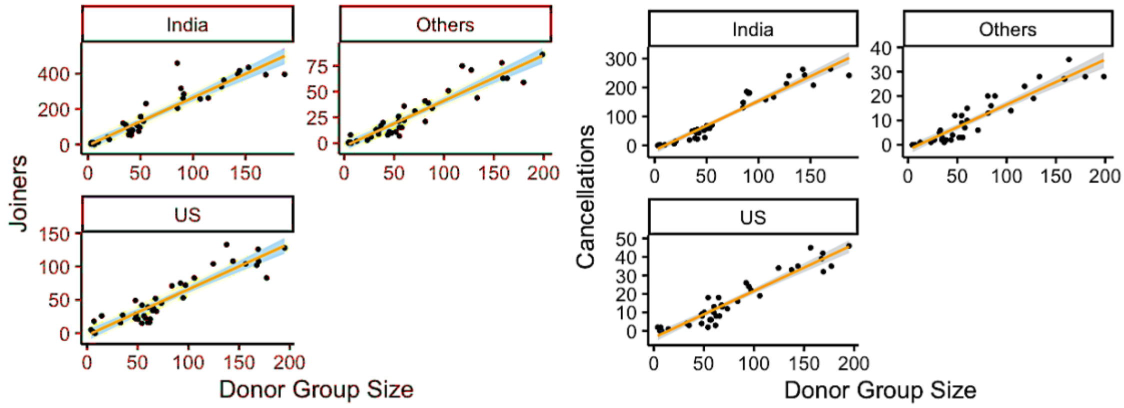

Figure A3: The left panel (a) shows the relationship of joiners and donor group size by location. The right panel (b) shows the relationship between cancellations and donor group size by location. Others includes mostly developed countries such as UK, Canada, Australia etc.

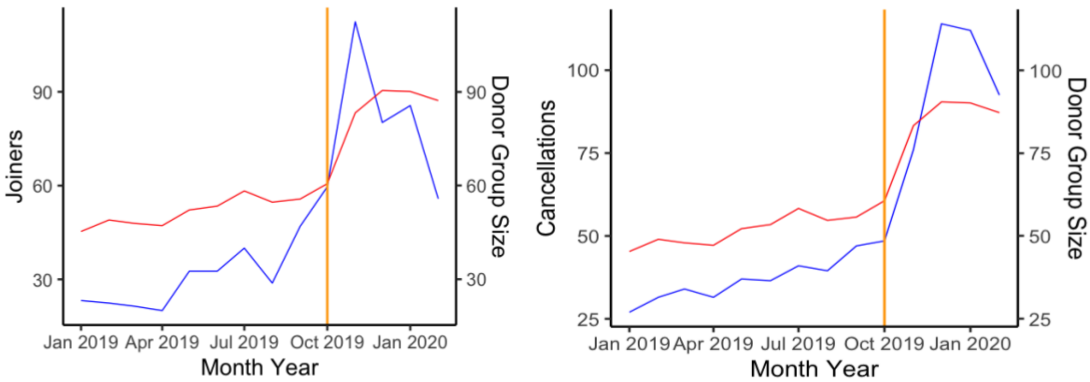

Figure A4: Raw Trends Around the Event: The left panel (a) shows raw trend of joiners and donor group size. The right panel (b) shows raw trend of cancellations and donor group size. (Not drawn to scale to present on same graph for comparison and coincidence) (Red lines are donor group size trend, and blue lines can be joiners or cancellations)

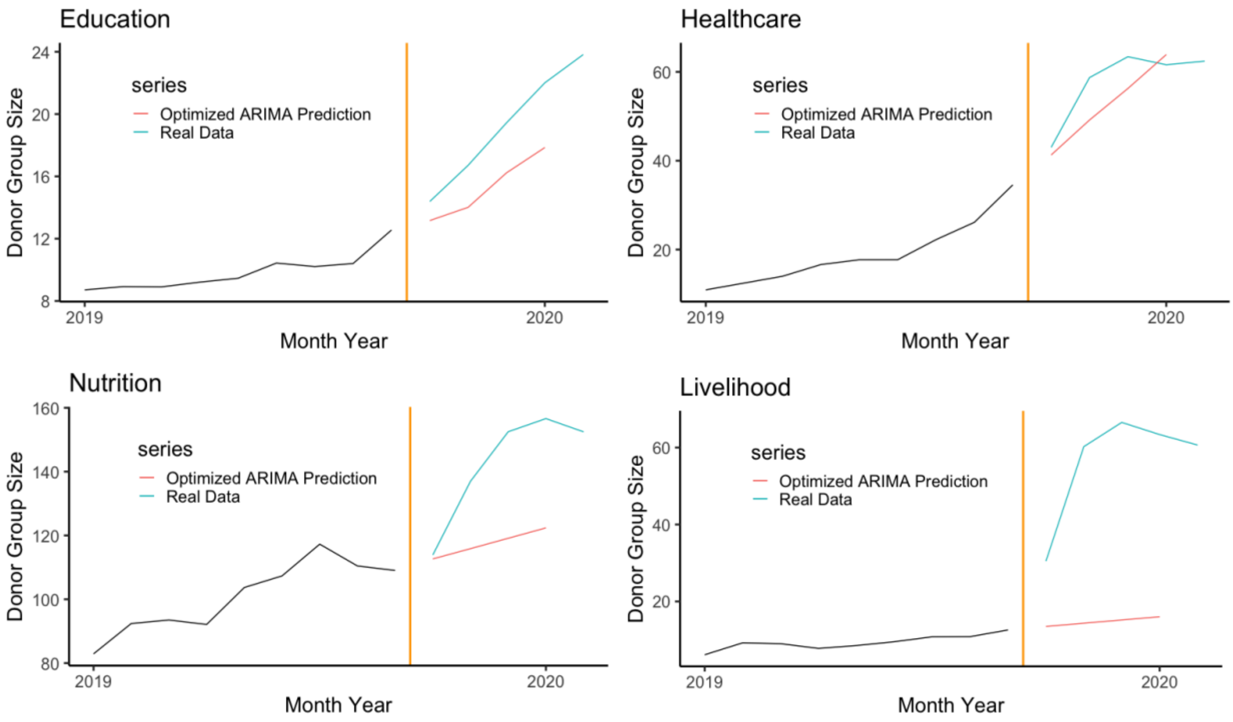

Figure A5: Event shock by cause category

Table A4: Joiners vs Donor Group Size (DID - Inc vs Not Inc)

	Dependent variable:			
	Joiners			
	(1)	(2)	(3)	(4)
Increase	1.002***	0.988***	2.940**	2.942**
	(0.257)	(0.257)	(1.270)	(1.270)
Utsav	0.188	0.508	0.278*	0.260
	(0.196)	(0.317)	(0.157)	(0.248)
Increase x Utsav	1.301***	1.316***	1.727***	1.727***
	(0.348)	(0.348)	(0.278)	(0.278)
Constant	0.733***	1.106***	0.129	0.105
	(0.146)	(0.326)	(0.948)	(0.981)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5,059	5,059	5,059	5,059
R^2	0.024	0.024	0.440	0.440

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

Note: This table reports the results from DID regression, expressed by Eq 2. It compares the difference in joiners of causes which experienced an increase in donor group size with the ones which didn't experience an increase.

Table A5: Cancellations vs Donor Group Size (DID - Inc vs Not Inc)

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Increase	0.378***	0.387***	1.136*	1.176*
	(0.138)	(0.138)	(0.638)	(0.636)
Event	0.214**	0.003	0.285***	-0.166
	(0.105)	(0.171)	(0.079)	(0.124)
Increase x Event	1.043***	1.033***	1.334***	1.312***
	(0.188)	(0.188)	(0.140)	(0.140)
Constant	0.307***	0.061	0.033	-0.557
	(0.079)	(0.175)	(0.476)	(0.492)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5,059	5,059	5,059	5,059
R^2	0.032	0.033	0.517	0.519

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

Note: This table reports the results from DID regression, expressed by Eq 2. It compares the difference in cancellations of causes which experienced an increase in donor group size with the ones which didn't experience an increase.

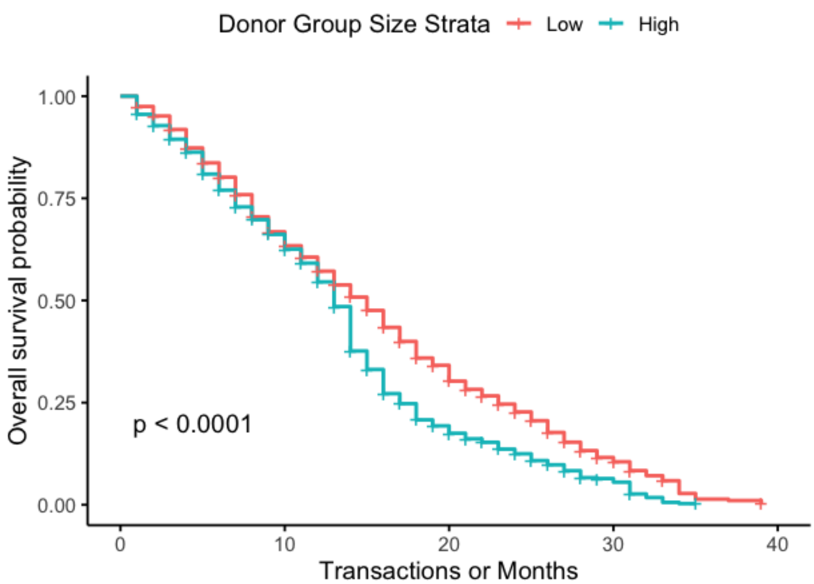

Figure A6: This figure reports the Kaplan Meir survival probabilities (1-Pr (Cancel)) for donors with high and low (median split) donor group size. It also reports the p-value from log rank test, indicating clear statistical difference between the two groups.

Table A7: Survival Probabilities using time varying covariates

	Without Controls			With Controls		
	slope	coef	se(coef)	slope	coef	se(coef)
Intercept	0.132	2.05E-04	4.64E-06	1.47E-01	5.28E-04	2.93E-05
Donor Group Size	0.000581	4.51E-07	2.67E-08	1.90E-04	1.17E-06	2.61E-07
Male				-2.20E-02	-6.91E-05	2.65E-05
Others-Location				1.56E-02	3.49E-05	4.32E-05
US-Location				2.86E-03	-1.17E-05	3.06E-05
Donation Amt				1.16E-06	-2.08E-09	1.16E-08

Note: This table reports the results from estimation of survival probabilities using time varying covariates (donor group size for each donor)

Table A6: Dynamic Linear Probability Model

	Dependent variable:			
	Cancel			
	(1)	(2)	(3)	(4)
Platform Level				
Donor Group Size	0.004***	0.006***	0.002*	0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
No of cause choices	-0.0003	-0.002***	-0.003**	-0.005***
	(0.0003)	(0.001)	(0.001)	(0.001)
Donation Choice				
Multi Beneficiary	-0.255***	0.022	-0.142*	0.021*
	(0.050)	(0.015)	(0.082)	(0.011)
Donation Amt	0.00002***	0.00000	0.00001**	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Donor Demographics				
Male	-0.009	-0.013	-0.001	-0.006
	(0.012)	(0.013)	(0.010)	(0.010)
Other-Locations	-0.026	-0.055***	-0.019	-0.040**
	(0.018)	(0.019)	(0.013)	(0.017)
US-Location	-0.114***	-0.058***	-0.072**	-0.044***
	(0.024)	(0.016)	(0.033)	(0.014)
Time Trend			0.030**	0.035***
			(0.014)	(0.012)

Time Trend	N	N	Y	Y
Cause FE	N	Y	N	Y
Observations	7,368	7,368	7,368	7,368
Weak Instrument	40.41 (< 2e-16)	69.86 (< 2e-16)	7.39 (0.006)	16.339 (0.0005)
Wu-Hausman	95.88 (< 2e-16)	111.98 (< 2e-16)	5.87 (0.015)	8.917 (0.002)

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

Note: This table reports the results from estimation of Eqn 4. Female is the baseline for gender (we use only two genders to identify the genders of the donors). Location is classified into 3 categories. – India, US and Others (mostly – UK, Canada, Australia, UAE etc.). Single Beneficiary (only one recipient of donation) is the baseline for # no of beneficiary segment.

Table A8: Placebo Regressions

	Dependent variable:			
	Cancellations		Joiners	
	(1)	(2)	(3)	(4)
Increase	0.973	0.906	2.829	2.653
	(1.189)	(1.191)	(2.374)	(2.379)
Event	-0.343***	-0.206	-0.025	0.179
	(0.129)	(0.224)	(0.259)	(0.343)
Placebo		-0.147		-0.152
		(0.227)		(0.350)
Increase x Event	1.379***	1.022***	1.976***	1.186**
	(0.132)	(0.340)	(0.263)	(0.498)
Increase x Placebo		0.394		0.960
		(0.345)		(0.566)
Constant	-0.282	-0.230	0.284	0.430
	(1.116)	(1.117)	(2.228)	(2.230)
Placebo	N	Y	N	Y
Observations	5,014	5,014	5,014	5,014
R^2	0.522	0.522	0.442	0.442

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

Note: This table reports the results of placebo checks. The first two columns represent results on cancellations (without and with placebo respectively). Last two columns represent results on joiners (without and with placebo respectively)

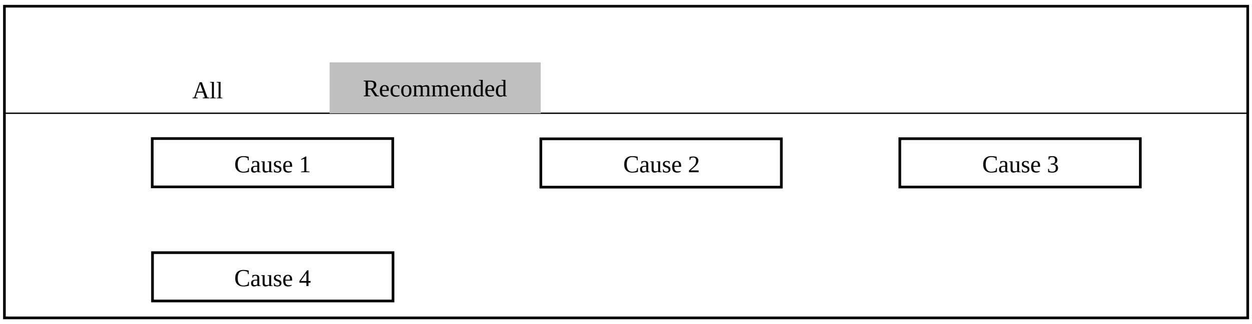

Figure A8: Position effects - This figure illustrates the landing page of the website.

Table A3: Comparing Donors characteristics pre and post event

	Dependent variable:
	Donor Join Pre vs Post Event
Healthcare	0.073
	(0.201)
Livelihood	0.045
	(0.271)
Nutrition	0.133
	(0.191)
Education	0.130
	(0.276)
Other Locations	-0.091
	(0.201)
US Location	-0.193
	(0.156)
Male	0.086
	(0.103)
Log (Min Donation Amt)	-0.405
	(0.667)
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. Dependent variant takes value 1 if donor joined after the event, 0 otherwise. We find the donors who joined after the event are similar to donors who joined before the event.

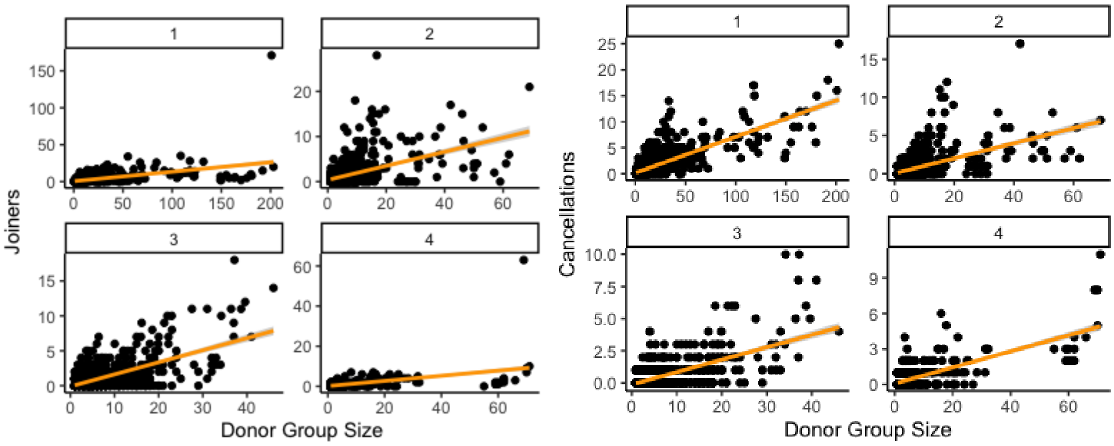

Figure A7: Outcomes vs donor group size by minimum donation amount quartile split. The left panel shows the relationship of joiners & donor group size and right panel shows the relationship between cancellations & donor group size. 1-4 top legend indicates quartile number.