Less is More? Maximizing Charitable Donations during Crises: An Online Field Experiment *

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Abstract

This paper examines the optimal choice set size in an online donation setting. We randomize the number of beneficiaries (3, 8, or 10) per screen (*screen size*) in a field experiment. *Across screens*, the total number and value of donations are highest in the 8-beneficiary treatment (pre-registered). To explore underlying mechanisms, we conduct an exploratory analysis and find that the results are largely driven by differences in refresh rates and beneficiary exposure (choice overload and search behavior). In the 3-beneficiary treatment, donors refresh twice as often but view only half as many beneficiaries compared to the 8- and 10-beneficiary treatments (12 vs 25). *Within screens*, we classify self-written beneficiary narratives using both manual and machine learning methods to extract key characteristics. Beneficiaries perceived as *more deserving* receive larger donations (exploratory). Finally, we observe strong evidence of female in-group bias (pre-registered), likely due to the heightened saliency of female poverty among female donors in a male breadwinner context. This study highlights low-cost choice architecture adjustments to maximize donations.

JEL Classification: D64, O10, C93, D91

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1. Introduction

Nonprofits raise hundreds of billions of dollars annually from individual giving. Globally, the proportion of donors who give through online channels has been growing rapidly (Paxton, 2020; Clark et al., 2019).[1] In particular, in developing countries, peer-to-peer giving through these channels can be an important source of aid. The lack of government infrastructure for making timely transfers (Hanna and Olken, 2018); low setup costs for digital platforms (Bhargava, 2022); and the widespread use of mobile e-payment systems has made it easier for beneficiaries to receive direct aid through mobile transfers (Suri et al., 2023). Yet, most prior work focuses on giving to charitable organizations (Kessler et al., 2019; Schmitz, 2021), and we know very little about what motivates peer-to-peer giving.

Importantly, the optimal number of beneficiaries that should be displayed to elicit the greatest value of donations is not well-understood. Specifically, given the identifiable victim effect,[2] limited donor attention, and an overwhelmingly large number of potential beneficiaries in times of crises, the optimal number of beneficiaries is unclear. Many laboratory experiments in consumer choice find that a smaller choice set leads to decreased choice overload.[3] However, both private consumption decisions (where other-regarding preferences are absent) and the laboratory setting might not be reflective of typical giving. Outside of the laboratory, credible causal estimates of choice set size on the total value of donations are rare.

To this end, we partnered with an online donation platform, in Indonesia, to conduct a field experiment on donor behavior during one of the largest public health crises in modern history: the COVID-19 pandemic. We randomize, at the donor-level, the number of alternative beneficiaries per screen that a donor views (henceforth, referred to as *screen-size*). Specifically, we randomize donors to one of three treatment arms. In each treatment arm, donors view either 3, 8, or 10 potential beneficiaries per screen for the duration of their entire session. The display of beneficiary characteristics are also as good-as-

[1]During the COVID-19 pandemic, nonprofits in the United States derived 13% of their total funding from online sources, with online giving emerging as the preferred response channel for individual donors (Blackbaud Institute, 2021).

[2]At the extreme, the identifiable victim effect would suggest displaying just one beneficiary per screen. See e.g., Small et al. (2007). In the context of natural disasters, however, this would lead to large welfare losses given the number of beneficiaries that would receive zero donations.

[3]See Chernev et al. (2015) for a meta-analysis. Separately, a growing literature studies the effects of number of recipients on donation decisions but nearly all study giving through intermediaries (Corazzini et al., 2015; Schmitz, 2021; Soyer and Hogarth, 2011). Giving through intermediaries largely abstracts away from the identifiable victim effect that is likely to be very salient in peer-to-peer giving decisions. Lastly, the number of choices studied largely vary from one to three: a margin that is less likely to be policy-relevant given negative welfare consequences from ex-ante precluding a large number of potential beneficiaries from receiving donations.

random. The platform's back-end algorithm chooses and displays a random draw of beneficiaries both in and across each and every screen. To preview our results: we find that beneficiaries in 8-screen sizes obtain the highest total value of donations.

The *Bagirata* platform connected potential donors to individuals impacted by COVID-19–related earnings and job losses.[4] Each time a potential donor logs on to the platform, the platform's algorithm selects and displays a random set of beneficiary cards to donors. Donors make donation decisions based on the menu of displayed cards (see Figure 1) and donations are required to be made directly through the digital payment system. Each beneficiary card contains a self-written narrative that details why he/she is asking for a donation. Based on these narratives, potential donors are then free to choose which beneficiary (or beneficiaries) to support and the amount that they wish to donate. Hence, after viewing the first screen, donors can make one of two non mutually-exclusive decisions: (i) they can make a donation to zero, one, or more than one beneficiary and (ii) they can hit the *refresh* button at the bottom of the screen to obtain a fresh draw of cards, the number of which will be identical to the first screen. After viewing the second screen, they are free to make the same decisions, screen-by-screen, ad infinitum or until they close the platform.

[INSERT FIGURE 1 HERE]

Our experimental setup involves two levels of randomization. One at the donor-session level, and another at the beneficiary-level. We leverage this to study (i) the impact of screen size on donor behavior (*between-donor analysis*), and (ii) the determinants of donations within a single donor-session (*within-donor analysis*). At the donor-session level, upon entering the platform, potential donors are randomized to view either 3, 8, or 10 beneficiaries per screen. This process serves as our first level of randomization. At the beneficiary-level, within each donor-session the platform displays a random selection of beneficiaries from its database. This guarantees that the array of beneficiary characteristics displayed to donors both within and across screens is as good as random. This process serves as our second level of randomization.

We note that we can test the effect of varying *screen-size* only in our between-donor analysis, and hence, interpret our results as capturing the effects of variation in the (total) number of alternatives in a donors' choice set, both *within and across screens*. This is due to two aspects of the platform's user interface. First, donors can always advance to the next screen (*refresh*) to obtain a new set of cards and each screen will display a fixed number of beneficiary cards. Second, once donors hit *refresh*, they cannot move back to

[4]This experiment ran from October 2020 to June 2021, at the height of the pandemic in Indonesia.

a previous screen. Hence, taken together, the (number of) beneficiaries in each screen could potentially influence donation decisions in all subsequent screens.

In our *between-donor* analysis, we analyze the effect of *screen-size* on donor behavior (pre-registered). If choice overload overwheming-ly affects donation decisions, we would see the best donation outcomes in 3-beneficiary *screen-sizes*. Leveraging on our between-donor randomization design, we use OLS regressions at the donor-session level to analyze differences in the number and value of donations given. To characterize mechanisms, in *exploratory analyses*, we leverage the platform's back-end database to explore differences in donor behavior. In particular, we focus on refresh rates and the probability of donating in the first screen.

In our *within-donor* analysis, we study the effects of *beneficiary display order, deservingness* (both exploratory analyses), and *in-group bias* on donation decisions (pre-registered). These are low-cost, policy-relevant factors that could further improve donation outcomes. Importantly, note that, due to the platform's algorithm, a beneficiary's (order of) placement within and across screens are as-good-as-random. Hence, we continue to use OLS regressions at the beneficiary-donor dyad level with donor session fixed effects. To study *display order*, we regress donation outcomes on indicators for display order. To study *deservingness*, we leverage comprehensive beneficiary information displayed to donors, including detailed beneficiary narratives.[5] From these narratives we code, both by hand and natural language processing (NLP) based textual analysis, an exhaustive set of characteristics that donors might perceive as signalling different dimensions of deservingness and capturing donor-beneficiary in-group biases.

In our between-donor analysis, we find that the total number donations is highest in the 8-screen size treatment (extensive margin). Specifically, donors assigned to a 8-screen make 0.18 more donations compared to a baseline of 0.36 in 10-screens. This translates into $1.84 higher total donations in 8-screens relative to 10-screens (mean of US$5.79). Importantly, our results do not appear to be driven by a mechanically higher probability that a beneficiary in smaller screen-sizes is more likely to receive a donation. Taken to the extreme, this would be the case if donors across all screen-sizes tend to make one donation per screen. We show, however, that donors across all screen-sizes make multiple donations per screen and donors in our 10-beneficiary screen treatment are significantly more likely to do so.

In an exploratory analysis to understand mechanisms, we test how screen-size influences donor (search) effort by analyzing refresh rates, total beneficiary exposure, and the probability of donation in the first screen (exploratory analysis). We interpret differences in these measures as evidence for donor effort, choice overload, and preference alignment.

[5] See Appendix Table A.1 for examples.

We find that donors in 3-screen sizes refresh 1.87 times more than donors in 10-screen sizes (mean of 4). Yet, they are exposed to only half the number of total beneficiaries (12 vs 25) and are significantly less likely to donate in the first screen relative to 10-screen sizes. In contrast, we find no differences in refresh rates between 8- and 10-screens (and hence, total beneficiary exposure). In addition, we find that 8-screens are the most likely to donate in the first screen.

Taken together, we interpret this as suggesting a concave relationship between screen-size and donation outcomes. These differences appear to be driven largely by differences in donor effort. Donors in 3-screen sizes encounter too few beneficiaries in the first screen and hence choose not to donate. Subsequently, despite refreshing more, the constant, small number of beneficiaries per subsequent screen results in persistently high effort; high search costs; and suboptimal matching of beneficiaries with donor preferences. Hence, 3-screen-size donors eventually give up and make fewer donations than donors in 8 and 10-screen sizes. On the other hand, donors in 8-screens make more donations than 3-screens because of lower search effort and higher preference alignment. Last, donors in 8-screens donate more than 10-screens because they view almost the same number of *total* beneficiaries across screens, but are perhaps less overwhelmed by the relatively lower number of beneficiaries encountered *per screen*.

Turning to our within-donor analysis, we document three main findings. First, we find document that beneficiaries whose information cards appear centrally within a screen are less likely to receive donations (exploratory analysis). Consistent with our main results, this dipping pattern is most pronounced in 8-screens. Second, we find that beneficiaries perceived as more deserving are more likely to receive donations (exploratory analysis). Specifically, those perceived as breadwinners with a dependent child (0.7 pp), those in the education sector (1.3 pp), and those who provided longer narratives (0.5 pp for each 50 words of the appeal) receive more donations. We corroborate this with a natural language processing (NLP) based textual analysis. Last, we find evidence of in-group bias: female donors are more likely to donate to beneficiaries with female sounding names (pre-registered).

In summary, we argue that our findings provide three externally valid insights for policy-makers and online platforms to leverage behavioral heuristics and optimize donor behavior. First, our findings highlight the potential for online donations in developing countries, where low fiscal capacity and high transaction costs of in-person donations make online donations a practical solution to redirect funds during large-scale disasters efficiently. Second, smaller screen sizes streamline information processing, allowing donors to focus more on each option and its characteristics, thereby facilitating more optimal decision-making. Third, minor differences in the amount, type, and presentation of information to donors can make a large difference in donation outcomes.

Overall, our between-donor results suggest that fewer alternatives are not always better. One possible interpretation is that the benefits of greater empathy from the identifiable victim effect are insufficient to outweigh those of greater donor-beneficiary preference alignment. In addition, our within-donor results suggest that, policy-wise it might be more effective to (i) position beneficiaries with the highest marginal benefit of receiving donations at the start or end of the screen, (ii) pre-select and highlight key beneficiaries' characteristics that are expected to attract higher donations; and (iii) leverage context-dependent, in-group biases by matching beneficiaries with similar identities to those of donors.

Our paper makes four novel contributions. First, we contribute to the literature about choice set size on individual decision-making behavior. While existing work has mostly focused on choice set size on consumer choice (Iyengar and Lepper, 2000; Iyengar and Kamenica, 2010; Reutskaja et al., 2011), we focus instead on the effects of the choice set size on charitable giving to individuals (peer-to-peer giving).[6] Specifically, our paper is, to the best of our knowledge, one of the first large-scale field experiments to study the effects of choice set size in charitable giving to individuals. Relative to laboratory experiments, donor motivations in our setting are likely to be more similar to those in other online, peer-to-peer giving platforms. This enhances the external validity of our findings and offers insights for broader applications to altruistic decision-making processes. Specifically, building on the 'voltage effect' (List, 2021), we provide novel, policy-relevant evidence of how concepts studied in the lab can be field-tested and scaled up.

Related-ly, Corazzini et al. (2015) uses a public goods game in a lab experiment to study the effects of number of alternatives on donor behavior. In that setting, donors have a fixed budget constraint and clear strategic considerations due to the receipt of matching monetary benefits making donations. Another related work is Iyengar and Kamenica (2010) who find that less is more: a smaller choice set size leads to more optimal decision-making behavior over asset allocations. In contrast, our paper is, to the best of our knowledge, one of the first to suggest that less is not necessarily more. We show that, in charitable, peer-to-peer giving, displaying a choice set of intermediate size (8-screens) boosts donations on the extensive margin relative to 3-screens by possibly providing a larger number of beneficiaries that are potentially better matches with donor own-preferences. Furthermore, our results demonstrate that the number of donations are possibly a concave function of choice set size: donors in 10-screens make fewer donations

[6] Kiva and GoFundMe are close analogues but both are instances of *conditional* giving. GiveDirectly is an example of unconditional giving but, again, the platform functions as an intermediary that channels donations to beneficiaries only after the donor has completed the donation process.

than 8-screens.

Second, this paper extends work that uses field experiments to study the determinants of charitable giving (Adena et al., 2024; Adena and Hager, 2024). Most prior work studies donations made through intermediaries (charitable organizations).[7] This paper, in contrast, studies peer-to-peer giving which is (i) more accurately viewed as a two-sided market, with donors on one side and beneficiaries on the other; and (ii) where behavioral biases are likely to be more salient given individuals being confronted with real-life beneficiaries. This paper provides the first large-scale evidence of the determinants of *peer-to-peer* giving: a setting that might become increasingly policy-relevant as large-scale crises become increasingly frequent and developing countries continue to struggle with poor digital infrastructure.

Third, we contribute to the literature on how perceptions of deservingness affect altruistic behavior. To the best of our knowledge, our study is the first to examine fairness principles (Konow, 2000; Cappelen et al., 2007) in a real-world field experiment setting. We innovate by presenting donors with a full menu of beneficiaries in a real-world setting, implicitly forcing donors to compare beneficiaries against each other when making donation decisions. This allows us to provide a direct test of the specific dimensions of perceived deservingness that are *comparatively* more important in altruistic decisions.

Fourth, we contribute to a small but growing literature on identity, social distance, and in-group biases in charitable giving (Charness and Holder, 2019; Kessler and Milkman, 2018; Adena et al., 2024). Kessler and Milkman (2018) investigates the positive effects of identity priming of *donors* on generating more charitable donations to the Red Cross. This paper, in contrast, focuses on (i) directed peer-to-peer giving (rather than to organizations) and hence, demonstrates the benefits from ensuring identity concordance between both donors *and* recipients; (ii) shows the potential importance of taking into account the context in which giving takes place, to enhance the efficacy of identity primes on giving behavior. Specifically, Indonesia is one of the most ethnically and religiously diverse countries in the world. Yet, in contrast to much of the literature that would suggest greater benefits from priming ethnic or religious identity, our results on female gender in-group bias show that the overwhelmingly dominant narrative of COVID-19 and predominantly male breadwinners (in Indonesia) increased the relative saliency of female vulnerability to female donors. Hence, our results suggest that, in direct giving, there are potentially greater benefits from adjusting identity primes depending on *both* country and crises-specific contexts.

This paper is organized as follows. Section 2 describes the study context. Section 3

[7] Questions here revolve around factors that either motivate donor decisions or solicitation strategies that charities should adopt to increase donations (see e.g. Filiz-Ozbay and Uler (2019)).

presents our experimental manipulation, data, and order of analysis. Section 4 discusses our main results. Section 5 discusses additional results. Section 6 concludes.

2. Charitable Giving during COVID-19 and Bagirata

Globally, Indonesians rank among the top 10 most prolific givers, with much of this giving taking place through informal organizations (Charities Aid Foundation, 2019; Noor and Pickup, 2017). According to the Gallup World Poll, 78% of respondents in Indonesia donated money, 53% volunteered their time, and 40% helped a stranger (Charities Aid Foundation, 2018).[8] The ubiquity of such giving behavior would play an important role in Indonesian society's largely grassroots-driven COVID-19 response.

On 10 April 2020, in response to the COVID-19 pandemic, the government imposed widespread mobility restrictions in Jakarta in what essentially amounted to a city-wide lockdown. By August 2020, the pandemic and mobility restrictions combined had an enormous impact on the total workforce of 29.1 million workers: 0.76 million dropped out of the labor force, 1.77 million were furloughed, 2.56 million were laid off, and 24 million saw their incomes reduced (Aria, 2021). A nationwide survey revealed widespread vulnerability: nearly 50% of households reported having no emergency savings, with another quarter pawning their assets and a quarter borrowing money from friends and families to make ends meet (SMERU Research Institute, 2021). In response, the Indonesian government allocated USD 49 billion toward, among other measures, spending to strengthen social protection programs. However, gaps remained, especially for the near-poor.

Bottom-up initiatives to raise and disburse resources quickly sprung up. For example, COVID-19–related fundraisers on *Kitabisa*, a popular Indonesian crowdfunding platform, successfully raised USD 3.5 million in the first week of Jakarta's city-wide lockdown. One way it did this was by capitalizing on the increasing trend in the adoption of digital financial services to facilitate direct giving between potential donors and beneficiaries.[9] Our study focuses on one such bottom-up fundraising platform: *Bagirata*. Launched as a response to the COVID-19 pandemic, *Bagirata* is an online platform in Indonesia designed to facilitate direct donations between individual donors and beneficiaries. The beneficiaries are individuals suffering from COVID-19–related income and job

[8]This high level of giving is often linked to *zakat* or almsgiving, one of the five pillars of Islam, the dominant religion in Indonesia. The National Board of Zakat reported an overall collection of IDR 6.2 trillion/USD 434 million of alms in 2017 (Baznas, 2019).

[9]A J-PAL Southeast Asia survey found that 21% of men and 22% of women used digital financial services for the first time during the COVID-19 outbreak (J-PAL SEA, 2020). Combined with existing users, this influx of users raised the proportion of active users to 75% of men and 70% of women. A majority of respondents expected to continue using these services after the pandemic subsided.

losses, and the primary objective of the platform was to enable unconditional charitable donations from potential donors to these individuals.[10]

The *Bagirata* platform shares similarities with popular crowdfunding platforms like Kiva or GoFundMe, albeit with two key differences. First, Bagirata's model centers around unconditional giving. This is distinct from Kiva, which centers around a lending model providing access to affordable loans. Second, the donation process involves direct and personal transfers from donors to beneficiaries, with beneficiaries receiving mobile cash immediately from donors. This is distinct from GoFundMe, where the platform functions as an intermediary between donors and beneficiaries.

At the heart of the *Bagirata* platform is an online, centralized beneficiary database. To be registered as a beneficiary, individuals submit details such as their employment status, economic situation, social media handles, mobile payment QR codes, and contact information to *Bagirata*. This information is then verified by *Bagirata*, and only successfully validated applicants are included in the beneficiary database (a group henceforth referred to as potential beneficiaries).[11]

When a user enters the platform as a potential donor from the landing page, the platform's algorithm randomly draws and presents a set of beneficiary cards (Figure 1, see also Figure A.1 for the landing page). These cards are based on the information provided by registered beneficiaries. In Section 3.1, we discuss how our experimental manipulation leverages this algorithm and how the experience of potential donors differs based on the treatment group to which they are assigned. Potential donors then decide if and how they want to donate. Specifically, after viewing the first set of beneficiaries, donors can make the following decisions that are non-mutually exclusive. First, they can donate to zero, one, or more than one beneficiary from the list on display. Second, they can obtain a new set of beneficiary cards by clicking the *refresh* button at the bottom of the screen. The number of beneficiaries shown in the new draw will be identical to the first screen. In the second screen, they are faced with the same decision-making problem which is repeatable ad infinitum screen-by-screen until they leave the website. Donations are transferred directly from potential donors to their chosen beneficiaries through one of the three popular digital payment systems in Indonesia. After donating, donors are prompted to confirm their donation by reporting the donation amount and donation status on the *Bagirata* platform. Our analysis includes all donations verified in this manner.

To facilitate the donation process, the platform allows potential donors to donate anonymously. The only identifiable information that donors voluntarily provide is their email address. This design has two implications. First, we do not have access to donor

[10] *Bagirata* received coverage from various media outlets; e.g., see https://youtu.be/wrhxL5vfMQQ.
[11] See Table A.1 for a selection of appeal narratives written by beneficiaries.

characteristics. We address this by conducting a follow-up user survey where we collect email handles, thereby enabling us to match a subset of donation data from *Bagirata*'s back-end database to donor characteristics. Throughout the paper, however, our analysis focuses on the full set of donation data. In cases where our analysis uses the subset of matched data, we explicitly state so. Second, we cannot identify a donor that initiates multiple sessions if he/she does not provide an email address. Consequently, such a donor will appear in our dataset as multiple sessions.[12] We discuss the implications of this in the following section.

The beneficiary side of the platform can be described as follows. Each beneficiary is displayed as a compact card (Figure 1), which provides a set of standardized information. This includes the beneficiary's name, occupation, area of residence, and whether he possesses any social media accounts (Instagram, Facebook, or Twitter). Furthermore, it provides a brief narrative on the impact of COVID-19 on the beneficiary's life and the reasons why monetary assistance is needed, outlines the minimum amount of monetary assistance required, and details the duration for which the assistance would be needed. The card also displays the total amount of donations collected thus far as a share of the ask amount and indicates the e-payment channels through which donations can be transferred.

3. Empirical Strategy

3.1. Experimental Manipulation

We administered our experiment to all potential donors who visited the *Bagirata* website during our study period.[13] We manipulate screen-size by randomly assigning potential donors to one of the following three between-subject experimental treatments, featuring a 3-, 8-, or 10-set of beneficiaries.

[INSERT FIGURE 2 HERE]

Upon entering and navigating beyond the landing page, each donor has an equal chance of being assigned to one of the three treatments. Figure 2 illustrates the treat-

[12] From our user survey, 13% of donor-sessions (N=312) have a nonunique email associated with them. And and out of these tagged donor-sessions, 60% have a unique email tag (N=190).

[13] *Bagirata* connects potential donors and beneficiaries as a two-sided platform. Figure A.1 provides a screen capture of the landing page. The button "*mulai mendistribusikan dana*" is for donors to browse beneficiary cards, while the button "*masuk sebagai penerima dana*" is for beneficiaries to click to initiate the process of asking for aid.

ment assignment. The donor assigned to the 3-beneficiary treatment would see three beneficiaries on her device's screen. Similarly, those assigned to the 8- and 10-beneficiary treatments would see eight and ten beneficiaries on their screen, respectively. The treatment assignment remains effective for three hours. This implies that, as long as potential donors refresh the page or re-access the *Bagirata* platform using the same device within the designated three-hour window, they would remain in the same screen-size treatment. To encourage donations, the platform did not require users to provide any identifying information. As a result, we are unable to identify donors who may have accessed the platform across multiple distinct 3-hour sessions. Nevertheless, we gauge from our donor survey, that this incidence is likely to be small given only 13% of donors in our donor survey had a non-unique email address.[14] Henceforth, we do not distinguish between donors and sessions, and refer to our unit of analysis as the *donor-session* level.

After viewing the first screen, donors have the option of clicking a button at the bottom of each page to trigger a fresh draw of beneficiaries (*refresh*).[15] There is no limit to the number of times potential donors can click refresh. It is important to note, however, that our treatment assignment can lead to differences in the frequency of refresh and variations in the actual number of beneficiaries seen. This variation occurs both within and across treatments. We interpret refresh as a key measure of donors' search effort.

Throughout the paper, we focus on two levels of analysis: (i) the impact of screen-size on donor behavior, where the unit of analysis is at the donor-session level (*between-donor analysis*), and (ii) the determinants of donations within a single donor-session, where the unit of analysis is at the beneficiary display level (*within-donor analysis*).

For the between-donor analysis, we examine whether donors' search and donation behaviors differs across various screen sizes. Specifically, we ask whether a smaller screen size prompts potential donors to find a larger sample of beneficiaries by clicking the refresh button more frequently. We are also interested in understanding whether the decision to initiate another search is dependent on the outcome of the previous search. Finally, we examine whether there is any significant difference in the likelihood of a beneficiary receiving a donation or the amount received.

For the within-donor analysis, a potential donor would encounter multiple beneficiaries across sets/screens in a session. Here, we consider each dyadic pair of a potential donor and a beneficiary within a donor-session as a single unit of observation. Crucially,

[14] Specifically, the same donors might access the website multiple times, potentially spanning multiple three-hour windows. This might result in them being associated with several web sessions within the same set-size treatment or being randomly reassigned to different set-size treatments. We are unable to distinguish between these cases.

[15] As the screenshot in Figure 1 shows, this button was labeled "*acak*" at the bottom left corner, which has the literal translation "to randomize." Hereafter, we refer to this action, and also the action of pressing the back button, as a "refresh" action to combine it with a browser refresh.

we leverage the platform's algorithm to study the effect of beneficiary characteristics on donation behaviors. In particular, the platform's algorithm selects a random card from the database of all potential beneficiaries for each screen that the donors see, allowing us to leverage the as-good-as-random display of beneficiary characteristics to study the effects of deservingness on donor behavior. We discuss this in detail in Section 5.

In both the desktop and mobile versions of the website, the beneficiary cards are displayed to donors in vertical succession. The random draw from the beneficiary database that the platform performs for each card also means that the order in which beneficiary cards are displayed is random. This allows us to estimate the effect of sequential order on donations, i.e., whether there are differences in donation outcomes between beneficiaries displayed closer to the top vis-à-vis those displayed closer to the bottom of each draw.

3.2. Hypothesis

We hypothesize that changing the choice structure of charitable options could influence potential donation outcomes. In particular, we test the following hypotheses:

H1. The more the number of potential beneficiaries displayed to donors, the lower the donors' probability of donating.

The first hypothesis tests the tension between better match probabilities with more options vs. choice overload. Ex ante, we are agnostic on the direction of donors' responses to changes in the number of donation options presented from the original default of 10-beneficiaries displays. Nevertheless, two strands of the literature suggest that the effects from choice overload may prevail. First, the empirical literature from lab experiments indicates that competition among charities reduce charitable giving (Filiz-Ozbay and Uler, 2019). Second, a rich literature in psychology also demonstrates that the "identifiable victim" garners more donation (Sudhir et al., 2016), and presenting fewer options at the time increase the salience of each possible beneficiary that can generate this effect. Chernev et al. (2015) reviewed choice overload in many consumer choice domains, but none of the papers in their review tests choice overload with a field experiment involving charities.

H2. The larger the sum of donations that a beneficiary has already secured, the lower the donors' probability of donating.

The second hypothesis tests how donors allocate their resources to multiple donation options. Donors can observe how much donation a potential beneficiary has received, and it may influence their decision to give to this particular beneficiary. We test whether donors decide to crowd-in existing donations or pull back and give to other beneficiaries.

On one hand, the literature on nudges (see, e.g., Thaler and Sunstein (2008)) highlights the susceptibility of individual decision making processes. In our case, all potential donors on the platform are exposed to the same messaging through the platform's name ("*Bagirata*" means divide equally) and Indonesia is a context where village leaders often diffuse food aid to households outside of the official eligibility list to correct exclusion error (Banerjee et al., 2018). On the other hand, potential donors may see donations from other donors as a positive signal and crowd in existing donations (Huck and Rasul, 2011; Meer, 2014).

H3. Potential donors exhibit in-group favoritism, preferring to donate to beneficiaries who share some identity similarity

The third hypothesis test whether donors are influenced by in-group biases when allocating donations. This hypothesis relates to the concept of social distance (Chen and Li, 2009; Meer and Rigbi, 2013; Sudhir et al., 2016). For this analysis, we investigate four dimensions of identity: gender, religion, ethnicity, and location.

All hypotheses are preregistered at the Open Science Framework (OSF).[16] We discuss and explain all deviations to our pre-registered plan in Appendix B. Throughout this paper, we state which analyses were pre-registered and which are exploratory (non pre-registered). In all analyses, our main outcome variables consist of two measures of donor behavior. Our first measure is a binary indicator that denotes whether a potential donor donates to a beneficiary.[17] Our second measure is the amount of money that a donor chooses to donate. While donations are made in Indonesian rupiah (IDR), throughout the analysis, we express the donation amounts in US dollars.[18]

3.3. Summary Statistics and Beneficiary Characteristics

Table 1 presents selected summary statistics on donor behavior. Our main data set comprises 2,405 unique donor–sessions and 2,054 unique beneficiaries. Each beneficiary is randomly drawn to be displayed to donors 26 times on average.[19] Eighty-one percent of beneficiaries received at least one donation, with the average beneficiary receiving 2 donations for a cumulative sum of USD 17.84. Compared to the average annual beneficiary's earning from the user survey of USD 1,882, the amount of the donation received

[16]The preregistration document can be accessed from (https://osf.io/c4xgd). In addition, we also registered it at the AEA RCT Registry AEARCTR-0012563 (Hilmy et al., 2023).

[17]The hypotheses in our pre-registration uniformly imply the use of the donation indicator as a primary outcome. In addition, we specified the donation amount as an additional main outcome.

[18]We use a conversion rate of USD 1 = IDR 14,000.

[19]Each beneficiary is limited to only one appearance per session. Hence, on average, beneficiaries are displayed 26 times: once per set, across 26 unique sets.

by a beneficiary is approximately 11% of average monthly earnings.

[INSERT TABLE 1 HERE]

Beneficiary Characteristics

On average, a beneficiary asked for USD 139 per month over a duration of 2.2 months. Our systematic coding from beneficiaries' narratives and names allows us to classify beneficiaries across a wealth of dimensions such as gender, religion, whether a beneficiary is a breadwinner or has child dependents, region, and employment sector. From their names, we can impute that our beneficiary sample has a substantially larger number of men (63%) than women (37%). The majority of the beneficiaries have Muslim names (82%). With respect to their household structures, 22% of the beneficiaries mention being the family breadwinner or having dependents and 12% mention having, specifically, one or more children as dependents. For employment, the majority of beneficiaries are employed in the hospitality, retail, and food service sector (61%), followed by art and creatives (16%), others (12%), and transportation (which comprises mainly ride-share drivers for online platforms).[20] Regarding location, the majority of our beneficiaries are located in the Jakarta metro area (67%), followed by other major cities in Java, Indonesia's most populous island, with the remainder based outside of Java (9%).

Comparing donors to beneficiaries, beneficiaries have lower levels of education and earn less. Table 1, Panel B presents selected summary characteristics of *Bagirata* beneficiaries and donors from a user survey posted on the platform landing page website.[21] The average beneficiary who completed the survey has a little more than a high school education, while the average donor has closer to a college degree. Donors also earn more: the average donor earns USD 8,626/year, almost five times the average beneficiary's earning. Beneficiaries are also more likely to be male and married. Despite this disparity, however, both donors and beneficiaries report allocating a similar percentage of their earnings to charity: approximately twice the amount of mandatory *zakat* charity of 2.5% that Islam requires its adherents to provide. As a comparison, the millennial age group in the US reports giving on average only 0.9% of its income (Clark et al., 2019). This suggests that, perhaps due to the lack of a strong social safety net, the altruistic motives of donors in our setting might be distinct from developed countries.

[20] See Table A.3-A.5 in the appendix for detailed tabulations on beneficiary appeals, donation outcomes by characteristics, and donation outcomes by display and characteristics.

[21] *Bagirata* users interested in the survey could click the button "*ikuti survei sekarang*" on the landing page (see Figure A.1). *Bagirata* also advertised the survey on Twitter and Instagram.

4. Main Results: Between-Donor Analysis

We present two key results. First, we show that 8-screen-sizes leads to higher total donation values. This is driven by donors making a higher number of donations in 8-screen-sizes. Second, we provide evidence consistent with fewer alternatives leading to greater donor effort and decreasing choice overload.

4.1. Empirical Specification

We estimate the effects of screen size on donor behavior at the *donor-session* level, using ordinary least squares (OLS). This specification is valid for two reasons: (i) We randomly assign variation in the number of beneficiaries per screen (*screen-size*) across donors. (ii) The probability that a single beneficiary appears across multiple donor-sessions is as-good-as-random. Hence, for donor-session i, we estimate:

$$Outcome_i = \alpha_1 + \beta_1 ScreenSize3_i + \beta_2 ScreenSize8_i + \varepsilon_{1,i} \tag{1}$$

where $Outcome_i$ is a measure of donor behavior, such as the probability of making a donation or the donation amount and $ScreenSize3_i$ and $ScreenSize8_i$ are indicators for whether a donor was assigned to see 3- or 8-beneficiaries per screen. The ε term is the idiosyncratic error term. β_1 and β_2 measure the difference in donor behavior between donors assigned to a 3- or 8-beneficiary screen arm relative to donors assigned to a 10-beneficiary screen donor session. Throughout, we cluster standard errors by week given that (i) COVID-19 statistics were released on a weekly basis in Indonesia; (ii) two social media publicity events led to a spike in donations in two separate weeks.

4.2. Donation Outcomes (Pre-Registered)

Table 2 presents our main results. Columns (1)—(3) estimates Equation (1) and regresses the probability of donations; the total number of donations; and the total value of donations, on indicators for donors being assigned to 3 and 8-screen sizes. Beginning from Column (1), there are no differences in donation probabilities across all 3 treatment arms. Column (2) shows that differences in the total number of donations is small and statistically insignificant between 3 and 10-screen sizes. In contrast, however, the total number of donations in 8-screen sizes are nearly 50% higher than those in 10-screen sizes (0.18 relative to a control group mean of 0.37). Last, Column (3) again estimates that differences in the total value of donations is small and statistically insignificant between

3 and 10-screen sizes. In contrast, though the coefficient is imprecisely estimated, the quantitative magnitude of the difference between 8 and 10-screen sizes is economically significant. Donors in 8-screens donate US$1.84 more relative to US$5.79 in 10-screens.

Taken together, these results suggest that 8-screen sizes are the most effective at increasing the total value of donations and this is primarily driven by the higher number of donations being made. To further understand the mechanisms driving differences in donor behavior, we next conduct an exploratory analysis (i.e. not pre-registered) to test for differences in donor effort and choice overload.

[INSERT TABLE 2 HERE]

Alternative Interpretation: Smaller Screen Sizes Mechanically Increasing Likelihood of Donation

Our results show that fewer alternatives per screen leads to more donations and we provide evidence consistent with both higher donor effort and lower choice overload. An alternative interpretation is that fewer alternatives per screen might simply increase the mathematical probability that any one beneficiary receives a donation.

To illustrate this, consider, a database comprising identical beneficiaries, and 2 donors, each assigned to the 3- and 10-beneficiary screen size treatment arm. The first donor would view 3 beneficiaries, and the second donor would view 10 beneficiaries. Further consider the extreme case, where each donor makes at most one donation per screen due to e.g., a fixed altruism budget. If so, results might simply reflect the simple probability that any one beneficiary in a 3-beneficiary screen has a 30% probability of receiving a donation versus any one beneficiary in the 10-beneficiary screen having a 10% probability of receiving a donation. This would still represent a causal effect of screen-size but the interpretation of our results would differ.

We argue that this is unlikely for two reasons. First, we show that donors are not constrained to making at most one donation per screen. To test this, we restrict our sample to all donor sessions in which at least one donation occurred and regress two outcomes on our screen-size indicators. The first outcome is an indicator that equals 1 if a donor made exactly one donation in at least one screen (and 0 if, in any screen, they made more than one donation). The second outcome is an indicator that equals 1 if a donor makes more than one donation per screen in at least one screen.[22]

Table A.6 presents results. On average, the constant in Column (2) shows that 37%

[22] Note the sum of the means across both columns do not add up to one, because there are, for example, donor-sessions in which a donor makes exactly one donation in screen A but more than one donation in screen B.

of 10-beneficiary set donor sessions make more than one donation per screen and there is little difference between 8 and 10-screen sizes. We interpret this as evidence suggesting that a large proportion of donors, across all screens-sizes, tend to make more than one donation per screen.

Second, we show that 3- and 10-screen size donors tend to make a different number of donations per screen. Column (1) shows that 3-screen size donors are 15.4p.p. more likely to make exactly one donation. Column (2) shows that 3-screen size donors are 10.9p.p. less likely to make multiple donations per screen. Throughout, there is again, little difference between 8 and 10-screen size donors. Taken together, we interpret these results as evidence against smaller screen sizes simply mechanically increasing the probability of donation likelihood.

4.3. Mechanisms: Choice Overload and Search Behavior (Exploratory Analysis)

One key mechanism behind the observed treatment effect, in line with extant studies on choice overload, is that a larger number of choices per screen, might lead to lower donation outcomes through choice overload. We test for this using rich back-end data to examine the effect of screen size on donor (i) refresh rates; (ii) total beneficiary exposure; and (iii) search behavior. We find that 3-screens lead to suboptimal donor behavior: despite putting in greater effort, donors are exposed to fewer beneficiaries on average and, perhaps, due to suboptimal donor-beneficiary preference alignment, are more likely to skip the first screen but, encountering substantially fewer beneficiaries in subsequent end up making fewer donations.

Refresh Rates and Beneficiary Exposure The donation platform is designed such that, at the bottom of each screen, donors are able to hit the *refresh* button to obtain a new, random draw of beneficiaries. Given the large number of potential beneficiaries, it is possible that positive results on donor behavior in 8-screens are driven by relatively fewer alternatives leading to more optimal search behavior.

Specifically, we posit that differences in donor-driven refresh rates might be interpreted as donors exerting more fine-grained control over the search process for donation targets. Naturally, differences in refresh rates would also affect the total number of beneficiaries that each donor is exposed to. Hence, we regress our donation outcomes on refresh rates and total number of beneficiaries exposed to as proxies for choice overload and search behavior.

Table 3 displays regression results. Column (1) estimates that, on average, donors assigned to 3-screen sizes click *refresh* 1.9 additional times relative to a baseline of 4.6 times in 10-screen sizes. In contrast, there is little difference between refresh rates in 8 and 10-screen sizes. Column (2) shows that donors in 3-screen sizes are exposed to 12 *fewer* beneficiaries relative to nearly 32 beneficiaries in 10-screens — nearly a third less. Again, there is little difference between 8- and 10-screen sizes.

[INSERT TABLE 3 HERE]

Taken together, these results suggest that 8-screens lead to the most optimal search behavior. Donors in both 8 and 10-screens refresh the same number of times and are exposed to a similar number of total beneficiaries. In contrast, 3-beneficiary screens induce greater but less optimal donor effort: donors refresh more often to search for more optimal targets but, given fatigue, end up being exposed to a smaller number of total beneficiaries and hence, donating less on average. One possible interpretation is that the benefits of greater empathy from the identifiable victim effect are insufficient to outweigh those of greater preference donor-beneficiary preference alignment.

Search Behavior Across Screens Column (3) in Table 3 shows that donors in 3-screens are 40% (3p.p.) less likely to donate in the first screen (i.e. more likely do donate only after the first screen). The coefficient on 8-screens is imprecisely estimated but suggests that donors in 8-screens are more likely to donate in the first screen.

We interpret this as suggestive evidence that even in the first screen, 8-screen donors feel that they have viewed a sufficiently large number of beneficiaries to make a sound donation decision and hence are more likely to click donate. In contrast, 3-screen donors feel that they have viewed too few beneficiaries and hence continue to defer the donation decision and click refresh. Yet, 3-screen donors continue to view significantly fewer potential beneficiaries in all subsequent screens. In the end, they possibly end their search earlier and end up making fewer donations on average.

Taken together, our findings suggest three key mechanisms of donor effort, choice overload and preference alignment, through which 8-screens lead to a higher total value of donations. In 3-screens, donors face too few alternatives per screen, have to exert too much additional effort to search and refresh across screens and hence, eventually end up making fewer donations. In 10-screens, lower donation rates, even in the first screen, suggests that donors are overwhelmed by the large number of alternatives on display. Furthermore, each time donors hit refresh, another equally large number of beneficiaries are displayed, increasing their cognitive load and potentially overwhelming 10-screen donors. In contrast, donors in 8-screens face relatively fewer alternatives per screen and hence, despite having already made a donation, continue to search for additional targets in subsequent screens, allowing them to meet beneficiaries more aligned with donation preferences.

5. Within-Donor Analysis

5.1. Display Order and Deserving-ness (Exploratory Analysis)

Taken together, our results thus far suggest that our 8 screen-size treatment leads to the highest total value of donations through (i) exposing donors to a sufficiently large number of beneficiaries relative to 3-screens, and yet (ii) reducing donor effort and choice overload relative to 10 screen sizes. A natural, policy-relevant question to ask is whether, holding screen size constant, it might be possible to direct donations towards individuals with the highest marginal value of receiving donations.

To that end, we leverage our as-good-as-random displays of beneficiaries to investigate two possible determinants of within donor-session donation behavior: display order and deserving-ness. Throughout, we run regressions at the 52,086 donor-beneficiary dyad level with donor-session fixed effects.

5.1.1. Display Order: Dipping Behavior Here, we present novel evidence that the effects of attention overload on donors follows a nonlinear dipping pattern. Beneficiaries placed at the top and bottom of 8-beneficiary sets are much more likely to receive donations than those placed in the middle. Figure 3 presents results on donation probability; Table 4 presents results on donation probability and amount of donations received.

Empirical Specification We leverage the as-good-as-random display order of beneficiary cards to study how display order affects donor behavior. As mentioned, beneficiaries are randomly selected from *Bagirata's* back-end database, and displayed in a as-good-as-random order. Importantly, donors view beneficiary cards in a sequential manner, scrolling from top to bottom.

Hence, we regress donor behavior on beneficiary display order at the beneficiary-dyad level. Using notation identical to Equation (1), we estimate:

$$Donate_{ijkl} = \alpha_2 + \beta_3 DisplayOrder_j + \phi_i + \varepsilon_{2,ijkl} \tag{2}$$

For donor session i seeing beneficiary j in the k-th screen, with l indexing beneficiary's order within the screen and $DisplayOrder$ is a vector capturing each beneficiary's within-screen display order. Last, we hold set size constant with donor–session fixed effects ϕ_i. Hence, the β_3 coefficient estimates the effect of display order on donation outcomes of each beneficiary relative to all other beneficiaries within the same donor–session-screen.

Figure 3 plots the likelihood of donation by sequential display order across each of our 3-, 8-, and 10-screen size treatments.[23] To illustrate, consider the ninth beneficiary. In a 3-screen size treatment, this beneficiary appears at the *bottom* of the third screen. In contrast, in a 8- (10-) screen size treatment, this beneficiary appears as the *first* (penultimate) beneficiary on the second (first) screen.

Across all screen-size treatment arms, we observe evidence of a within-screen, non-linear dipping pattern. Beneficiaries placed at the top and bottom of screens are the most likely to receive donations. Conversely, the 5th beneficiary in both the 8- and 10-screens, and the 2nd beneficiary in 3-screens are the least likely to receive a donation. This pattern is especially pronounced in our 8-screen size treatment arm.

[FIGURE 3 ABOUT HERE]

Table 4 presents regression results on donation probability (Panel A) and donation value (Panel B). We regress donation outcomes separately on (i) a continuous variable that takes the value of the beneficiary's position within a screen (Column (1)); (ii) and a set of two dummy variables that pool the first (few) and last (few) beneficiaries. Specifically, the first variable "Top (4) in set" equals one if a beneficiary appears in the first position (within the first four positions) in a 3- (8- or 10-) screen size treatment arm; the second variable "Bottom (3 or 5) in set (8 or 10)" equals one if a beneficiary appears in the last position (within the last three or five positions) in a 3- (8- or 10-) screen size treatment arm (Columns (2) - (4)). (i) measures the marginal difference in donation probability across each beneficiary display; (ii) provides a formal test of the dipping pattern in Figure 3.

Panel A, Column (1) shows that displaying a beneficiary one position lower leads to a 0.06pp decrease in the probability of receiving a donation. In a 10-screen size treatment, this translates to a 26% decrease in donation probability between the first and last beneficiary. Columns (3) shows our results for the 8-screen size treatment. There is a large and statistically significant effect of being displayed in the first four and last three positions: beneficiaries displayed in the first four (last three) positions experience a nearly 50% (30%) increase in donation probability. In contrast, Columns (2) and (4) show a much smaller and statistically insignificant difference in donation probabilities within our 3- and 10-screen size treatment arms.

[23] For exposition, we plot this only for the first twenty beneficiaries per donor. Results are similar across complete beneficiary-sets.

In contrast, Columns (1)—(3) in Panel B show that there are few differences in donation value across all coefficients and treatment arms.

[TABLE 4 ABOUT HERE]

Taken together, we interpret these results as evidence that donors pay more attention to beneficiaries displayed at the start and end of screens (and the least to those in the middle) and hence are more likely to donate to these individuals. In other words, donor attention dips as they move down a screen, towards the middle, but recovers again as they near the end.[24] Hence, our results suggest that policy-makers/donation platforms that seek to maximize donations towards certain individuals or causes, should place them towards the start or end of display screens.

5.1.2. Deserving-ness In the midst of nation-wide COVID-19 lock-downs in Indonesia, sectors like schools and restaurants were ordered shut for an extensive period of time. Given the theoretical literature on deserving-ness (Konow, 2000; Cappelen et al., 2007), and the potentially different way in which donors view educational (essential) workers vis-a-vis restaurant workers, we next explore if deserving-ness of beneficiaries might be a key driver of donations.

We hand-code thousands of self-written beneficiary narratives to obtain a complete set of *all* potential beneficiary characteristics that donors might consider as markers of deserving-ness. In particular, we focus on reasons cited by donors for making donations. Table A.8 summarizes donor response and finds that beneficiaries who are breadwinners (86%); individuals in persistent poverty (85%); those hit by unforeseen circumstances such as disasters, illnesses', or job loss (82%); and female beneficiaries (69%); were thought of as the *most* deserving of donations. Conversely, beneficiaries with low educational attainment (53%); from similar neighborhoods (56%); the same religion (49%); or ethnicity (42%) are perceived as *least* deserving.

To ensure accuracy, and to mirror donors' reading of beneficiary narratives, we task two Indonesian research assistants with manually reading each narrative.[25] Following donor survey responses, we hand-code characteristics on whether a beneficiary is a primary breadwinner, based on keywords indicating financial responsibility for his/her family members. We also create indicator variables for occupational sector, gender, religious

[24]Similarly, marketing studies have showed that the placement of products closer to eye-line on supermarket shelves and at the cashier line are likely to receive more attention and higher sales.

[25]To minimize biases in coding, the two research assistants have complementary backgrounds: one is female, and the other is male; their ethnic backgrounds include Javanese and Batak from Sumatera; and their religious affiliations encompass Muslim and Protestant Christian. Disagreements in coding between the two assistants are resolved through a detailed manual review by one of the authors.

identity, and regional location. In addition, we measure the length of each narrative.[26]

Empirical Specification We regress donor behavior on measures of *deservingness* characteristics at the beneficiary-dyad level. Using notation identical to Equation (1), we estimate:

$$Donate_{ijkl} = \alpha_2 + \beta_3 Characteristics_j + \phi_i + \varepsilon_{2,ijkl} \tag{3}$$

For donor session i seeing beneficiary j in the k-th screen, with l indexing beneficiary's order within the screen and $Characteristics$ is a vector of beneficiary characteristics inferred from beneficiary narratives. Since we code and observe all beneficiary characteristics encountered by donors, this specification allows us to minimize concerns about omitted variables. We continue to use donor-session fixed effects, ϕ_i. Hence, the β_3 coefficient estimate on binary characteristic x is the effect on donation outcomes, of x taking on the value of 1 on the probability of receiving a donation relative to the probabilities of all other beneficiaries within the same donor–session-screen with characteristics similar to the focal beneficiary's but have x taking the value of 0.

We regress donation outcomes on a comprehensive set of observable beneficiary characteristics, including donor–session fixed effects according to Equation 3 at the donor–beneficiary dyad level. Our analysis focuses on the effect of various beneficiary traits on the occurrence of donations and the amount donated. We delve into how deservingness is perceived in relation to four main characteristics visible on the platform and ranked by popularity in our survey: *family breadwinner status*, *vulnerability to poverty or shocks*, *demographics*, and *donations received from other donors*. Full regression results are presented in Table A.9. Here, we focus on Figures 4 and 5, where we display selected coefficient estimates.[27]

[INSERT FIGURE 4 AND 5 HERE]

Figures 4 and 5 show that beneficiaries who are primary breadwinners are more likely to receive a donation and obtain larger donations. This is consistent with donors' self-reported responses. Next, we consider *occupational sector* and *economic shocks*. For

[26]We illustrate this process in Table A.1. For Beneficiary #5, a former drink shop attendant: "I lost my job because the drink shop where I work is closed. My wife recently gave birth, I need help to buy my child's needs.", we assigned a value of 1 to "Breadwinner/has dependent(s)", "Breadwinner/mentions dependent child(ren)", and his occupational sector is classified as "hospitality, retail, and food service". In contrast, for Beneficiary #8: "My office closed in July ... I deepen my design and illustration and copywriting skills, building updated portfolios to get freelance opportunities", we assigned a value of 0 to "Breadwinner/has dependent(s)", and "Breadwinner/mentions dependent child(ren)", and his occupational sector is classified as "art and creatives".

[27]In Table A.10 we present regressions from a sparse specification with just the share of donation ask, corresponding to a planned randomized treatment arm which was instead uniformly provided to all potential donors. See Supplementary Materials in Appendix B for additional note on implementation.

example, teachers (or those who are education workers) are considered more deserving than cafe workers. Using beneficiaries in the hospitality industry as the baseline, Table 9 and Figures 4 and 5 show that those in the education sector are 1.3 pp more likely to attract donations and receive USD 0.18 more in donation value. In contrast, we find little evidence that individuals experiencing *economic shocks* are more likely to receive donations. The coefficient estimate for *retrenchment* is statistically insignificant in any of the regressions.

Textual Analysis: Keyness Statistics and Latent Semantic Scaling To corroborate our hand-coded measures, we employ textual analysis to classify and construct a composite score/*deservingness index* for each narrative using *Keyness Statistics* and *Latent Semantic Scaling* (LSS) (Zollinger, 2022). Figure 6 displays our *keyness* statistics. The black bars depicted in the upper part of the figure show the terms mentioned with the greatest relative frequency and results align closely with our hand-coded results. Keywords positively associated with donations are those related to beneficiaries with child dependents or affiliations with the education sector.

[INSERT FIGURE 6 HERE]

To compute a composite score for each beneficiary narrative (i.e. a *deservingness index*), We rescale the LSS statistic for each narrative to take a value between 0 to 1. The index takes the value of 0 for narratives scored as having the highest similarity to narratives that were the *least* likely to receive donations. The index takes the value of 1 for narratives scored as having the highest similarity to narratives that were the *most* likely to receive donations.[28]

Table 5 presents regression results of the probability of receiving a donation and the donation amount on our deservingness index (together with a parsimonious set of controls). Column (1) shows that a beneficiary narrative with a higher deservingness index is more likely to receive a donation and this significance remains (Columns (2) - (3)) when we add additional control variables. We find similar results for donation amounts in Columns (4) - (6).

[INSERT TABLE 5 HERE]

Taken together, we interpret our hand-coded and textual analysis results as suggesting that perceptions of deserving-ness matter, above and beyond all other beneficiary characteristics. In our setting, teachers were particularly hard hit by the COVID-19 pandemic given that Indonesian schools were closed for one of the longest duration in the

[28] We describe this methodology in detail in Appendix B.

world. In contrast, *economic shocks*, despite donors' self reported preferences, had a possibly lower impact on donor behavior given nearly all workers had their income sources cut off, given restrictive, large-scale movement controls throughout Indonesia.

More broadly, our results provide novel empirical evidence for the accountability principle (Konow, 1996, 2000): donors are more likely to donate to beneficiaries whose neediness corresponds with factors he cannot reasonably influence or change in the short run through his or her own effort. Our setting also allows us to provide a direct test of *which* notions of perceived deservingness are *comparatively* more important in altruistic decisions when donors are presented with a full menu of beneficiaries.

5.2. In-Group Bias (Pre-Registered)

An alternative mechanism driving differences in donor behavior is in-group biases. It is possible that donors give more generously to individuals that share a similar identity. For example, individuals might have a higher level of trust and sympathy towards in-group members, leading to higher donations in the presence of concordance between donor-recipient identity.[29]

We test for in-group biases by matching beneficiary demographics from the *Bagirata* database, and donor demographics from our primary donor survey. We do so using email addresses. Hence, our sample size in this analysis is smaller, given that only a subset of donors left their emails on both the platform and our donor survey.[30] To that end, we successfully match donors in 78 sessions with 1,283 beneficiaries, giving us a total sample size of 2,396 observations.

We continue to estimate Equation (3) by regressing donation outcomes on indicators for concordance in donor-beneficiary identity. Specifically, we test for concordance on four characteristics that might capture in-group biases based on gender; religion; ethnicity; and location.[31] We code donor and beneficiary gender, religious and ethnic identities from

[29] Altruistic decision-making shares similarities with the decision process about a public benefit that will accrue to someone other than the donor. In this vein, researchers have argued that heterogeneous communities contribute less to social organizations and activities (Alesina and La Ferrara, 2000; Miguel and Gugerty, 2005; Okten and Osili, 2004). Individuals might be less willing to contribute to a public good if it benefits other groups because of mistrust across groups or inability to enforce within-group reciprocity (Alesina and La Ferrara, 2002; Habyarimana et al., 2007).

[30] As noted, the donor survey was decoupled from the donation process to minimize the possibility that any perceived reduction in anonymity would discourage donations.

[31] We illustrate our coding process using narratives in Appendix Table A.1, which originally contains beneficiaries' names and locations. In the table, personal identifiers have been replaced with numbers for anonymity. For example, Beneficiary #5 has a first name that is a masculine Javanese word and a surname that is an Arabic word, our assistant coded his name as both masculine and Muslim. Furthermore, as this beneficiary resides in Central Java, an area with a predominantly ethnic Javanese population, we coded his ethnicity as Javanese, which is concordant with information from his name. Similarly, because

donor and beneficiary names. We code location from beneficiary and donor's self-reported place of residence.

Across regressions, we find evidence of in-group bias in terms of female gender identity and, to a smaller extent, ethnic identity. Table 6 presents the full results. For donation indicators, coefficient estimates on the concordance indicators for female gender identity are statistically different from zero. We find similar results for the regression with donation amounts as the outcome variable. In comparison, the coefficients for all other concordance variables are statistically indistinguishable from zero except for ethnicity alignment which is marginally significant at the 10% level in donation indicator regression.

[INSERT TABLE 6]

These results provide novel evidence complementary to that of existing studies on in-group biases in non charitable giving contexts. We introduce a novel finding by showing that the activation of in-group bias in altruistic settings is highly context-dependent and can be attenuated by the *nature* of disasters. First, our weak results on ethnic identity concordance could potentially be explained by the fact that COVID-19 was a global public health disaster that, arguably, affected all individuals equally, regardless of ethnic identity. Hence, ethnic biases might have been less central in donors' decision-making processes. Second, in contrast, our strong results on female identity concordance suggest an interactive effect between gender in-group bias and deserving-ness. Female donors were more likely to consider female beneficiaries to be more deserving of donations.

6. Conclusion

This paper documents that donors are susceptible to choice overload in the context of online charitable giving in a developing country. Beneficiaries displayed in a 8-beneficiary screen-size receive the most donations relative to 3- and 10-screen sizes (pre-registered). In an exploratory analysis, we show that higher donations in 8-screens possibly arise from 8-screen sizes both reducing choice overload and improving search behavior through (i) presenting a relatively fewer number of alternatives vis-a-vis 10-screens; and (ii) enabling greater donor-beneficiary preference alignment between by presenting a sufficiently large number of alternatives vis-a-vis 3-screens.

Beneficiary #8's name resembles an Arabic word related to the popular male Muslim name Muhammad, our assistants inferred his name to be masculine and Muslim. We omit the beneficiaries' actual names from the table for privacy.

Within-screens, we find strong evidence of deserving-ness and female gender in-group biases leading to higher donations. Furthermore, we document novel evidence of dipping behavior: beneficiaries placed in the middle of screens are the least likely to receive donations.

Our results provide novel, policy-relevant evidence of a low-cost way to possibly attenuate suboptimal heuristics in online charitable giving platforms: presenting just the right number of alternatives. This could reduce informational overload by allowing donors to pay more attention to each beneficiary choice and attendant characteristics that platforms deem as being correlated with the highest marginal value of donations.

In addition, our findings have implications for thinking about the optimal way to optimize charitable giving above and beyond those associated with crises response. In particular, given near-zero setup and transaction costs of online donation platforms, our findings suggest that policy makers could play a valuable role in overseeing and guiding these online platforms to help minimize donor fatigue and reduce the potential depersonalization of donation experiences (Andreoni and Payne, 2013). Our findings also offer the tantalizing possibility that small adjustments in choice architecture could be used to increase giving towards reparations and redistributive causes (e.g. climate change).

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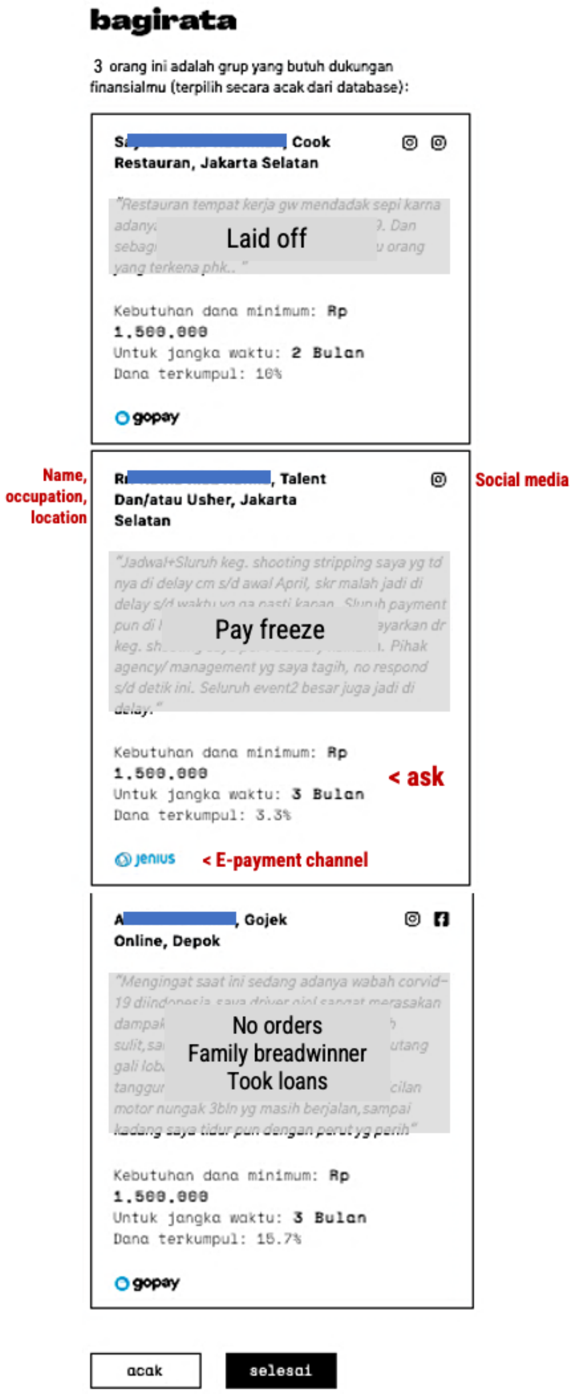
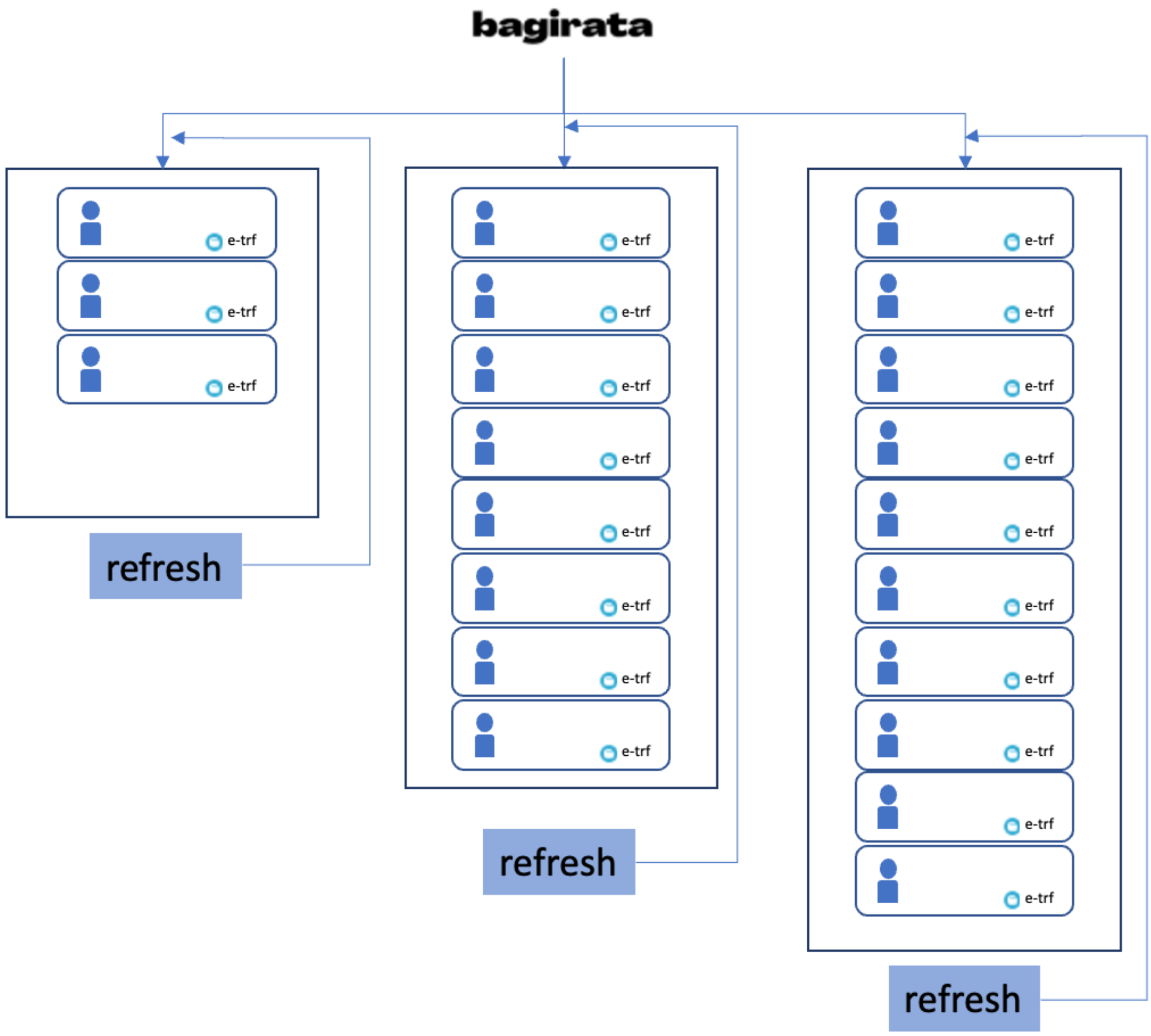
Figure 1: Set of Beneficiary Cards Presented to Donors on the Platform



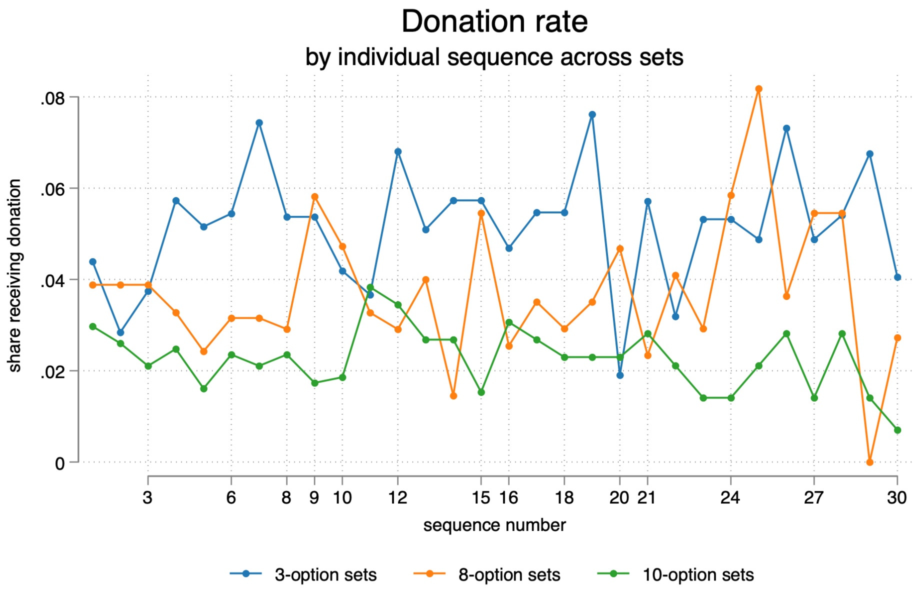
Note: An example of a set of beneficiary cards that potential donors encounter on the *Bagirata* platform. In this example, the donor was randomly assigned to view sets of three beneficiaries at a time. The randomization of the choice set size and the random selection of beneficiaries from the database to be displayed took place after the visitor clicked the button on the landing page expressing her wish to donate. Donors are informed that beneficiaries are randomly selected (as indicated by the top text below the *Bagirata* logo). Each beneficiary card includes the beneficiary's name, occupation, and location (top left), social media links (top right), a free text narrative appeal from the beneficiary (center), nominal ask, duration of ask, overall donation progress, and a link to e-payment channels (bottom). In this example, key aspects of the appeal in English have been superimposed onto the original Indonesian text in the center. For detailed sample appeals and their English translations, see Table A.1. Cards are arranged in a vertical sequence on the website, requiring users to scroll to subsequent cards in the set. Donors have the option to click the "*acak*" button to generate a fresh random selection of beneficiaries or to directly donate through the e-payment link provided.

Figure 2: Schematic of Randomization Procedures for Platform Visitors



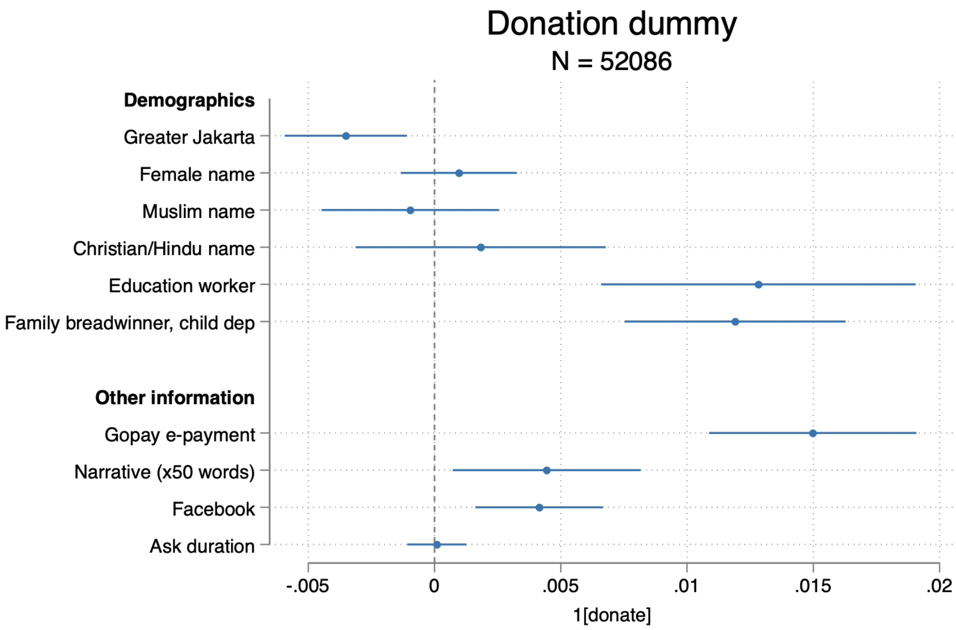
Note: Schematic of randomization procedures for platform visitors. Visitors are randomly assigned with equal probability to one of our three treatment groups, which present sets of 3, 8, or 10 beneficiaries. This randomization scheme is maintained throughout the duration of a web session, which typically lasts three hours. Within a web session, every time a donor refreshes the webpage or clicks the "*acak*" button (see Figure 1), she would encounter a new display set of the same number beneficiaries within her assigned treatment group.

Figure 3: Donation Rate for Beneficiaries, Ordered in Individual Sequence Display



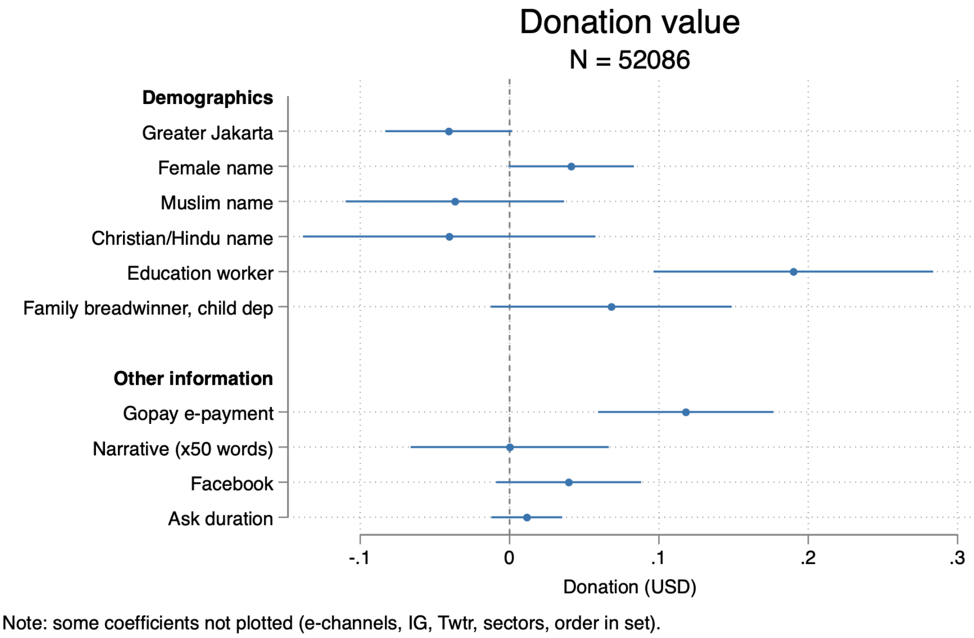
Note: Display sequence is counted sequentially across sets. For example, the sequence number 9 refers to the bottom card in a third set for a visitor assigned to the 3-beneficiary treatment arm, the top card in the second set for a visitor assigned to the 8-beneficiary treatment arm, and the penultimate card in the first set for a visitor assigned to the 10-beneficiary treatment arm.

Figure 4: Effects of Beneficiary Characteristics on Donation Indicator



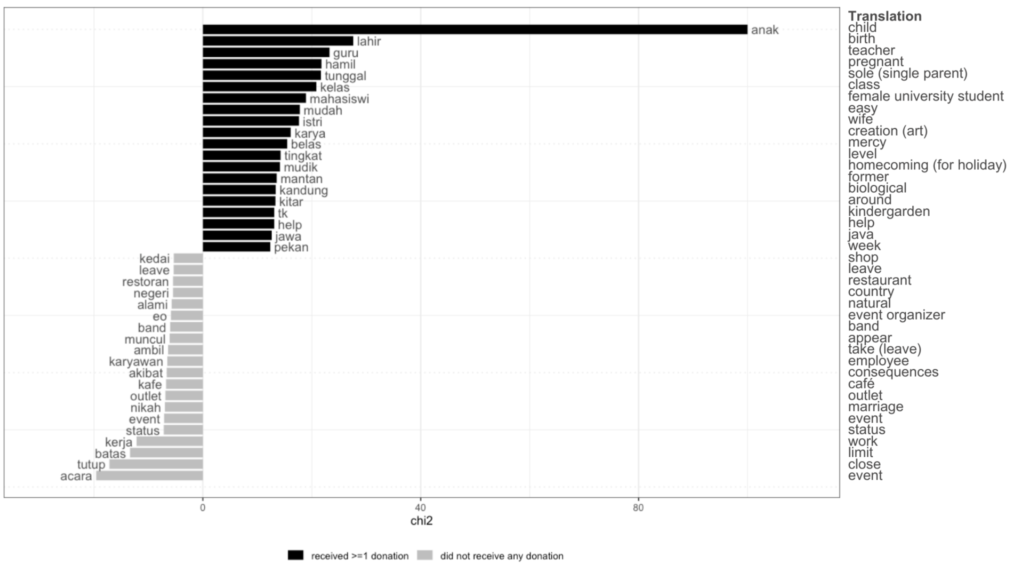
Note: Chart plots coefficients from $Y_{ijkl} = \alpha_2 + \beta_2 Characteristics_j + DonorFE_i + \varepsilon_{1,ijkl}$. Range for each coefficient indicates the 90% confidence interval.

Figure 5: Effects of Beneficiary Characteristics on Donation Values



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

Figure 6: Keyness Statistics on Donor Behavior: Characteristics of Beneficiaries Who Received a Donation versus Those Who Did Not



Note: Black (gray) bars show terms mentioned with greatest relative frequency in beneficiary narratives that received at least one donation relative to those that did not receive any donations (and vice versa).

Table 1: Summary Statistics of Platform Users

A. Donations and Appeals on Platform	(1) Mean	(2) SD	(3) Max	(4) Count
Received any donations	0.81	0.40	1	2054
Number of donations	2.09	2.14	27	2054
Total received donations (USD)	17.84	26.01	646	2054
Frequency being displayed to donors	26.21	18.52	68	2054
Narrative length (words)	30.13	14.87	70	2054
Appeal duration (month)	2.19	0.87	3	2054
Appeal (USD, winsorized)	139.09	91.06	643	2054

B. Characteristics	Platform Database		Platform User Survey (Averages/Shares)	
	Count	% of Benef.	Recipients	Donors
	(5)	(6)	(7)	(8)
Gender				
Masculine name	1302	63%		
Male			57%	30%
Household status				
Breadwinner/mentions dependent(s)	462	22%		
Mentions child(ren) as dependents	254	12%		
Married			43%	34%
Household size			3.7	3.2
Religion				
Muslim name	1678	82%		
Islam			87%	68%
Region/Ethnicity				
Jakarta metro area	1385	67%		
Java, non-Jakarta Metro	491	24%		
Outside Java	178	9%		
Javanese			48%	56%
Employment sector				
Hospitality, retail, food service	1243	61%	35%	7%
Government, education, or health	111	5%	3%	17%
Art and creatives	326	16%		
Transportation	131	6%		
Finance or IT			3%	21%
Other	243	12%	38%	36%
Other characteristics				
Age			30	29
Years of education			13	15
Earning (USD)			$1,882	$8,626
Earning for charity			5%	6%
Mobile money platform in use			1.4	2.3
Employer is corporation/international			17%	49%
Employer is small			38%	13%
Amount received from platform (USD)			$25.68	$0
Amount donated via platform (USD)			$0	$26.33
Obs	2054		60	216

Note: Columns 1-6 display statistics from the platform database. Columns 7 and 8 display statistics from responses to a user survey fielded between October 2020 to July 2021. Survey is voluntary and decoupled from the donation process. Some characteristics are not exactly identical as they were either generated from imputation (gender from masculine name) or from direct survey questions. See text for details.

Table 2: Impact of Screen Size on Donation Outcomes

	(1) 1(Donation)	(2) Number of Donation	(3) Total Value of Donations
set=3	-0.004	0.042	-0.669
	(0.015)	(0.080)	(1.124)
set=8	0.017	0.182**	1.842
	(0.019)	(0.082)	(1.365)
Constant	0.118***	0.367***	5.790***
	(0.011)	(0.090)	(1.024)
Observations	2405	2405	2405

Notes: Regression of donation outcomes on choice set size. Observation unit is a donor-session. Robust standard errors are displayed in parentheses. Sample is from Oct 2020 to Jun 2021. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 3: Impact of Screen Size on Search Behavior

	(1) Refresh button action (times)	(2) Total beneficiary exposure (cards)	(3) Donate in first screen
3-opt sets	1.870***	-12.958***	-0.030**
	(0.489)	(3.683)	(0.012)
8-opt sets	0.515	-0.976	0.023
	(0.308)	(2.674)	(0.016)
Constant	4.633***	32.842***	0.075***
	(0.417)	(2.445)	(0.010)
Observations	2405	2405	2405

Notes: Regression of variables on search behavior outcomes on choice set size. Observation unit is a donor-session, restricting to donor-sessions where at least one donation was made in columns 1, 2, 5, 6, 7. Robust standard errors are displayed in parentheses. Sample is from Oct 2020 to Jun 2021. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 4: Impact of Display Order within Set on Probability of Donation

	(1) All	(2) 3-opt	(3) 8-opt	(4) 10-opt
	A. Outcome: 1(Donate)			
Display order	-0.0006**			
	(0.0002)			
Top (4) in set		0.0065	0.0088***	0.0050*
		(0.0043)	(0.0030)	(0.0026)
Bottom (3 or 5) in set (8 or 10)		0.0051	0.0063**	0.0028
		(0.0038)	(0.0027)	(0.0024)
Constant	0.0253***	0.0299***	0.0166***	0.0130***
	(0.0011)	(0.0023)	(0.0024)	(0.0021)
FE	donor	donor	donor	donor
R2	0.243	0.272	0.239	0.216
Observations	52086	10620	20776	20690
	B. Outcome: Donation (USD)			
Display order	-0.0042			
	(0.0037)			
Top (4) in set		0.0370	0.0686	0.0816**
		(0.0573)	(0.0438)	(0.0393)
Bottom (3 or 5) in set (8 or 10)		0.1050	0.0451	0.0426
		(0.0664)	(0.0402)	(0.0321)
Constant	0.2678***	0.2723***	0.2132***	0.1443***
	(0.0170)	(0.0356)	(0.0353)	(0.0274)
FE	donor	donor	donor	donor
R2	0.192	0.184	0.304	0.089
Observations	52086	10620	20776	20690

Notes: Regression of donation outcomes on a continuous variable representing the position of the beneficiary's display position within a set, across all treatment groups (Column (1)), and two dummy variables representing the top and bottom (groups) in the set for each treatment group (set of 3, 8, and 10 in Columns (2)–(4)). Observation is a donor–beneficiary dyad. Standard errors are clustered at the donor and beneficiary levels and displayed in parentheses. Sample is from Oct 2020 to Jun 2021 and excludes outliers. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 5: *Deservingness* (Latent Semantic Scale) and Donation Outcomes

	(1) 1(Donate)	(2) 1(Donate)	(3) 1(Donate)	(4) Donation (USD)	(5) Donation (USD)	(6) Donation (USD)
Deservingness (index)	0.0822***	0.0687***	0.0685***	0.8871***	0.5076*	0.5022*
	(0.0168)	(0.0162)	(0.0163)	(0.2719)	(0.2627)	(0.2646)
% Ask fulfilled		0.0009***	0.0009***		0.0241***	0.0242***
		(0.0001)	(0.0001)		(0.0046)	(0.0046)
Set counter		-0.0000	-0.0000		-0.0001	-0.0001
		(0.0000)	(0.0000)		(0.0002)	(0.0002)
Ask amount (USD)		0.0000**	0.0000**		0.0011***	0.0011***
		(0.0000)	(0.0000)		(0.0003)	(0.0003)
Ask duration		0.0002	0.0001		0.0158	0.0155
		(0.0008)	(0.0008)		(0.0151)	(0.0151)
Greater Jakarta			-0.0015			-0.0357
			(0.0015)			(0.0250)
Order in set			-0.0006**			-0.0038
			(0.0002)			(0.0037)
Constant	-0.0183**	-0.0236***	-0.0201**	-0.1928	-0.3963**	-0.3572**
	(0.0084)	(0.0087)	(0.0088)	(0.1358)	(0.1567)	(0.1550)
FE	donor	donor	donor	donor	donor	donor
R2	0.244	0.253	0.253	0.193	0.213	0.213
Observations	52072	52072	52072	52072	52072	52072
Deservingness SD	0.177	0.177	0.177	0.177	0.177	0.177

Notes: Regression of donation outcomes on beneficiary characteristics with donor session fixed effects. Observation unit is donor–beneficiary dyad. Standard errors are clustered at donor and beneficiary levels and displayed in parentheses. Sample is from Oct 2020 to Jun 2021, excluding outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

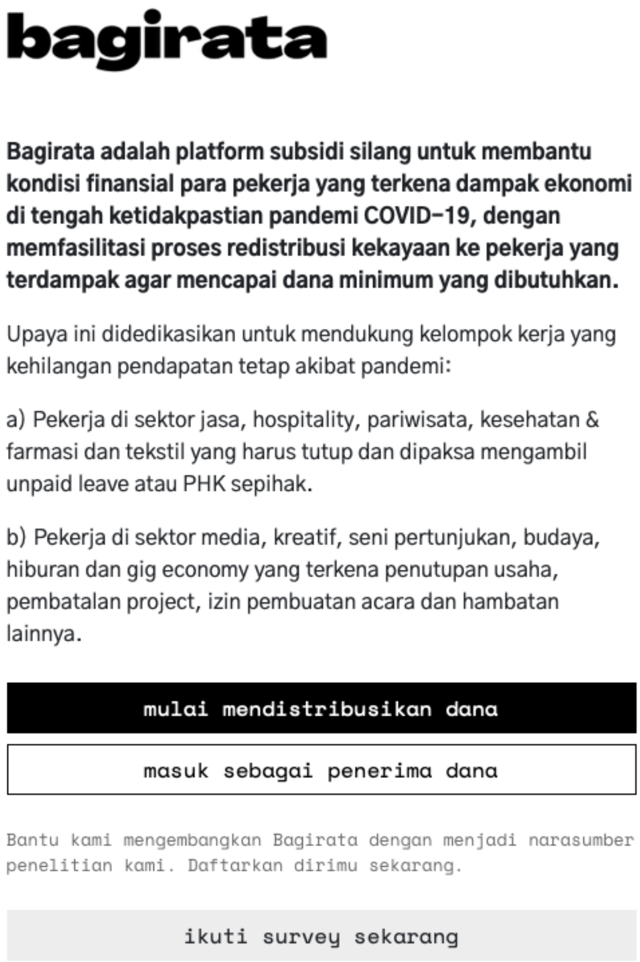
Table 6: In-Group Bias: Regression of Donation Indicator and Value on Alignment of Donor–Beneficiary Characteristics

	(1)	(2)	(3)	(4)	(5)
	A. Outcome: 1(Donate)				
Female donor-feminine name beneficiary	0.0590***				0.0588***
	(0.0147)				(0.0148)
Muslim donor-muslim name beneficiary		-0.0047			-0.0001
		(0.0287)			(0.0284)
Ethnicity alignment donor-beneficiary			0.0151		0.0506*
			(0.0243)		(0.0292)
Donor-beneficiary in same district				-0.0009	0.0067
				(0.0175)	(0.0175)
Dep. Var. Mean	0.087	0.087	0.087	0.087	0.087
R2	0.138	0.132	0.132	0.132	0.140
Observations	2396	2396	2396	2396	2396
	B. Outcome: Donation (USD)				
Female donor-feminine name beneficiary	0.8680**				0.8846**
	(0.3729)				(0.3838)
Muslim donor-muslim name beneficiary		0.0139			0.0481
		(0.4266)			(0.4426)
Ethnicity alignment donor-beneficiary			0.4988		0.5253
			(0.3865)		(0.4018)
Donor-beneficiary in same district				0.2510	0.3419
				(0.3506)	(0.3688)
Dep. Var. Mean	0.957	0.957	0.957	0.957	0.957
R2	0.117	0.113	0.113	0.113	0.117
Observations	2396	2396	2396	2396	2396

Notes: Regression of the donation indicator and value on indicators for alignment between donor and beneficiary characteristics. The observation unit is a donor–beneficiary dyad. Standard errors are clustered at the donor email, session and beneficiary levels and displayed in parentheses. The sample is matched dyads between platform user survey and activity trace, with singletons omitted. The sample is comprised of 40 donor-emails in 78 sessions, presented with 1283 unique beneficiaries from the database. This is the only sample for which we can separately identify donors from sessions based on the email addresses that they entered in both the *Bagirata* database and the user–donor survey. All regressions include set counters and beneficiary order within set. All regressions include session FE (absorbing set size assignment), and donor email FE (absorbing donor-email-invariant indicators from survey indicating gender, religious affiliation, and ethnicity). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

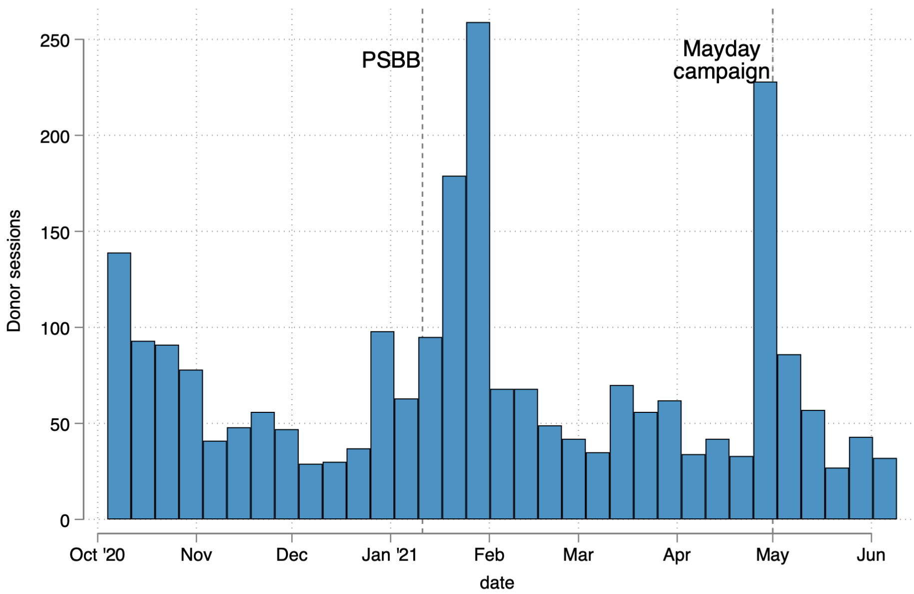
A. Appendix Tables and Figures

Figure A.1: Landing Page of the Platform



Note: This is the first page that potential donors see upon entering the *Bagirata* website.

Figure A.2: Unique Sessions on Platform over Time



Note: The two spikes correspond to the large-scale mobility restriction (*Pembatasan Sosial Berskala Besar*/PSBB) implemented in January 2021 and a Labor Day/May Day donation drive campaign. Randomization remained ongoing during these two events.

Table A.1: Sample of Appeals

No.	Appeal (Indonesian/English translation) and beneficiary characteristics
#1.	"*Sy bkrja di resto sbg staf dapur yg saat ini sdh tdk lg brproduksi akibat dampak epidemi covid19. Sy memiliki 5 anak. 2 putri dn 3 putra. Sy tdk tau smpai kpn epidemi ini brakhir. Sy tdk miliki apa2 selain brgantung pd pkerjaan sy.*" / "I work as a kitchen staff in a restaurant that is currently no longer open due to COVID-19. I have 5 children, 2 daughters and 3 sons. I don't know how long this epidemic will last. I have nothing but my job." Chef in Jakarta, not a feminine name, Muslim name, family breadwinner, has dependent child(ren). Asks US$67.
#2.	"*Di PHK karena murid sekolah berkurang sehingga, sekolah tidak sanggup bayar gaji.*" / "I was laid off because my school enrollment has dropped, the school could not pay for my salary." A principal in a private kindergarten in Sumatera, female name, Muslim name, not a breadwinner. Asks US$100.
#3.	"*hotel saya tutup dan saya termasuk yang terkena dampak dan harus resign/PHK*" / "My hotel was closed and I was among those affected and had to resign/be laid off." Server/attendant in an overseas location, not a feminine name, not a Muslim name, not a breadwinner. Asks US$100.
#4.	"*Sebelum adanya wabah ini pendapatan hasil ojol saya 250 sehari tetapi untuk saaat ini hanya 15 sehari ini pun haru muter muter cari orderan*" / "Before the pandemic, my earning from driving is 250 per day but now only 15 daily, even after driving around everywhere to get customers." Motorcycle rideshare driver in Jakarta, not a feminine name, Muslim name, not a breadwinner. Asks US$200.
#5.	"*Saya kehilangan pekerjaan karena Kedai minunan tempat saya kerja tutup. Padahal istri saya baru saja melahirkan. Saya membutuhkan bantuan untuk membeli kebutuhan anak saya.*" / "I lost my job because the drink shop where I work is closed. My wife recently gave birth. I need help to buy my child's needs." Drink shop attendant in Central Java, not a feminine name, Muslim name, family breadwinner, has dependent child(ren). Asks US$67.
#6.	"*Saya sudah 1 tahun putus kontrak, dan saya blom bisa bekerja lagi. Sya butuh tambahan biaya buat orang tua sya yg sedang sakit stroke*" / "I've been out of contract for 1 year, and I could not find work. I need additional help for my parents who suffered from a stroke." Hotel steward in Jakarta, not a feminine name, Muslim name, family breadwinner, no dependent child(ren). Asks US$100.
#7.	"*semenjak adanya pandemi covid19 melanda,tempat kerja kami sepi pengunjung.sedangkan saya harus membiayai kedua anak saya yang telah ditinggal ibunya meninggal dunia, mereka semua masih kecil2. dan sebentar lagi anak2 mendaptar sekilah TK dan PAUD.*" / "Since the COVID-19 pandemic hit, our coffeeshop has been empty. Meanwhile, I have to pay for my two children whose mothers have died, they are all still small. Soon the children will enroll in kindergarten and PAUD." Coffeeshop attendant in East Java, not a feminine name, Muslim name, family breadwinner, has dependent child(ren). Asks US$100.

#8.	"*Kantor saya tutup di bulan Juli. Sejak saat itu saya belum dapat kerja hingga hari ini. Saya sudah melamar ke berbagai kantor, namun masih belum mendapatkan kabar baik. Saya memperdalam kemampuan desain dan ilustrasi dan Copywriting, mengumpulkan portofolio terbaru agar mendapatkan peluang dari Freelance.*" / "My office closed in July. Since then I have not been able to work. I have applied to various offices but still have not received any good news. I deepen my design and illustration and copywriting skills, building updated portfolios to get freelance opportunities." Social media officer in Jakarta, not a feminine name, Muslim name, not a breadwinner. Asks US$47.
#9.	"*Restaurant tempat saya kerja ditutup sampai waktu yang belum ditentukan, saya dipaksa diPHK*" / "The restaurant where I work is closed until further notice; I was laid off." Guest relations officer in Jakarta, female name, Muslim name, not a breadwinner. Asks US$100.
#10.	"*Saya housekeeping di kapal pesiar. Setahun lebih tak ada kejelasan kontrak. Tabungan habis untuk kontrakan dan biaya kuliah anak sulung saya. Tunggakan spp anak kedua 7 bulan. Sudah 5 tahun kami mempunyai shelter straycats, ada 21 kucing yg kami rawat. Ini adalah salahsatu ihtiar saya demi mereka. Doakan kami mampu bertahan ya.*" / "I am housekeeper on a cruise ship. For more than a year, there is no clarity on the contract. My savings are used up for rent and my eldest child's college fees. The tuition for my second child is late for 7 months. We also have a shelter for stray cats for 5 years, with 21 cats. This is an appeal for their sake. Pray for us to survive." Housekeeping in Jakarta, not a feminine name, Muslim name, family breadwinner, has dependent child(ren). Asks US$100.

Table A.2: Summary of Visits, Assignments by Donation Outcome

	Set = 3			Set = 8			Set = 10			Overall		
	Mean	Med	N	Mean	Med	N	Mean	Med	N	Mean	Med	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Donation (USD)												
Beneficiaries with donation	9.46	7.14	359	11.35	7.14	484	12.07	7.14	340	10.98	7.14	1,183
All displayed beneficiaries	0.32	0.00	10,620	0.26	0.00	20,776	0.2	0.00	20,690	0.25	0.00	52,086
Total set seen by visitors												
Nondonating	3.8	1	642	3.0	1	669	2.3	1	668	3.0	1	1979
Donating	8.5	5	132	3.8	2	155	4.0	2	139	5.3	3	426
All visitors	4.6	1	774	3.2	1	824	2.6	1	807	3.4	1	2405
When donation is made												
The earliest set	3.9	2	132	1.9	1	155	2.1	1	139	2.6	1	426

Notes: Table shows the mean set seen by visitors, disaggregated by eventual donation outcome (donating visitors versus nondonating visitors) and assignment to treatment arms (choice set size). Columns show the mean number of sets, median number of sets, and number of visitors in each category.

Table A.3: Summary statistics on beneficiaries' total appeal (in USD), by subsample

	Mean	SD	Count	% of Total
Employment sector				
Hospitality, retail, food service	344.40	1157.41	1,243	61%
Art and creatives	425.90	721.84	326	16%
Transportation	394.63	321.62	131	6%
Education	289.19	359.69	77	4%
Healthcare	195.59	100.56	34	2%
Other (incl. media, textile)	265.95	200.64	243	12%
Region				
Jakarta metro area	342.95	713.44	1,385	67%
Java, non–Jakarta metro	378.84	1534.68	491	24%
Outside Java	287.56	257.77	178	9%
Mobile money channels				
Go-pay	338.74	771.79	1,317	64%
Dana	353.63	1150.40	808	39%
Jenius	388.37	466.39	216	11%
Social media				
Instagram	355.21	1076.71	1,579	77%
Facebook	307.50	442.55	895	44%
Twitter	314.55	294.96	315	15%
Gender				
Masculine name	363.56	1140.01	1,302	63%
Feminine name	317.58	489.07	752	37%
Religion marker				
Muslim name	330.30	705.37	1,678	82%
Non-Muslim name	420.03	1660.99	376	18%
Household status				
Breadwinner/mentions dependent(s)	362.45	557.41	462	22%
No mention of dependents	342.17	1042.18	1,592	78%
Dependent children				
Mentions child(ren) as dependents	362.68	327.24	254	12%
No mention of a child	344.48	1012.50	1,800	88%

Note: % of total describes the proportion of each subgroup out of the 2,054 total beneficiaries. Total appeal is calculated from appeal per month times the number of months that the beneficiaries requested a donation.

Table A.4: Summary Statistics of the Display Counter and Donations among Platform Beneficiaries from Donor Perspective

Platform beneficiaries	# times displayed Mean	SD	% receive donations	# donations Mean	SD	Donation (USD) Mean	SD
Employment sector							
Hospitality, retail, food service	26.60	18.65	81%	2.06	2.05	17.94	29.05
Art and creatives	21.20	17.38	82%	2.09	1.85	17.86	19.27
Transportation	12.91	9.31	94%	3.82	3.62	26.31	24.64
Education	33.69	18.17	73%	2.26	2.32	23.14	23.97
Healthcare	40.38	16.54	91%	1.38	0.85	10.84	12.14
Other (incl. Media, Textile)	33.71	17.31	68%	1.34	1.34	12.04	17.20
Region							
Jakarta metro area	24.48	18.44	83%	2.24	2.20	18.64	27.45
Java, non–Jakarta metro	28.63	18.48	80%	1.91	2.14	17.29	23.41
Outside Java	32.96	17.02	65%	1.45	1.51	13.20	20.31
Mobile money channels							
Go-pay	25.10	18.16	88%	2.55	2.32	21.88	29.62
Dana	28.04	18.99	71%	1.58	1.90	13.15	20.14
Jenius	22.19	17.62	84%	2.26	1.97	20.54	23.85
Social media							
Instagram	25.19	18.43	81%	2.17	2.27	18.10	26.52
Facebook	27.75	18.53	80%	2.03	1.96	18.27	23.62
Twitter	23.09	17.94	80%	2.05	2.26	16.89	19.39
Gender codes							
Masculine name	26.37	18.48	78%	1.98	2.15	16.75	27.51
Feminine name	25.92	18.61	85%	2.27	2.12	19.74	23.09
Religion marker							
Muslim name	26.32	18.59	81%	2.13	2.22	18.17	27.00
Non-Muslim name	25.72	18.24	78%	1.91	1.78	16.39	20.99
Household status							
Breadwinner/has dependent(s)	25.61	18.22	90%	3.10	2.78	27.80	28.82
No mention of dependents	26.38	18.61	78%	1.80	1.82	14.95	24.40
Dependent children							
Mentions child(ren) as dependents	26.86	18.39	93%	3.39	2.71	31.74	31.81
No mention of a child	26.11	18.54	79%	1.91	1.99	15.88	24.47

Note: % receive donations describes the share of beneficiaries in the subgroup who receive donation out of the total beneficiaries in their respective subgroup.

Table A.5: Summary Statistics of Donations among Platform Beneficiaries with Respect to Frequency of Display to Donors

	N times displayed	Donation count	Share display receiving donation	Mean donation (USD)	Uncond. mean donation (USD)
Employment sector					
Hospitality, retail, food service	32,008	732	0.023	10.91	0.25
Art and creatives	6,632	126	0.019	10.89	0.21
Transportation	1,596	49	0.031	11.85	0.36
Education	2,523	87	0.034	12.98	0.45
Healthcare	1,353	28	0.021	7.95	0.16
Other (incl. Media, Textile)	7,974	161	0.020	10.53	0.21
Region					
Jakarta metro area	32,753	741	0.023	10.86	0.25
Outside Jakarta metro	19,333	442	0.023	11.18	0.26
Mobile money channels					
Go-pay	31,929	966	0.030	11.41	0.35
Dana	22,007	333	0.015	10.06	0.15
Jenius	4,607	110	0.024	9.14	0.22
Social media					
Instagram	38,442	836	0.022	10.60	0.23
Facebook	24,061	596	0.025	11.68	0.29
Twitter	7,018	155	0.022	9.95	0.22
Gender codes					
Masculine name	33,238	698	0.021	10.50	0.22
Feminine name	18,848	485	0.026	11.68	0.30
Religion marker					
Muslim name	42,737	957	0.022	11.10	0.25
Non-Muslim name	9,349	226	0.024	10.49	0.25
Household status					
Breadwinner/mentions dependent(s)	11,440	387	0.034	11.44	0.39
No mention of dependents	40,646	796	0.020	10.76	0.21
Children dependents					
Mentions child(ren) as dependents	6,597	260	0.039	12.01	0.47
No mention of a child	45,489	923	0.020	10.69	0.22

Table A.6: Impact of Screen Size on Number of Donations Per Screen

	(1) Exactly 1 donation	(2) > 1 donation
3-opt sets	0.154***	-0.109*
	(0.043)	(0.056)
8-opt sets	-0.002	0.019
	(0.049)	(0.057)
Constant	0.770***	0.374***
	(0.036)	(0.041)
Observations	426	426

Notes: Regression of donation outcomes on choice set size. Observation unit is a donor-session, restricting to donor-sessions where at least one donation was made. Robust standard errors are displayed in parentheses. Sample is from Oct 2020 to Jun 2021. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Impact of Choice Set Size on Donation Indicator, Various Fixed Effects

	(1) 1(Donate)	(2) 1(Donate)	(3) 1(Donate)	(4) 1(Donate)	(5) Donation (USD)	(6) Donation (USD)	(7) Donation (USD)	(8) Donation (USD)
3-opt sets	0.0174***	0.0179***	0.0202***	0.0170***	0.1214*	0.1409**	0.1666***	0.1300**
	(0.0053)	(0.0052)	(0.0043)	(0.0043)	(0.0649)	(0.0611)	(0.0577)	(0.0551)
8-opt sets	0.0069	0.0070	0.0112***	0.0103***	0.0661	0.0785	0.1280**	0.1190**
	(0.0047)	(0.0047)	(0.0037)	(0.0037)	(0.0668)	(0.0631)	(0.0579)	(0.0575)
Constant	0.0164***	0.0162***	0.0141***	0.0152***	0.1983***	0.1890***	0.1640***	0.1761***
	(0.0022)	(0.0021)	(0.0017)	(0.0016)	(0.0358)	(0.0301)	(0.0288)	(0.0272)
Beneficiary FE		Yes	Yes	Yes		Yes	Yes	Yes
Set FE			Yes				Yes	
Display order FE			Yes				Yes	
Sequence FE				Yes				Yes
R2	0.002	0.050	0.059	0.061	0.000	0.069	0.073	0.076
Observations	52086	52081	52081	51905	52086	52081	52081	51905

Notes: Regression of donation outcomes on choice set size. Observation unit is a dyad. Sample excludes outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Platform Users' Self-Declared Reasons for Charitable Donations

Donors' responses to user survey on the platform	%
Donated to an organization/volunteered in the last year	92
Donated blood in the last year	18
Reasons to donate	
The beneficiary needs my donation	58
The organization is trustworthy	56
I support humanitarian causes	54
The organization uses donations effectively	50
Following religious teaching	43
I support education causes	41
I support health causes	41
I support a disaster relief program	40
I support the causes behind the fundraiser	38
I wished to not be bothered anymore by the fundraisers/beggars/buskers	3
Stated "very likely" to donate to beneficiaries with particular characteristics	
The beneficiary needs to take care of their family (children or elderly)	86
The beneficiary has been poor for a long time/came from a poor family	85
The beneficiary needs help because of an unexpected event (disaster, illness, layoff)	82
The beneficiary is a woman	69
The beneficiary lives in the same neighborhood as the donor	56
The beneficiary did not have a good education	53
The beneficiary has the the same religion as the donor	49
The beneficiary has the the same ethnicity as the donor	42
The beneficiary has also received donations from other donors	34
The beneficiary has a young age	32
Observations	216

Notes: Survey responses from Oct 2020 to July 2021.

Table A.9: Beneficiary Characteristics and Donation Outcomes

	(1)	(2)
	1(Donate)	Donation (USD)
Breadwinner	0.007***	-0.009
	(0.002)	(0.041)
Transportation worker	-0.005	-0.092
	(0.005)	(0.128)
Laid off	0.001	-0.017
	(0.002)	(0.029)
Arts	-0.004**	-0.075**
	(0.002)	(0.034)
Education worker	0.013***	0.188***
	(0.004)	(0.056)
Narrative (x50 words)	0.005**	0.020
	(0.002)	(0.040)
Female name	0.001	0.042
	(0.001)	(0.026)
Muslim name	-0.002	-0.014
	(0.002)	(0.031)
Non-formal language	0.000	-0.005
	(0.001)	(0.023)
Facebook link	0.004***	0.042
	(0.002)	(0.030)
Instagram link	-0.001	-0.038
	(0.002)	(0.038)
Twitter link	-0.003*	-0.036
	(0.002)	(0.032)
Greater Jakarta	-0.004**	-0.042
	(0.001)	(0.026)
Order in set	-0.001**	-0.004
	(0.000)	(0.004)
Gopay e-channel	0.015***	0.118***
	(0.003)	(0.036)
Dana e-channel	0.001	-0.037
	(0.002)	(0.033)
Jenius e-channel	0.006	-0.003
	(0.004)	(0.048)
No donations yet	-0.019***	0.089
	(0.003)	(0.071)
% Ask fulfilled	0.001***	0.025***
	(0.000)	(0.006)
Set counter	-0.000	-0.000
	(0.000)	(0.000)
Ask amount (USD)	-0.000	0.001***
	(0.000)	(0.000)
Ask duration	0.000	0.012
	(0.001)	(0.014)
Constant	0.018***	-0.223*
	(0.005)	(0.130)
Dep. Var. Mean	0.023	0.249
R2	0.259	0.214
Observations	52086	52086

Notes: Regression of donation outcomes on beneficiary characteristics with donor session FE. Observation unit is donor–beneficiary dyad. Standard errors are clustered at the donor and beneficiary levels and displayed in parentheses. Sample is from Oct 2020 to Jun 2021, excluding outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Regression of the Donation Outcomes on Beneficiary's Donation Progress

	(1) 1(Donate)	(2) 1(Donate)	(3) 1(Donate)	(4) 1(Donate)	(5) Donation (USD)	(6) Donation (USD)	(7) Donation (USD)	(8) Donation (USD)
% Ask fulfilled	0.001***	0.001***	0.004***	0.003***	0.027***	0.024***	0.109***	0.109***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.005)	(0.004)	(0.021)	(0.022)
FE	_cons	donor	beneficiary	donor beneficiary	_cons	donor	beneficiary	donor beneficiary
R2	0.015	0.252	0.076	0.303	0.029	0.212	0.147	0.312
Observations	52086	52086	52081	52081	52086	52086	52081	52081

Notes: Regression of the donation outcomes on beneficiary's donation progress (% of asked donation amount received so far from other donors). The observation unit is a donor–beneficiary dyad. Standard errors are clustered at the donor and session levels and displayed in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B. Further Supplementary Materials

Note on pre-registration. Our pre-registration at OSF was made public on May 21, 2021, from an associated project (https://osf.io/wnz46) that was created in Jan 29, 2021. The pre-registration was created and made public prior to the full dataset made available to the researchers (see Olken JEP 2015 for discussion on timing). We subsequently also registered this experiment with the AEA registry. Table B.2 compared our preregistration with notes from the implementation.

Beneficiary Coding Guidelines. We coded gender and religion from the beneficiaries' names to create indicators for feminine names and Muslim names. We rely on beneficiary's location at the district level to approximate his neighborhood origin. We do not have explicit markers for education and age, but we use beneficiaries' writing style from their narrative appeals and use of social media to provide information. Assistants coded the use of nonformal written Indonesian with reliance on abbreviations, regional slang for pronouns, and (mis)use of punctuation marks, which are typically associated to individuals with lower education. We include indicators of social media links, which also provide hints about the beneficiary's age: a social media analytics tool company reports that Instagram is mostly used by younger age groups, while Facebook is more popular among older people in Indonesia. Specifically, slightly more than 50% of Instagram users in Indonesia are 13–24 years old, compared to 40% of Facebook users in the same age group. Facebook also has a larger share of users from the 35+ age group than Instagram at 28% versus 18%, respectively (NapoleonCat, 2023).

Keyness Statistics. This method computes a χ^2 statistic for each term that appears in a beneficiary narrative and ranks, across all narratives, the most frequently mentioned terms for beneficiaries who received at least one donation vis-à-vis those who did not receive any donations. In our context, this method approximates asking donors for the motivations behind their decision to donate to a specific beneficiary, based on various perceived measures of deservingness drawn from textual analysis of beneficiary narratives. In political science, this method has been used to identify right- versus left-leaning voters from self-written voter descriptions (Zollinger, 2022). The results for this statistic are displayed in Figure 6, although one should interpret the appearance and ranking of individual terms with caution (Zollinger, 2022).

Keywords positively associated with donation are those related to beneficiaries with dependent children or affiliations with the education sector. Narratives containing terms related to children, pregnancy and childbirth, or marriage are more likely to attract donations. Likewise, narratives containing the terms "teacher" or "college student" receive more favorable donation outcomes. In contrast, narratives that contain terms indicative of employment hardship, such as references to restaurant closures or cancelled events, are less likely to secure donations. The original Indonesian words for these translations are as follows: *anak, hamil/kandung, lahir, istri* for beneficiaries as family breadwinners; *guru, mahasiswi* for education-sector markers; and *kafe, restoran, tutup, acara, event, EO* for the hospitality industry and performing arts. We incorporate these individual seed words into a regression analysis by computing the deservingness index as a composite score for each beneficiary narrative using latent semantic scaling.

LSS: Latent Semantic Scaling. Latent semantic scaling (LSS) utilizes an initial set of user-defined "seed words" to assign scores to other words based on their contextual proximity to the seed words. In addition to these user-defined seed words, LSS requires a substantial corpus of documents, typically ranging from 5,000 to 10,000 documents. To calculate the semantic proximity between words in the corpus, LSS employs a word-embedding technique, generating word vectors that represent low-dimensional representations of word semantics. These produced

Table B.1: Top 10 Keywords: Keyness Statistics

donate = 1 (***deserving***)	anak	lahir	madrasah	guru	separuh	mother	goyang	hamil	tunggal	pantomim
donate = 0 (***undeserving***)	acara	tutup	batas	kerja	hibur	status	event	nikah	outlet	kafe

Notes: The first row lists 10 keywords among the narratives of beneficiary who received at least one donation.

word vectors are then used by LSS to calculate proximity scores for each word in relation to each seed word. The score of a given word to all predefined seed words is then weighted to calculate the proximity score of each word. Subsequently, LSS computes the proximity score of documents by weighting the proximity scores of individual words provided in the documents based on their frequency within the documents.

Table 1 presents the seed words utilized in the computation, based on the keyness statistics. Words with closer contextual associations with the deservingness markers are assigned scores closer to 1, while words with closer contextual associations with undeservingness are assigned scores closer to -1. For example, the word "*mahasiswi*" (female student) receives the highest score, as it is contextually closer to the 10 deservingness seed words. Conversely, the word "*tutup*" (close(d)) receives the lowest score, as it is contextually closer to the 10 undeservingness seed words. This process is repeated for every single word that appears in a beneficiary's narrative. For each beneficiary narrative, *latent semantic scaling* maps *keyness statistics* to a composite score by computing and assigning a weighted proximity score for each word, in each narrative, to the seed words listed in Table 1.

To illustrate this procedure, we discuss two beneficiary narratives, one with the lowest and one with the highest proximity score. Take the beneficiary narrative with the lowest proximity score, "*Saya bekerja sebagai Disk Jockey DJ paruh waktu untuk dua outlet [Group name] yaitu [Bar name] dan [Pizza name has the word party] dan minimal saya mendapat giliran 3 kali dalam sebulan. Itu adalah satu-satunya sumber pemasukan saya sebelum Covid 19 menyerang dan tempat itu tutup sampai waktu yang tidak ditentukan*". Collectively, every (stemmed) word in this narrative possesses minimal contextual similarities with any of the top 10 deservingness seed words. Instead, they demonstrate very close contextual meanings with the top 10 undeservingness seed words. For example, the word "party" shares a close contextual meaning with the seed word "event" and the word "bar" to the seed word "cafe."

In contrast, the document with the highest score, "*[School name] sebagai yayasan pengelola tenaga alih daya outsourcing yang menampung guru-guru praktikum di sekolah-sekolah swasta ditutup karena pendemi covid 19. Saya dan semua guru diberhentikan baik guru full time maupun part time Saya sebagai guru full time pun diberhentikan dan hanya menerima gaji terakhir saya bekerja tanpa pesangon*", contains several words that possess close, if not identical, contextual meanings with the deservingness seed words. For instance, the word "*guru*" appears multiple times in the document and is one of the top 10 seed words, contributing to the higher score assigned to this document.

Hence, we are interested in using the LSS statistic as our key measure of *deservingness*. To do so, we transform the LSS statistic to take values between 0 and 1, with 0 indicating the lowest level of similarity to our *deservingness* key words (and conversely, the highest similarity to our *undeservingness* key words, and 1 indicating the highest level of similarity to our *deservingness* key words (and conversely, the lowest similarity to our *undeservingness* key words). We call this constructed LSS statistic our deservingness index. This index is transformed to take values between 0 and 1, with 0 indicating the lowest level of similarity to our *deservingness* key words (and conversely, the highest similarity to our *undeservingness* key words, and 1 indicating the highest level of similarity to our *deservingness* key words (and conversely, the lowest similarity to our *undeservingness* key words).

Saliency in Multiple Dimensions. Consider a donor who sees Table A.1 with beneficiaries #1–3 drawn as the first set and refreshes to have beneficiaries #4–6 drawn in the second set. In the first set, Beneficiary #1 is the only one in Jakarta, Beneficiary #2 is the only one with a feminine name, and beneficiary #3 is the only one without a Muslim name. Beneficiary #1 is also the only one who is a family breadwinner with child dependents. In the second set, all of them have masculine and Muslim names. Two of them are based in Jakarta. Both Beneficiaries #5 and #6 are family breadwinners, but only Beneficiary #5 mentions a child (Beneficiary #6 mentions ailing parents).

For saliency variations due to different sizes of the choice sets, consider two donors assigned to different treatments: the first one views only the initial three entries (3-choice set), while the second one observes the entire list of beneficiaries (10-choice set), as presented in Table A.1. Beneficiary #1 is the only feminine name in the 3-choice set, but not in the 10-choice set. Likewise, she is the only beneficiary who is a family breadwinner in the smaller set, but not in the larger one. Depending on the random draw, a beneficiary may still be the only one with the salient characteristics in both large and small choice sets. In this example, Beneficiary #3's status as the only beneficiary with a non-Muslim name persists in both sets.

Table B.2: Notes on pre-registration

Pre-registration at OSF	Implementation comment
Hypotheses We aim to test the following hypotheses:	
1. The more the number of potential beneficiaries displayed to donors, the lower the donors' probability of donating.	Hypothesis 1 test is reported in Table 2
2. The higher the number of existing donors who have already donated to a beneficiary, the lower a potential donor's incentive to help the beneficiary.	Hypothesis 2: N/A. Experiment for this hypothesis was scrapped from implementation by the partner.
3. The larger the sum of donations that a beneficiary has already secured, the lower a potential donor's incentive to help the beneficiary.	Hypothesis 3 tests are reported in Table A.10. This hypothesis is renumbered as H2 in main text.
4. Potential donors exhibit in-group favoritism, preferring to donate to beneficiaries who share some identity similarity (e.g., religion, location, gender, etc.)	Hypothesis 4 tests are reported in Table 6. This hypothesis is renumbered as H3 in main text. Where the experiments are implemented, the hypotheses imply and necessitates analyzing whether a beneficiary receives a donation, i.e., an indicator of donation. We also analyze donation amount, a pre-specified outcome in the following section of pre-registration.
Study Design We will conduct an online experiment amongst the Indonesian population using Bagirata's platform. Our primary tool will be a randomized number of potential beneficiaries and the beneficiaries shown, the number of other donors who have donated, and the amount of donation that has been collected so far out of the targeted donation amount.	Treatments 1-2-3 were implemented as planned. In our analysis, we used treatment 3 as the control treatment, because it was the arm that was originally implemented prior to the introduction of the experiment.
There will be four main treatments in the experiment. 1. Donors are presented with three recipients at a time upon their visit to the website. 2. Donors are presented with eight recipients at a time upon their visit to the website. 3. Donors are presented with ten recipients at a time upon their visit to the website.	Treatment 4 is implemented by randomly selecting beneficiaries from the beneficiary list. The implementation departs from the planned design by instead crossing this with treatments 1-2-3 (instead of only treatment 3).
4. Donors are presented with a menu/choice set of randomly selected beneficiaries of varying characteristics ranging from gender composition, occupation, social status, and other salient characteristics. In this treatment, donors would see ten recipients at a time upon their visit to the website. 5. Donors are presented with information similar to Treatment 1, and also, they are provided with information on the number of other donors who have donated to the same beneficiaries. 6. Donors are presented with information similar to Treatment 1, and also, they are provided with information on the magnitude of donations that beneficiaries have received so far.	Treatment 5 were scrapped from implementation. Treatment 6 were instead uniformly provided to all potential donors (in all treatments). We did not field a follow-up phone survey due to funding limitations. However, we were able to conduct an online survey to a subset of our sample to collect demographics data and corroborate donation activities.

The first treatment will serve as our control treatment. Donors will first undergo treatment 1, 2, or 3: Donors are randomly assigned to view either 3, 8, or 10 recipients at a time upon their visit to the website. Using this variation, we can analyze if donors are susceptible to choice overload/psychic numbing when they decide to donate. After treatment 1 to 3, they will be shown varying characteristics of potential beneficiaries. Donors see a random draw of potential beneficiaries from the Bagirata database. Each draw will vary in gender composition, occupation, social status, and other salient characteristics that influence their decision to give. Using this variation, we can investigate the most salient drivers of altruism among donors. After the treatments have ended, we plan to do a follow-up phone survey on beneficiaries to collect more information on demographics, asset ownership, receipt of government assistance, use of donation received, health behaviors, and recipients' well-being. We can compare Bagirata targeting performance by the overlap between its beneficiary database with government assistance receipt. The Bagirata website also prompts its users to fill an online survey on the research team's altruism. Our primary outcome variable is a continuous variable that measures the donation amount.	
Sample size The organic reach of the platform limits the dataset's size. To determine the sample size necessary, we conducted a power analysis in STATA. Referring to Table 1B, our study would require a sample size of 2481, which means an addition of 2000 new individuals to our existing pool is needed, to obtain 80% power in testing the equality of means between our three treatment groups if the treatments have effects of 0.05 σ and 0.15σ, respectively.	In total, we included data from 2405 website visit sessions in our analysis. Each session visitor saw a mean (median) set of 3.4 (1), generating 52,086 donor-beneficiary dyads.