Less Is More: Choice Overload, Saliency, and Deservingness in Online Charitable Donations *

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Abstract

Online charitable donations can serve as a vital source of mutual aid, but the proliferation of donation choices could lead to information overload, potentially reducing donations. In collaboration with an Indonesian donation platform, we conduct a field experiment to investigate the impact of the choice set size and beneficiary traits on online giving. Smaller choice sets significantly increase the likelihood of donating and the donation amount, primarily due to heightened donor attention and reduced information overload. Donors spend more time deliberating over their donation decisions. In addition, regardless of the choice set size, donors pay greater attention to beneficiaries with greater perceived deservingness. Strikingly, this preference is more pronounced in smaller choice sets, possibly due to the heightened *saliency* of beneficiary characteristics in this context. Taken together, our results highlight the susceptibility of online donor behavior to choice overload and demonstrate the potential role of choice architecture in optimizing online donations and altruistic decision-making.

JEL Classification: C90, C93, D64, D91

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1. Introduction

Nonprofits raise hundreds of billions of dollars annually from individual giving, and, throughout the world, the proportion of donors who give through online channels has been growing rapidly (Paxton, 2020; Clark et al., 2019). 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). In developing countries, the increasing adoption of mobile money has made it easier for people to receive aid through direct transfers from individual donors (Suri et al., 2023).

At the same time, however, the ease of setting up donation platforms, and beneficiary profiles on such platforms, has led to a proliferation of choices for donors in terms of what and whom to donate to. Under these circumstances, it is unclear whether we should expect to see an increase in overall donations or otherwise. On the one hand, conventional wisdom suggests that the availability of more choices could be good, as it allows more effective alignment of donor preferences. On the other hand, a growing literature that studies how individuals choose private goods (Iyengar and Lepper, 2000; Iyengar and Kamenica, 2010) suggests that the proliferation of choices could, instead, lead to choice overload and a fall in donation rates.[1]

To answer this question, we partnered with an online donation platform in Indonesia that connects potential donors to individuals impacted by COVID-19–related job losses (henceforth, beneficiaries). Together, we conducted a randomized online field experiment to investigate the impact of choice set size and beneficiary deservingness on donor behavior.[2] Donors would log on to the platform, the platform's algorithm would select a random set of beneficiary cards to donors, and donors would make their donation decision based on the menu of displayed cards (see Figure 1).

[INSERT FIGURE 1 HERE]

Each beneficiary card contains a narrative on the beneficiaries' circumstances and characteristics, such as their previous occupation and intended use of the donation. Based

[1]It is unclear, however, whether results from the existing literature on choice overload (e.g., Reutskaja et al. (2011)) would translate directly to altruistic behavior. Specifically, the existing literature largely investigates the effect of choice overload on the purchase of goods with private benefits. These results may not extend to altruistic, nonrivalrous, and nonexcludable goods such as charitable donations. Altruistic donors might instead split donations across all beneficiaries rather than choosing one over the rest.

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

on these descriptions, potential donors are free to choose which beneficiary (or beneficiaries) to support and the amount that they wish to donate. Our experimental setup involves three treatment groups, and potential donors are randomly assigned to one of these three treatments, each varying the size of the beneficiary set that a donor encounters. These sets consist of 3, 8, or 10 potential beneficiaries. We arranged for the platform to randomly showcase a selection of beneficiaries from its database[3]. This guarantees that the array of beneficiary characteristics displayed to donors is as good as random.

Using data from 52,086 actual beneficiary displays, we answer two specific questions.[4] First, how does donor behavior respond to variations in choice set size? In particular, do donors behave differently when faced with a smaller choice set? If so, what are the reasons for the differences in donor behavior? We use the following design to answer this question: each of the 2,054 unique beneficiaries in the platform's database has an equal chance of being displayed in a 3-, 8-, or 10-set. Hence, we are able to keep all other characteristics constant and test how donor behavior toward the *same beneficiary* differs depending on whether she views a 3-, 8-, or 10-set. In addition, we leverage the platform's back-end database to characterize donors' information-seeking and attention behavior using an unusually rich set of variables. These include, among others, beneficiary display order, refresh rates, and the time taken for donors to make their donation decision.

Second, we investigate how the saliency of beneficiary characteristics might be a driving mechanism behind any observed differences in donor behavior. We also attempt to test and distinguish the saliency effect from two other hypotheses: deservingness and in-group bias. To test for saliency effects, we define a beneficiary as having a *salient* characteristic if he is the only beneficiary with that characteristic in the displayed group of beneficiaries. We then test whether the effects of saliency depend on choice set size. If so, this would support our initial hypothesis: smaller choice sets affect donor choice through the attenuation of information overload and direction of donor attention toward donors possessing certain more salient characteristics. To investigate the effects of deservingness, we utilize comprehensive beneficiary information displayed to donors. This includes, among others, the donation amount requested by the beneficiary, employment status, and number of dependents, if any. We hand-code proxies for deservingness. Last, to test for in-group bias, we test whether donor behavior changes when there is concordance between the the ethnic and religious identity of donors and beneficiaries. Much of the

[3]Several months into our experiment period, the platform introduced into the random selection process stratification conditional on whether a beneficiary card had received any donation, with a view toward promoting equity. We conduct several robustness checks and find little effect on the randomized display of beneficiaries, and this change did not affect our main results

[4]The total beneficiary displays comprise 2,054 unique beneficiaries displayed across 3,540 3-sets, 2,597 8-sets, and 2,096 10-sets for a total of 2,405 unique donor sessions. See Table A.2 for details.

existing literature has explored the concepts of saliency, deservingness, and in-group bias separately and across varied contexts.[5] Our setting allows us to collectively evaluate these hypothesis in a single, unified framework.

Our experiment uncovers three main findings. *First*, we find evidence of choice overload: a reduction in choice set size leads to an increase in both the donation rate and (unconditional) donation amount. Donors assigned to a 3-beneficiary (8-beneficiary) choice set are 1.8 pp (0.7 pp) more likely to donate to an otherwise identical beneficiary (compared to an average donation rate of 1.6% for donors assigned to a 10-beneficiary choice set). We also find that the unconditional donation amounts are 14 US cents (8 cents) larger in the 3-beneficiary (8-beneficiary) choice sets than in the 10-beneficiary choice set group, although only the result for the 3-beneficiary set is statistically significant at the 5% significance level. We hypothesize that the smaller choice set size reduces information overload. Indeed, we find that donors in 3-sets spend 55 seconds longer deliberating on each beneficiary than the average of 45 seconds in 10-sets, a 122% increase. Donors in 3-sets are also more likely to *refresh* their beneficiary displays and search for additional donation targets. Interestingly, we find suggestive evidence that beneficiaries whose information cards appear centrally within a set may be less likely to receive a donation. This suggests a unique dipping pattern in donors' behavior, where their inclination to donate diminishes somewhat for centrally positioned beneficiaries. This dipping pattern is less pronounced in 3-sets.

Second, we find that donor behavior is jointly shaped by notions of both deservingness and saliency. From the hand-coded narratives, we find that beneficiaries perceived as more deserving are more likely to receive donations. 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). Beneficiaries requesting higher donations are not more likely to receive a donation. We verify our hand-coded results using latent semantic scaling (LSS) and keyness statistics to construct a deservingness index. We find that narratives scored with a higher similarity to seed words related to deservingness (e.g., childbirth, teachers, pregnancy, students) are more likely to receive (larger) donations.

Third, we uncover the presence of saliency effects, which vary depending on the characteristics of beneficiaries and the size of the choice set. Beneficiaries who are the sole breadwinners, have child dependents or work in the education sector consistently attract more donations across all set sizes. However, the saliency effect of having the most comprehensive narrative proves significant only within the 3-choice set size. Interestingly,

[5] See, e.g, Jenq et al. (2015) for deservingness, Fong & Luttmer (2009) for racial group loyalty, and Perroni et al. (2022) for salience.

despite our previous findings on deservingness, we notice a saliency effect for the highest requested donation amount, but this holds only within the 3-choice set size.

Taking these results together, we interpret this as evidence that saliency effects matter, above and beyond deservingness. Specifically, characteristics such as the longest story in a set might matter more in smaller sets because there is already so much information from all presented beneficiaries in larger sets such that having a long story does not stand out. Comparatively, when there is a lot of information in larger sets, donors are more likely to home in on easily distinguishable characteristics. Hence, we provide novel evidence suggesting a potential strategy to capitalize on behavioral heuristics, aligning with the choice overload hypothesis and donors' inclination towards perceived deservingness, to encourage higher donation amounts. Smaller choice set sizes alleviate information overload, allowing individuals to focus more on each option and its respective characteristics, thereby facilitating more optimal decision-making processes. Finally, information about beneficiaries can be curated and presented to highlight the characteristics considered most salient by donors.

Our paper directly contributes to the literature on charitable donation and online giving. Online fundraising has become increasingly common. Recent studies have looked into microdonations on various platforms (Cersosimo et al., 2022; Jiang et al., 2023) and found that the beneficiary's appearance (Jenq et al., 2015), salience of charitable causes (Perroni et al., 2022), and urgency of disaster relief (Jayaraman et al., 2020) influences online giving. Our paper is most closely related to Altmann et al.'s (2019) experiment with default options on an online charity platform in Germany. The default options induced some people to donate more, although with defaults set at a higher donation amount, people opted out of donation altogether. We experiment with another aspect of choice architecture, choice set size, that has potentially rich implications for maximizing donations for online charitable causes.

To this end, we make the following contributions. *First*, we use a field experiment to study the effect of choice architectures on donors' giving behavior. In laboratory experiments, Scheibehenne et al. (2009) argue that choice overload is activated among study participants only when they have to justify their decisions. Filiz-Ozbay and Uler (2019) study how competition among substitutable charities reduces giving among laboratory participants. Researchers have also used crowdworker samples to argue that helpers prefer to allocate aid across multiple individuals (Sharps and Schroeder, 2019). Our setting allows us to study actual donors whose behavior could be distinct from laboratory participants, and to the extent that this is true, our findings might map more readily to real-world settings. In particular, the donors in our study make decisions based on their own endowments rather than endowments handed out in a lab environment. Typical lab experiments often implement charitable giving in a controlled, dictator game–like setting, with modifications ranging from using earnings from real effort tasks within the experiment to designating charities rather than student participants as beneficiaries. In such a limited context, List (2007) argues that giving decisions may not accurately reflect true charitable behavior.

Second, we examine charitable giving to beneficiaries in a developing country from donors in the same population. Most studies on (online) giving examine charitable giving from rich to poor countries (e.g., Altmann et al., 2019; Jenq et al., 2015). To the extent that donors are most responsive to charities and disasters in their own country, our single setting is important for understanding the contours of giving in developing countries. Moreover, different contextual environments could make choice overload and identity markers more salient in these settings.

Third, we contribute to the literature that studies the effects of deservingness and in-group biases on altruistic behavior. The closest study to ours is that of Fong and Luttmer (2011), who, through a dictator game, show that perceptions of worthiness of beneficiaries have a greater effect on the level of donations made vis-à-vis the concordance of race between donors and beneficiaries. Our study differs in two ways. First, in Fong and Luttmer (2011), donors make their donation decisions using cash received from the experimenters, and second, the donations are paid out to a charitable organization (i.e., an intermediary). In contrast, donors in our setting make donations using their own funds and do so directly to beneficiaries.

Fourth, we contribute to a growing field of experimental literature that studies the impact of the design decisions of online platforms on individual behavior. In particular, much of this literature has focused on estimating the effects of content removal or production on user attention on online social media platforms. Beknazar-Yuzbashev et al. (2022) find that the removal of toxic content significantly reduces the content consumption of Facebook users. Relatedly, Srinivasan (2023) finds that the effects of attention on the production of user-generated content is positive but concave.[6] We innovate by linking the effects of choice architecture on user attention to concrete economic outcomes of altruistic giving.

This paper is organized as follows. Section 2 describes the study context. Section 3 presents our empirical strategy. Section 4 discusses our results. Section 5 concludes.

[6]More concretely: A Reddit post that receives 3 bot-generated comments causes users to supply 15% more posts, but 6 bot-generated comments do not lead to any increases in output.

2. Charitable Giving during COVID-19 and Bagirata

Globally, Indonesians rank among the top 10 most prolific givers (World Giving Index), with much of this giving taking place through informal organizations (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, 2019). 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). 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.[7]

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 losses, and the primary objective of the platform was to enable unconditional charitable donations

[7] A J-PAL SEA 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.

from potential donors to these individuals.[8]

The *Bagirata* platform shares similarities to popular crowdfunding platforms, albeit with significant differences. Similar to crowdfunding platforms such as GoFundMe or Kiva, on *Bagirata*, donors can browse through a list of potential beneficiaries who are appealing to raise funds for certain cause(s). Typically, donors then provide support for the causes by making donations through the platform. The *Bagirata* platform differs from these crowdfunding websites in two aspects. First, its model is centered on unconditional charitable giving. Indeed, its name literally translates to "divide equally" in Indonesian. This fundraising model is distinct from Kiva's approach, which centers on a lending model that provides 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 differs from GoFundMe's method, where the platform functions as an intermediary between donors and beneficiaries.

At the heart of the 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).[9] In section 3.4, we provide details of beneficiaries' characteristics and the manner in which they are presented to donors.

Each time a prospective donor visits the website, the platform algorithm randomly draws and presents a set of beneficiary cards (Figure 1).

[INSERT FIGURE 1 HERE]

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 to whom and how much they wish to donate. Donations are transferred directly from the potential donors to their chosen beneficiaries through one of three popular digital payment systems in Indonesia. After donating, donors are prompted to confirm their donation by reporting the donation amount and

[8] *Bagirata* received coverage from various media outlets; e.g., see https://youtu.be/wrhxL5vfMQQ.

[9] See Table A.1 in the appendix for a selection of appeal narratives written by beneficiaries. Throughout the paper, we use distinct labeling for tables and figures intended for the main text versus those for the supplementary appendix. The latter are designated with a capital letter A preceding the numbering sequence. For example, Table 1 can be found in the main text, while Table A1 can be found in the supplementary appendix.

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 if they wish to do so. 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 characteristics. To address this issue, we conduct a follow-up *Bagirata* user survey where we collect email handles, thereby enabling us to match a subset of *Bagirata* data to their donor characteristics. However, the main focus of our analysis remains on the full data of the beneficiaries, particularly to examine the likelihood of receiving a donation and the amount of the donation received given the variations in the choice set size presented to potential donors through the beneficiary cards and the beneficiaries' characteristics. Second, we cannot differentiate a donor initiating multiple sessions if the donor does not provide an email address. Consequently, such a donor will appear in our dataset as multiple sessions.[10]

3. Empirical Strategy

3.1. Experimental Manipulation

Our experiment was preregistered at the Open Science Framework (OSF), and the preregistration document can be accessed from (https://osf.io/c4xgd). We administered our experiment to all potential donors who visited the *Bagirata* website during our study period.[11] We manipulate choice set 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 treatment assignment. The donor assigned to the 3-set beneficiary treatment would see three

[10]Thirteen percent of donor-sessions (N=312) have a nonunique email associated with them, and out of these tagged donor-sessions, 60% have a unique email tag (N=190).

[11]*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.

beneficiaries on her device's screen. Similarly, those assigned to the 8-set and 10-set beneficiary treatments would see eight and ten beneficiaries on the computer screen, respectively. The treatment assignment remains effective for three hours. This implies that, as long as potential donors refresh the page or reaccess the *Bagirata* platform using the same device within the designated three-hour window, they would remain in the same set-size treatment.[12] While the platform preserves the set size assignment upon browser refresh/reaccess, these actions will provide donors with a fresh mix of beneficiaries. The donors also have the option of triggering a fresh draw of the beneficiaries with a button at the bottom of each page.[13] There is no limitation on the number of times potential donors can refresh the web page. We interpret "refresh" as a measure of search behavior.

We aim to examine whether the search and donation behaviors differ across various set sizes. Specifically, we ask whether a smaller choice set size prompts potential donors to find a larger sample of beneficiaries by clicking the refresh button more frequently. We are also interested in finding out whether the decision to initiate another search is dependent on the outcome of the previous search. Finally, we examine the relevance of the size of the choice sets—that is, whether there is any significant difference in the likelihood of a beneficiary receiving a donation or the amount received when different set sizes are compared.

For our data analysis purposes, we focus on the beneficiary display level as our unit of analysis. Recall that, in each web session, a potential donor would encounter multiple beneficiaries, the number of which is determined by the choice set size treatment to which the donor has been assigned. We consider each dyadic pair of a potential donor and a beneficiary within a web session as a single unit of observation.

We also 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 display that the donors see. This random selection provides variations in the beneficiary characteristics displayed to the donors within and across treatment arms. In the initial months of the study period, the algorithm executed unconditional random draws of beneficiary cards from the database. After the *Bagirata* platform conducted additional beneficiary recruitment drives to expand the platform's reach, the process was refined. The random draws of beneficiary cards became conditional on whether a card had previously received a donation as a measure to improve equity among all potential beneficiaries. Despite this stratifica-

[12]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.

[13]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 as a "refresh" action to combine it with a browser refresh.

tion, from the donors' perspectives, the display of beneficiaries and their characteristics remains effectively random, both across and within treatment arms.

The beneficiary side of the platform can be described as follows. Each beneficiary is displayed as a compact card (Figure 1), which provides 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.

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. Empirical Specification

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

$$Donate_{ijkl} = \alpha_1 + \beta_1 SetSize3_i + \beta_2 SetSize8_i + \theta_j + \varepsilon_{1,ijkl} \tag{1}$$

where $Donate$ is either the donation indicator or the donation amount and $SetSize3$ and $SetSize8$ are indicators for whether a beneficiary was displayed in a 3- or 8-set of beneficiaries. The ε term is the idiosyncratic error term. Standard errors are clustered at donor and beneficiary levels to account for possible error correlations within nonnested donor and beneficiary clusters (Cameron et al., 2010). We estimate this equation with beneficiary fixed effects θ_j. By using within-beneficiary variation, we hold beneficiary identity constant, and hence, β_1 and β_2 measure how much more likely a beneficiary displayed in the 3- or 8-recipient group is to receive a donation (or higher donation amount) than when he is displayed in the 10-recipient group.

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

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

where $Characteristics$ is the beneficiary characteristics displayed, including characteristics such as gender and religion that we infer from their names and characteristics that we code from their narratives, such as breadwinner status or an indicator for being laid off. In section 3.4, we describe the set of characteristics that we include in this analysis, most of which are coded as binary variables. As above, the ε term is an idiosyncratic error term. Because we observe the full beneficiary characteristics displayed on the platform, this allows us to alleviate concerns about omitted variables.

With donor fixed effects, the β_3 coefficient estimate on binary characteristic x is the effect 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 with characteristics similar to the focal beneficiary's but have x taking the value of 0. We also hold set size constant with the donor–session fixed effects ϕ_i. The coefficients β_3 are interpretable as the effect on the probability of receiving a donation (or donation amount) in a linear unit change.

We run our analysis on datasets from the *Bagirata* operation, which includes the beneficiary roster, session trace, and donation trackers. The session data track which beneficiaries are displayed to a donor in each session, self-reported indicators of donation status and amount after the transfer is completed, and unique donor session identifier. Donors are also prompted to disclose their email addresses after donating, although the disclosure is not mandatory.

We also augment the regression analysis with *Bagirata* user survey data. This survey captures a rich set of demographic variables, altruistic behaviors both on the platform and beyond, and altruistic preferences. The survey sample size is considerably smaller, and our analysis of this dataset will be more limited. The reasons for the small sample are twofold: participation was voluntary, and the survey was decoupled from the main user interaction flow to minimize friction in user experience toward donation activities.

3.3. Outcome Variables and Donor Behavior

Our main outcome variables consist of two measures of donor behavior to COVID-19 victims. Our first measure is a binary indicator that denotes whether a potential donor donates to a beneficiary. 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.[14]

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.[15] 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, which is USD 1,882, the amount of the donation received by a beneficiary is approximately 11% of average monthly earnings.

[INSERT TABLE 1 HERE]

Our unit of analysis is at the beneficiary–display level. The number of beneficiaries within each display varies based on the choice set that donors are presented with in the different treatment conditions. Of the 52,086 beneficiary displays, 1,183 receive donations, translating to a 2.23% conversion rate between displays and donations. While this donation rate may appear low, it is consistent with conversion rates documented in the general charitable giving literature.[16] The vast majority of beneficiary displays do not ultimately result in donations.

3.4. Beneficiary Characteristics

To understand how beneficiary characteristics shape donation behavior, we hand-code an exhaustive set of objective and subjective measures of beneficiary characteristics. To ensure accuracy and to mirror as closely as possible how donors might have perceived our beneficiaries' narratives, we employed two Indonesian research assistants with diverse and complementary backgrounds to review each narrative.[17] In this manner, we meticulously code and quantify the comprehensive set of beneficiary characteristics that potential donors are likely to observe. These characteristics include demographic attributes (sex and religion inferred from names), geographical location, and employment sector. We also account for the donation request details (specified amount of money needed and

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

[15] 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.

[16] Altmann et al. (2019) report a conversion rate of 3.3% in their Betterplace experiment. They also note that a study on online fundraising sites reported a median conversion rate of just 0.76%.

[17] 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.

duration of need), social media presence (indicators for links to Facebook, Twitter, or Instagram accounts), e-payment channel options, and narrative attributes (length and content of the narrative). Moreover, we extract information from the narratives to assess whether a beneficiary might be perceived as a primary breadwinner, based on keywords related to children, parents, siblings, or bearing financial responsibility for their family.

We illustrate our classification of beneficiary characteristics with a selection of narratives from beneficiary donation cards in Table A.1. For example, Beneficiary #5, a former drink shop attendant requesting a donation of USD 67, shared, "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." Based on this narrative, our assistants assigned a value of 1 to the following indicators: "Breadwinner/has dependent(s)", "Breadwinner/mentions dependent child(ren)", and his occupation is categorized under "hospitality, retail, and food service".

Contrast the above with Beneficiary #8, who shared, "My office closed in July ... I deepen my design and illustration and copywriting skills, building updated portfolios to get freelance opportunities". Our assistants assign a 0 for the aforementioned variables for this beneficiary, as there is no mention of children or dependent family members or of being the primary breadwinner. This individual's white-collar occupation is classified in the "art and creatives" employment sector.

For the analysis of in-group bias, we consider the beneficiaries' names and locations. 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 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.[18]

[INSERT TABLE 2 HERE]

Table 2 presents selected summary statistics from the beneficiary perspective. On average, a beneficiary asked for USD 155 per month over a duration of 2.2 months for a total appeal of USD 346. Our systematic coding from beneficiaries' narratives allows us to classify beneficiaries across a wealth of dimensions such as employment sector, region, gender, religion, whether a beneficiary is a breadwinner or has child dependents, and occupation type. For employment, the majority of beneficiaries are employed in the

[18]We omit the beneficiaries' actual names from the table for privacy.

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).[19] 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%). With respect to gender, our beneficiary sample has a substantially larger number of men (63%) than women (37%). Regarding religion, the majority of the beneficiaries are Muslim (82%). Lastly, 22% of the beneficiaries mention being the family breadwinner or having dependents and 12% mention having, specifically, one or more children as dependents.

Compared to donors, beneficiaries have lower education and earn less. Table 3 presents selected summary characteristics of *Bagirata* beneficiaries and donors from a user survey posted on the platform landing page website.[20] 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 almost five times the average beneficiary's earning (USD 8,626/year versus USD 1,882). 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 social safety net, the altruistic motives of donors in our setting might differ from broader trends in developed countries.

[INSERT TABLE 3 HERE]

3.5. Measures of Salience

Donors see a different mix of beneficiary characteristics depending on the random draw from the database. In some draws, donors may be drawn to a beneficiary because this beneficiary is the only beneficiary with a particular characteristic. For example, donors facing the 3-set beneficiary treatment can obtain 0–3 beneficiaries with the particular characteristic (e.g., a feminine name or residence in a certain location) in the set. If donors hit the refresh button multiple times within the designated three-hour window, donors will receive multiple random draws of three beneficiary sets, and each set generates a new mix of characteristics. This means that, for donors seeing multiple sets, the mix

[19] See Table A.6 in the appendix for a further breakdown.

[20] *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.

of characteristics will also vary across consecutive sets. On average, each donor in our data sees 3.4 sets indicating that they refreshed the draw 2–3 times, providing us with random variations at the set level for the same donor.

The random mixes of beneficiaries thus allow us to understand whether salience is driving our results. We define the salience at the set level. A beneficiary is coded as having a *salient* characteristic x if he is the only beneficiary in that set with that particular characteristic. 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).

Saliency may also be influenced by the size of the set. 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.

We thus investigate the role of salience in charitable decisions (Bordalo et al., 2013). In a theory of choice under salience, consumers respond disproportionately to variation in attributes of the goods available to them. We examine the salience of beneficiary characteristics along different dimensions: gender, religion, household status, occupation, requested donation amount, and length of information.

Investigating the salience of specific characteristics also allows us to compare its role vis-à-vis other mechanisms such as deservingness and in-group bias. A religious affiliation encoded in the beneficiary's name may elicit in-group sympathy that leads to a donation. Gender and location information could also activate similar processes, albeit mixed with notions of deservingness, if donors believe women and individuals in similar environments are more (or less) deserving of a charity. On the other hand, markers of neediness such as having the largest donation request and household statuses (whether a beneficiary is a family breadwinner and whether he has a child) correspond with notions of deservingness separate from in-group identification.

4. Results

In this section, we present the results of our experiments. We begin by presenting some stylized facts about donor behavior. We then proceed by analyzing how donation patterns vary with the size of the beneficiary sets presented to donors. Subsequently, we explore the impact of beneficiary characteristics on donation behaviors.

4.1. Choice Overload: Choice Set Size and Donor Behavior

4.1.1. Some Stylized Facts about Donor Behavior

Refresh Rates

The smallest choice set size offers donors finer information control. Each time donors encounter a set of beneficiaries, they can choose to donate or refresh the page to receive a new batch of beneficiaries from the same choice set size. This feature allows us to investigate whether displaying fewer target beneficiaries encourages donors to actively seek out additional potential beneficiaries. We do this by examining the effect of choice set size on refresh rates, which we define as the number of times a donor requests the website to draw a new set of beneficiaries after viewing the current beneficiary card on display. To verify this, we aggregate our observations at the donor level and estimate the impact of set size on information-seeking behavior, using refresh rates as a proxy.

On average, allocating donors to the smallest 3-choice set induces donors to search for additional donation targets, as indicated in Column (4) of Table 4 and the left panel of Figure 4. Donors assigned to the 3-beneficiary set are likely to refresh the page twice as often as those in the control group (the largest 10-choice set size). The control group has an average refresh rate of 2.58. Nevertheless, because of the difference in set size, donors assigned to the smallest set size still encounter 12 fewer potential beneficiaries overall. No significant difference exists between donors assigned to 8- and 10-beneficiary sets. Taken together, these findings suggest that one mechanism by which choice overload occurs in this setting is the donors' tendency to stop seeking additional suitable donation targets when overwhelmed by the large number of choices in a 10-beneficiary choice set.

[INSERT TABLE 4 HERE]

[INSERT FIGURE 4 HERE]

Beneficiary Display Order and Dipping Behavior

Next, we investigate whether donors pay equal attention to all beneficiaries. If some beneficiaries receive more attention, the imbalance in attention could lead to unequal donations. We leverage the random display order of beneficiary cards to provide suggestive evidence for this imbalance by examining how the sequence of beneficiary card displays affects donor behavior. As mentioned earlier, beneficiary cards are randomly selected from the database, and their order of presentation is also determined randomly. Donors view these selected beneficiary cards in a sequential manner, scrolling from top to bottom. Hence, the display order of beneficiaries as presented within a set is also randomly assigned.

In Figure 5, we plot the proportion of beneficiaries receiving donations against their sequential display order within a given set. In the context of a 3-beneficiary set, 1–3 would indicate the order position of a beneficiary in that set. Thus, for example, the dot on the graph for the 3-beneficiary set at the order position 1, 2, or 3 represents the proportion of all beneficiaries positioned in order 1, 2, or 3 who received donations. In addition, note that the graph's length aligns with the total number of displayed beneficiaries within the corresponding choice set. We observe a nonlinear pattern resembling a dip. This dipping behavior stems from higher donation rates attributed to beneficiaries placed at the top and bottom of choice sets. The proportion of beneficiaries receiving donations declines from beneficiaries positioned first in each set to those positioned in subsequent positions until a certain point, after which it rises again. The effect is most pronounced for beneficiaries in the middle of the set. Specifically, beneficiaries placed in the 5th position in the 8- and 10-beneficiary choice sets and those in the 2nd position in the 3-beneficiary choice set are the least likely to receive any donations. While this pattern is evident across all treatment groups, it is especially pronounced for the 8-beneficiary choice set.[21]

This pattern suggests a possible heuristic that donors use to decide their donation choices. We interpret this as suggestive evidence that donors pay more attention to beneficiaries displayed at the start and end of sets and the least attention to those in the middle. In other words, donor attention dips as they move sequentially down a set and recovers as they near the end of a set.[22]

[21]We explore this pattern further using regression analysis, and the results are shown in Table A.3. Being placed one card lower results in a decrease of 0.06 pp in the average likelihood of receiving a donation. This translates to a decrease of 26% in donation probability between the top and bottom cards in a 10-beneficiary choice set. However, estimated coefficients from regressions by choice set size illustrate the suggested nonlinearity pattern.

[22]This is similar to the logic of the placement of products closer to eye-line on supermarket shelves and at the cashier line. These are areas that are likely to receive relatively more attention, and hence, products placed there are expected to obtain relatively higher sales.

4.1.2. Effect of Choice Set Size on Donation Likelihood and Amount

Next, we examine the relationship between the choice set size and the donation likelihood and amount. Our findings indicate that differences in the size of the donors' choice set significantly impact both the donors' willingness to donate and the donation amounts given. As shown in Column (1) of Table 4 and the left panel of Figure 3, we find that donors assigned to the smallest choice set size (3-beneficiary choice set) are more likely to donate than those assigned to the largest choice set size (10-beneficiary choice set). In particular, from a baseline donation rate of 1.6% for the 10-beneficiary choice set, donors assigned to a 3-beneficiary choice set group (8-beneficiary choice set group) are 1.8 pp (0.7 pp) more likely to donate. However, only the difference between the 3- and 10-choice set groups is statistically significant. Note that these regression estimates include beneficiary fixed effects and hence estimate the marginal effects of choice set size on donor behavior toward the *same* beneficiary. Taken together, our findings suggest that a given beneficiary is twice as likely to receive a donation when displayed within a set of three as when displayed in a set of ten.

[INSERT FIGURE 3 HERE]

This result is also mirrored in how the likelihood of donors giving is influenced by the sequence with which beneficiaries are displayed to donors in a given choice set size presented to the donors. Figure A.2 illustrates the proportion of the first twenty beneficiaries receiving donations, arranged according to their positions in the sequence across the three choice set sizes. A bit of explanation on how to read the figure is in order. Let us take the ninth beneficiary in the sequence as an example. In a 3-beneficiary set treatment, this beneficiary would appear as the third beneficiary at the bottom of the third beneficiary set viewed by a potential donor. In an 8-beneficiary (10-beneficiary) set treatment, this ninth beneficiary would be the first (the penultimate) beneficiary on the second (first) beneficiary set. Regardless of the beneficiaries' position in the sequence, the graph for the 3-beneficiary sets is visibly on top of the other two graphs, implying that the proportion of beneficiaries receiving donations in a 3-beneficiary set is higher than that in larger sets.

In Table A.4, we conduct a robustness test on our results by running a regression analysis on the likelihood of a donor giving to beneficiaries across all choice set sizes in general (Column (1)), to the first set of beneficiaries a donor encounters—the first three in a 3-beneficiary set, the first eight in an 8-beneficiary set, and the first 10 in a 10-beneficiary set (Column (2))—or the first three, eight, or ten beneficiaries in the sequence of beneficiaries regardless of the size of the choice set (Columns (3)-(5)). For example, in a

3-beneficiary choice set, the first eight beneficiaries (1–8) are captured by the first two sets and the top two beneficiary cards in the third set that a donor encounters. However, in an 8-beneficiary (10-beneficiary) choice set, these first eight beneficiaries are presented in the first beneficiary set. Overall, our results suggest that a donor viewing a 3-beneficiary choice set is more likely to donate to a beneficiary than a donor viewing a 10-beneficiary choice set, particularly for cards in the sets following the first sets (i.e., to the fourth individuals onward rather than to the first 1–3 individuals that they encounter).[23]

Turning to the donation amount transferred to beneficiaries, we observe in Column (2) in Table 4 and the right panel of Figure 3 that a higher likelihood of donation translates into a statistically significant increase in the average donation amount. In a 3-beneficiary choice set group, the donation amount is larger by USD 0.14 than that in the 10-beneficiary choice sets, which is the control group. This effect represents a 75% increase from the average donation amount in the control group (USD 0.19). Similarly to what we find on the likelihood of donating, we do not find any statistically significant difference between the 8- and 10-beneficiary choice set groups. We hypothesize that these estimates are driven by the conversion of new donors on the extensive margin who would not have otherwise donated.

In summary, the greater likelihood of donating and the increased average donation amounts from donors presented with the smallest choice set size is in line with the choice overload paradigm. Donors presented with ten beneficiaries may feel overwhelmed by the prospect of evaluating a large number of beneficiaries on display. As a result, they are more likely to refrain from donating. Furthermore, each time they refresh the webpage, more beneficiaries are displayed, increasing their cognitive load and potentially exacerbating their feelings of overwhelm. In comparison, donors confronted with a 3-beneficiary choice set experience a lighter cognitive load and are more capable of evaluating the available alternatives.[24]

Time Spent Deliberating over the Beneficiaries' Appeals

Next, we delve deeper into donors' behavior when visiting the *Bagirata* platform and making the donation decision to uncover further evidence to reinforce our choice overload findings. Specifically, we examine the duration of time deliberating on the beneficiaries' appeals. Column (3) in Table 4 presents a regression of the average time spent per

[23]Table A.5 presents the results of testing the relationships with the inclusion of various fixed effects. We test a specification without the beneficiary fixed effects, with beneficiary–set–display order fixed effects, and with beneficiary–sequence fixed effects. The relationship between the smaller choice set size and higher donation likelihood remains, and additional fixed effects increase the precision of some coefficients.

[24]Similarly, Sudhir et al. (2016) find that individual profiles draw higher donations than profiles on groups of beneficiaries during a charity mailer experiment in India.

beneficiary, differentiated by set sizes, and is conditional on a donor having donated. We do not directly observe the duration of time a donor spends on each individual potential beneficiary. Instead, we compute the average time spent per beneficiary by taking the difference between the final timestamp for when a donor's donation is made and the timestamp for when the donor initiated the web session. This average time spent per beneficiary is then divided by the total number of beneficiaries whom the donor viewed (across all displayed sets). We use this measure as our proxy for the amount of attention a donor devotes to choosing a donation.

The first row of Column (3) in Table 4 reveals that a donor spends an average of 0.92 minutes (55 seconds) longer on each beneficiary when the beneficiary is displayed in a 3- rather than in a 10-beneficiary set. This effect is significant at the 1 percent level. The second row shows a much smaller, statistically insignificant difference between the 8- and 10-beneficiary sets. The difference between the 3- and 10-beneficiary sets is economically large: the average duration spent on each beneficiary for the donors assigned to the 10-beneficiary group is 0.75 minutes (45 seconds). Donors in the 3-beneficiary set take almost 1.25 times longer to finalize their donation decisions, suggesting that a smaller choice set size prompts donors to dedicate more attention and time to deliberating on their donation choice, leading to higher average donations. This might explain why, in larger choice sets, both the likelihood of a donor donating and the amount donated tend to be smaller.

Taken together, our results thus far suggest that donors employ a heuristic thinking process: a smaller choice set size induces donors to spend more time deliberating and seeking information on beneficiaries. Their decision-making processes under the smallest choice set size are captured through a higher refresh rate and longer duration of time spent viewing each beneficiary. We interpret these as proxies for attention. The amount of attention spent across beneficiaries, however, is influenced by display order. We find suggestive evidence that the effects of attention overload on donors follows a nonlinear dipping pattern. Beneficiaries placed at the top and bottom of 8-sets receive a disproportionately larger share of donations than those placed in the middle.

4.2. Beneficiary Characteristics: Deservingness, In-Group Bias, and Saliency

Thus far, we have examined the influence of choice set size on donor behavior while holding beneficiary characteristics constant. However, an equally important question is whether beneficiary characteristics could affect donor behavior. Are there specific characteristics that matter for the likelihood of a donor donating and the donation amount, irrespective of the choice set size? Conversely, do donors pay less attention to certain characteristics when the choice set size varies?

To answer the above questions, we analyze the effect of beneficiary characteristics on donation outcomes, utilizing the random selection of beneficiary cards from our database. We hold donor characteristics constant within each web session to evaluate whether there are some beneficiary characteristics that make donors perceive beneficiaries as more deserving than beneficiaries without those characteristics.

4.2.1. Deservingness

We begin by analyzing the influence of beneficiary characteristics on donor behavior by exploring donors' self-reported responses in an auxiliary user survey. Table 5 presents donors' self-reported reasons for making a donation. The most common reason to donate among respondents who have used the *Bagirata* platform is a perception that a "beneficiary needs my donations" (58%).[25]

[INSERT TABLE 5 HERE]

Who do donors perceive as in need of or deserving of their donations? To explore this, we surveyed donors regarding how likely they would be to donate to beneficiaries possessing various characteristics. The responses are summarized at the bottom part of Table 5. The findings indicate a strong inclination among donors to donate to breadwinners with dependents, either children or elderly (86%), individuals in persistent poverty (85%), and those afflicted by unforeseen calamities such as disasters, illnesses, or job loss (82%). Female beneficiaries also receive significant support (69%). On the other hand, fewer donors support beneficiaries with lower educational attainment (53%), those from neighborhoods similar to the donors' own (56%), and those sharing the same religion (49%) or ethnicity (42%). Even fewer donors state that they support beneficiaries who have already received donations (34%) and those who are younger (32%).

We regress donation outcomes on a comprehensive set of observable beneficiary characteristics, including donor–session fixed effects according to Equation 2 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*

[25] The next most common reasons are: finding the organization trustworthy (56%), supporting humanitarian causes (54%), and adhering to religious teaching (43%). N = 216.

shocks, *demographics*, and *donations received from other donors*. Full regression results are presented in Table A.7. Here, we focus on Figures 6 and 7, where we display selected coefficient estimates.

[INSERT FIGURE 6 AND 7 HERE]

Figures 6 and 7 show that beneficiaries who are primary breadwinners are more likely to receive a donation and obtain larger donations. On the basis of hand-coded individual narratives, Table A.8 further disentangles the effects of three distinct variables related to breadwinner status. First, beneficiaries who simply mention being a breadwinner (of any type) have a 0.6 pp higher probability of receiving a donation (although they do not receive larger donations). Second, we then classify beneficiaries' dependents into five distinct categories (spouse, children, siblings, parents, and other relatives). The breadwinner effect is strongest for beneficiaries with children. Breadwinners with children as dependents have a 1.1 pp higher probability of receiving a donation. In contrast, the estimates for other dependents are not statistically significantly different from zero. Third, the larger the number of dependents, the higher is the probability of receiving a donation (0.4 pp per dependent). Taken together, these results provide evidence that a breadwinner with child dependents is perceived as being relatively more deserving of and hence is more likely to receive donations.

Next, we consider *occupational status* and *economic shocks* as two other possibly important measures of deservingness. For example, perhaps teachers might have been considered more deserving than cafe workers during the COVID-19 pandemic. As proxies, we consider the effects of beneficiary occupation and layoffs. Specifically, based on beneficiary narratives, we hand-code and classify beneficiaries into various employment sectors and whether a beneficiary mentioned having been laid off from his previous workplace.

Figures 6 and 7 also show that, compared to the reference group from the hospitality industry, beneficiaries working in the education sector have a 1.3 pp higher likelihood of receiving donations and an average donation increase of USD 0.18. We do not find, however, any evidence that laid-off individuals have a higher likelihood of receiving donations. The coefficient estimated for an indicator variable for retrenchment is statistically insignificant across all our regressions. These results suggest that beneficiary occupation could matter as a measure of deservingness. In particular, teachers were particularly hard hit by the COVID-19 pandemic, given that the Indonesian school closures were among those with the longest durations worldwide. Conversely, the lack of differential results for laid-off beneficiaries could be because all occupations had an equal likelihood of facing layoffs during the pandemic. Hence, a beneficiary's having been laid off might not be as salient an economic shock for potential donors to consider in our context.

Last, as three other plausible proxies for deservingness, we turn to beneficiary narrative length (in 50-word increments), the requested donation amount, and the duration for which beneficiaries ask to be funded. Figure 6 shows that an increase in narrative length of approximately two sentences leads to a 0.5 pp increase in the probability of receiving a donation. While asking for a higher donation and/or for a longer duration of support could indicate that a beneficiary is particularly needy, neither the requested donation amount nor its duration have any effect on the probability of receiving a donation. This suggests that extended narratives could enhance the perception of deservingness, persuading donors to donate. The lack of effects for the requested amount and duration, however, could possibly be due to information overload. This information is perhaps treated by donors as merely auxiliary given the wealth of information presented to them on each beneficiary card. This overload, moreover, could be greater in larger than in smaller choice sets. We test this possibility in our subsection on saliency effects.

Textual Analysis: Keyness Statistics and Latent Semantic Scaling

Thus far, we have relied on self-reported donor preferences and regressions based on coders' definitions of deservingness. To corroborate this result, we employ machine learning methods to classify and construct a deservingness index specific to each beneficiary narrative. We utilize *keyness statistics*, a method that political scientists have applied to identify right- versus left-leaning voters from self-written voter descriptions (Zollinger, 2022). In our context, this method analyzes beneficiary narratives to approximate the salient information that donors focus on when making donation decisions, revealing their motivations. Figure 8 depicts the resulting *keyness* statistics. The black bars depicted in the upper part of the figure show the terms mentioned with the greatest relative frequency.

From the individual words' keyness statistics, we then use the *latent semantic scaling* (LSS) algorithm to construct an index by computing a composite score for each beneficiary narrative, which we term the *deservingness index*. We rescale the LSS statistic for each narrative to take a value between 0 to 1, with 0 indicating the lowest similarity to words with the strongest associations with donations and 1 indicating the highest level of similarity to words associated with donations. We then include the index as a regressor in our regression analysis. The methodology of our textual analysis is detailed with examples in the appendix. The insights generated from the keyness statistics align with those from the hand-coded narratives. Keywords positively associated with donations are those related to beneficiaries with child dependents or affiliations with the education sector.

Table 6 presents regression results of the probability of receiving a donation and the donation amount on our LSS-constructed deservingness index, together with a parsimonious set of control variables shown to be potentially important in our previous analyses.

In Table 6, Column (1) shows that a higher deservingness index increases donation likelihood. This significance remains (Columns (2)–(3)) when we the add control variables. For donation amounts, Column (4) shows that higher deservingness index values correspond to larger donations. The significance remains in Columns (5)–(6) of Table 6. These findings affirm the importance of deservingness beyond other beneficiary traits, aligning with donor perceptions.

[INSERT FIGURE 8]

[INSERT TABLE 6]

Summary

Overall, our results suggest several distinct characteristics that shape the perception of deservingness among donors. Donors are more likely to donate to breadwinners with child dependents, blue-collar workers, individuals residing outside the capital metro area, Facebook users, and those who had previously received donations from other donors. Donors' revealed preferences from our regressions thus turn out to be aligned with approximately half of their self-reported preferences (breadwinners, poverty, age), although not with the other half (bad shocks, women, giving by others, locations). Some of these results provide empirical support for the accountability principle (Konow, 1996, 2000): donors are more likely to donate to individuals whose neediness corresponds with factors he cannot reasonably influence or do anything to change in the short term. Naturally, a breadwinner can do little to change the fact that he has a child to support.

We do, however, find an effect with respect to beneficiaries' location. Donors are more likely to donate to those located outside of Jakarta. To this end, we note that the non-Jakarta comparison group is predominantly distributed in other cities across the Java island. This possibly carries a signal about their ethnicity that a location in mostly migrant Jakarta could obfuscate. The donors might thus simply be donating more to coethnic beneficiaries, considering that the majority of donors are also Javanese. We consider this alternative hypothesis further in the next section on in-group bias, together with in-group biases based on gender identification and religious affiliation.

4.2.2. Saliency

The salience theory posits that consumers choose options with the most salient attributes, focusing on the variation in those attributes (Bordalo et al., 2013). Porting this theory to an online charity platform setting, we ask the following: do donors decide who is worthy of donation based on inherent characteristics and how easily they can pick up these characteristics from their choice sets? For instance, donors might not favor a beneficiary for being a breadwinner if multiple beneficiaries in the choice set share that trait. However, they may prefer the beneficiary if he is the only breadwinner among the presented options, making this beneficiary stand out among other beneficiaries in the same set. Thus, a characteristic may matter to donors due to its saliency and not as a determinant of deservingness. If this is the case, we should expect similar results for saliency across all characteristics, regardless of their relations to the notion of deservingness.

To examine the effect of saliency, we run a regression analysis with the salience indicators constructed following the definitions in Section 3.5. We define our measures of salience at the set level and include indicators for salience along the dimensions of gender, religion, occupation, having the largest donation request, breadwinner status, and narrative length. We regress our donation dummy on the salience indicator for each beneficiary characteristic that donors may perceive as being a marker of deservingness. We present our regression results for the donation indicator as the outcome variable in Table 7. Consecutively, we look at the effect of being the sole beneficiary who is a breadwinner with dependent children (Column 1); the sole beneficiary in the education sector or in the transportation sector; the sole beneficiary whose information mentions his having been laid off (Column 2); the beneficiary with the longest narrative, normalized by the average length of the narrative in the set (Column 3); the sole beneficiary in Jakarta; the sole beneficiary with a female name, a male name, a Muslim name, or a non-Muslim name (Column 4); and the beneficiary with the highest appeal amount, normalized by the average amount of the request in the set (Column 5). We include the donor–session fixed effects in the regression, allowing us to compare two beneficiaries sharing the same characteristics presented to the same donor but for whom, in one set, certain characteristics are made salient relative to the alternatives in the set.

[INSERT TABLE 7]

We find that beneficiaries who are the only one in the set mentioning that they provide for their family and have dependent children are 2.7 pp more likely to receive donations. Being the only option in the set with employment in the education sector or in the transportation sector and being the only one mentioning being laid off have salient effects on the donor's donation. We also find evidence for a positive effect of saliency for having the longest narrative. In contrast, we do not find any evidence of saliency for the various demographic markers such as location, age-associated social media, gender, religious markers or having the highest ask amount. Our estimates are qualitatively similar when we regress the donation amount as the outcome variable on these saliency indicators, with a notable USD 0.34 higher donation for beneficiaries who are the only one with children dependent (Table A.9).

Variation in set sizes allows us to test whether the saliency effects matter above and beyond deservingness. If deservingness is what matters to donors, we should see that beneficiary characteristics related to deservingness matters across all set sizes. On the other hand, if saliency matters above and beyond deservingness, we should see that certain characteristics (related to deservingness or otherwise), matter only in small but not larger sets. The saliency effects of beneficiary characteristics thus may differ depending on the set size. For a given beneficiary characteristic, it is easier to stand out when there are fewer alternatives. At the same time, conditional on a beneficiary's being able to attract attention, saliency is starker when there are many alternatives. In other words, if the effects of saliency differ depending on set size, saliency might be an anchoring heuristic that is activated only when set sizes are small (or conversely, when they are too large).

Tables 8–9 present our analysis for whether and how saliency effects depend on the set size. Columns (1)–(4) present analysis for subsamples of 3-choice sets, Columns (5)–(8) for 8-choice sets, and Columns (9)–(12) for the 10-choice sets. Comparing coefficients across the columns, we see that a striking pattern emerges.

[INSERT TABLE 8-9]

The pattern of saliency effects across set size differs depending on the focal characteristic. The effect of saliency persists regardless of the set size for beneficiaries with a child dependent. The coefficient size for the only beneficiaries working in the education sector also suggests persistence of the effect for this characteristic, although the estimate loses precision for the 3-choice sets.

In contrast, the saliency of the highest appeal amount and longest narrative has a statistically significant effect only for donors in 3-option sets. This suggests that donors are more likely to use the narrative and the appeal amount as decision-making heuristics, using the entire suite of information available to them in small choice sets. Conversely, having the highest appeal amount and having the longest narrative are characteristics that do not stand out in larger set sizes. This is in line with our earlier results on information overload: smaller choice set sizes induce larger donations perhaps because donors can confidently use all available information to inform their donation choice. In contrast, larger choice set sizes result in information overload.

Overall, saliency effects appear to matter above and beyond deservingness. Furthermore, the effects of saliency appear to differ depending on the beneficiary characteristics and set size. A smaller choice set allows easier comparison of alternatives for the donors.

Conversely, when there is a great deal of information in larger sets, donors are more likely to home in on characteristics that are more easily distinguishable.

4.2.3. In-group Bias

Beyond deservingness, an alternative explanation for donors' charitable behaviors involves in-group biases. It is possible that donors give charitably to individuals in the same identity group as their own. There are various rationales for this view. For example, the shorter social distance among members of the same could engender a higher level of trust and sympathy. Alternatively, donations may allow donors to demonstrate their loyalty to the group. These may lead donors to give disproportionately more to other members of their own groups.[26]

We test for an effect of group ties on donation by pairing our beneficiary data with demographic information about our donors from the survey. We caution that this part of our analysis uses a much smaller subset of the data, owing to the fact that our donor information is limited to potential donors who leave their emails on the *Bagirata* platform and also independently complete our user survey that collects their demographics. As we have noted, the survey was decoupled from the donation process so as to reduce the possibility that reduced anonymity might discourage potential donors from making donations and/or simply result in a lower response rate to our survey. In this context, we are able to match donors in 76 sessions with 639 beneficiaries, giving us a sample of 1,750 observations.

We regress the donation outcomes on indicators for matching characteristics between donors and beneficiaries. We test four characteristics: gender, religion, ethnicity, and location. For gender, we use an indicator that takes a value of 1 for the donor–beneficiary pair when a female donor is exposed to a beneficiary with a feminine name. We create a similar indicator for religious identity: we surveyed donors on their religious beliefs, and we match them with information from the beneficiary's name, e.g., Muslim donor–Muslim-name beneficiary. For ethnicity, we use beneficiaries' locations to determine whether they are of the same ethnicity as the donors. Beneficiaries in Central or Eastern Java are presumed to be ethnic Javanese, while beneficiaries in Western Java are presumed to be ethnic Sundanese. We also use an indicator for concordance between donor and beneficiary district. The shorter physical distance between donors and benefi-

[26] 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).

ciaries in this case would mean that they have shared environments, which could activate in-group bias.

Across all our regressions, we find little evidence for in-group bias. Table 10 presents the results from regressing donation indicators and donation amount on the donor–beneficiary identity concordance indicators. For the donation indicators, the coefficient estimates on the concordance indicators for gender identity, religious group, ethnicity, or physical proximity are not statistically different from zero. We find similar results for the regression with donation amounts as the outcome variable, where none of the coefficients are precisely estimated.

[INSERT TABLE 10]

Our null result for in-group bias suggests that donors' perception of deservingness outweighs in-group biases and is broadly in line with the finding in Fong and Luttmer (2011). In an online dictator game, the authors test the effects of perceived worthiness vis-à-vis those of race on charitable giving and find that perceived worthiness has a greater impact on giving behavior. Our results, however, stand in contrast to those of Fong and Luttmer (2009) who, in studying charitable giving to victims of Hurricane Katrina, show that donors who report feeling closer to their own racial group give substantially more to victims of their own racial group. There could be two reasons for this divergence in results. First, we do not have a measure of how "close" donors in our sample feel to members of their own group. It is possible that our results mask heterogeneity for donors who feel closer to their own group. Second, COVID-19 was a global public health disaster that, arguably, affected all individuals equally, regardless of group identity. In contrast, Hurricane Katrina might have been a relatively more localized disaster that affected "poorer" income groups that might have been more predominantly Black. Hence, group-identity biases in giving to Hurricane Katrina victims might have been more central in donors' decision-making processes.

5. Conclusion

This paper documents that donors are susceptible to choice overload in the context of online charitable giving in a developing country. Donors randomly assigned to a 3-beneficiary (8-beneficiary) choice set are 1.8 pp (0.7 pp) more likely to make a donation, and on average, donations made by these donors are 75% (42%) larger in size than those made by donors assigned to a 10-choice set. We hypothesize that the higher donation rates possibly arise from the smaller choice sets' enabling the donor to provide greater attention to each beneficiary in their choice set and to optimize their search process both across beneficiaries and over the entire menu of beneficiary characteristics. In this vein, we find strong evidence that donors are more likely to donate to beneficiaries whose characteristics are possibly linked to perceptions of higher deservingness. Beneficiaries who mention that they are a family breadwinner with dependent children, beneficiaries who are education workers, and beneficiaries outside of Jakarta are more likely to receive donations from the donors.

Furthermore, we uncover saliency effects, above and beyond the effects of deservingness. We also find little evidence for in-group bias. In particular, it is especially striking that the saliency of beneficiary characteristics such as requested donation amount and narrative length leads to higher donations only in small set sizes. We interpret this as further evidence that the higher donations in smaller choice set sizes are driven by a reduction in information overload and a greater ability for potential donors to home in on beneficiary characteristics that should, ex ante, be plausibly important as markers of beneficiaries' perceived deservingness.

In conclusion, our results provide novel evidence of a low-cost way to possibly attenuate suboptimal heuristics in online charitable giving platforms: reducing the choice set size. Smaller choice set sizes might reduce informational overload by allowing individuals to pay more attention to each of the presented choices and characteristics of their choices that are important for optimal decision-making. We believe that these findings have implications for thinking about the ways to optimize giving behavior on online donation platforms above and beyond that associated with disaster responses. In particular, our findings offer the tantalizing possibility that adjustments in choice architecture could be used to attenuate attentional bias to increase individual empathy toward causes that an organization and/or society at large might possibly care more about. For example, in the ensuing decades of (potentially catastrophic) climate change, redistributional efforts such as climate reparations for individuals living in different countries or regions and/or individuals of lower income could potentially leverage advances in choice architecture to increase public acceptability and improve perceptions of such reparations and/or donations.

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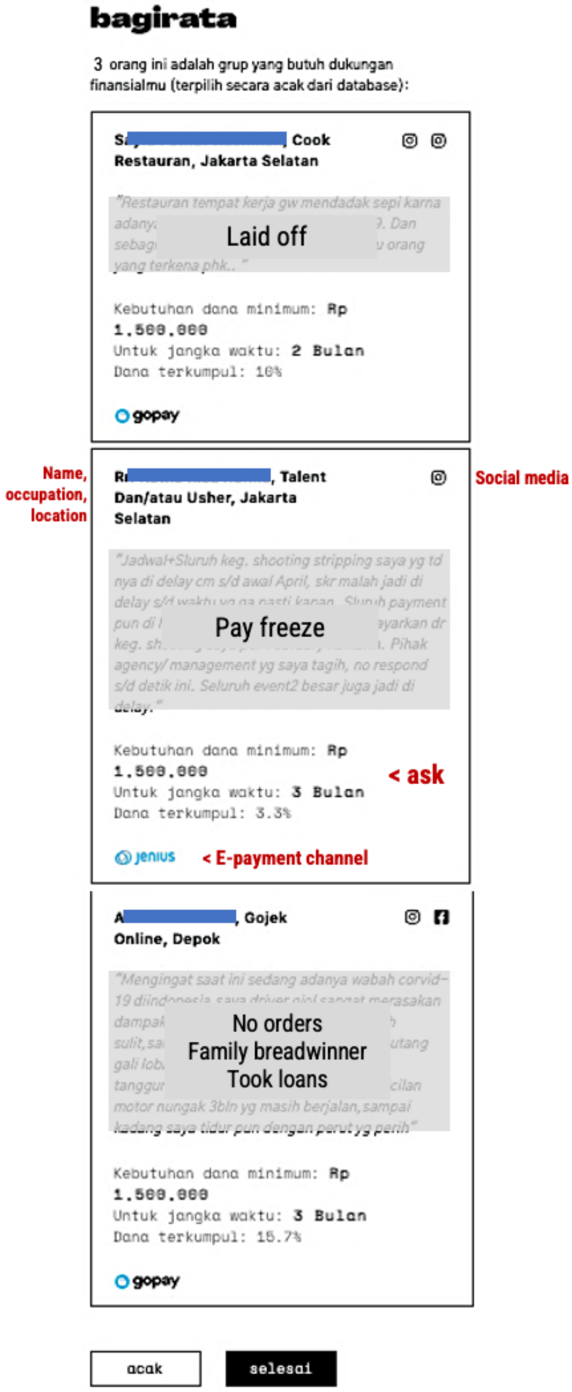
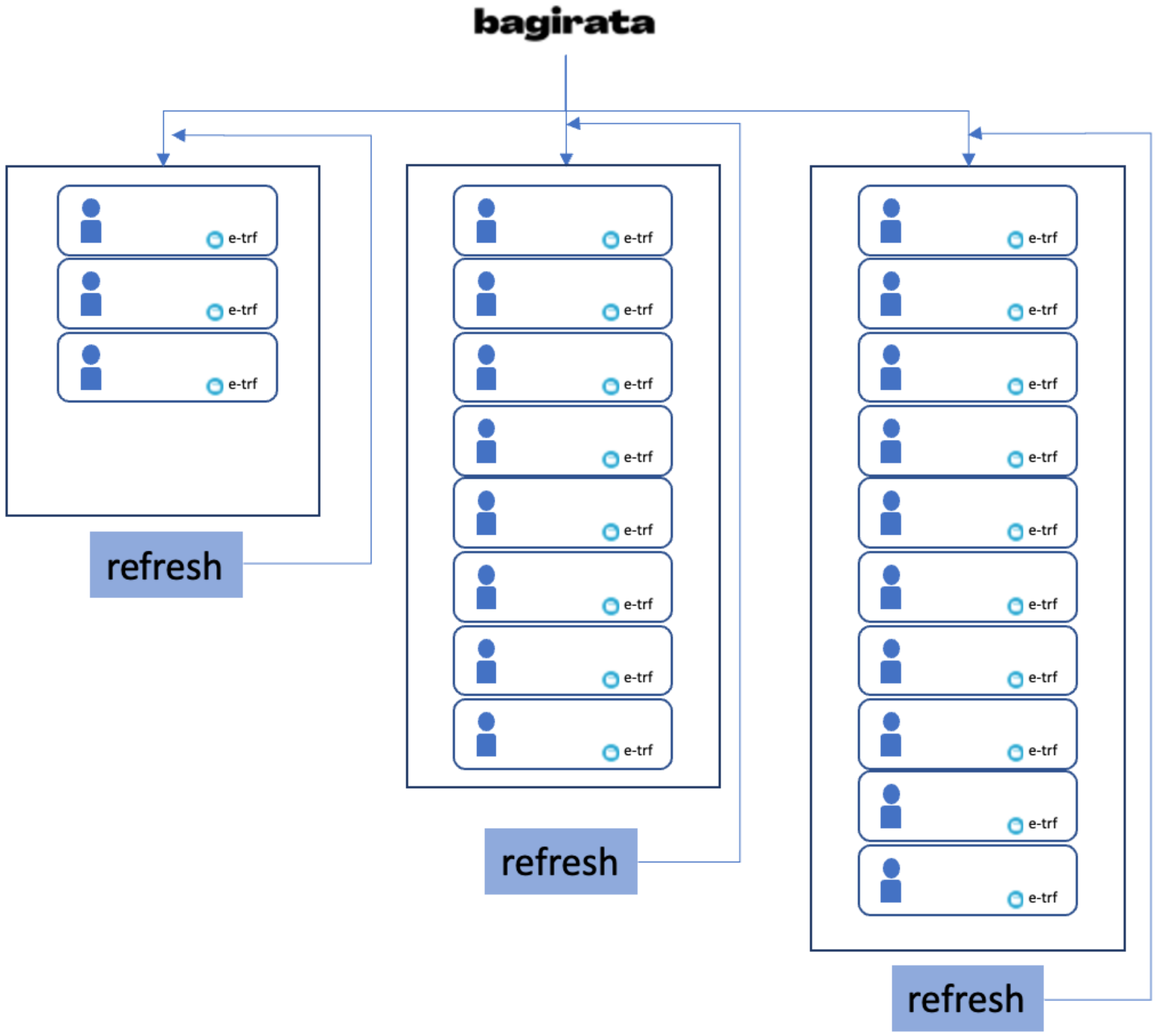
Figure 1: Set of Beneficiary Cards Presented to Donors on the Platform



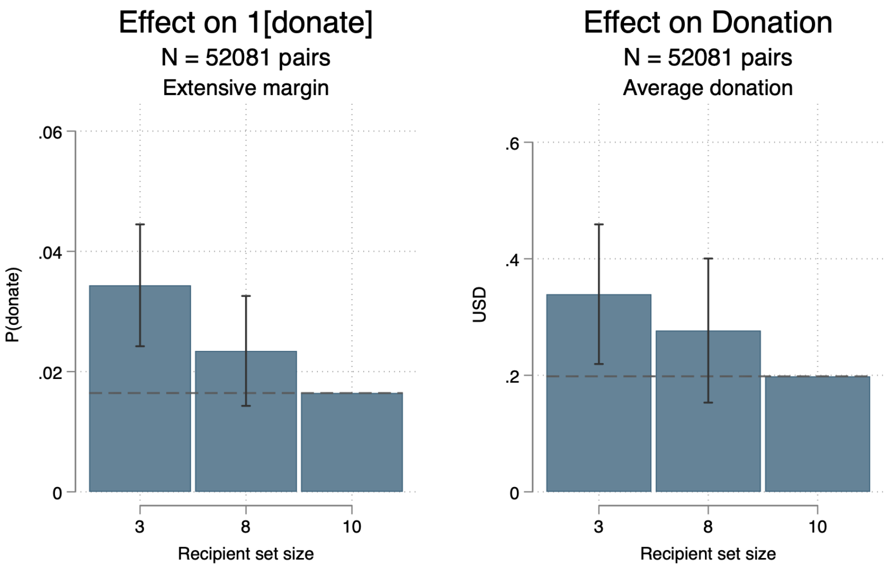
Note: An example of a set of beneficiary cards that potential donors encounter on the *Bagirata* platform. In this example, the donor was randomly assigned to view sets of three beneficiaries at a time. The randomization of the choice set size and the random selection of beneficiaries from the database 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. 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



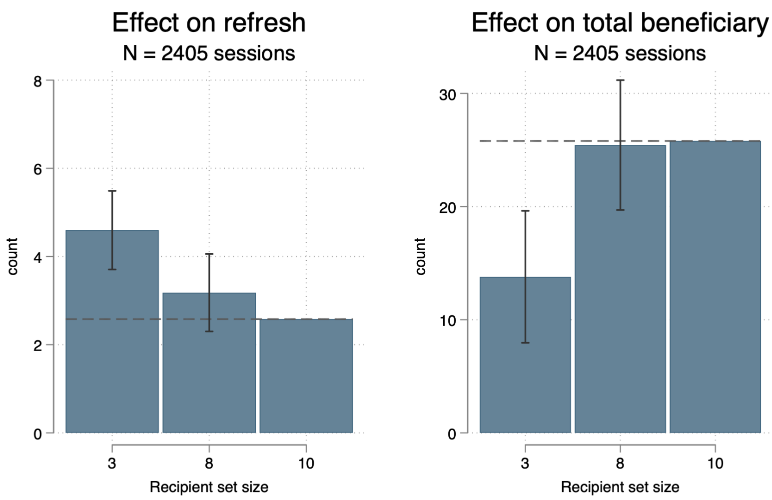
Note: Schematic of randomization procedures for platform visitors. Visitors are randomly assigned with equal probability to one of our three treatment groups, which present sets of 3, 8, or 10 beneficiaries. This randomization scheme is maintained throughout the duration of a web session, which typically 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: Effects of Choice Set Size on Donation



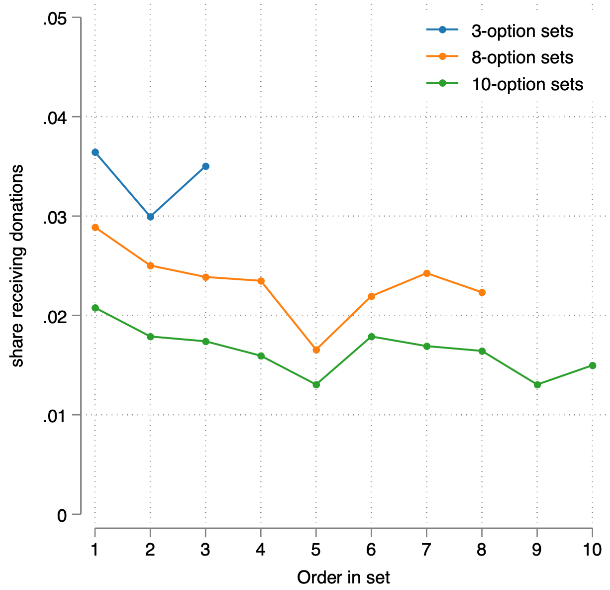
Note: Charts plot the mean for the control group (set of 10) plus the coefficients for the treatment groups (sets of 3 or 8). Coefficients in the plot are from $Y_{ijkl} = \alpha_1 + \beta_1 SetSize_i + BeneficiaryFE_j + \varepsilon_{1,ijkl}$, with standard errors clustered at the donor–session and beneficiary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

Figure 4: Effects of Choice Set Size on Potential Donor Behavior and Total Choice Exposures



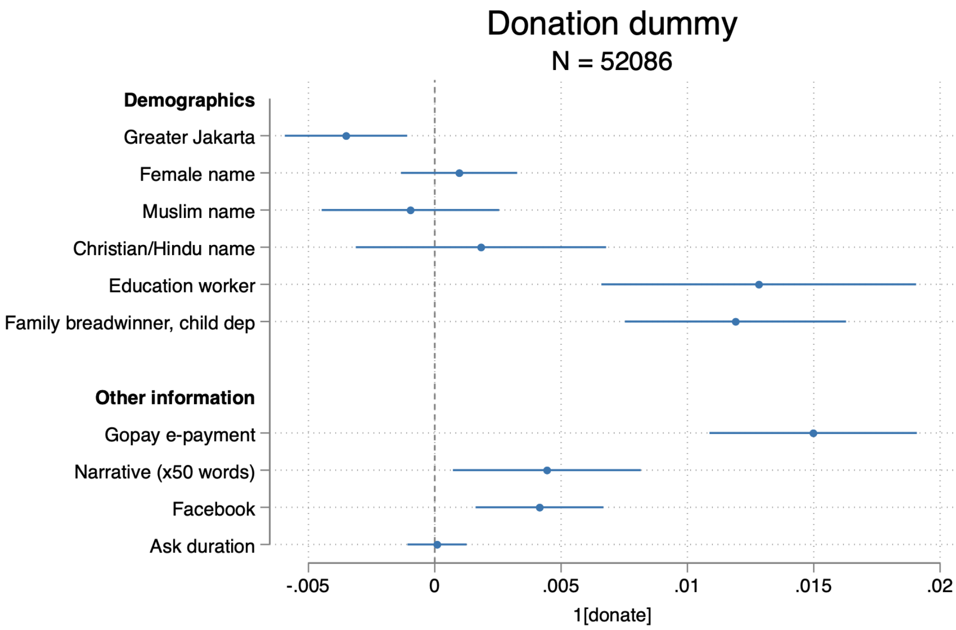
Note: Charts plot the mean for the control group (set of 10) plus the coefficients for the treatment groups (sets of 3 or 8). Coefficients from equation (1). Groups are assigned randomly. The sample consists of donor sessions from Oct 2020 to Jun 2021, excluding outlier donors. Whisker for each bar indicates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

Figure 5: Donation Rate for Beneficiaries, by Position in a Set



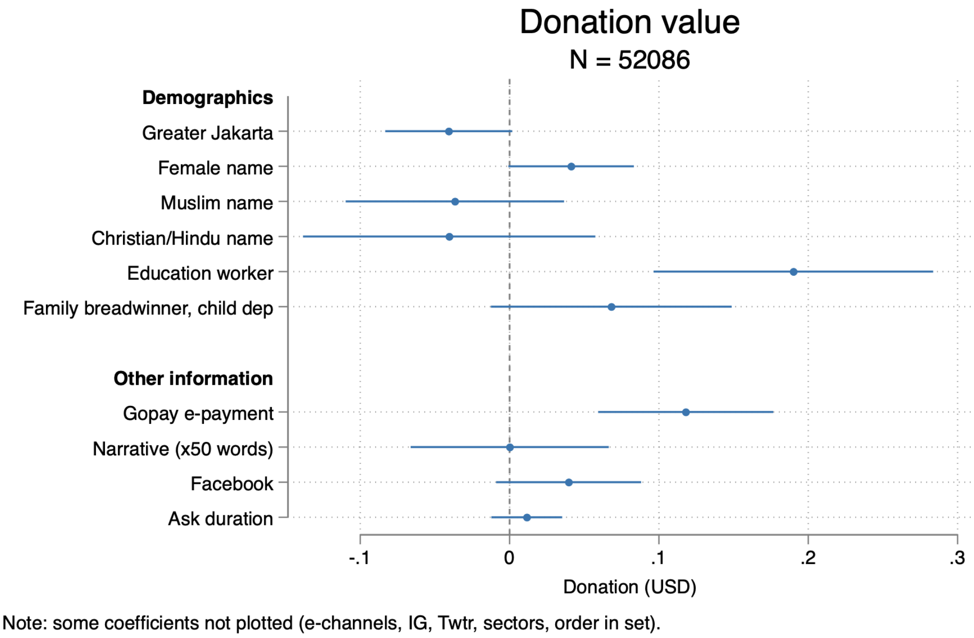
Note: Order in set refers to placement of cards within each set, in descending/sequential order. Number 1 thus is the topmost display for all three treatment groups, with number 3 at the bottom for the 3-beneficiary treatment arms. Numbers 8 and 10 refer to the bottom display in the 8- and 10-beneficiary displays, respectively.

Figure 6: Effects of Beneficiary Characteristics on Donation Indicator



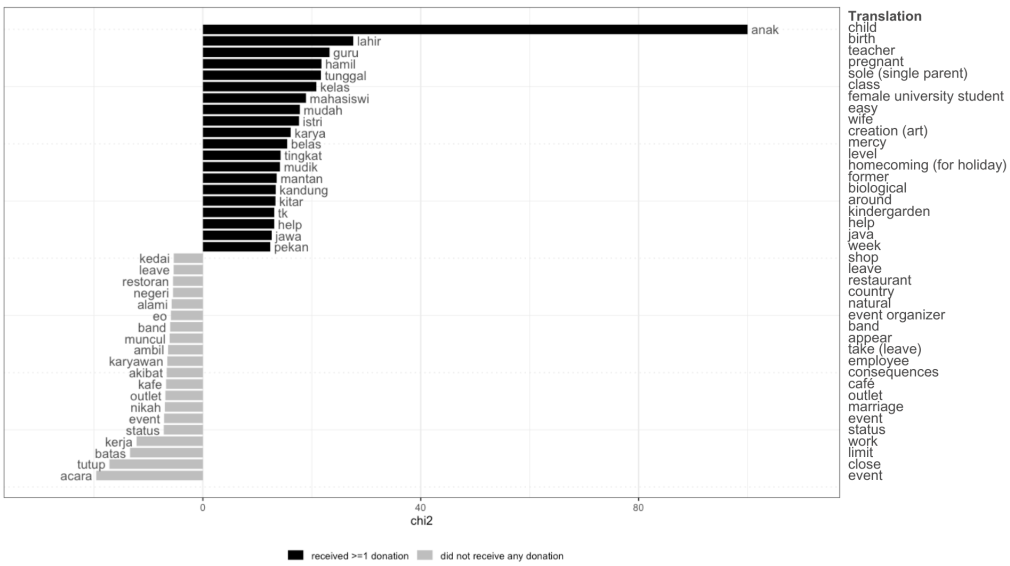
Note: Chart plots coefficients from $Y_{ijkl} = \alpha_2 + \beta_2 Characteristics_j + DonorFE_i + \varepsilon_{1,ijkl}$. Range for each coefficient indicates the 90% confidence interval.

Figure 7: 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 8: 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 the Display Counter and Donations among Platform Beneficiaries from Donor Perspective

	Mean	SD	Min	Max	Count
Frequency being displayed to donors	26.21	18.52	1	68	2,054
Received any donation	0.81	0.40	0	1	2,054
Numbers of donation	2.09	2.14	0	27	2,054
Total received donation (USD)	17.84	26.01	0	646	2,054

	# times displayed		% receive	# donations		Donation (USD)	
Platform beneficiaries	Mean	SD	donations	Mean	SD	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 2: Summary Statistics of Platform Beneficiaries

	Mean	SD	Count	% of Total
Summary statistics of beneficiary characteristics and appeals				
Appeal (USD)	155.94	435.29	2,054	
Appeal duration (month)	2.19	0.87	2,054	
Total appeal (USD)	346.73	954.76	2,054	
Number of mobile money channels	1.14	0.39	2,054	
Number of social media links	1.36	0.58	2,054	
Appeal narrative length (words)	30.13	14.87	2,054	
Summary statistics on beneficiaries' total appeal (in USD), by subsample				
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 3: *Bagirata* User Profiles – Summary Statistics

	Donors	Recipients
Male	.30	.57
Age	29	30
Married	.34	.43
Years of education	15	13
Javanese	.56	.48
Islam	.68	.87
Migrant	.60	.50
Earning (USD)	8,626	1,882
Household size	3.2	3.7
Earning for charity	.06	.05
Uses mobile money	.97	1.00
Mobile money platforms in use	2.3	1.4
Employer corporation or international	.49	.17
Employer small	.13	.38
Occupation in finance or IT	.21	.03
Occupation in government, education, or health	.17	.03
Occupation in retail or hospitality	.07	.35
Occupation in other sectors	.36	.38
Amount donated via platform (USD)	26.33	0.00
Amount received from platform (USD)	0.00	25.68
Observations	216	60

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

Table 4: Impact of Choice Set Size on Donation Outcomes

	(1)	(2)	(3)	(4)	(5)
	1(Donate)	Donation (USD)	Average deliberation time per benef. card (minute)	Refresh button action (times)	Total beneficiary exposure (cards)
3-opt sets	0.018***	0.141**	0.924***	2.017***	-12.009***
	(0.005)	(0.061)	(0.303)	(0.542)	(3.543)
8-opt sets	0.007	0.079	0.170	0.600	-0.362
	(0.005)	(0.063)	(0.292)	(0.533)	(3.488)
Constant	0.016***	0.189***	0.753***	2.588***	25.799***
	(0.002)	(0.030)	(0.212)	(0.379)	(2.479)
FE	beneficiary	beneficiary			
R2	0.050	0.069	0.024	0.006	0.006
Observations	52081	52081	426	2405	2405

Notes: Regression of donation outcomes on choice set size. Observation unit is a donor–beneficiary dyad in Columns (1)–(2) and web sessions in Columns (3)–(5). Column (3) restricts sample to websessions where donation occurs. Standard errors in Columns (1)–(2) 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: 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 6: *Deservingness* (Latent Semantic Scale) and Donation Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Donate)	1(Donate)	1(Donate)	Donation (USD)	Donation (USD)	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 7: Regression of Donation Indicator on Set-Level Salient Characteristics with Donor Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)
Sole with dependent children	0.0269***				
	(0.0044)				
Sole in education sector		0.0166***			
		(0.0057)			
Sole in transportation		0.0126**			
		(0.0059)			
Sole laid off		0.0064**			
		(0.0032)			
Longest narrative			0.0070***		
			(0.0020)		
Set-average narrative length			0.0006***		
			(0.0002)		
Sole in Jakarta				-0.0084	
				(0.0053)	
Sole Facebook link				0.0069	
				(0.0051)	
Sole female name in set				0.0033	
				(0.0038)	
Sole male name in set				0.0055	
				(0.0053)	
Sole Muslim name in set				0.0098	
				(0.0118)	
Sole non-Muslim name in set				0.0063**	
				(0.0031)	
Highest appeal amount					-0.0012
					(0.0015)
Set-average appeal amount					-0.0000
					(0.0000)
Constant	0.0213***	0.0216***	0.0045	0.0220***	0.0269***
	(0.0004)	(0.0004)	(0.0046)	(0.0005)	(0.0046)
FE	donor	donor	donor	donor	donor
R2	0.245	0.244	0.244	0.244	0.243
Observations	52086	52086	52086	52086	52086

Notes: Regression of the donation indicator on choice set size and indicators for various characteristics' salience in each set presented to the donor. The observation unit is a donor–beneficiary dyad. Standard errors are clustered at the donor and session levels and displayed in parentheses. All regressions include donor FE. The sample omits singleton observations, and we also omit outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Regression of Donation Indicator on Set-Level Salient Characteristics with Donor Fixed Effects, by Set Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	3-option sets				8-option sets				10-option sets			
	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)	1(Donate)
Sole with dependent children	0.0288***				0.0272***				0.0243***			
	(0.0081)				(0.0076)				(0.0069)			
Sole in education sector		0.0158				0.0165**				0.0174**		
		(0.0116)				(0.0070)				(0.0082)		
Sole in transportation		0.0144				0.0116				0.0122		
		(0.0123)				(0.0109)				(0.0094)		
Sole laid off		0.0089*				0.0004				0.0097		
		(0.0052)				(0.0047)				(0.0066)		
Longest narrative			0.0135***				0.0036				0.0034	
			(0.0038)				(0.0033)				(0.0031)	
Set-average narrative length			0.0009***				0.0003				0.0002	
			(0.0002)				(0.0003)				(0.0002)	
Highest appeal amount			-0.0054*				-0.0003				0.0010	
			(0.0028)				(0.0024)				(0.0024)	
Set-average appeal amount			-0.0000**				-0.0000				0.0000	
			(0.0000)				(0.0000)				(0.0000)	
Sole in Jakarta				-0.0083				-0.0112**				
				(0.0054)				(0.0057)				
Sole Facebook link				0.0065				-0.0007				0.0502
				(0.0055)				(0.0116)				(0.0440)
Sole female name in set				0.0026				0.0085				-0.0023
				(0.0046)				(0.0083)				(0.0123)
Sole male name in set				0.0063				-0.0465				0.0000
				(0.0054)				(0.0297)				(0.0000)
Sole Muslim name in set				0.0099				0.0000				0.0000
				(0.0119)				(0.0000)				(0.0000)
Sole non-Muslim name in set				0.0071				0.0080				0.0030
				(0.0058)				(0.0049)				(0.0047)
Constant	0.0310***	0.0316***	0.0187**	0.0319***	0.0220***	0.0225***	0.0142	0.0228***	0.0155***	0.0155***	-0.0017	0.0163***
	(0.0009)	(0.0010)	(0.0080)	(0.0014)	(0.0004)	(0.0005)	(0.0125)	(0.0004)	(0.0004)	(0.0004)	(0.0111)	(0.0003)
FE	donor	donor	donor	donor	donor	donor	donor	donor	donor	donor	donor	donor
R2	0.274	0.272	0.275	0.272	0.240	0.239	0.238	0.238	0.217	0.217	0.216	0.216
Observations	10620	10620	10620	10620	20776	20776	20776	20776	20690	20690	20690	20690

Notes: Regression of the donation indicator on choice set size and indicators for various characteristics' salience in each set presented to the donor. The observation unit is a donor–beneficiary dyad. Standard errors are clustered at donor and session levels and displayed in parentheses. All regressions include donor FE. The sample omits singleton observations and outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Regression of Donation Amount on Set-Level Salient Characteristics with Donor FE, by Set Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	3-option sets				8-option sets				10-option sets			
	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)	Donation (USD)
Sole with dependent children	0.3361**				0.3835***				0.2995**			
	(0.1400)				(0.1191)				(0.1427)			
Sole in education sector		0.2559*				0.2026**				0.4519*		
		(0.1305)				(0.0923)				(0.2333)		
Sole in transportation		0.3661				0.1066				0.0876		
		(0.2659)				(0.1203)				(0.1357)		
Sole laid off		0.0344				-0.0017				-0.0225		
		(0.0606)				(0.0511)				(0.0625)		
Longest narrative			0.1564***				0.0185				0.0919	
			(0.0534)				(0.0425)				(0.0945)	
Set-average narrative length			0.0094***				0.0046				0.0129	
			(0.0031)				(0.0060)				(0.0114)	
Highest appeal amount			-0.0836**				0.0282				0.0302	
			(0.0415)				(0.0366)				(0.0485)	
Set-average appeal amount			-0.0000				0.0000				0.0000*	
			(0.0000)				(0.0000)				(0.0000)	
Sole in Jakarta				-0.0287				-0.1145*				
				(0.0957)				(0.0680)				
Sole Facebook link				0.1015				0.0152				1.7824
				(0.0831)				(0.0592)				(1.4562)
Sole female name in set				0.1059				0.1662				-0.1721**
				(0.0866)				(0.1758)				(0.0728)
Sole male name in set				-0.0220				-0.2091*				0.0000
				(0.0674)				(0.1099)				(0.0000)
Sole Muslim name in set				0.1057								0.0000
				(0.1499)								(0.0000)
Sole non-Muslim name in set				-0.0504				0.1481*				-0.1010*
				(0.0698)				(0.0761)				(0.0520)
Constant	0.2874***	0.2958***	0.1423	0.2964***	0.2464***	0.2558***	0.1084	0.2543***	0.1869***	0.1842***	-0.5138	0.2006***
	(0.0140)	(0.0124)	(0.1015)	(0.0185)	(0.0063)	(0.0058)	(0.2720)	(0.0056)	(0.0060)	(0.0075)	(0.4695)	(0.0027)
FE	donor	donor	donor	donor	donor	donor	donor	donor	donor	donor	donor	donor
R2	0.185	0.185	0.186	0.185	0.305	0.304	0.304	0.304	0.089	0.090	0.090	0.090
Observations	10620	10620	10620	10620	20776	20776	20776	20776	20690	20690	20690	20690

Notes: Regression of the donation amount in USD on indicators for various characteristics' salience in each set presented to the donor. The observation unit is a donor–beneficiary dyad. Standard errors are clustered at the donor and session levels and displayed in parentheses. All regressions include donor FE. The sample omits singleton observations and outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Regression of Donation Indicator on Donor–Beneficiary Characteristics Alignment

	(1)	(2)	(3)	(4)	(5)
	A. Outcome: 1(Donate)				
Female donor–feminine name beneficiary	0.0457				0.0463
	(0.0362)				(0.0363)
Muslim donor–Muslim name beneficiary		0.0161			0.0203
		(0.0529)			(0.0542)
Javanese donor–beneficiary in Central/Eastern Java			0.0193		0.0224
			(0.0413)		(0.0430)
Sundanese donor–beneficiary in Western Java			-0.1022		-0.1053
			(0.0714)		(0.0730)
Donor–beneficiary in same district				0.0049	0.0099
				(0.0293)	(0.0306)
Dep. Var. Mean	0.086	0.086	0.086	0.086	0.086
R2	0.494	0.494	0.494	0.494	0.495
Observations	1750	1750	1750	1750	1750
	B. Outcome: Donation (USD)				
Female donor–feminine name beneficiary	-0.2165				-0.2139
	(0.8902)				(0.8917)
Muslim donor–Muslim name beneficiary		0.3034			0.3426
		(0.9454)			(0.9439)
Javanese donor–beneficiary in Central/Eastern Java			-0.4120		-0.3724
			(0.5410)		(0.5584)
Sundanese donor–beneficiary in Western Java			-0.8195		-0.8860
			(0.8657)		(0.8491)
Donor–beneficiary in same district				0.2831	0.2565
				(0.3595)	(0.3655)
Dep. Var. Mean	0.807	0.807	0.807	0.807	0.807
R2	0.527	0.527	0.528	0.527	0.528
Observations	1750	1750	1750	1750	1750

Notes: Regression of the donation indicator on indicators for alignment between donor and beneficiary characteristics. The observation unit is a donor–beneficiary dyad. Standard errors are clustered at the donor, 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 39 donors in 76 sessions, presented with 639 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 also include beneficiary FE (absorbing beneficiary-invariant indicators indicating feminine name, Muslim name, and location), session FE (absorbing set size assignment), and donor FE (absorbing donor-invariant indicators from survey indicating gender, religious affiliation, and ethnicity). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A. Appendix Tables and Figures

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: 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)). As per Column (1) of Panel A, being placed one card lower results in a decrease of 0.06 pp in the likelihood of receiving a donation. This translates to an average decrease of 26% in donation probability between the top and bottom cards in a 10-beneficiary choice set. Columns (2)–(4) illustrate the suggested nonlinearity pattern. Particularly in 8-beneficiary groups, the top four beneficiaries are 0.8 pp more likely to receive a donation than the middle card, and the bottom three beneficiaries are 0.6 pp more likely to receive a donation than the middle card. Observation unit 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 A.4: Impact of Choice Set Size on Donation Indicator, Selected Sample Regression

	(1)	(2)	(3)	(4)	(5)
	All	Only first set	1-3	1-8	1-10
set=3	0.0179***	0.0139**	0.0104	0.0211***	0.0222***
	(0.00517)	(0.00600)	(0.00680)	(0.00620)	(0.00603)
set=8	0.00700	0.0117**	0.0120*	0.0109**	0.0135***
	(0.00466)	(0.00490)	(0.00630)	(0.00511)	(0.00487)
Constant	0.0162***	0.0220***	0.0262***	0.0230***	0.0220***
	(0.00208)	(0.00289)	(0.00388)	(0.00312)	(0.00295)
FE	beneficiary	beneficiary	beneficiary	beneficiary	beneficiary
Observations	52081	16873	6813	16788	19423

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.5: 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.6: 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.7: Beneficiary Characteristics and Donation Outcomes

	(1) 1(Donate)	(2) 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.8: Breadwinner Definitions and Donation Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1(Donate)	Donation (USD)	1(Donate)	Donation (USD)	1(Donate)	Donation (USD)	1(Donate)	Donation (USD)
Breadwinner	0.0065***	-0.0099						
	(0.0021)	(0.0408)						
Breadwinner, dependent child			0.0115***	0.0264				
			(0.0034)	(0.0676)				
Breadwinner, dependent spouse			0.0004	0.0874				
			(0.0046)	(0.0875)				
Breadwinner, dependent sibling			0.0005	-0.2077*				
			(0.0053)	(0.1190)				
Breadwinner, dependent parent			0.0032	0.0553				
			(0.0044)	(0.0950)				
Breadwinner, other dependent relative			0.0086	0.1314				
			(0.0072)	(0.1342)				
Number of dependents					0.0038***	0.0133		
					(0.0010)	(0.0193)		
Number of dependents=1							0.0102***	0.0158
							(0.0038)	(0.0678)
Number of dependents=2							0.0099***	0.0256
							(0.0035)	(0.0591)
Number of dependents=3							0.0087**	-0.0002
							(0.0043)	(0.1034)
Number of dependents=4							0.0114	0.2252
							(0.0072)	(0.2195)
Number of dependents=5							0.0231	-0.1905
							(0.0229)	(0.2126)
Number of dependents=6							-0.0549**	-0.0970
							(0.0239)	(0.1009)
FE	donor	donor	donor	donor	donor	donor	donor	donor
R2	0.259	0.214	0.260	0.215	0.259	0.214	0.260	0.214
Observations	52086	52086	52086	52086	52086	52086	52086	52086

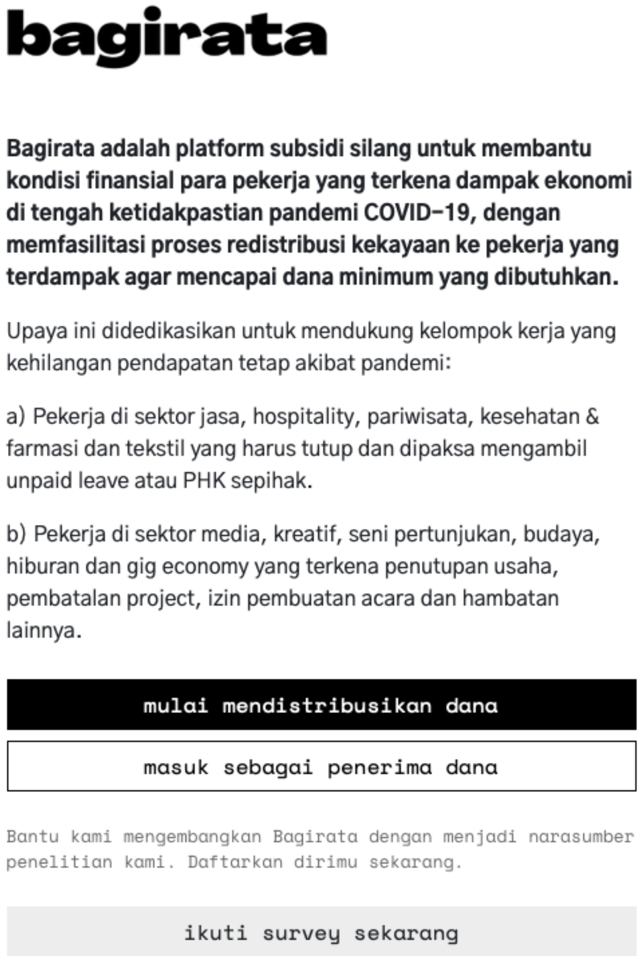
Notes: Regression of donation outcomes on beneficiary characteristics with donor session FE. Observation unit is donor–beneficiary dyad. Standard errors are clustered at the donor and beneficiary levels and displayed in parentheses. Sample is from Oct 2020 to Jun 2021, excluding outliers. * $p < 0.1$,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

Table A.9: Regression of the Donation Amount on Set-Level Salient Characteristics with Donor Fixed Effects

	(1) Donation (USD)	(2) Donation (USD)	(3) Donation (USD)	(4) Donation (USD)	(5) Donation (USD)
Sole with dependent children	0.3424***				
	(0.0749)				
Sole in education sector		0.3017***			
		(0.1046)			
Sole in transportation		0.1717*			
		(0.0957)			
Sole laid off		0.0102			
		(0.0361)			
Longest narrative			0.0885**		
			(0.0365)		
Set-average narrative length			0.0087**		
			(0.0035)		
Sole in Jakarta				-0.0296	
				(0.0939)	
Sole Facebook link				0.1319	
				(0.0813)	
Sole female name in set				0.0934	
				(0.0713)	
Sole male name in set				-0.0283	
				(0.0661)	
Sole Muslim name in set				0.1119	
				(0.1495)	
Sole non-Muslim name in set				0.0151	
				(0.0407)	
Highest appeal amount					-0.0007
					(0.0251)
Set-average appeal amount					0.0000
					(0.0000)
Constant	0.2311***	0.2357***	-0.0207	0.2415***	0.2181***
	(0.0054)	(0.0055)	(0.1020)	(0.0058)	(0.0662)
FE	donor	donor	donor	donor	donor
R2	0.193	0.193	0.193	0.192	0.192
Observations	52086	52086	52086	52086	52086

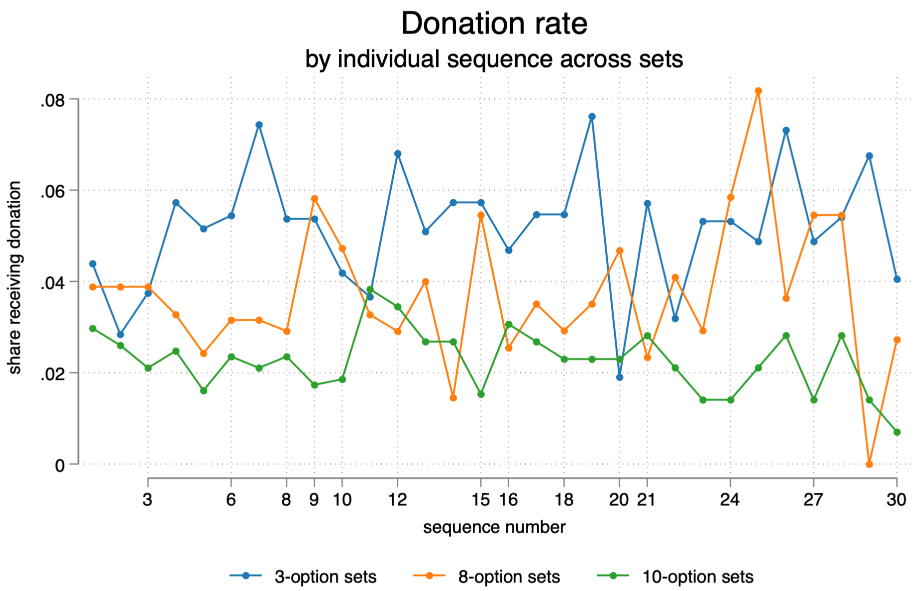
Notes: Regression of the donation amount (in USD) on choice set size and indicators for various characteristics' salience in each set presented to the donor. The observation unit is a donor–beneficiary dyad. Standard errors are clustered at the donor and session levels and displayed in parentheses. All regressions include donor FE. The sample omits singleton observations and outliers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: Landing Page of the Platform



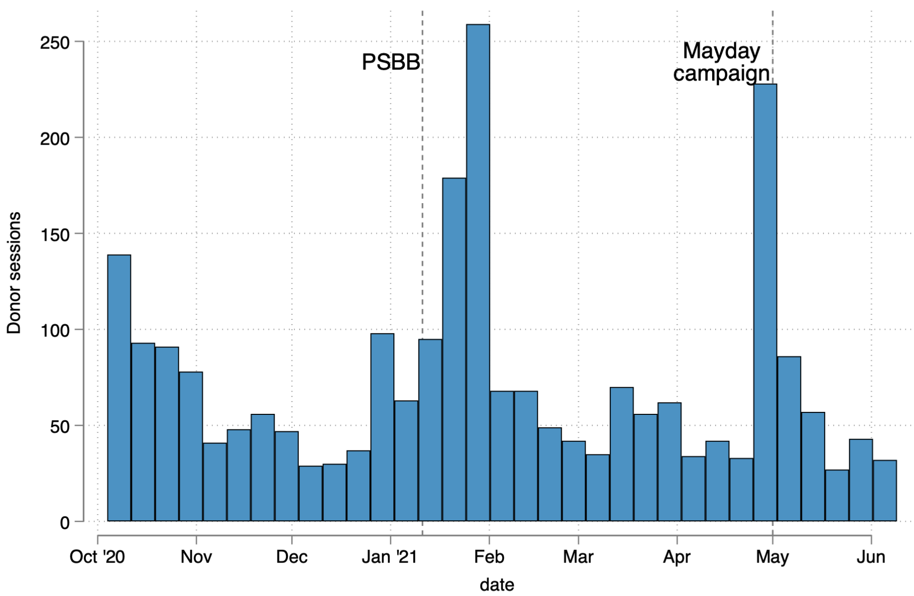
Note: This is the first page that potential donors see upon entering the *Bagirata* website.

Figure A.2: 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 A.3: 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.

B. Further Supplementary Materials

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 8, 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 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 B.1 presents the seed words utilized in the computation, based on the keyness

Table A.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.

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 B.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).