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Independent vs. Collaborative Fundraising: Understanding the Role of Information

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Abstract

We use "real donation" laboratory experiments to compare *independent* fundraising, where donation requests from different charities arrive sequentially to potential donors, with *collaborative* fundraising, where donation requests from different charities arrive simultaneously. We find that collaborative fundraising generates significantly larger total donations compared to independent fundraising. We show that the order of requests affects the level of donations only in independent fundraising; in particular, participants donated larger amounts to charities whose requests arrived earlier. We then test whether these differences might be explained by the informational asymmetry between these two fundraising mechanisms by varying the information received by the subjects.

Keywords: Charitable giving, independent fundraising, simultaneous solicitation, information, laboratory experiment

JEL Codes: C90, D62, H41

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1 Introduction

A considerable amount of research on charitable giving uses laboratory and field experiments to compare the effectiveness of different fundraising techniques (see Andreoni (2006), List (2011), Vesterlund (2016) for surveys). For example, Yoruk (2010) compares the effect of direct mailing, phone calls and TV commercials on donations. Eckel and Grossman (2003, 2008, 2017), List and Lucking-Reiley (2002), Karlan and List (2007), List (2011), and Huck and Rasul (2011) compare various types of subsidies, including rebates, matches or seed money.[1] In addition, a growing literature focuses on competition among charities (*e.g.*, Reinstein, 2011; Harwell et al. 2015; Krieg and Samek, 2017; Meer, 2017; Deck and Murphy, 2017; Scharf et *al*., 2017; Filiz-Ozbay and Uler, 2018) and studies whether competition shifts donations among charities or whether it increases total giving.[2]

This paper contributes to both literatures. We experimentally investigate an understudied fundraising technique—collaborative fundraising—by comparing it with independent fundraising in terms of total donations generated. In addition, for both mechanisms, we study whether the order in which a request is received has an effect on donations to a given charity. Moreover, we investigate the underlying reasons behind observed differences in donation behavior between mechanisms. In particular, we design treatments to test the effect of informational differences inherent in independent versus collaborative solicitation techniques in a controlled manner.

In *independent fundraising*, charities send solicitation requests independently from each other and donors end up making donation decisions sequentially for different charities. Such independent fundraising efforts create informational uncertainty, as individuals are unaware of which charities will approach them next, or how many organizations may approach them in a given time period. When charities collaborate in their fundraising efforts, however, a fuller information setting is provided.

[1] Scharf and Tonin (2018) provide a number of additional examples of tests of fundraising practices. For a study of donor premiums see Eckel, Herberich and Meer (2018).

[2] A related strand studies the effect of the number of charities (*e.g*., Andreoni, 2007; Soyer and Hogarth, 2011; Bernasconi et al., 2009; Corazzini et al., 2012) and optimal market structure (*e.g*., Rose-Ackerman, 1982; Bilodeau and Slivinski, 1997; Thornton, 2006; Mungan and Yoruk, 2012; Krasteva and Yildirim, 2016) on voluntary giving.

Several organizations allow charities to apply to participate in *collaborative fundraising* effort. One example is the United Way Worldwide, which is a coalition of 1800 local United Way offices that pool efforts in fundraising and support. Another example is Alaska's Pick-Click-Give program, which allows recipients of the Alaska's Permanent Fund Dividend to donate a portion of their dividend to approved organizations. In addition, many states and organizations run so-called combined giving campaigns that allow employees to donate to organizations through payroll deductions. For all of these umbrella organizations, individual charitable organizations apply to be approved members of the coalition or campaign.[3] In addition, a plethora of online platforms evaluate charities and facilitate contributions to different charities, such as charitynavigator.org, globalgiving.org, networkforgood.org, justgive.org, and onedonation.com.au. Moreover, we see examples of large collaborative fundraising campaigns such as #GivingTuesday.[4] All of these examples share the common element that they provide individuals with a chance to donate to multiple charities simultaneously (whether or not the charities take part in this collaboration actively).

There are two informational dimensions that distinguish independent fundraising mechanisms from collaborative mechanisms. In independent fundraising, potential donors are unaware of (1) the total number of, or (2) the identities of the charities. That is, they do not know how many charities might request contributions, or which charities will subsequently approach them. In collaborative fundraising, by contrast, donors are fully informed on both dimensions.

The potential impact of each dimension on the pattern of giving over time and on total giving is unknown. Uncertainty about the number of requests might lead a donor to hold back on giving to early requests, with more generous behavior reserved for later requests. On the other hand, a donor might give generously to early requests, exhausting her "budget" for charitable giving, leading to lower later donations (Thaler, 1999). Similarly

[3] See Unitedway.org, pickclickgive.org, secctexas.org, or www.seca.pa.go for examples.
[4] #GivingTuesday is a global campaign which started in 2012. It generated more than $180 million in donations online in a single day in 2016 to benefit a broad range of causes.
See https://www.givingtuesday.org/lab/2017/07/givingtuesday-insight-report-2017.

for total donations, a donor might end up giving more or less in total. Total donations might be lower in independent fundraising, if individuals save part of their charitable budget waiting for a "better" charity to show up later (and one never does). Alternatively, total donations might be higher in independent fundraising, if individuals feel they need to donate when a new donation request arrives with an unexpected worthy cause even if they have already donated large amounts early on. A salient example is the efforts in 2017 to raise funds for victims of Hurricane Harvey in Texas and of Hurricane Irma in Florida and the Caribbean islands. Donors may have given generously for Harvey, which may have reduced their gifts for Irma, or donors may have ended up giving more in total than they planned in response to the surprise occurrence of Irma.[5] The philanthropy literature provides little guidance as to which outcome we might predict when comparing collaborative and independent fundraising mechanisms. In our study, we aim to both (a) compare performances of these mechanisms in generating donations, and (b) to shed light on how both types of informational uncertainty impact donation behavior in each mechanism separately.

Although we encounter both collaborative and independent fundraising efforts in real life, the relative performance of these two different mechanisms is not well understood (Abdy and Barclay, 2001). The difference between the two mechanisms is difficult to test using observational data, because charities do not often engage in both strategies simultaneously, and many factors change between instances of the two.[6] In addition, the data that would be needed to isolate the role of information on donations in a field setting are simply not available. Our paper, on the other hand, provides the first systematic analysis of whether collaborative fundraising can increase overall giving in a society by overcoming

[5] While not in the context of multiple charities, a related example is provided by Cairns and Slonim (2011). They look at the substitution effects of the presence of 2nd collections on 1st collections at Catholic Masses and find a negative effect on 1st donations and a positive effect on total donations. In addition, there is recent literature on how natural disasters affect total donations (*e.g.*, Deryugina and Marx (2015) and Scharf et *al.* (2015)). Note that our paper studies a different question. We compare two different fundraising mechanisms where the identity of charities and the number of requests are exactly the same.

[6] For example, different fundraising methods might occur at very different times which would imply income available for donation might differ between these different methods. One needs to carefully isolate the effect of fundraising technique from that of differing income (as well as other confounds). Moreover, charities that engage in collaborative fundraising may have different characteristics from charities that engage in independent fundraising, and the direct effect of collaborative solicitation is hard to disentangle. In an experimental set-up one can control for all factors other than the ones under consideration.

informational problems that might arise with independent fundraising efforts.[7] By using real donations in a lab setting, we can control all other factors that might constitute confounds, and experimentally test the difference in the two mechanisms holding everything else (including the identity of charities and the number of requests) constant. Furthermore, in a laboratory experiment, we can exogenously vary the level of information and isolate its effect on donations.

We conduct a laboratory experiment where subjects make actual donation decisions to eight charities under both independent fundraising, where the donation requests arrive sequentially without prior information about either the total number or identity of the charities, and collaborative fundraising where donation requests arrive simultaneously, with information about both the number and identity of the charities. We further conduct two additional treatments that allow us to identify the effects of uncertainty about the number and identity of charities separately. In addition, we also introduce a payoff-relevant surprise phase which gives subjects the opportunity to revise their donation decisions. We investigate whether and how subjects update their initial donations under different fundraising mechanisms in our treatments. Finally, we elicit emotions subjects experienced while donating, subjects' attitudes towards risk and uncertainty, and demographics, and incorporate these into our analyses as controls.

We find that the collaborative fundraising mechanism outperforms the independent one in total donations generated. When full information regarding the number and identity of charities is given to subjects prior to the sequential arrival of any requests, there remains no significant difference in total donations as compared to collaborative fundraising. Therefore, potential donors' lack of information turns out to be the reason behind the poorer performance of independent fundraising relative to collaboration. We also study whether the order of a request (*i.e.*, early versus late) matters in terms of donations collected for an individual charity. We see that order has an effect only in the independent fundraising technique: early requests generate higher donations on average. When individuals are

[7] While writing this paper, we came across a related working paper, Vance-McMullen (2017), which also compares simultaneous and sequential fundraising campaigns experimentally, but does not study the role of information. Our papers complement one another, and we return to a discussion of this paper in the conclusion.

provided with prior information regarding how many solicitation requests they will receive, the order effect disappears. When subjects are offered a surprise opportunity to revise their donations to all charities, subjects in all treatments increase donations. The amount of the update is highest under independent fundraising, though it is not large enough to increase donations to the levels seen in collaborative fundraising. Our results are robust to controlling for emotions, risk and ambiguity attitudes as well as demographics.

Our study differs from the literature on united charities (Ghosh et al. 2007; Bilodeau, 1992). A united charity refers to a centralized fundraising effort where small charities are unified under the same umbrella and the total revenue is distributed among the members of the united charity, typically according to a fixed rule. By contrast, in a collaborative fundraising effort of the form we study, multiple charities that are completely independent from each other fundraise simultaneously (i*.e.,* a pool of potential donors is provided with a list of charities so that individuals can decide how much to donate to each specific charity at the same time). As such, our collaborative treatment more closely resembles state combined campaigns or Alaska's Pick Click Give program than the United Way.

The findings of the current paper are relevant from both academic and policy perspectives. To our knowledge, we are the first study to systematically examine the role of information on the performance of these two different fundraising mechanisms. Our paper shows that under full information, how charitable requests are presented (simultaneous versus sequential) by itself does not matter for the amount of charitable donations attracted; that is, charitable sector cannot affect the charitable pie by just changing how the requests will be presented. On the other hand, if individuals are not fully informed regarding the upcoming requests, then collaborative fundraising helps donations increase by eliminating two primary sources of uncertainty present in the independent fundraising. While it is very difficult to disentangle the effectiveness of collaborative and independent fundraising using observational data, our results demonstrate the effectiveness of full collaboration over full independent fundraising in a laboratory setting.

From a policy perspective, our results constitute an initial step in demonstrating that charities would benefit from increased participation in collaborative fundraising mechanisms. In the field, eliminating all uncertainties via collaborative fundraising mechanisms akin to those studied in this experiment might not be possible. In fact, we do not expect all charities to restrict themselves to collaborative fundraising (that is, outside the lab, collaborative fundraising requests might still be accompanied by additional requests sent independently from other non-participating charities). In this paper, in order to disentangle the relative effectiveness of collaborative and independent fundraising and to understand the role of information, we focus on two extreme scenarios on purpose. Our results provide a foundation upon which further lab or field experiments might build.

The remainder of this paper is organized as follows. Section 2 outlines the experimental design. Section 3 presents our main findings. Section 4 concludes. Additional analyses and instructions are provided in the Appendices.

2 Experimental Design

We conducted a computer-based experiment at the experimental laboratory of Ozyegin University (OzU) in Turkey during March-May 2017. The computer program was coded using z-Tree (Fischbacher, 2007). Subjects were recruited via Sona Systems from the participant pool at OzU. A total of 187 subjects participated in our experiment.[8]

There were eight experimental sessions. Instructions were read aloud to ensure that each subject was exposed to complete instructions and that they did not skip any parts. Throughout the experiment, Turkish Lira (TL) was used.[9] Each subject was paid a show-up fee of 10 TL, and given the chance to earn additional monies during the experiment. The average total payment per subject across all sessions was 32.5 TL (excluding their donations to the charities). At the end of each experimental session, subjects received their payments in private. The entire process lasted approximately 60 minutes. After all of the

[8] Our subjects are experienced with charitable giving in general. At Ozyegin University where we ran our experimental sessions, charitable events take place. Students participate in such events by donating goods (such as books, toys etc.) to kids in need and taking part in voluntary activities such as working at the university's animal shelter.
[9] At the time of the experiment, the average exchange rate was about $1=3.55 TL.

eight experimental sessions were over, we sent the total donations to the charities used in the study on behalf of the subjects.

The experiment is composed of six parts. In Parts 1 and 3, subjects make decisions regarding real donations to charitable organizations. We selected eight charities in Turkey, each operating in a different area: the environment, animals, violence against women, search and rescue, cancer, education, homeless people, and art.[10] The order in which the donation requests for the charities were presented was randomized for each subject at the outset of the experiment. To ensure that order did not play a role in a given subject's decisions *within* different parts of the experiment, the order of charities was fixed throughout the experiment for each subject. In Part 2, subjects are asked to indicate feelings they experienced during their donation decisions in Part 1. In Parts 4 and 5, they are given tasks designed to reveal their attitudes towards ambiguity and risk, respectively. In Part 6, they fill out a questionnaire.

In Part 1, subjects start with an endowment of 50 TL provided by the experimenters, make real donations to charities out of their endowment, and keep the remaining amount as part of their earnings from the experiment.[11] Individuals are asked to make one donation decision for each charity. For each treatment, since there are eight charities, subjects make eight donation decisions in total. We use a between-subjects design with four treatments. One dimension of variation across our treatments is the way subjects receive donation requests. In the SIM Treatment, subjects receive all donation requests *simultaneously*. A table with the names and short descriptions of eight charities is shown to subjects. They are asked to decide how much to donate to each charity and submit their donation decisions to all charities at once. Subjects participating in the SIM treatment make all their donation decisions knowing the number and identity of all charities in the experiment. We consider the SIM treatment in our experiment as representing a collaborative fundraising effort in real life.

[10] This is also in line with different major groups in the NTEE-CC classification system.

[11] In 2017, the opportunity cost of students in our subject pool was approximately 7 TL per hour, and therefore 50 TL is a substantial amount for our subject pool. In addition, *daily* minimum wage in Turkey in 2017 was 59.25 TL.

The next three treatments have a SEQ component, indicating that donation requests arrive *sequentially*. In these treatments, donation decisions are made one at a time: subjects are provided with the name and a short description of a particular charity and asked to decide how much to donate to that specific charity. Only after they submit their donation decision for that particular charity does the next donation request from a different charity arrive (subjects are not allowed to go back and modify their earlier decisions within Part 1). We call each of these donation requests a "stage".

In treatments with a SEQ component, we also vary the level of *information* that subjects possess at the time they submit a donation decision. In the SEQ-NOINFO Treatment, subjects know nothing in advance about the total number of donation requests to arrive or the identity of the charitable organizations from which they will receive requests. They find out the identity of a charity only when a specific request arrives. We consider the SEQ-NOINFO Treatment as representing an independent fundraising effort in real life. In the SEQ-LOWINFO Treatment, subjects know in advance that they will receive donation requests from eight charities in total, while they do not know in advance from which charities specifically they will receive donation requests. Subjects find out the identity of a charity when a request from that charity arrives. In the SEQ-FULLINFO Treatment, subjects are first provided with a table including the names and short descriptions of all eight charities they will face when the donation stages start. After they examine this information table, they move on to the donation stages in which requests arrive one at a time. Note that while treatments SIM and SEQ-FULLINFO differ in the way the requests arrive, the information structure of these two treatments is exactly the same, as subjects know both the total number of forthcoming donation requests and the identity of all charities in the experiment prior to making all their donation decisions.

On the donation screens of all treatments, subjects are shown: (1) their current endowment, and (2) the amount of money they keep for themselves following their intended donations. The current endowment information indicates the total amount of money a subject has for donations in the current donation screen and the forthcoming ones, if there are any.[12] To see the amount of money subjects keep for themselves after their intended donations, subjects need to type their donation decision(s) in the current screen and press the "calculate" button, and they are shown the difference between their current endowment and the total donations they enter in the current screen.[13] Before actually submitting their donation decisions, subjects are allowed to calculate this amount under various donation decisions as many times as they like. The aim of providing such information to subjects is to decrease the likelihood that they make calculation errors and to prevent any potential differences that might arise in the data due to variations in the computational demands of each treatment (*i.e.*, the SIM treatment has only one stage with eight donation decisions made simultaneously, while other treatments have eight stages each with a single donation decision).[14]

Regardless of the specific treatment a subject has experienced in Part 1, all the remaining parts (2-6) of the experiment are exactly the same for all subjects. Motivated by the considerable amount of attention emotions have received in the charitable giving literature (*i.e.*, Andreoni, 1989, 1990; O'Keefe and Figge, 1997; Andreoni, 2006; Van Diepen et al. 2006, 2009a; Harbaugh et al., 2007; Andreoni et al., 2011; Gneezy et al., 2012; Fiala and Noussair, 2017), we elicit information regarding subjects' emotions in Part 2. In order to isolate the role of information, we study the extent to which different fundraising mechanisms lead to different emotions. Subjects are provided with a list of feelings in a random order (happiness, shame, pride, sadness, guilt, irritation, excitement, nervousness, surprised, regret) and asked to indicate which ones they have experienced during Part 1 where they have made donation decisions. They are also allowed to type feelings that are

[12] For the SIM treatment, the current endowment shows 50 TL, as there is only one donation screen in which all the donations are made at once. For the other three treatments in which donation requests arrive sequentially, the current endowment is 50 TL in the first donation stage, and in subsequent stages, 50 TL minus the sum of total donations made in the previous stages (if any).

[13] In the SIM treatment, the sum of donations entered for multiple charities simultaneously is subtracted from the current endowment, whereas in treatments with a SEQ component, a single donation entered for the specific charity at the current stage is subtracted from the current endowment.

[14] It is possible that, outside our controlled environment, individuals make such calculation mistakes (or forget their previous donations), which might create additional differences between simultaneous and sequential fundraising. By providing a way to eliminate or minimize such mistakes in our experiment, we are able to isolate the role of information in explaining the differences between these fundraising methods.

not on the list. This part of the experiment not only enables us to control for subjects' emotions in our analyses, but also serves as a filler between Part 1 and Part 3.

Part 3 is another novel component of our experimental design. It consists of a payoff-relevant *surprise* question. Subjects are provided with a table specifying the identity and descriptions of the charities they have encountered in Part 1 and their own donations to each charity there. They are asked whether and how they would like to update their earlier decisions. For each charity in the table, subjects are asked to type a "final donation decision" and then submit all final decisions at once. A final donation decision for a charity could be the same amount as the earlier decision the subject has made in Part 1 or a different amount if he/she is now willing to change the earlier decision. Subjects are told that only their final donation decisions will be taken into account when we calculate their earnings from the experiment and send donations to charities. On the screen of this part, subjects are again provided with the information regarding their current endowment and the amount of money they will keep for themselves if they submit the final donation decisions they have just entered. Additionally, the amount of money they will keep for themselves if they do not change their earlier donations is also shown to them on the screen. The vitality of Part 3 lies in it coming as a surprise: subjects have decided about their donations in Part 1 without knowing that they will be given the opportunity to revise their choices in Part 3. This surprise feature allows us to observe whether and how subjects update their decisions after they have been exposed to different treatments in Part 1.

The purpose of Parts 4 and 5 in this experiment is to elicit subjects' attitudes towards ambiguity and risk, respectively. We later use these attitudes as controls in the analyses of subjects' donation decisions across different treatments. In Part 4, based on Charness et al. (2013), we use a variant of an Ellsberg experiment, wherein each subject is asked to consider six containers, each containing a total of 100 balls with colors red, blue, and green. Subjects are told the *exact* number of red balls and the *total* number of blue and green balls in each container. They are not told the exact number of blue balls or the exact number of green balls. The first container has 50 red balls and 50 blue and green balls. The second container has 40 red balls and 60 blue and green balls, while the sixth container has 0 red balls and 100 blue and green balls. For each container, they are asked to bet on the color of a randomly selected ball. To determine a subject's earnings from Part 4, one container is randomly selected and a subject receives 5 TL upon correctly guessing the color of a randomly selected ball from that container, and 0 TL otherwise. The outcome is revealed to subjects after they complete all parts of the experiment. Our measure of ambiguity aversion is based on the total number of red ball choices.

In Part 5, we use a variant of a multiple price list technique in order to elicit the certainty equivalent of a risky lottery (e.g., Schubert et al. (1999), Barr and Packard (2002) and Harrison and Rustrom (2008)). Subjects are asked to make choices in six situations, each involving a lottery and a certain amount of money. The lottery is always the same (50-50 chance of earning 5 TL or 1 TL) while the certain amount of money varies from 1 TL up to 3.5 TL (with an increment of 0.5 TL) across all six situations. Subjects are asked to decide whether they prefer the lottery or the certain amount in each of the six situations. One situation from Part 5 is randomly selected at the end of the experiment and the subject is paid according to the choice he/she has made in that situation. We use the number of safe choices as a measure of risk aversion.

Finally, in Part 6, subjects fill out a questionnaire about their liking and prior knowledge of charitable organizations in the experiment, their overall donations in the last 12 months, the importance of religion in their life, demographics, *etc*. Then, each subject privately receives his/her payment, calculated as the sum of the 10 TL show-up fee and the amount of the endowment the subject has not donated in Part 3 (50 TL – subject’s total final donations in Part 3) and the subject’s earnings from Parts 4 and 5.

We have three main hypotheses we wish to investigate with our experiment. First, we ask whether donations in the SIM and SEQ-NOINFO differ. A case can be made that donations will be larger or smaller with collaborative fundraising. If donors give generously to early-arriving charitable requests, and later receive solicitation from unexpected but worthy causes, then total donations would be higher under independent than under collaborative fundraising. On the other hand, independent fundraising may lead donors to hold back their giving to early-arriving requests, anticipating that an attractive opportunity may arrive later. In this case, donations could be lower with independent fundraising. Therefore, while we hypothesize that donation behavior will differ between the two mechanisms, we do not presume a direction for the difference. Second, if donations differ, is this because of informational asymmetries across mechanisms? In other words, if donors are provided with full information in advance regarding the number and the identity of the charities, would the gap between sequential and simultaneous solicitation methods disappear? Our hypothesis is that there is no difference in total donations among SIM and SEQ-FULLINFO treatments. Third, if information is important, is the information about the *number* or *identity* of organizations most relevant? In particular, we test (i) whether the total donations between SEQ-NOINFO and SEQ-LOWINFO differ, (ii) whether total donations between SEQ-NOINFO and SEQ-FULLINFO differ. We examine these questions and test our hypotheses in Section 3.1.

In addition to our main hypotheses, we also explore whether and how early versus late requests have an effect on donations for an individual charity under each treatment. This gives us additional insight into understanding the two mechanisms. Note that in the SIM treatment all donation requests are presented on the same screen, but it is possible that being at the top of the list or at the bottom of the list might matter for donations collected at the individual charity level. Having said that, we expect to have a larger effect of early versus late requests in the SEQ-NOINFO treatment, since subjects do not know the number of requests to come or the identities of the forthcoming charities. Whether donations will increase or decrease with upcoming requests is an open question. Section 3.2 addresses this topic.

Finally, in Part 3 of our experiment, we also investigate whether and how subjects revise their earlier donation decisions. Subjects in the SEQ-NOINFO and SEQ-LOWINFO may realize that they have made incorrect (suboptimal) decisions in Part 1 due to absent information and therefore, they may improve their giving decisions in Part 3 when they are fully informed. While subjects in all treatments may revise their donations also for reasons not related to information, we conjecture the largest amount of revisions to happen in the

SEQ-NOINFO treatment where subjects are not provided with any information (regarding the total number of charities and the identities of subsequent charities) in advance. Section 4 will discuss alternative explanations for revisions and will test the hypothesis that largest revisions are observed in the SEQ-NOINFO treatment.

For each treatment, we initially planned to recruit 50 subjects. Due to different show-up rates, the actual number of participants in each treatment ranged from 42 to 54. The power of our study to find a 10 TL (7.5 TL) difference in total donations at the 5% significance level between SIM and SEQ-NOINFO treatments is approximately 0.89 (0.67).[15]

3 Main Findings

In this section, we focus on donations made in Part 1 of the experiment. In Section 3.1, we study total donations (the sum of donations to eight charities). In Section 3.2, we concentrate on donations to individual charities and study whether they are affected by the order of requests.

3.1 Total Donations in Part 1

The first question we study is whether there is any difference in total donations between the collaborative (SIM) and independent fundraising (SEQ-NOINFO) mechanisms. The answer is, yes. Table 1 shows the mean and median *total* donations to all eight charities (as well as standard errors in parentheses) for Part 1 of all treatments. The mean (median) donation in SIM is 35.75 (40) while the mean (median) donation in SEQ-NOINFO is 25.95 (25). Relative to the SEQ-NOINFO treatment, donations are about 38 percent larger in the SIM treatment. A Mann-Whitney test shows that the difference in total donations between these two treatments is statistically significant at the 1% significance level (see Table 2).[16]

[15] Reported power analysis relies on the assumption that donations have a standard deviation of 15.

[16] Out of 187 subjects, only 4 subjects made zero donations in total. Note that, surprisingly, 42 out of 187 subjects donated all of their endowment of 50 TL. While house money effect and cultural differences might partly explain this high generosity, they should not affect treatments differently. In contrast, we find that 18 of these subjects are from SIM treatment, 11 of these subjects are from SEQ-FULLINFO, 9 of these subjects are from SEQ-LOWINFO and only 4 subjects are from SEQ-NOINFO. In other words, different fundraising mechanisms lead to different generosity levels. This also leads to an important observation. Since SIM treatment induces more subjects to become constrained by their

Table 1. Summary Statistics

	Total Donations in Part 1		No. of obs.
	Mean	Median	
SIM	35.75 (2.38)	40	44
SEQ-NOINFO	25.95 (2.18)	25	47
SEQ-LOWINFO	28.91 (2.60)	30	42
SEQ-FULLINFO	32.38 (2.12)	38	54

Table 2. Pairwise Comparisons of Total Donations in Treatments in Part 1

	SEQ-NOINFO	SEQ-LOWINFO	SEQ-FULLINFO
SIM	0.00	0.04	0.15
SEQ-NOINFO		0.40	0.04
SEQ-LOWINFO			0.36

Each cell reports p-values associated with the Mann-Whitney Tests.

Further evidence on the comparison between these treatments can be obtained via OLS regression analyses (presented in Table 3). The dependent variable in our regressions is the total donation a subject makes in Part 1. The independent variables in Regression (1) are the dummies for treatments SIM, SEQ-LOWINFO and SEQ-FULLINFO where SEQ-NOINFO is left out as the base category. Once more we see that donations are significantly higher in the SIM treatment compared to the SEQ-NOINFO treatment at the 1% significance level.

We now ask whether the observed differences in donations among treatments could be due to different mechanisms generating different emotions. In Appendix A.1, we analyze whether the likelihood of experiencing certain emotions is statistically significantly different across treatments. We observe very little difference. In fact, none of the emotions

endowments compared to SEQ-NOINFO treatment, we would expect the SIM treatment to generate even larger donations relative to the SEQ-NOINFO treatment if our subjects were not constrained by their endowment. In other words, the difference we observe could be a *lower-bound* for the actual difference.

are statistically significantly different between SEQ-NOINFO and SIM treatments (see Appendix A.1 for further details). Nevertheless, it is important to control for emotions in our regression analyses to make sure the differences in donations still persist. Similarly, in order to isolate the effect of information on donations, it is important to control for risk and ambiguity preferences as well as demographics (see Appendix A.2 and A.3 for detailed analysis on these topics). In Regression (2) of Table 3, we control for emotions (elicited in Part 2), as well as ambiguity (elicited in Part 4) and risk attitudes (elicited in Part 5), demographics and other related variables (questionnaire – Part 6). Regression (2) shows that the difference in donations among treatments SIM and SEQ-NOINFO still persists (and, in fact, becomes even stronger) when these controls are included. [17] These observations lead to our first main result.

Result 1. Total donations generated via collaborative fundraising (SIM) are significantly higher than those raised in independent fundraising (SEQ-NOINFO).

Table 3. OLS Regressions with and without control variables (for Part 1)

Dep. Var : TotalDonationPart1	(1)	(2)
sim	9.80***	10.92***
	(3.23)	(3.26)
seq-lowinfo	2.96	3.08
	(3.39)	(3.43)
seq-fullinfo	6.44**	7.72**
	(3.04)	(3.55)
constant	25.95***	7.73
	(2.18)	(24.47)
Controls added	NO	YES
N	187	187
R^2	0.05	0.28

Note: * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%. Robust standard errors in parentheses.

[17] Since most of the control variables turn out to be statistically insignificant, we do not show the controls in Table 3 to simplify the presentation. A detailed analysis of control variables is presented in Appendices A1-A3, where we study the correlation of donations with emotions, ambiguity and risk attitudes, and the variables from the questionnaire.

Next, our aim is to understand whether the difference in donations between collaborative and independent fundraising mechanisms could be due to different levels of information potential donors possess at the time they decide about their donations. Recall that independent fundraising (SEQ-NOINFO) is associated with subjects' lack of information about the identity and the number of charities prior to their donation decisions whereas a full information structure is present in collaborative fundraising (SIM). We now analyze the impact of prior information on total donations, specifically whether information can be a reason for why collaborative fundraising outperforms independent fundraising in attracting donations.

Table 2 shows p-values associated with Mann-Whitney tests for all pairwise comparisons. One may think the reason behind donations being lower in the SEQ-NOINFO relative to the SIM treatment is that individuals do not know how many donation requests they will receive. Interestingly, Table 2 shows that total donations in treatments SEQ-NOINFO and SEQ-LOWINFO are not significantly different from each other. This is confirmed through the regression analyses, in Table 3 (in which the coefficient on SEQ-LOWINFO is insignificant). Hence, revealing only the number of requests in advance does not result in any significant change in total donations when requests arrive sequentially. On the other hand, revealing the identity of charities from which sequential requests to arrive does make a difference. According to Table 2, total donations increase from SEQ-NOINFO to SEQ-FULLINFO, and this increase is statistically significant at the 5% level. Table 3 provides additional evidence, at the 5% significance level, that total donations in SEQ-FULLINFO are higher than the total donations in SEQ-NOINFO (even when emotions, ambiguity and risk attitudes, as well as other related factors from the questionnaire are controlled for). Moreover, as depicted in Table 2, between Treatments SIM and SEQ-FULLINFO where the information structure is the same, the difference in donations is not statistically significant. Result 2 summarizes these findings and leads us to the conclusion that full information is the main driver behind the collaborative fundraising mechanism's (SIM) better performance relative to the independent fundraising (SEQ-NOINFO) in attracting donations.

Result 2. Providing partial information (regarding the number of charitable requests) does not lead to higher total donations when requests arrive sequentially, but providing full information significantly increases total donations. As long as full information is possessed at the time donation decisions are made, total donations do not significantly change depending upon whether requests arrive sequentially or simultaneously.

3.2 Does the Order of Requests Matter for Donations to Individual Charities?

Our previous analyses focus on total donations to understand how different fundraising mechanisms affect the charitable sector as a whole. We now study the relationship between the order of requests (early versus late arrival) and donations to individual charities in each fundraising mechanism.[18] Note that, for the SIM treatment, early (late) corresponds to being at the top (bottom) of the list. For all the other treatments, early (late) request means donation request received at an early (late) stage. Analyzing whether and how this relationship varies with different fundraising mechanisms could also shed light on why these mechanisms differ in attracting donations.

Figure 1 shows the mean donations to individual charities for each order under each treatment. We see that donations to early requests do not differ much between the SEQ-NOINFO and SIM treatments.[19] In contrast, late requests in the SEQ-NOINFO treatment generates much lower donations compared to the SIM treatment. While we observe a significant order effect in the SEQ-NOINFO treatment, we do not observe order effect in the other treatments. Controlling for the identity of the charities as well as other variables that might influence donation decisions, we run OLS regressions (not shown here), separately for each treatment and find that the order of requests matters only for the SEQ-NOINFO treatment and this effect is statistically significant at the 1% level. For treatments

[18] This section reports our results on donations to individual charities. We have also studied whether different treatments lead to different fraction of positive donations. We do not see any significant differences at the extensive margin (see Appendix B).

[19] In fact, when we regress donations on treatment dummies taking into account only the early donations, we find that none of the treatment dummies are statistically significant at the 95% confidence level. Alternatively, an OLS regression (not shown here) with treatment dummies as well as interactions of these dummies with the "order" of requests confirm that early donations in the SEQ-NOINFO treatment are not significantly different than early donations in any of the other treatments.

SIM, SEQ-NOINFO, SEQ-LOWINFO and SEQ-FULLINFO, p-values are 0.88, 0.00, 0.29 and 0.14, respectively.[20]

Given that the order of requests does not have a significant impact on donations to individual charities in treatments SIM, SEQ-LOWINFO and SEQ-FULLINFO, one can conclude that in these fundraising mechanisms, it does not really matter where a charity is presented in the donation stage(s). In the SEQ-NOINFO treatment, however, we see a strong effect related to the order of solicitation arrival: subjects donate large amounts to early arrivals (similar to donation levels in the SIM treatment), but then their donations drop rapidly (especially after the 3rd request).

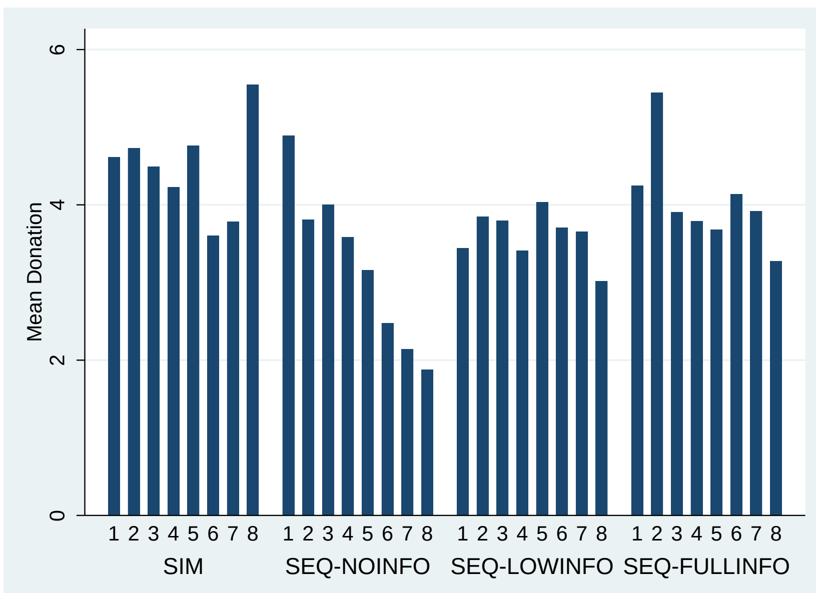

Figure 1

Next, we compare the SEQ-NOINFO and SEQ-LOWINFO treatments to gain insight on whether partial information has an impact on donation behavior at all. Remember that these two treatments differ only in the information available to subjects regarding the *number* of charities: in the SEQ-LOWINFO treatment, subjects know the number of charities in

[20] Our analysis here controls for the identity of the charities. To see how donations differ among different charities, see Table B.1 in Appendix B. Note that our aim in this subsection is not to study the order effect of different causes. Our experimental design ensures that this order is randomized for each subject. Instead, we aim to study the effect of early versus late solicitation requests on generated donations controlling for the identity of charities. Since the order of charities is randomized for each subject, order effects due to different causes are expected to cancel out on average.

advance whereas in the SEQ-NOINFO, they do not. Even though total donations attracted do not differ significantly across these treatments, how subjects respond to individual requests differs significantly. While we observe a significant order effect in SEQ-NOINFO, order effect is absent in the SEQ-LOWINFO. Knowing the number of requests to come in advance, subjects in the SEQ-LOWINFO donate evenly over them.

Result 3. A significant order effect of solicitation requests is present *only* in the SEQ-NOINFO treatment, where donations to early requests are large and then drop rapidly in later stages.

Result 3 shows that the number of upcoming requests influences the distribution of total donations. When the number is known in advance, subjects allocate their total donations more evenly across individual charities and the order of requests becomes unimportant. Moreover, this result also suggests that charities that perform collaborative fundraising do not need to worry about the order in which their charity is listed on the donation page.

4 Additional Findings

In this section, we study whether and how subjects update the donation amounts they have chosen in Part 1 of the experiment when they are given a chance to revise them in Part 3. In line with our main analyses, we first focus on total donations and then study order effects by examining donations to individual charities.

4.1 Revised Total Donations

In Part 3 of the experiment, subjects are presented with a screen that shows the donation decisions they have made in Part 1 for each of the eight charities and are asked to enter their revised donation decisions on the same screen simultaneously. The aim of Part 3 is simply to see how individuals react to a surprise second chance under different fundraising techniques.

There might be several reasons why subjects may want to revise their donation decisions.[21] Subjects might revise their donations just because they are asked to (*i.e.*, experimenter-demand effect). Another possibility is that asking for emotions between Parts 1 and 3 may have played a role. When we ask subjects in Part 2 to think about the emotions they felt during Part 1, some indicated that they felt guilt, pity, sadness, *etc*. Being encouraged to think about their emotions and given a chance to revise their donations right after might lead subjects to increase their donations while revising. These two factors are present in all treatments and therefore they are expected to influence all treatments similarly. A third possible reason for the revisions could be the absent prior information. This factor is present only in treatments SEQ-NOINFO and SEQ-LOWINFO and, hence, it is expected to yield different revision amounts across treatments. We conjecture, among all four treatments, the largest amount of revisions to happen in the SEQ-NOINFO treatment where subjects are not provided with any information (regarding the total number of charities and the identities of subsequent charities) in advance.

Table 4 shows the mean and median of *revised total* donations to all eight charities as well as standard errors in parentheses for all treatments. Comparing total donations in Part 1 (Table 1) and the revised total donations in Part 3 (Table 4) shows an increase in total donations from Part 1 to Part 3 in all treatments. [22]

[21] Given our Result 2 and the fact that all subjects have reached the same full information level by the beginning of Part 3, the revisions in SEQ treatments cannot be attributed to the simultaneous donation structure in Part 3.
[22] The surprise question in our design allows subjects to revise their donations downward as well. The majority of subjects are observed to revise upwards, not downwards.

Table 4. Summary Statistics for Revised Total Donations in Part 3

	Revised Total Donations in Part 3		No. of obs.
	Mean	Median	
SIM	36.84 (2.40)	47	44
SEQ-NOINFO	30.55 (2.26)	30	47
SEQ-LOWINFO	30.07 (2.47)	31	42
SEQ-FULLINFO	34.06 (2.07)	40	54

When comparing total donations in Parts 1 and 3, our main focus is not whether *there is a revision* for a given treatment but rather to see how the *magnitude of revisions* differs between treatments. A formal analysis of this comparison is presented in Table 5: total donations in Part 1 of all treatments significantly increase when subjects are given a chance to revise in Part 3. The biggest and most significant increase is observed in treatment SEQ-NOINFO, while the increase in SIM is the smallest in magnitude compared to other treatments (and significant only at the 10% level).

Table 5. Comparisons of donations in Part 1 and Part 3

	SIM	SEQ-NOINFO	SEQ-LOWINFO	SEQ-FULLINFO
Mean difference (Standard error)	1.091 (0.506)	4.606 (1.049)	1.167 (0.664)	1.671 (0.676)
Median diff.	0	3	0	0
p-value	0.058	0.000	0.067	0.022

The p-values come from Wilcoxon signed-rank tests.

To make a statistical comparison between the magnitudes of the increases we observe in each treatment above, we use Mann-Whitney tests (not shown). We find that the increase in SEQ-NOINFO is significantly greater than the increase in SIM at the 1% level. A similar comparison reveals a significant difference between the increases in SEQ-NOINFO and the other treatments at 95% confidence level, whereas none of the remaining pairwise comparisons of the increases are significantly different from each other.

Result 4. When subjects are given a chance to revise their donations, they increase their total donations in all treatments. The largest increase is observed in SEQ-NOINFO.

According to Result 4 above, the largest revision in total donations is observed between Parts 1 and 3 of the SEQ-NOINFO treatment—consistent with the intuition that subjects are correcting their previous donation decisions when they were not fully informed. The differences in the amounts of revisions among collaborative (SIM) and independent (SEQ-NOINFO) mechanisms stay statistically significant even when emotions are controlled for (see Column (3) of Table A.2). This strengthens our conclusion that informational differences among treatments are the main driver for the differences we observe among treatments.

Given that subjects increase their total donations at different rates in all treatments, we now check whether revised total donations in treatments are still significantly different from each other. One would expect the gap between donations to disappear among the treatments once the informational differences disappear. Surprisingly, however, Table 6 shows that even after donations are revised, a difference in total donations at the 5% significance level still exists between treatments SIM and SEQ-NOINFO: revised total donations in SIM are significantly higher than those in SEQ-NOINFO as before. Moreover, comparing the revised total donations in Treatments SIM and SEQ-FULLINFO, which share the same information structure initially, reveals again no significant difference. OLS regressions also confirm these results (see Table 7).

Table 6. Pairwise Comparisons of Total Donations in Treatments in Part 3

	SEQ-NOINFO	SEQ-LOWINFO	SEQ-FULLINFO
SIM	0.027	0.034	0.193
SEQ-NOINFO		0.914	0.278
SEQ-LOWINFO			0.257

Each cell reports the p-value from a Mann-Whitney test.

Table 7. OLS Regressions with and without control variables (for Part 3)

Dep. Var : TotalDonationPart3	(1)	(2)
sim	6.29*	7.20**
	(3.30)	(3.34)
seq-lowinfo	-0.48	-0.81
	(3.35)	(3.37)
seq-fullinfo	3.5	4.62
	(3.07)	(3.61)
constant	30.55***	2.43
	(2.26)	(23.01)
Controls added	NO	YES
	187	187
R^2	0.03	0.28

Note: * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%. Robust standard errors in parentheses.

Result 5. The difference in total donations between independent (SEQ-NOINFO) and collaborative (SIM) fundraising persists even when subjects are given a chance to revise their donations. More precisely, collaborative fundraising continues to attract significantly more total donations than independent fundraising even after revisions.

One possible explanation for this persistent gap in total donations could be a reference effect (Tversky and Kahneman, 1991; Masatlioglu and Ok, 2005, 2014).[23] Subjects might perceive their donations in Part 1 as a reference point and make revisions accordingly. Therefore, starting with a lower reference point, total donations in SEQ-NOINFO cannot reach the levels in SIM and as a result, while lower in magnitude, the gap remains.

One might argue that independent fundraising would indeed do better in reality (as opposed to our Part 1 findings), as individuals always have a chance to update their decisions in real life by going back to the charities and making additional donations. By giving subjects the opportunity to change their donation decisions, Part 3 of our experiment takes this possibility into account. Therefore, this feature enriches our design and strengthens our real-life applications showing that collaborative fundraising still outperforms independent fundraising even when revisions are possible.[24]

4.2 Does the Order of Requests Matter in Revising Donations to Individual Charities?

Results from Section 4.1 show that, when given a second chance, subjects increase their total donations in all treatments with the largest increase observed in the SEQ-NOINFO treatment. We now analyze revisions in donations to individual charities.

The horizontal axis in Figure 2 shows different donation requests (for each treatment) with one corresponding to the first donation request, two corresponding to the second donation request, *etc*. The vertical axis shows the mean revision in donations. Figure 2 also confirms that subjects in the SEQ-NOINFO treatment increase their overall donations more compared to the other treatments. Interestingly, the increase takes place mostly for the charities that were presented in later stages in Part 1. In other words, subjects in the SEQ-NOINFO treatment also even out their donations, at least to some extent. While this suggests a possibility that the order of requests does not matter for donations in Part 3,

[23] See Ericson and Fuster (2014) for an overview of reference dependence.

[24] It is possible that the reason we see reference dependence is due to some subjects trying to be consistent with their Part 1 choices. These individuals might choose not to revise their donations. In fact, in real life donations, we also do not see individuals to make more than one donation to a given charity in a short period of time. Therefore, this alternative explanation would also imply a persistent gap between independent and collaborative fundraising techniques.

when we perform an OLS regression analysis (not shown here), we find that the order effect in the SEQ-NOINFO treatment is still present at the 5% significance level. Nevertheless, the magnitude of this order effect is much smaller compared to that before revisions (the coefficient in front of *order* changes from -0.36 to -0.14). Similar to Part 1, we do not find statistically significant order effect of requests in any of the other treatments (p-values are 0.73, 0.14 and 0.15 in treatments SIM, SEQ-LOWINFO and SEQ-FULLINFO, respectively).

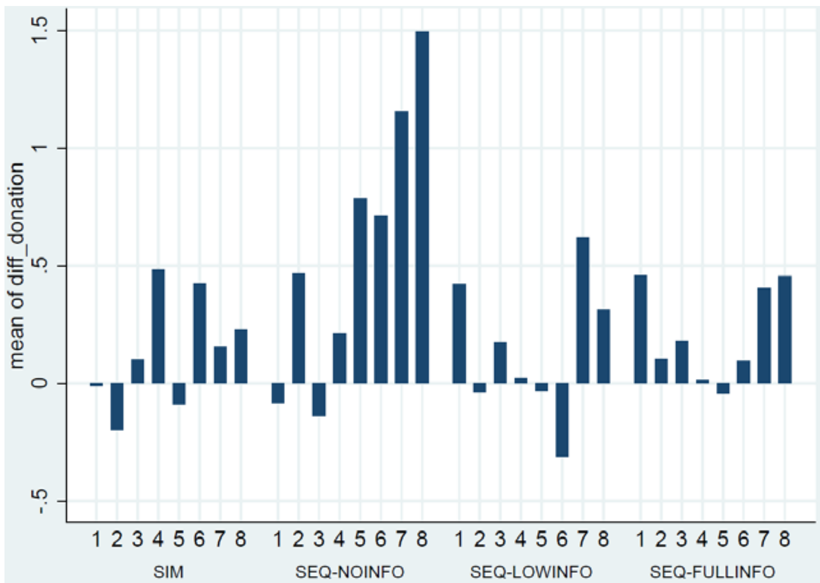

Figure 2

5 Conclusion

In this paper, we focus on two fundraising mechanisms: independent fundraising where donation requests arrive sequentially with no information at all regarding forthcoming requests and collaborative fundraising where all donation requests arrive simultaneously. We experimentally compare performances of the two mechanisms in generating donations and find that collaborative fundraising outperforms independent fundraising. This result persists even when we control for emotions, ambiguity and risk attitudes as well as demographics. To understand the underlying reasons behind this difference, we introduce treatments where we vary the informational structure. We find that total donations do not change when partial information regarding the number of charities is provided, but significantly increase when full information regarding charities to send donation requests is provided to subjects before the sequential arrival of any requests. Moreover, there is no difference in total donations between collaborative fundraising and independent fundraising with full information. Hence, the lack of information in independent fundraising regarding the upcoming donation requests is likely the cause for its underperformance relative to the collaborative fundraising mechanism. In addition, we study whether early versus late arrival of solicitation requests matter. We show that the order of requests matter only in the independent fundraising, but when individuals are provided with information regarding the number of charities, this effect disappears.

We interpret these results in the following way. The fact that we do not observe any difference in total donations between SEQ-NOINFO and SEQ-LOWINFO suggests that individuals might have a mental budget for charitable donations. While we see the same total donations between these two treatments, we also see a difference regarding how these donations are distributed across different solicitation requests. When individuals know how many solicitation requests they will receive, they allocate their donations evenly across requests. While individuals may have a mental budget for charitable giving, our additional treatments confirm that this budget does not need to be fixed. In both SEQ-NOINFO and SEQ-LOWINFO treatments, since individuals are not aware of the identities of the upcoming charities, they seem to save part of their charitable budget thinking that a "better" charity may show up later. This tendency does not exist in SEQ-FULLINFO and SIM treatments, and hence, total donations generated in these two treatments are higher.

According to the additional novel feature our design offers, subjects receive a second chance to revise their initial donation decisions. Our findings reveal that total donations in all treatments increase when subjects are given a chance to update, but donations are updated the most in the independent fundraising scenarios. Nevertheless, collaborative fundraising still outperforms the independent one even after revisions. This suggests that earlier low donations in independent fundraising might be creating a reference point and individuals do not fully adjust their giving behavior even when they are offered a revision possibility.

During the course of writing this paper, we became aware of a working paper that compares simultaneous and sequential fundraising (see Vance-McMullen (2017)). Both the methodology and the main focus of Vance-McMullen (2017) differ from ours. Vance-McMullen conducts a survey experiment with Amazon Mechanical Turk participants and studies how independent and collaborative fundraising techniques affect donations to lesser-known charities relative to more well-known ones.[25] In contrast, our paper provides a real donation laboratory experiment with all subjects making incentivized decisions. More importantly, we study the role of informational asymmetry in explaining the differences observed between these two mechanisms.

Our results have important policy implications for the charitable sector. Competition through independent fundraising does not help individual charities. While early requests generate more funds relative to late requests under independent fundraising, we observe no evidence for early charities benefiting from independent fundraising relative to the case if they had instead participated in a simultaneous fundraising. Moreover, competition hurts the charitable sector as a whole (total donations are lower in independent fundraising relative to collaborative fundraising). That being said, we acknowledge that collaborative fundraising faces challenges. First, the success of collaborative fundraising depends on whether similar or dissimilar charities (in terms of their missions) are participating. Our experiment uses charities that do not share a common mission. If, instead, similar charities participate in collaborative fundraising, these charities could be judged as substitutes, and the impact of collaboration on donations could differ from that observed here. Our paper shows that collaborative fundraising with dissimilar charities improves donations, whereas Vance-McMullen (2017) does not find higher donations under collaborative fundraising when similar charities collaborate in fundraising.[26] Charities should take this into

[25] In order to study this question, different from our paper, Vance-McMullen includes organizations with similar mission types. In particular, she uses four mission types in the broad areas of health and human services. Within each mission type, she selects three charities with identical causes.

[26] Vance-McMullen finds no significant differences in total donations between simultaneous and sequential fundraising techniques when similar charities participate, but less well-known charities perform worse under simultaneous donations.

consideration while designing collaborative fundraising events as well as when deciding which fundraising techniques to use. Second, it is unrealistic to expect full collaboration, *i.e.*, not all charities will participate in collaborative fundraising events. Therefore, at a given time, collaborative fundraising events may be accompanied by additional opportunities to give independently to other non-participating charities, and this may mitigate the effectiveness of collaboration. Our paper does not make any claim on the feasibility of full collaboration in reality. Concentrating on the two extreme scenarios of fully collaborative and fully independent mechanisms, this paper sheds light on how the attracted donations might be increased via additional participation by charities in collaborative fundraising efforts and provides a foundation upon which further lab or field experiments might build.

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She argues that individuals compare charities with similar missions more strongly in the simultaneous treatment and, therefore, this creates a disadvantage for low familiarity organizations. This is consistent with why in her experiment simultaneous fundraising does not significantly increase donations as in our study.

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