What Determines Online Charitable Giving to Pandemic Victims? Evidence from a Field Experiment on Choice Overload & the Deservingness of Beneficiaries *

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Abstract

In the wake of unprecedented natural disasters, online giving can be an important source of aid, especially in developing countries with weak social safety nets. Yet, in these contexts, there is little evidence on the optimal way to elicit donations. We investigate the impact of randomizing choice set size and quasi-randomization of beneficiary characteristics on the propensity and size of donations in the context of a COVID-19 mutual aid platform in Indonesia, . We find that users assigned to a smaller choice set of potential beneficiaries are more likely to make a donation. This leads to higher average donations in smaller choice set groups as compared to larger choice set groups. Remarkably, we find no significant decrease in the amount transferred per donation. We also find that donors are more likely to donate to self-reported breadwinners and females. Our results suggest that donors are susceptible to choice overload and identity markers.

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1 Introduction

Non-profits raise hundreds of billions of dollars annually from individual giving, and the proportion of those that give through online channels has been growing (Paxton 2020, Clark et al., 2019). During the Covid-19 pandemic, online giving has become the first response channel of choice for individual donors, and 13% of total US non-profit funds now come from online sources (Blackbaud, 2021). Online giving could play an especially important role in supplementing state-provided disaster response in developing countries, especially in the immediate aftermath of crises or disasters. Developing countries often lack robust social safety nets but, at the same time, have experienced huge increases in the uptake of e-payment platforms that could potentially be leveraged to disburse funds to needy beneficiaries.

Yet, this potential might be compromised by the increasingly large numbers of online causes that one can donate to and the large number of potential beneficiaries in the wake of disasters/crises. A large literature on choice overload (E.g. Iyengar & Kamenica 2010) and the identifiable victim effect (e.g. Small, Lowenstein & Slovic 2007) suggests that the provision of more choices might lead to a decrease in donations. In contrast, however, previous studies in the social psychology literature have shown that a larger choice set increases aggregate donation size but donations in these settings have either been made not towards individuals but substantively different charitable causes/issues (Wiesz & Cikara 2020) where considerations of empathy or fairness, two key drivers behind the identifiable victim effect, might be weaker, or resolving personal hardships unrelated to broader disasters (Sharps & Schroeder 2019). Hence, the optimal way to maximize charitable donations for disaster response in the face of *choice overload* remains an open question.

To address this gap, we partner with an online donation platform based in Jakarta, Indonesia whose explicit objective was to connect potential donors to individuals who had suffered COVID-related job or income losses. In the first two months of operation, the median donation amount is IDR 100,000 (US$7), and the maximum amount was IDR 3 million. In 2020, the platform channeled an estimated amount of ∼IDR 500 million to 1,475 recipients. Uniquely, both donors and beneficiaries in our sample are entirely based in Indonesia[1]. In our partnership, we implement a randomized field experiment on beneficiary choice set size by assigning potential donors to view a display of 3, 8, or 10 beneficiary cards whereby each beneficiary card contains a short narrative description of beneficiary circumstances and characteristics including, among others, their previous job and how they would put the donation to use. From these beneficiary-card narratives, donors are free to choose which beneficiaries(s) to donate to and the amount to donate. Importantly, each card has an equal chance of being displayed and hence, by encoding a rich set of beneficiary characteristics, we combine set size randomization with the quasi-

[1]This evaluation is run in partnership with Bagirata (`https://bagirata.id`). The experiment is pre-registered on the OSF platform. DOI: 10.17605/OSF.IO/C4XGD

random allocation of beneficiaries (and their characteristics) to study the impact of choice set size and the saliency of identity markers that could maximize both the likelihood and size of donations.

Our core results are consistent with a choice overload framework: we find that a reduction in choice set size leads to an increase in both the donation rate and average donation amount. Donors assigned to a 3 (8) beneficiary choice set are 1.8p.p. (0.7p.p.) more likely to donate to any single beneficiary compared to an average donation rate of 1.6% for donors assigned to a 10-beneficiary choice set. We also find that, on average, donors make donation amounts that are 42% (75%) larger in 3 (8) beneficiary choice sets compared to the 10-beneficiary choice set group. Do higher donation rates come at the expense of lower average donations per beneficiary? Much of the literature on charitable donations have found a mixed pattern of substitution or internal displacement across charitable causes depending on whether the altruism budget is fixed or flexible (Gee and Meer 2019). We test for this in our setting and do not find strong evidence for a substitution effect. Conditional on having made a donation, donors in the smallest choice set group donate about US$0.4-2.5 less per donation than the 10-beneficiary control group and this estimate is not statistically significant albeit, in certain specifications, is somewhat large given the average size of donations in the control group is US$10.63.

To what extent do identity markers of beneficiaries affect the decision of individual donors? We analyze the individual effects of the entire set of displayed beneficiary characteristics on the incidence and size of donations. The ability to use all available information displayed to donors allows us to better alleviate omitted variables concerns typical of observational studies. We find three salient features that donors respond to. First, donors respond positively to longer appeals containing more detailed information about the beneficiaries. Every additional 50 words in narrative length is associated with a 1.3pp increase in donation rate. Second, donors who indicate they are breadwinners are 0.7pp more likely to receive a donation. Third, donors respond to gender markers – beneficiaries with feminine names experience higher donation rates. The effects of other notable demographic characteristics vary: there is no significant effect on donation associated with religion/Muslim names, but beneficiary location matters. Beneficiaries located on the island of Java, Indonesia's most populous island, are generally more likely to receive donations, but being located in the Jakarta capital metropolitan area itself is negatively associated with donation receipts.

The advantages of our setting are two-fold. First, most studies on (online) giving examines charitable giving from rich to poor countries (E.g. Altmann et al., 2019). To the extent that own-country donors are the key demographic most responsive to own-country disasters and the extent to which crises will continue to hit the world in a global manner, our single-country donor-beneficiary setting is important for understanding the contours of future disaster giving in developing countries. This is especially given the saliency of both choice overload and identity markers might differ in cross-country/institutional settings. Second, we innovate by studying differences in charitable giving in response to a *single* natural disaster. By holding broader disaster characteristics constant, we can parse out specific characteristics of beneficiaries that maximize the incidence and size of donations.

Our paper connects to three broad strands of literature. First, a large body of research in psychology and economics finds that a smaller choice set is associated with greater participation in various markets. These studies include evidence that a person's willingness to take up loans (Bertrand et al., 2010) and purchase goods (Iyengar & Lepper 2000, Boatwright and Nunes 2001) decreases when the size of choice set increases. The closest paper to ours, Iyengar and Kamenica (2010) studies the effects of choice set size on the characteristics of alternatives chosen by in-dividuals and shows that larger choice sets lead to a greater preference for simpler, less risky options in both hypothetical gambles and allocation of 401(k) plans. Our paper contributes to this literature by extending these results to charitable giving in online settings.

Second, our results provide new evidence to an emerging literature on online giving. This paper is most closely related to Altmann et al. (2019)'s experiment with default options on an online charity platform in Germany. They found that default options induced some people to donate more, although people opted out of donation altogether at a higher default amount. From the same platform, Jayaraman et al. (2020) documented patterns in the donations to disaster reliefs that are consistent with donor fatigue: donations tend to dry up after an initial surge of generosity. Our study contributes to this literature by showing that choice set size, an important aspect of the structure of online giving platforms, can strongly influence donation outcomes. This is especially important given that the marginal cost of listing an additional beneficiary, once beneficiaries have signed up to a platform, is close to zero.

At the same time, our results point to the limits of extrapolation of findings on charitable actions from laboratory and convenience samples. Sharps & Schroeder (2019) and Weisz & Cikara (2020) showed donations increase with the number of recipients, which diverges from our findings. Furthermore, unlike Sharps and Schroeder (2019), we do not find evidence that donors prefer to allocate donations equally across requesters. These studies used U.S. MTurk worker samples, who are willing to be compensated with US$1 or less to participate in studies. Goodman et al. (2013) compared MTurk workers with community respondents to show that they have greater materialistic values than community participants. In contrast, our experiment is embedded in a real-world donation platform, where we can naturally observe individual donor behaviors.

Last, we contribute to the empirical literature on discrimination. In particular, a recent literature studies the prevalance of discrimination in various online microlending platforms. Jenq et al. (2015) used data from the platform Kiva to show that lenders favor more attractive, lighter-skinned, and less obese borrowers. Similarly, Pope and Sydnor (2011) documented racial discrimination on Prosper.com, where listings with Black people in the picture were less likely to be funded. An important difference, however, is that we draw our data from a Covid-19 donation platform and hence, provide novel evidence of what drives charitable, no-strings-attached giving to needy individuals, not loans. In our setting, we find that women are more likely to receive donations, but information matters too. Our finding that donors favor requesters who mention that they are the breadwinners of their family connects to results by Andreoni (2007) and Cryder et al. (2013).

We organize the remainder of this paper as follows. Section 2 describes the context of charitable giving in Indonesia and the donation platform. Section 3 and 4 provide details of our empirical strategy and results. Section 5 concludes.

2 Context

2.1 Charitable giving and Covid-19 in Indonesia

Indonesia ranked 10th in the World Giving Index that reports aggregate giving behaviors between 2009 and 2018 (CAF 2019). Using data from the Gallup World Poll, Charity Aid Foundation reported that in 2018, 78% of respondents in Indonesia donated money, 53% volunteered their time, and 40% helped a stranger (CAF 2018). They linked the high donation rate with zakat or Islamic almsgiving, one of the Five Pillars of Islam.

Almsgiving in Indonesia is individualized and primarily informal, with only one-quarter of total zakat contributions channeled through formal organizations (Noor and Pickup 2017). Unless they meet specific requirements (e.g., paid to government-recognized institutions), zakat and other charitable donations are not tax-deductible, and the state does not collect mandatory zakat payments. While the National Board of Zakat reported an overall collection of IDR 6.2 trillion/USD 434 million of alms in 2017, this number represents only 1.6% of the estimated zakat potential that reaches 3.4% of the Indonesian GDP (Baznas 2019).

When the Covid-19 pandemic began spreading to Indonesia, the government first imposed mobility restrictions in Jakarta on April 10th, 2020. By August 2020, the pandemic has negatively affected 29.1 million workers: 0.76 million dropped out of the labor force, 1.77 million furloughed, 2.56 million laid off, and 24 million saw their incomes reduced (Aria 2021). A nationwide survey revealed widespread vulnerability, with half of the households reporting that they have no emergency savings, one-quarter of households pawned their assets to make ends meet, and another quarter of households borrowing money from friends and families (SMERU 2021).

The Indonesian government allocated USD 49 billion from its budget for economic recovery in 2020, which included spending to strengthen its social protection programs. However, gaps remain, especially for the near-poor. Bottom-up initiatives to raise and disburse resources quickly sprung up to fill the gap: Kitabisa, the biggest crowdfunding platform in Indonesia, listed 242 Covid-related fundraisers by April 15th, 2020. These campaigns successfully raised USD 3.5 million by the first week of a city-wide lockdown in the capital.

The pandemic has also increased the adoption of digital financial services (DFS). A J-PAL SEA survey found that 21% of men and 22% of women use DFS for the first time during the Covid-19 outbreak (J-PAL SEA 2020). Combined with existing users, they raise DFS users to 75% of men and 70% of women. A majority of them expect to continue using DFS after the pandemic subsides. As users cite money transfer as one of the primary triggers of use, DFS can facilitate direct giving that could mitigate the effect of Covid-19. In the next section, we describe our partner platform that leverages this potential.

2.2 Bagirata

Bagirata (`https://bagirata.id`) is an online platform based in Jakarta, Indonesia. It was launched in April 2020 as a direct response to the COVID-19 pandemic and it's stated objective was to facilitate unconditional, charitable donations from potential donors to individuals/potential beneficiaries facing Covid-related income and job losses. The platform centers around an online, central beneficiary database where workers facing COVID-induced income and job losses can sign up to join, allowing them to receive donations through the platform. These workers provide their employment status, economic hardship details, financial needs, social media handles, mobile payment QR codes, and other contact details to Bagirata. Volunteers verify these workers' information, and only verified applicants are included in the beneficiary database.

The majority of beneficiaries are workers in the food and beverage sector, with a substantial fraction working as ride-share drivers for popular ride-sharing platforms Gojek and Grab, or in the hospitality and services sector (Table 1). They are mainly located in Greater Jakarta (including Bogor, Depok, Tangerang, and Bekasi), followed by other major cities in Java (Bandung, Yogyakarta, Surabaya, Semarang, Malang), with a small fraction based off Java (mainly Bali and Sumatera). Less than half of the beneficiaries work as permanent employees. On average, beneficiaries ask for slightly less than IDR 2 million ($\sim$ US$ 133). Many describe how they were laid off or had their salary cut as their employers could not afford to retain them or pay their full salary. They describe their families' pressing needs for baby milk or children's school fees, and some described skipping meals to stretch their budget.

Bagirata connects these beneficiaries to potential donors visiting the Bagirata website. Each time a potential donor visits the website, they are presented with a random selection of beneficiaries from the database, from which they can choose whom to donate to and how much (Figure 1). Donors can also refresh their displays to view additional sets of random beneficiaries. Donors then make direct donations to their chosen beneficiary through one of three existing digital payment systems (Go-Pay, Dana, Jenius) and, after having made the the donation, are directed to report the donated amount and donation status in the Bagirata platform.

Who donates in this setting and how do they compare to beneficiaries? Table 2 describes the demographic characteristics of Bagirata donors from a voluntary survey posted on the Bagirata website. Compared to beneficiaries, donors are more likely to be female and unmarried. Donors are also more educated, and nearly one in ten explicitly declared the lack of any religious affiliation. Donors also earn more: the average donor earns four times the average beneficiary's (US$8,626/year vs. US$1,882). Despite this disparity, however, both donors and beneficiaries report allocating a similar percentage of their earnings for charity: 4.9% for donors and 4.3% for beneficiaries – nearly twice the amount of mandatory *zakat* charity of 2.5% that Islam requires its adherents to provide. This figure is even higher for individuals who only filled up our survey: Indonesians in this category report giving up to 8% of their income to charity. These figures are higher than the average 3.7% of income given to charities for donor households in the US (Clark et al., 2019) but we note, that this figure in the US is driven by individuals in the US born between 1928-1945 and 1901-1927 (who respectively gave 3.9% and 8.8% of their income). A more appropriate comparison group of millennials in the US report giving on average only 0.9% of their income. This suggests that, perhaps, due to the lack of social safety nets, altruistic motives for donors in our setting might differ from broader trends in developed countries.

In the first two months of operation, the median donation amount executed through the Bagirata platform was IDR 100,000 (US$7), and the maximum amount was IDR 3 million and, in 2020, Bagirata channeled an estimated amount of ∼IDR 500 million to 1,475 recipients. The Bagirata platform shares similarities with crowdfunding websites such as GoFundMe and Kiva. However, there are two important differences. First, Bagirata's model unambiguously involves unconditional charitable giving (the literal translation of the name is "divide equally" in Indonesian). This is in contrast to platforms like Kiva that operate as a microlending platform. Second, the donation process involves donors giving direct donations to recipients without the use of an intermediary like GoFundMe. In our setting, beneficiaries receive mobile cash, much like transfers from GiveDirectly, but straight from donors.

3 Empirical strategy

3.1 Randomized evaluation

We investigate the effect of beneficiary set size on donation outcomes by implementing a randomized experiment on the platform where, upon entering the website and moving past the landing page, each potential donor is randomly assigned to view a fixed set size of 3, 8, or 10 beneficiaries. Operationally, set sizes are assigned to a potential donor's IP address with each assignment lasting for a duration of three hours. I.e. As long as an individual logs on using the same device/browser, he/she will continue to see the same number of beneficiaries in each choice set. In this manner, donors and sessions in our setting are interchangeable unless otherwise stated.

Each beneficiary is displayed as a card to the donor in vertical successions, and they are randomly selected from the recipient database. At the bottom of each display, donors have the option to 'refresh' the beneficiary set and get a new random draw of the same set size. For example, a donor assigned to the eight-sized group will obtain a new set of eight beneficiaries upon hitting 'refresh.' As discussed above, this randomization persists for a session of three hours, so if the donor closes their browser and revisit the platform within a session timeframe, they will see the same number of recipients with a newly drawn set of beneficiaries. This ensures a consistent user experience on the website and, at the same time, minimizes donors' awareness of the experiment. The experiment ran from October 2020-June 2021.

3.2 Regression specifications

Because the variation in choice set size is randomly assigned, we can estimate its effects on donation decisions using simple OLS. For donor session i seeing beneficiary j in k-th set, with l indexing beneficiary's order within the set and $L \in \{3, 8, 10\}$, we estimate:

$$Donate_{ijkl} = \alpha_1 + \beta_1 SetSize_i + BeneficiaryFE_j + \varepsilon_{1,ijkl} \tag{1}$$

where $Donate$ is either donation indicator or amount and $SetSize$ is an indicator for either the 3- or 8-recipient groups. The ε term is the idiosyncratic error term. Standard errors are clustered at donor- and beneficiary levels to account for possible error correlations within non-nested donor and beneficiary clusters (Cameron et al., 2010). We estimate this equation both without and with the beneficiary fixed effects, with the latter being our preferred specification.

We separately estimate the effect of beneficiary's characteristics on display with the following estimation (same notation as above):

$$Donate_{ijkl} = \alpha_2 + \beta_2 Characteristics_j + DonorFE_i + \varepsilon_{2,ijkl} \quad (2)$$

where $Characteristics$ is a vector of all beneficiary characteristics displayed and considered by donors in the donation process. Broadly, we consider two sets of beneficiary characteristics. The former are inferred from beneficiary names and includes characteristics like gender and religion, and the latter are characteristics we code from beneficiary narratives. These include breadwinner status and indicators for having been laid off from their previous job. As above, the ε term is an idiosyncratic error term. Because we observe all beneficiary characteristics as displayed on the platform, this allows us to alleviate concerns that, in their donation decision, donors might be considering other omitted variables that we do not observe.

The backbone of our analysis is based on Bagirata's full database, which includes their beneficiary roster, session trace, and donation trackers. The session data tracks which beneficiaries are displayed to each donor, self-reported indicators of donation status and amount after the transfer is completed, and unique donor session identifier. Donors are also prompted to disclose their email addresses after donating, although the disclosure is not mandatory. When donors provide their emails, we can link individuals across donor sessions and construct the $DonorFE$ indicators.

We will also augment the regression analysis with Bagirata user survey data. This survey captures a rich set of demographic variables, altruistic behaviors both on the Bagirata platform and beyond, as well as altruistic preferences. The survey sample size is considerably smaller, and analysis of this dataset will be limited to descriptive statistics. The reasons for the small sample are twofold: participation is voluntary, and the survey is decoupled from the main user interaction flow to minimize friction in user experience toward donation activities. In this dataset, we also observe respondents who had not used the platform as a donor or recipient but likely participated in the survey from the link that Bagirata promoted through Instagram and Twitter.

4 Results

4.1 Choice Overload

Choice set size Differences in choice set size matters for both donation outcomes and the size of donations made. We find that donors assigned to the smallest 3-choice beneficiary set size are more than twice as likely to make a donation compared to donors assigned to the largest 10-choice beneficiary set (Table 3 and Figure 2, left panel). Specifically, from a baseline donation rate of 1.6% for the 10-beneficiary choice set,[2], donors assigned to a 3-beneficiary choice set group (8-beneficiary choice set group) are 1.8 p.p. (0.7 p.p.) more likely to make a donation. Only the difference between the 3 and 10-choice set group, however, is statistically significant.

Columns (3) and (4) in Table 3 (and Figure 2, middle panel) shows that this translates into a statistically significant increase in average donations of IDR1699-IDR1972 in the 3-beneficiary choice set group compared to the control group. This is a 75% increase compared to the control group mean of IDR2776. Similar to our results on donation rates, we do not find a statistically significant difference between the 8 and 10-beneficiary choice set group. We hypothesize that these estimates are driven by the conversion of new donors on the extensive margin who wouldn't have otherwise donated[3]. Last, on the intensive margin, conditional on having made a donation, donors in the smallest choice set group donate about US$0.4-2.5 less per donation compared to the the control group, but none of these differences are statistically significant.

The higher donation rate for donors presented with the smallest choice set size is consistent with a choice overload framework. Donors seeing ten beneficiaries may feel overwhelmed evaluating the large number of beneficiaries on display and hence, decide not to donate. In comparison, donors confronted with three beneficiary choice sets face a lighter cognitive load and can better evaluate alternatives on offer. We present two sets of additional evidence in support of this interpretation.

Donor behavior: refresh rates The smallest set size gives donors finer information control. Each time donors are faced with a set of beneficiaries, they can choose to donate or refresh and obtain a new draw of beneficiaries of the same choice set size. This allows us to test whether the display of fewer beneficiaries/donation targets induces donors to actively search for more potential beneficiaries through examining the effect of choice set size on refresh rates. I.e. The number of times a donor requests the website to draw a fresh set of beneficiaries after reaching the last beneficiary card on display. To test this, we aggregate our observations up to the donor-level and estimate the impact of set size on information-seeking behavior using refresh rates as a proxy.

On average, assignment to the smallest 3-choice set induces donors to search for additional donation targets (Table 4 and Figure 3, left panel). Donors in the 3-choice set are twice as likely to hit refresh compared to donors assigned to the largest 10-choice set size (control average: 2.58). Nevertheless, because of the difference in set size, donors in the smallest set size still see the 12 fewer potential beneficiaries overall. There is no significant difference between donors seeing eight and ten beneficiaries at a time. Taken

[2]While this donation rate seems low, this is in line with the conversion rate in the general charitable giving literature as well as in the Betterplace experiment (3.3%). Altmann et al. (2019) also noted that a study on online fundraising sites reported a median conversion rate of just 0.76%.

[3]Similarly Sudhir et al. (2016) finds that individual profiles boost donation in comparison to profiles on groups of beneficiaries during a charity mailer experiment in India

together, this suggests that one mechanism by which choice overload occurs in this setting is that donors might feel overwhelmed by the large number of characteristics from a 10-beneficiary choice set and simply give up looking for additional suitable donation targets.

Beneficiary display order The display order of beneficiaries within a set is also randomly assigned. Hence, we can estimate the impact of display order by including a regressor that indicates the numerical value of the order in which each beneficiary was displayed. Table 5 reports the estimates from this regression. Being placed at the lower end of a set significantly reduced a beneficiary's likelihood of receiving a donation. Column (2) indicates that each lower position leads to a 0.068p.p. decrease in the likelihood of receiving a donation. This means a request randomly placed at the bottom of a 10-set beneficiary display has on average a 26% lower chance of receiving a donation compared to beneficiaries displayed in pole position.

Are these effects driven by cognitive overload? To test this hypothesis, we further split our sample by set size. Columns (3) - (5) show that the average effect in column (2) masks significant heterogeneity across set sizes. The negative coefficient in Column (2) is driven by 8- and 10-beneficiary sets. This suggests that donors make sequential decisions within a set only when faced with large, overwhelming choice sets. Indeed, for the smallest set size, the coefficient estimate is positive, although not statistically different from zero. Table 6 reports similar, albeit mostly statistically insignificant, estimates when we look at the effects of display order on the value of donation made.

4.2 Beneficiary Characteristics

We now turn to the analysis of the characteristics that move donors to send donations. We include in this analysis all beneficiary's characteristics that the donors observe on the platform: demographic characteristics (sex and religion inferred from the name, location, employment sector), donation ask (amount of money needed, duration of need), social media presence (indicators for links to their Facebook, Twitter, or Instagram accounts), e-payment channels (GoPay, Ovo, Dana), and narrative (length of narrative, content). In addition, we code from the narrative whether the beneficiary is perceived to be a breadwinner (based on keywords referring to children, parents, siblings, or being responsible for their family needs).

Figure 4 and Table 7 presents the coefficients from the analysis of beneficiary characteristics on the donation receipt indicator. Both intrinsic and situational characteristics seem to matter to a different degree. Beneficiaries with feminine names tend to receive more donations, but donors also tend to donate more to beneficiaries that provide a more detailed narrative in their ask. Each additional 50 words in the narrative are associated with a 1.3pp increase in donation rate. If they indicate they are the breadwinners, this information is associated with a 0.7pp increase in donation rate. Employment in the education sector (e.g., as teachers, para-teachers, or tutors) is associated with a 1.4pp higher donation rate than workers in the food and service category (the comparison category). On the other hand, information about being laid off or uncertainty in work and the amount of aid the beneficiaries ask have no significant effect on donation outcomes. Similarly, explicitly Muslim names do not have any significant correlation with the donation receipt.

We also see some evidence of how alignment between donor and beneficiaries' characteristics may matter. A key aspect of aid is its delivery channel and payment frictions matter for donors. As most donors use the GoPay platform, beneficiaries also using this platform tend to receive a 2.2pp higher donation rate.

Descriptive statistics on donor-beneficiary matches Beyond looking at beneficiary characteristics, we can obtain further insights using a sub-sample of donor-beneficiary dyads which we are able to link to our voluntary user survey data. Table 9 provides descriptive statistics for two salient markers of identity: gender and religion.

Alignment in religious identity seem to matter more for non-Muslim donors, the minority group in Indonesia, but has little effect on Muslim donors. Non-muslim donors donate to beneficiaries who do not have Muslim names with an average donation of Rp.27,194, a higher amount than the average donation of Rp.20,710 to beneficiaries with Muslim names. Muslim donors are also less likely to donate to beneficiaries with Muslim names (5% for Muslim-named beneficiaries in this subsample vs. 10% for non-Muslim names). As a result, the average donation for Muslim-named beneficiaries from Muslim donors is only about three-fifths of the average donation for non-Muslim-named beneficiaries (Rp. 6,787 and Rp.11,159, respectively).

Alignment in gender identity seems to matter less for all donor types. Both male and female donors donate at a higher rate with higher amounts to beneficiaries with typical woman names. Note, however, that while the statistics in this table summarizes the effects of random pairing between donor characteristics and beneficiary characteristics, we are only able to do this for a limited subsample where we can match activity traces with user survey data. Hence, the dramatically smaller sample size limits our statistical power.

5 Conclusion

This paper documents that donors are susceptible to choice overload in the context of online charitable giving in a developing country context. Donors randomly assigned to a three (eight)-beneficiary choice set are 1.8p.p. (0.7p.p.) more likely to make a donation and, on average, donations made by these donors are 75% (42%) larger in size compared to donors assigned to a ten-beneficiary choice set. At the same time, we do not find a statistically significant decrease in donation size on the intensive margin, suggesting that higher donation rates do not come at the expense of lower average donations. We also find that two salient identity markers of female gender and breadwinner status leads to higher donation rates on average. These findings have implications for thinking about the ways to maximize charitable giving in disaster response.

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Figure 1: An example of a beneficary-card that potential donors view upon clearing the landing page of the Bagirata website. Cards are shown sequentially on the website where users must swipe/scroll down to view the next card in the set.

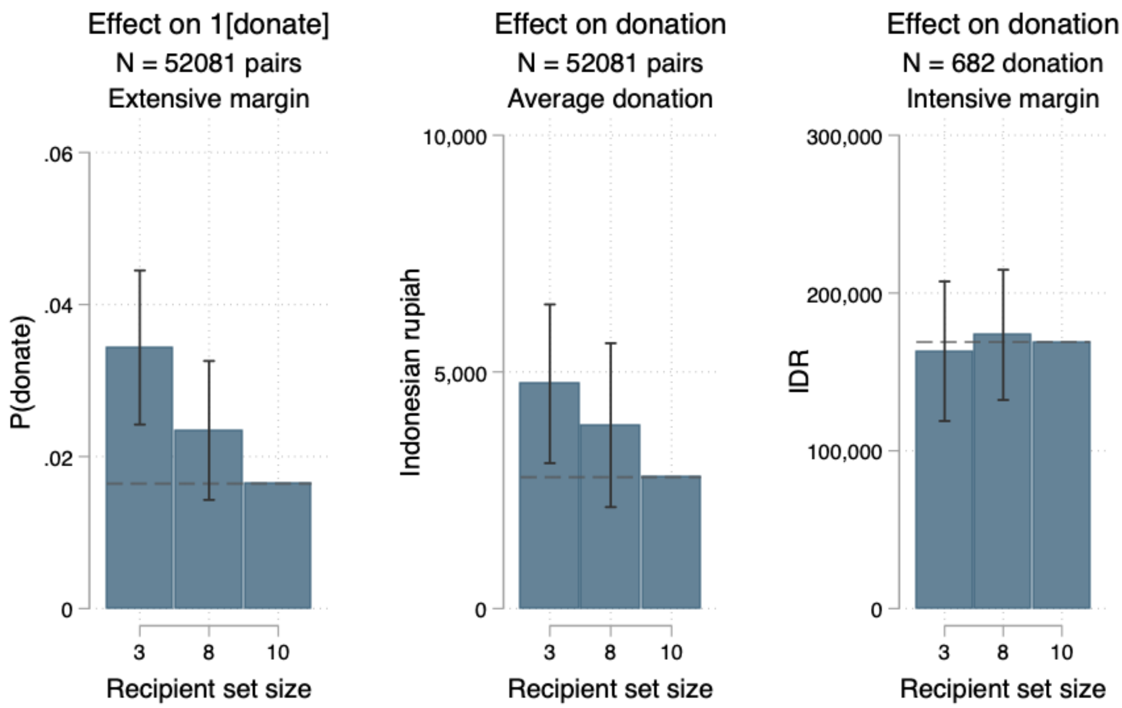

Figure 2: Charts plot the mean for control group (set of 10) plus the coefficient for treatment groups (set of 3 or 8). Coefficients in plot is from $Y_{ijkl} = \alpha_1 + \beta_1 SetSize_i + BeneficiaryFE_j + \varepsilon_{1,ijkl}$, with standard errors clustered at donor session and benefeciary levels. Groups are assigned randomly. The sample uses data from Oct 2020-Jun 2021, excluding outlier donors. Samples for left and center plots are donor-beneficiary pairs, sample for right plot is pairs where donation occurred, excluding singleton beneficiaries. Whisker for each bar indicates the 90% CI.

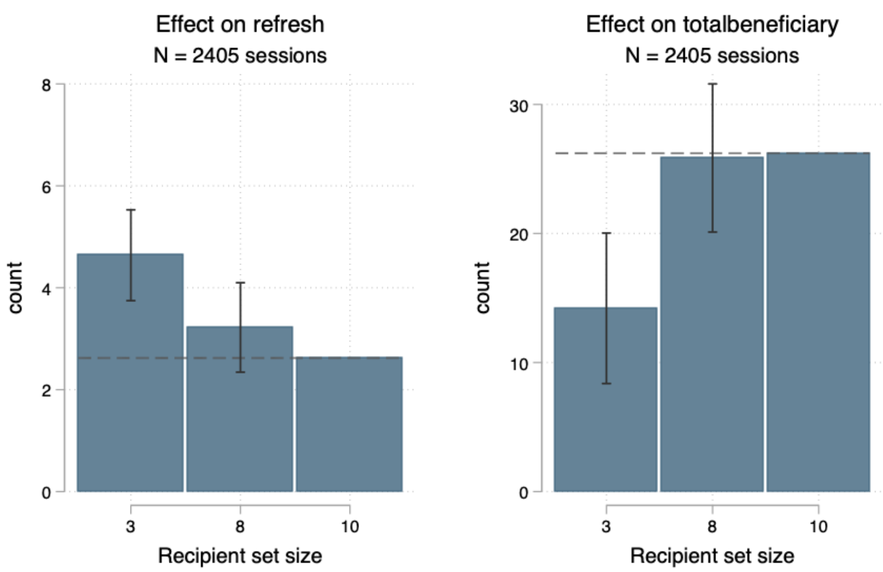

Figure 3: Charts plot the mean for control group (set of 10) plus the coefficient for treatment groups (set of 3 or 8). Coefficients from equation (1). Groups are assigned randomly. The sample consist of donor sessions from Oct 2020-Jun 2021, excluding outlier donors. Whisker for each bar indicates the 90% CI.

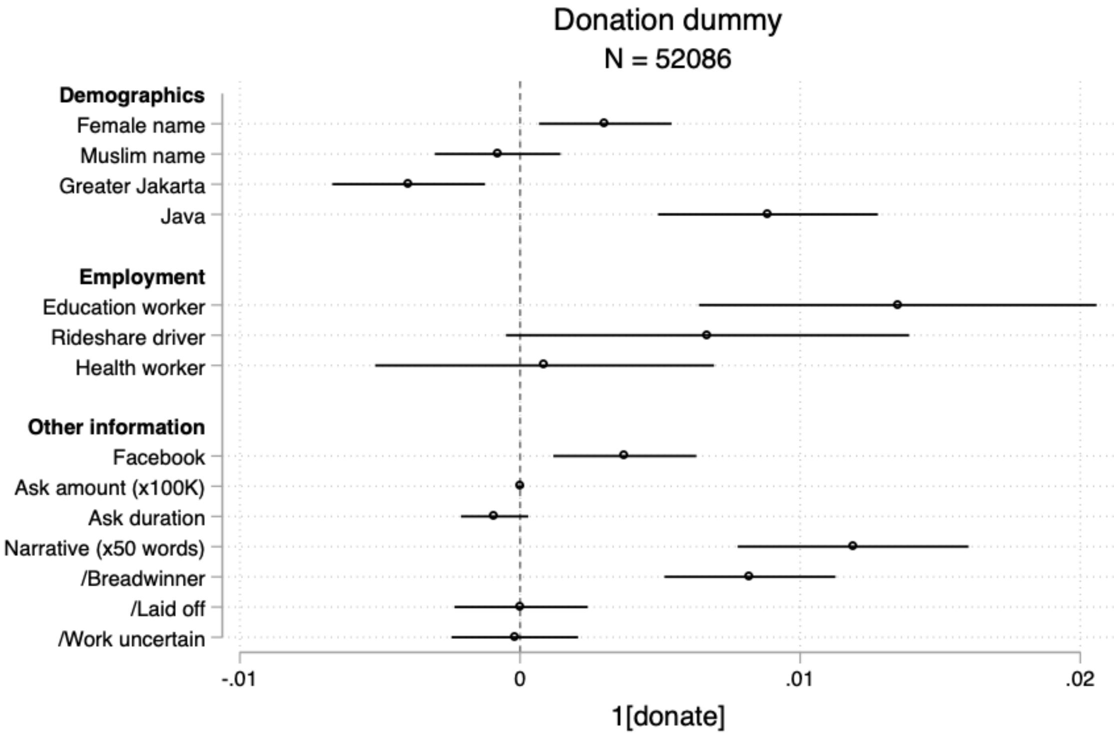

Figure 4: Chart plots coefficients from $Y_{ijkl} = \alpha_2 + \beta_2 Characteristics_j + DonorFE_i + \varepsilon_{1,ijkl}$. Range for each coefficient indicates 90% confidence interval.

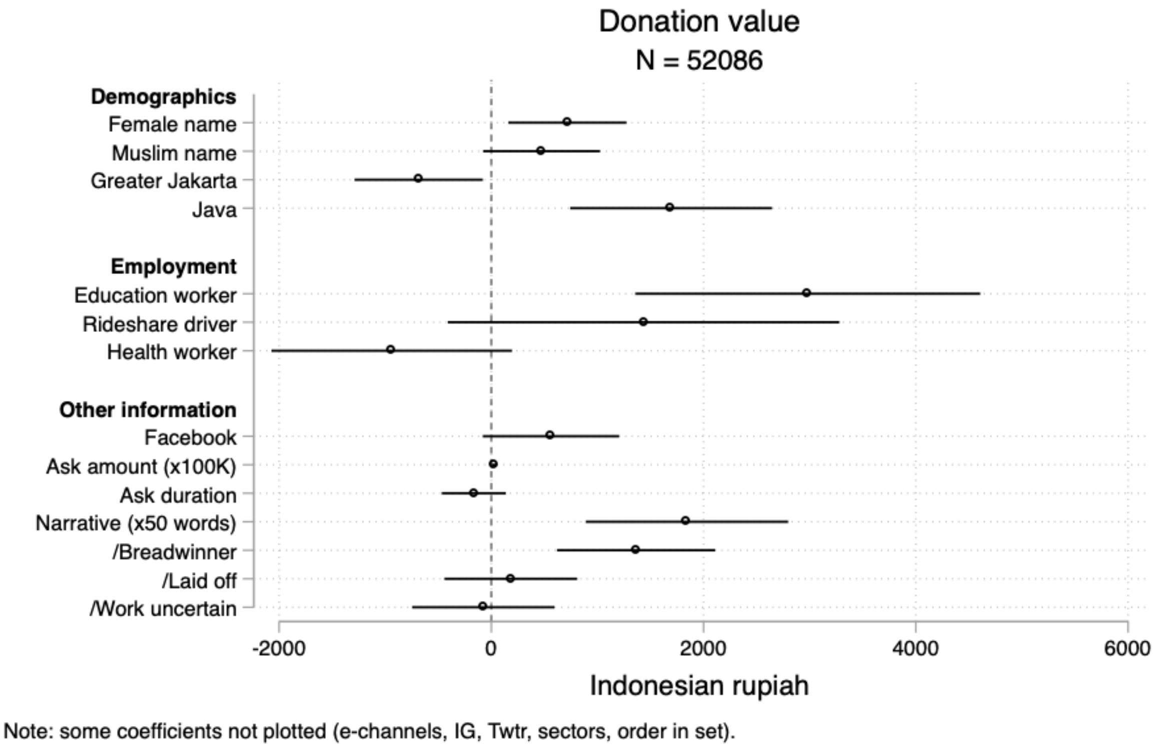

Figure 5: Chart plots coefficients from $Y_{ijkl} = \alpha_2 + \beta_2 Characteristics_j + DonorFE_i + \varepsilon_{1,ijkl}$. Range for each coefficient indicates 90% confidence interval.

Table 1: Applicants and Verified Beneficiaries - Summary Statistics

	(1) All applicants		(2) Verified	
Female	.34	(.47)	.35	(.48)
Muslim	.15	(.35)	.24	(.43)
Christian or Hindu	.037	(.19)	.06	(.24)
Breadwinner	.25	(.43)	.21	(.41)
Greater Jakarta	.69	(.46)	.67	(.47)
Java	.91	(.28)	.91	(.28)
Facebook	.45	(.5)	.44	(.5)
Instagram	.71	(.45)	.77	(.42)
Twitter	.13	(.34)	.15	(.36)
Gopay	.62	(.49)	.64	(.48)
Dana	.39	(.49)	.39	(.49)
Jenius	.089	(.28)	.11	(.31)
Ask amount (USD)	133	(75)	134	(72)
Narrative (x50 words)	.59	(.3)	.6	(.3)
Ask duration (months)	2.1	(.9)	2.2	(.88)
Formal language	.59	(.49)	.59	(.49)
Laid off	.45	(.5)	.46	(.5)
Work uncertain	.58	(.49)	.56	(.5)
Permanent employee	.42	(.49)	.48	(.5)
uber driver	.099	(.3)	.064	(.24)
F&B, hospitality	.55	(.5)	.6	(.49)
Arts	.13	(.33)	.16	(.37)
Education	.032	(.18)	.037	(.19)
Health	.015	(.12)	.017	(.13)
Observations	3549		2054	

Notes: Statistics from beneficiary database until June 2021. Bagirata runs the verification process to ensure each applicants are a real person and fill all requisite fields in the application form correctly. Only verified beneficiaries are displayed to potential donors. Table displays the means and standard deviations (in parentheses).

Table 2: Bagirata User Profiles - Summary Statistics

	All	Donors	Recipients	Survey only
Male	.4	.31	.77	.41
Age	29	28	29	30
Married	.42	.3	.37	.46
Years of education	14	16	13	13
Javanese	.5	.55	.48	.48
Islam	.79	.66	.89	.83
Not religious	.018	.076	0	.0037
Refuse declare religion	.0098	.034	0	.0037
Earning (x2019 GDP/cap)	1	2.2	.48	.76
HH size	3.7	3.2	3.9	3.9
Earning for charity	.072	.049	.043	.08
Donation to bagirata	76,199	373,837	0	0
Donated frm bagirata	16,248	0	422,074	0
Observations	714	145	27	541

Notes: Survey responses from Oct 2020-July 2021. Survey is voluntary and decoupled from donation process (see text).

Table 3: Impact of choice set size on donation outcomes

	(1) P(give)	(2) P(give)	(3) Donation	(4) Donation	(5) Donation| Give	(6) Donation| Give
set=3	0.0174***	0.0179***	1699.0*	1972.9**	-36537.6	-5819.1
	(0.00533)	(0.00517)	(908.7)	(855.2)	(26032.9)	(22468.9)
set=8	0.00686	0.00700	925.6	1099.1	-10027.7	4546.1
	(0.00468)	(0.00466)	(934.9)	(882.8)	(29363.8)	(20959.6)
Constant	0.0164***	0.0162***	2775.7***	2646.2***	168911.1***	150863.3***
	(0.00215)	(0.00208)	(500.9)	(421.1)	(22282.4)	(13757.4)
FE		beneficiary		beneficiary		beneficiary
Observations	52086	52081	52086	52081	1183	682

Notes: Regression of donation outcomes on choice set size with and without beneficiary FEs (even numbered columns and odd, respectively). Observation unit is a donor-beneficiary dyadic pair. Change in observation numbers is due to dropping singleton beneficiaries when running the specification with beneficiary FEs. Columns 5 and 6 are restricted to pairs where donation occurred. Standard errors are clustered at donor- and beneficiary-level, displayed in parenthesis. Sample is from Oct 2020-Jun 2021, excluding outliers. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 4: Impact of choice set size on user behavior and information exposure

	(1) Beneficiaries seen	(2) Refresh
set=3	-12.0***	2.02***
	(3.54)	(0.54)
set=8	-0.36	0.60
	(3.49)	(0.53)
Constant	25.8***	2.58***
	(2.48)	(0.38)
Observations	2405	2405

Notes: Regression of information and behavior outcomes on choice set sizes. Observation unit is a donor session. Sample is from Oct 2020-Jun 2021, excluding outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Impact of display order within set on the probability of donation

	(1) P(give)	(2) P(give)	(3) P(give| Set3)	(4) P(give| Set8)	(5) P(give| Set10)
3.set	0.0154***				
	(0.00270)				
8.set	0.00628***				
	(0.00225)				
Order in set	-0.000724***	-0.000680***	0.000667	-0.000815*	-0.000499
	(0.000247)	(0.000260)	(0.00201)	(0.000444)	(0.000327)
Constant	0.0202***	0.0257***	0.0318***	0.0269***	0.0190***
	(0.00197)	(0.000936)	(0.00377)	(0.00167)	(0.00151)
N	52081	52081	10317	20673	20585

Notes: Regression of 1[donate] on beneficiary order and set counter with beneficiary FE. Observation unit is donor-beneficiary dyadic pair. Standard errors are clustered at donor- and beneficiary-level, displayed in parenthesis. Sample is from Oct 2020-Jun 2021, excluding outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Impact of display order within set on the value of donation

	(1) Donation	(2) Donation	(3) Donation| Set3	(4) Donation| Set8	(5) Donation| Set10
3.set	1757.8***				
	(548.1)				
8.set	1037.8*				
	(551.0)				
Order in set	-61.59	-65.11	551.7	-78.09	-59.59
	(68.60)	(70.64)	(490.0)	(94.25)	(108.8)
Constant	2984.8***	3772.6***	3240.6***	4022.8***	3073.1***
	(438.7)	(266.5)	(953.8)	(362.3)	(522.4)
N	52081	52081	10317	20673	20585

Notes: Regression of donation values on beneficiary order and set counter with beneficiary FE. Observation unit is donor-beneficiary dyadic pair. Standard errors are clustered at donor- and beneficiary-level, displayed in parenthesis. Sample is from Oct 2020-Jun 2021, excluding outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Correlations between beneficiary characteristics and donation outcomes

	(1) donatedummy		(2) value	
Female	0.003**	(0.001)	679.954**	(337.583)
Muslim	-0.001	(0.001)	467.898	(334.776)
Christian or Hindu	0.005	(0.003)	718.764	(773.097)
Breadwinner	0.007***	(0.002)	1174.948***	(445.845)
Greater Jakarta	-0.004***	(0.002)	-742.680**	(367.494)
Java	0.008***	(0.002)	1524.480***	(567.648)
uber driver	0.005	(0.004)	1098.918	(1135.140)
F&B, hospitality	0.002	(0.002)	183.501	(384.538)
Facebook	0.004***	(0.002)	635.261	(388.668)
Instagram	-0.001	(0.002)	-516.183	(536.016)
Twitter	-0.004*	(0.002)	-743.450*	(424.206)
Gopay	0.022***	(0.003)	3574.730***	(649.486)
Dana	0.001	(0.002)	-197.707	(460.972)
Jenius	0.010**	(0.004)	797.520	(660.007)
Ask amount (x100K)	-0.000	(0.000)	12.889	(13.915)
Narrative (x50 words)	0.013***	(0.003)	1993.115***	(581.803)
Ask duration	-0.001	(0.001)	-132.597	(183.467)
Formal language	-0.000	(0.001)	317.418	(301.458)
Laid off	-0.003**	(0.001)	-405.663	(378.159)
Work uncertain	-0.004***	(0.001)	-773.024**	(384.356)
Order in set	-0.001**	(0.000)	-52.102	(52.179)
Permanent employee	0.000	(0.001)	794.236***	(278.695)
Arts	-0.003	(0.002)	-129.528	(456.368)
Education	0.014***	(0.004)	3022.452***	(996.745)
Health	0.000	(0.004)	-1040.204	(717.661)
Constant	0.000	(0.005)	-1141.615	(1096.783)
r2	0.250		0.196	
N	52086		52086	

Notes: Regression of donation outcomes on beneficiary characteristics with donor session FE. Observation unit is donor-beneficiary dyadic pair. Standard errors are clustered at donor- and beneficiary-level, displayed in parenthesis. Sample is from Oct 2020-Jun 2021, excluding outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Bagirata Users Self-Declared Preferences of Donation

	All	Donors	Survey only
Very likely give to Breadwinner	.74	.87	.7
Very likely give to ChronicPoor	.78	.86	.77
Very likely give to Laid off/bad shock	.74	.86	.71
Very likely give to Female	.56	.69	.53
Very likely give to SameEnviron	.61	.58	.61
Very likely give to LessEdu	.46	.52	.45
Very likely give to SameRelig	.56	.46	.58
Very likely give to SameEthnic	.45	.39	.47
Very likely give to OtherDonorPick	.41	.31	.44
Very likely give to Young	.31	.3	.31
Observations	714	145	541

Notes: Survey responses from Oct 2020-July 2021.

Table 9: Donor-Recipient characteristic match

	1[donate]	Donation	N	1[donate]	Donation	N
	Recipient name not muslim			Recipient name muslim		
Donor is not muslim	0.12	27,194	556	0.11	20,710	169
	(0.33)	(123,226)		(0.32)	(76,814)	
Donor is muslim	0.10	11,159	1,045	0.05	6,787	333
	(0.30)	(53,491)		(0.22)	(37,510)	
	Recipient name male			Recipient name female		
Donor is male	0.08	10,358	446	0.12	30,795	220
	(0.28)	(45,023)		(0.33)	(128,780)	
Donor is female	0.08	12,974	965	0.13	18,276	472
	(0.28)	(68,816)		(0.34)	(90,133)	

Notes: Summary statistics of donation outcomes by donor and recipient characteristics. Donor informations from user survey, beneficiary informations from recipient database.