Less is More: Using Choice Architecture to Improve Donation Outcomes *

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Abstract

This paper tests and studies optimal choice set size in an online donation setting. We randomize the number of beneficiaries per screen (*screen-size*) in a field experiment set during one of the largest global public health crises. *Across screens*, donors facing smaller screen sizes are more likely to make a donation and donate larger amounts. Donors invest more effort, as proxied by the amount of time spent reviewing alternatives, and this appears to be driven by the heightened saliency of beneficiary characteristics (identified from self-written narratives). *Within-screens*, beneficiaries with more deserving characteristics and who are positioned at the top of screens receive larger donations. Last, we find strong (little) evidence of female gender (ethnic) in-group bias. We posit that this is possibly driven by context-dependency and the heightened saliency of female poverty to female donors. Together, we provide evidence for low-cost adjustments in choice architecture for optimizing online donation outcomes.

JEL Classification: C90, C93, D64, D91

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1. Introduction

Natural disasters are fast becoming an everyday reality with staggering human costs. Yet, globally, states have struggled to channel aid in a timely manner. Online giving can serve as a timely and low-cost complement to government transfers. The acceptance of e-payment systems have continued to increase,[1] in tandem with the low fixed costs of setting up online platforms. The potential for online giving is even higher in developing countries who suffer disproportionately, both from climate-induced disasters and the lack of digital government infrastructure (Hanna and Olken, 2018).[2]

Existing studies on charitable giving, however, focuses on donations made through intermediaries, with a sole focus on either donors *or* charities (Filiz-Ozbay and Uler, 2019). In contrast, we know very little about peer-to-peer giving.[3][4] The external validity of the former is especially unclear given behavioral and psychological biases when an individual is confronted with the stark choice of dividing their altruism budget among a set of beneficiaries, all of whom, for which, an extra dollar could have life-changing consequences.

This paper asks the following question: Given an overwhelmingly large number of potential beneficiaries in large-scale natural disasters, is there an optimal number of beneficiaries that should be displayed online to optimize donations? On one hand, given limited donor attention, insights from the choice overload literature suggest that presenting fewer beneficiaries might lead to more donations.[5][6] On the other hand, the

[1]Suri et al. (2023) discusses how e-payment systems can serve, more generally, as a timely source of aid and substitute for government transfers.

[2]The proportion of donors who give through online channels has been growing rapidly (Paxton, 2020; Clark et al., 2019). During COVID-19, 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).

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

[4]The former can be more accurately characterized as a one-sided market and the latter, as a two-sided market with donors on one side and beneficiaries on the other.

[5]One possible mechanism, amongst others, is through the reduction of cognitive overload. Much of this literature, mainly from consumer psychology focuses, however, on choice over private goods. See Chernev et al. (2015) for a meta-analysis and Iyengar and Lepper (2000); Iyengar and Kamenica (2010); Reutskaja et al. (2011). Separately, a small literature studies how donation decisions are affected by the number of recipients but nearly all study giving through intermediaries and not direct giving to beneficiaries (Corazzini et al., 2015; Schmitz, 2021; Soyer and Hogarth, 2011). Furthermore, the number of choices vary from one to three which is unlikely to be a policy-relevant margin for direct giving in disaster contexts.

[6]In an even more extreme case, the identifiable victim effect would suggest displaying just one beneficiary per screen. The identifiable victim effect refers to the belief that people tend to be more willing to spend resources to save the lives of single, identified victims rather than a large number of unidentified individuals. This effect has been studied extensively in the psychology literature. See e.g., Small et al. (2007). In the context of natural disasters, however, this is largely impractical given the large number

low marginal costs of presenting an additional beneficiary would suggest displaying as many beneficiaries as possible to maximize the alignment of preferences.

To this end, we partnered with an online donation platform in Indonesia, *Bagirata*, to conduct an online field experiment on donor behavior by randomizing, at the donor-level, the number of alternative beneficiaries per screen (henceforth, referred to as *screen-size*). Specifically, donors are randomly assigned to one of three treatment groups where donors view either 3, 8, or 10 potential beneficiaries per screen for the duration of their entire session.

The *Bagirata* platform connected potential donors to individuals impacted by COVID-19–related earnings and job losses.[7] Each time a potential donor logs on to the platform, the platform's algorithm selects and displays a random set of beneficiary cards to donors. Donors make donation decisions based on the menu of displayed cards (see Figure 1) and donations are required to be made directly through the digital payment system. Each beneficiary card contains a self-written narrative that details why he/she is asking for a donation. Based on these narratives, potential donors are then free to choose which beneficiary (or beneficiaries) to support and the amount that they wish to donate. Hence, after viewing the first screen, donors can make one of two non mutually-exclusive decisions: (i) they can make a donation to zero, one, or more than one beneficiary and (ii) they can hit the *refresh* button at the bottom of the screen to obtain a fresh draw of cards, the number of which will be identical to the first screen. After viewing the second screen, they are free to make the same decisions, screen-by-screen, ad infinitum or until they close the platform.

[INSERT FIGURE 1 HERE]

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

of beneficiaries that would be left out.

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

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

In our *between-donor* analysis, we analyze the effect of *screen-size* on donor behavior. If choice overload negatively affects donation decisions, we would see the best donation outcomes in 3-beneficiary *screen-sizes*. Leveraging on our between-donor randomization design, we use OLS regressions at the donor-session level to analyze differences in the number and value of donations given. Furthermore, we leverage the platform's back-end database to characterize the mechanisms behind differences in donor behavior in terms of donor *search effort* (information-seeking) and *choice overload* (attention and saliency from Bordalo et al., 2013). This activity trace data includes a rich set of variables, such as refresh rates, the time taken for donors to make their donation decision, and search behavior across screens.

In our *within-donor* analysis, we study the effects of *beneficiary display order, deservingness*, and *in-group bias* on donation decisions. These are low-cost, policy-relevant factors that could further improve donation outcomes. Importantly, note that, due to the platform's algorithm, a beneficiary's (order of) placement within and across screens are as-good-as-random. Hence, we continue to use OLS regressions at the beneficiary-donor dyad level with donor session fixed effects. To study *display order*, we regress donation outcomes on indicators for display order. To study *deservingness*, we leverage comprehensive beneficiary information displayed to donors, including detailed beneficiary narratives.[8] From these narratives we code, both by hand and natural language processing (NLP) based textual analysis, an exhaustive set of characteristics that donors might perceive as signalling different dimensions of deservingness. This gives us, among others, indicators for being laid off from work, the number of dependents, and narrative length. Finally, to test for *in-group biases*, we regress donation outcomes on indicators for concordance between gender, ethnic, and religious identities of donors and beneficiaries.

From our between-donor analysis, we find that a reduction in the number of beneficiaries per screen leads to an increase in both donation rates and (unconditional) donation amounts. Donors assigned to a 3-beneficiary screen (8-beneficiary) are 1.7 pp (0.9 pp)

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

more likely to make a donation (compared to an average donation rate of 2.2% for donors assigned to a 10-beneficiary screen). Unconditional donation amounts are 16 US cents (14 cents) larger in the 3-beneficiary screen (8-beneficiary) than in the 10-beneficiary screen group. Importantly, these results do not appear to be driven by a mechanically higher probability that a beneficiary in smaller screen-sizes is more likely to receive a donation. Taken to the extreme, this would be the case if donors across all screen-sizes tend to make one donation per screen. We show, however, that donors across all screen-sizes make multiple donations per screen and donors in our 10-beneficiary screen treatment are significantly more likely to do so.

We hypothesize that the smaller number of beneficiaries per screen encourages greater donor search effort and decreases choice overload. As supporting evidence, donors in 3-beneficiary screens spend 55 seconds longer deliberating on each beneficiary than the average of 45 seconds in 10-beneficiary screens, a 122% increase. Additionally, donors in 3-beneficiary screens are more likely to *refresh* their beneficiary displays and search for additional donation targets, even after having already made a donation. Furthermore, donors in 3-beneficiary screens are 9 p.p. more likely to encounter a salient beneficiary characteristic, defined as a beneficiary having a unique characteristic in any one screen. This is nearly 5 times higher than in 10-beneficiary screens. In an IV analysis, we instrument for saliency using our screen-size treatment assignment. A back-of-the-envelope calculation suggests that saliency accounts for more than half of the difference in the incidence of donation between 3- and 10-beneficiary screen sizes.

Turning to our within-donor analysis, we document three main findings. First, 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-beneficiary sets. Second, 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) receive more donations. We corroborate this with a natural language processing (NLP) based textual analysis. Last, we find evidence of in-group bias: female donors are more likely to donate to beneficiaries with female sounding names.

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

Overall, our results suggest that it might be effective to (i) position beneficiaries with the highest marginal benefit of receiving donations at the start or end of the screen, (ii) pre-select and highlight key beneficiaries' characteristics that are expected to attract higher donations; and (iii) leverage in-group biases by matching beneficiaries (gender) identities with those of donors.

Our paper makes three novel contributions. First, to the best of our knowledge, our paper is one of the first large-scale field experiments to study the effect of choice architecture in a policy-relevant context: direct charitable giving to individuals. We argue that, in our real-world setting, donor motivations are more similar to those in other online donation and peer-to-peer lending platforms. This enhances the external validity of our findings and offers insights for applications to broader altruistic decision-making processes. Building on the 'voltage effect' (List, 2021), we show how concepts that are typically studied in the lab can be field-tested and potentially scaled up. In contrast, the extant literature largely uses lab or survey experiments to study individual decision-making processes in settings that are somewhat less policy relevant.[9]

Second, we contribute to the literature on how perceptions of deservingness affect altruistic behavior. To the best of our knowledge, our study is the first to examine fairness principles (Konow, 2000; Cappelen et al., 2007) in a real-world field experiment setting. The closest study to ours is that of Fong (2007) who show, in a single donor-single recipient lab experiment, that donors give more when they believe the recipient was poor because of bad luck rather than laziness. We innovate by presenting donors with a full menu of beneficiaries, implicitly forcing donors to compare beneficiaries against each other when making donation decisions. This allows us to provide a direct test of the specific dimensions of perceived deservingness that are *comparatively* more important in altruistic decisions.

Third, we contribute to the literature on the saliency of in-group biases in altruistic settings. We provide novel evidence of context-dependency: in-group biases can be shaped by the culture and context of different societies. In particular, we find strong (weak) evidence of female gender (ethnic) in-group bias. This stands in contrast to studies

[9]Most laboratory experiments that study the effects of number of alternatives on donor behavior utilize public good games, where donors typically have a fixed budget constraint and there exist strategic considerations of receiving direct monetary benefit from making contributions. See e.g. (Corazzini et al., 2015). Our context allows us to abstract away from these mechanisms.

like Fong and Luttmer (2009) who find strong evidence of racial in-group biases in a lab experiment on giving to victims of Hurricane Katrina. We hypothesize that in developing countries like Indonesia, where families are dominated by a single, male breadwinner, crises like COVID-19 increased the saliency of female vulnerability to female donors, resulting in larger and higher female-to-female pair donations.

This paper is organized as follows. Section 2 describes the study context. Section 3 presents our experimental manipulation, data, and order of analysis. Section 4 discusses our main results. Section 5 discusses additional results. Section 6 concludes.

2. Charitable Giving during COVID-19 and Bagirata

Globally, Indonesians rank among the top 10 most prolific givers, with much of this giving taking place through informal organizations (Charities Aid Foundation, 2019; Noor and Pickup, 2017). According to the Gallup World Poll, 78% of respondents in Indonesia donated money, 53% volunteered their time, and 40% helped a stranger (Charities Aid Foundation, 2018).[10] 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 ben-

[10]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).

eficiaries.[11] 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 from potential donors to these individuals.[12]

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

At the heart of the *Bagirata* platform is an online, centralized beneficiary database. To be registered as a beneficiary, individuals submit details such as their employment status, economic situation, social media handles, mobile payment QR codes, and contact information to *Bagirata*. This information is then verified by *Bagirata*, and only successfully validated applicants are included in the beneficiary database (a group henceforth referred to as potential beneficiaries).[13]

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

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

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

[13]See Table A.1 for a selection of appeal narratives written by beneficiaries.

three popular digital payment systems in Indonesia. After donating, donors are prompted to confirm their donation by reporting the donation amount and donation status on the *Bagirata* platform. Our analysis includes all donations verified in this manner.

To facilitate the donation process, the platform allows potential donors to donate anonymously. The only identifiable information that donors voluntarily provide is their email address. This design has two implications. First, we do not have access to donor characteristics. We address this by conducting a follow-up user survey where we collect email handles, thereby enabling us to match a subset of donation data from *Bagirata*'s back-end database to donor characteristics. Throughout the paper, however, our analysis focuses on the full set of donation data. In cases where our analysis uses the subset of matched data, we explicitly state so. Second, we cannot identify a donor that initiates multiple sessions if he/she does not provide an email address. Consequently, such a donor will appear in our dataset as multiple sessions.[14] We discuss the implications of this in the following section.

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

3. Empirical Strategy

3.1. Experimental Manipulation

We administered our experiment to all potential donors who visited the *Bagirata* website during our study period.[15] We manipulate screen-size by randomly assigning potential donors to one of the following three between-subject experimental treatments, featuring

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

[15]*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.

a 3-, 8-, or 10-set of beneficiaries. Our experiment was preregistered at the Open Science Framework (OSF),[16] we discuss and explain deviations from our pre-analysis plan in Appendix B.

[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-beneficiary treatment would see three beneficiaries on her device's screen. Similarly, those assigned to the 8- and 10-beneficiary treatments would see eight and ten beneficiaries on their screen, respectively. The treatment assignment remains effective for three hours. This implies that, as long as potential donors refresh the page or re-access the *Bagirata* platform using the same device within the designated three-hour window, they would remain in the same screen-size treatment. To encourage donations, the platform did not require users to provide any identifying information. As a result, we are unable to identify donors who may have accessed the platform across multiple distinct 3-hour sessions. Nevertheless, we gauge from our donor survey, that this incidence is likely to be small given only 13% of donors in our donor survey had a non-unique email address.[17] Henceforth, we do not distinguish between donors and sessions, and refer to our unit of analysis as the *donor-session* level.

After viewing the first screen, donors have the option of clicking a button at the bottom of each page to trigger a fresh draw of beneficiaries (*refresh*).[18] There is no limit to the number of times potential donors can click refresh. It is important to note, however, that our treatment assignment can lead to differences in the frequency of refresh and variations in the actual number of beneficiaries seen. This variation occurs both within and across treatments. We interpret refresh as a key measure of donors' search effort.

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

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

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

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

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

For the within-donor analysis, a potential donor would encounter multiple beneficiaries across sets/screens in a session. Here, we consider each dyadic pair of a potential donor and a beneficiary within a donor-session as a single unit of observation. Crucially, we leverage the platform's algorithm to study the effect of beneficiary characteristics on donation behaviors. In particular, the platform's algorithm selects a random card from the database of all potential beneficiaries for each screen that the donors see, allowing us to leverage the as-good-as-random display of beneficiary characteristics to study the effects of deservingness on donor behavior. We discuss this in detail in Section 5.1.

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. Outcome Variables Related to Donor Behavior and Beneficiary Characteristics

Outcome Variables

Our main outcome variables consist of two measures of donor behavior. Our first measure is a binary indicator that denotes whether a potential donor donates to a beneficiary. 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.[19] As mentioned earlier, we aggregate all variables to the donor-session level. We also calculate the proportion of beneficiaries who received donations, out of the total number of beneficiaries seen by a donor. Similarly, we also calculate the donation amount received over the total number of beneficiaries seen.

Table 1 presents selected summary statistics on donor behavior. Our main data set

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

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.[20] Eighty-one percent of beneficiaries received at least one donation, with the average beneficiary receiving 2 donations for a cumulative sum of USD 17.84. Compared to the average annual beneficiary's earning from the user survey of USD 1,882, the amount of the donation received by a beneficiary is approximately 11% of average monthly earnings.

[INSERT TABLE 1 HERE]

Beneficiary Characteristics

On average, a beneficiary asked for USD 139 per month over a duration of 2.2 months. Our systematic coding from beneficiaries' narratives and names allows us to classify beneficiaries across a wealth of dimensions such as gender, religion, whether a beneficiary is a breadwinner or has child dependents, region, and employment sector. From their names, we can impute that our beneficiary sample has a substantially larger number of men (63%) than women (37%). The majority of the beneficiaries have Muslim names (82%). With respect to their household structures, 22% of the beneficiaries mention being the family breadwinner or having dependents and 12% mention having, specifically, one or more children as dependents. For employment, the majority of beneficiaries are employed in the hospitality, retail, and food service sector (61%), followed by art and creatives (16%), others (12%), and transportation (which comprises mainly ride-share drivers for online platforms).[21] Regarding location, the majority of our beneficiaries are located in the Jakarta metro area (67%), followed by other major cities in Java, Indonesia's most populous island, with the remainder based outside of Java (9%).

Comparing donors to beneficiaries, beneficiaries have lower levels of education and earn less. Table 1, Panel B presents selected summary characteristics of *Bagirata* beneficiaries and donors from a user survey posted on the platform landing page website.[22] The average beneficiary who completed the survey has a little more than a high school education, while the average donor has closer to a college degree. Donors also earn more: the average donor earns USD 8,626/year, almost five times the average beneficiary's earning. Beneficiaries are also more likely to be male and married. Despite this disparity, however, both donors and beneficiaries report allocating a similar percentage of their earnings to

[20] 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.

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

[22] *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.

charity: approximately twice the amount of mandatory *zakat* charity of 2.5% that Islam requires its adherents to provide. As a comparison, the millennial age group in the US reports giving on average only 0.9% of its income (Clark et al., 2019). This suggests that, perhaps due to the lack of a strong social safety net, the altruistic motives of donors in our setting might be distinct from developed countries.

3.3. Order of Analysis

Between-Donor Analysis.

In our main results, we evaluate the impacts of our screen-set size treatment that was explicitly implemented on the donation platform. Specifically, we delve into three aspects of analysis. The first aspect relates to the impact of *choice architecture* on donation behavior. This includes the impact of varying screen set-size on the likelihood of a donor donating to a beneficiary; the number of donations made; the proportion of beneficiaries who received donations conditional on being seen by a donor; and the donation amount (USD) per beneficiary seen by a donor.

The second aspect, relates to the impact of choice architecture on donors' *search behavior* as measured by: the average time spent on a beneficiary card; the decision to continue searching for beneficiaries after the last donation; the number of screen refreshes; the total number of exposures to beneficiary cards; the decision to donate on the first screen; the decision to donate to beneficiaries shown beyond the first screen; and the decision to continue searching after making the first donation in the same session. From this analysis, we infer how screen-set size influences search behavior and, consequently, donation outcomes. This analysis allows us to understand whether the treatment effect is linked to different patterns in donors' search behavior across screen-set sizes.

The third aspect is the *saliency* of beneficiaries' characteristics, which potentially drives the effectiveness of smaller screen-set sizes in generating better donation outcomes for beneficiaries. In addition to search behavior, the saliency of beneficiaries is another potentially important mechanism driving treatment effects related to screen-set sizes.

Within-Donor Analysis.

Next, in our additional results, we examine factors unrelated to the treatment intervention but connected to factors influencing donors' giving behaviors that is observed in our data, including 1) the display of beneficiaries within a card, 2) perceived deservingness, and 3) donors' preference for beneficiaries within their in-groups. Specifically, our analysis focuses on two aspects. The first aspect is the *within-screen analysis*, irrespective of screen-set size. We focus on the placement of beneficiaries within a beneficiary card and the presence of beneficiaries' attributes that donors may perceive as deserving. This analysis allows us to scrutinize donors' giving behaviors further, particularly whether the placement and perceived deservingness of certain attributes direct donors to give to those beneficiaries. Second, we examine whether *in-group bias* motivates donors to give. For this analysis, we use data from our ex-post survey, which allows us to match donors with beneficiaries. We define in-group bias as concordance between donor and beneficiary identity leading to higher donations.

4. Main Results: Between-Donor Analysis

We present two key results. First, we show that smaller screen-sizes leads to more optimal donation outcomes. A higher proportion of beneficiaries displayed in smaller screen-sizes are more likely to receive donations and a higher amount of donations. Second, we provide evidence consistent with fewer alternatives leading to greater donor effort and decreasing choice overload. Donors assigned to smaller screens deliberated longer, more likely to search for additional targets, and more likely to view salient beneficiaries. This possibly induces greater preference alignment and more donations on average.

4.1. Empirical Specification

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

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

where $Outcome_i$ is a measure of donor behavior, such as the probability of making a donation or the donation amount and $ScreenSize3_i$ and $ScreenSize8_i$ are indicators for whether a donor was assigned to see 3- or 8-beneficiaries per screen. The ε term is the idiosyncratic error term. β_1 and β_2 measure the difference in donor behavior between donors assigned to a 3- or 8-beneficiary screen arm relative to donors assigned to a 10-beneficiary screen donor session.

4.2. Donation Outcomes

Columns (1) and (2) of Table 2 estimate equation (1) by regressing the likelihood of donors donating and the total number of donations made on indicators of $ScreenSize3$ and $ScreenSize8$. The difference in the likelihood of donation for donors assigned to 3-beneficiary (8-beneficiary) relative to 10-beneficiary screens is not statistically significant. For the total number of donations, donors in the smaller screen sizes donated slightly more often, although the coefficient for the 3-beneficiary sets is imprecisely estimated. Recall, however, that donors are free to *refresh* and draw a new set of beneficiaries at any point in time. This aspect of donor behavior is induced by our screen-size treatment assignment, and implies that the total number of beneficiaries that a donor sees is chosen by donors and potentially different across treatment arms. To account for this, in Columns (3) and (4), we normalize our outcome variables by the total number of beneficiaries seen by a donor.

Column (3) shows that beneficiaries displayed in the 3-beneficiary (8-beneficiary) screen donor-sessions are 1.7p.p. (0.9p.p.) more likely to receive a donation than those assigned to the 10-beneficiary screen size donor-sessions. In terms of magnitude, from a baseline rate of 2.2% for beneficiaries displayed in a 10-beneficiary screen size treatment, a beneficiary is nearly twice as likely to receive a donation in the 3-beneficiary screen size donor-session. Turning to donation amounts, Column (4) of Table 2 estimates that the average beneficiary in a 3-beneficiary (8-beneficiary) screen donor session, receives an additional US$0.16 ($0.14) in donations relative to those displayed in a 10-beneficiary screen size donor session. In percentage terms, this effect represents a 75% increase from the average donation amount in the control group (USD 0.21).

[INSERT TABLE 2 HERE]

4.3. Donor Search Behaviors

Deliberation Time

One key mechanism behind the observed treatment effect, in line with extant studies on choice overload, is that a larger number of choices per screen, might lead to lower donation outcomes through attention overload. To test this, we use rich data from Bagirata's back-end platform to examine the effect of screen size on deliberation time, or the duration that a donor spends deliberating on the beneficiaries' appeals. A longer deliberation time in smaller screen-sizes might suggest that results on positive donor behavior is being driven by donors paying more attention and making slower, but more informed donation decisions.

To test this, Column (1) in Table 3 regresses the average time spent per beneficiary on our screen-size treatment indicator.[23] The first row of Column (1) in Table 3 estimates that a donor spends an average of 0.92 minutes (55 seconds) longer on each beneficiary in a 3-beneficiary screen size donor session. This effect is statistically significant at the 1 percent level. The second row shows a much smaller, noisier difference between the 8- and 10-beneficiary screen size treatment arms. The difference between the 3- and 10-beneficiary screen sizes 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 screen take almost 1.25 times longer to finalize their donation decisions, suggesting that among eventual donors, a smaller screen size prompts donors to dedicate more attention and time to deliberating on their donation choice, leading to higher average donations.

[INSERT TABLE 3 HERE]

Given that deliberation time is measured as the duration between the point a session was initiated and the point the donor made his last donation, a natural question arises. Did donors continue searching for additional donation targets after making their last donation, and whether the probability of doing so differs across screen-sizes? If so, this would suggest that our measure of deliberation time could be underestimating the actual time donors spend on the platform. However, Column (2) of Table 3 finds no evidence of this behavior, suggesting that our measure of deliberation time is likely accurate and does not under-count the actual time spent by donors on 3-beneficiary screens compared 10-beneficiary screens. This strengthens our interpretation of deliberation time as the duration donors spend deciding whom to donate to.

Refresh Rates

Given the large number of beneficiaries in the platform database, and the limited number of alternatives in a 3-beneficiary screen perdonor-session, it is possible that the positive results on donor behavior we observe are driven by having fewer alternatives per screen leading to more optimal search behavior. In particular, the platform is designed such

[23]Note that we do not directly observe the duration of time a donor spends on each individual potential beneficiary, and we do not observe the exit timestamps for sessions where the donors eventually made zero donations overall. Therefore, 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 screens). We use this measure as our proxy for the amount of attention a donor devotes to choosing a beneficiary to donate to. We restrict the sample to all donor-sessions in which a donation was ever made.

that, at the bottom of each screen, donors are able to hit the *refresh* button to obtain a new, random draw of beneficiaries.

The refresh button allows donors finer control over the search process for donation targets. At each screen, donors can either choose to donate or refresh to view a new set of beneficiaries with the same screen-size. This feature allows us to investigate whether displaying fewer beneficiaries encourages donors to actively search for more potential beneficiaries. We do this by analyzing the effect of screen size on refresh rates, and examine how it affects the total number of beneficiaries a donor is exposed to. While it is perhaps natural to expect that donors on 3-beneficiary screens would tend to refresh more often, it is unclear whether this leads to them seeing a larger total number of beneficiaries.

Columns (3)-(4) of Table 3 and the left panel of Figure 3 estimate and plot our results. Column (3) estimates that, on average, donors assigned to the 3-beneficiary screens click *refresh* twice as often as donors in the 10-beneficiary screen treatment. Despite this, however, Column (4) shows that donors in 3-beneficiary screen treatment arms are exposed to 12 *fewer* beneficiaries. There is no significant difference between donors assigned to 8- and 10-beneficiary sets.

[INSERT FIGURE 3 HERE]

These results are consistent with our earlier results on a higher proportion of beneficiaries receiving donations; higher average donations across total beneficiaries seen; and longer deliberation times in 3-beneficiary screens. Taken together, they suggest that 3-beneficiary screens induce greater donor effort: donors refresh more often to search for more optimal targets and to concentrate their limited attention on a smaller choice set.[24]

Search Behavior Across Screens

Based on lower refresh rates in larger screen-sizes, we further hypothesize that one possible mechanism by which choice overload occurs might be donors' tendency to stop seeking additional donation targets in larger screen sizes. We investigate this by constructing three indicator variables: (i) Whether a donor makes a donation in the first screen; (ii) conversely, whether a donor makes his first donation only after the first screen; and (iii) whether, after the first donation in screen x, the donor continues to search for additional donation targets by hitting refresh. A positive effect on (iii) would support our hypothesis.

Columns (5) and (6) of Table 3 shows that donors in 3-beneficiary screens are 17.2p.p. less likely to donate in the first screen and 16.2p.p. more likely to make their first donation

[24]Specifically, a 3-beneficiary screens donor views, on average, a total of 12 beneficiaries per session, or 3 beneficiaries across 4 screens, as opposed to a 10-beneficiary screen donor who views 20-30 beneficiaries per session, or 10 beneficiaries across 2-3 screens.

after the first screen. Columns (7) shows that donors in 3-beneficiary screens are 13.0p.p. more likely to hit refresh to seek additional donation targets in a new screen after making their first donation.

Taken together, our findings suggest two key mechanisms through which fewer alternatives lead to more donations. First, choice overload. In 10-beneficiary screens donor sessions, lower donation rates, deliberation times, refresh rates, and tendency for donors to stop seeking additional donation targets after their first donation, suggests that donors are overwhelmed by the large number of alternatives on display. Furthermore, each time donors hit refresh, another equally large screen of beneficiaries are displayed, increasing their cognitive load and potentially exacerbating their feelings of being overwhelmed. Second, increased donor effort and preference alignment. Fewer alternatives per screen induces donors to seek out more donation targets, thereby increasing the probability of encountering an optimal beneficiary to donate to.

Alternative Interpretation: Do Smaller Screen Set Sizes Mechanically Increase the Likelihood of Donation?

Our results show that fewer alternatives per screen leads to more donations and we provide evidence consistent with both higher donor effort and lower choice overload. An alternative interpretation, however, is that fewer alternatives per screen might simply increase the mathematical probability that any one beneficiary receives a donation. Consider, for simplicity, a database comprising identical beneficiaries, and 2 donors, each assigned to the 3- and 10-beneficiary screen size treatment arm. The first donor would view 3 such identical beneficiaries, and the second, 10 such identical beneficiaries. Furthermore, consider the extreme case where each donor makes at most one donation per screen, e.g., due to a fixed altruism budget. If so, our results would reflect the probability that a beneficiary in a 3-beneficiary screen has a 30% probability of receiving a donation versus one in the 10-beneficiary screen having a 10% probability of receiving a donation. This would still represent a causal effect of our treatment manipulating the screen-set sizes, but the interpretation of our results would differ.

We argue that this is unlikely for three reasons. First, we show that, in our context, donors are not constrained to making at most one donation per screen. In Table 4, we restrict our sample to all donor sessions in which at least one donation occurred and construct and regress two outcome variables on our screen-size indicators. First, an indicator that takes the value of one if a donor made exactly one donation in at least one screen (and 0 if, in any screen, they made more than one donation). Second, an indicator that takes the value of one if a donor makes more than one donation per screen, in at least one screen.[25] On average, 37% of 10-beneficiary set donor sessions make more than

[25] Note the sum of the means across both columns do not add up to one, because there are, for example,

one donation per screen.

[INSERT TABLE 4 HERE]

Second, we show that our treatment leads to 3-beneficiary screen and 10-beneficiary screen size donors making, on average, a different number of donations per screen. Column (1) shows that 3-beneficiary screen donors are 15.4p.p. more likely to make exactly one donation. Column (2) shows, relatedly, that they are 10.9p.p. less likely to make multiple donations per screen.

Third, our results on longer deliberation time. If the mechanical argument is true, we would expect to see *equal* or *lower* deliberation times per beneficiary in 3-beneficiary screen sizes. Instead, Column (1) of Table 3 shows otherwise.

4.4. The Saliency of Beneficiary Characteristics

A possible leading mechanism in the choice overload literature is that of saliency (Chernev et al., 2015). In our context, smaller screen-sizes might lead to a higher percentage or probability of donors encountering beneficiaries that are salient in any one characteristic within a single screen. Thus, our treatment potentially increases donations by spotlighting the uniqueness of beneficiary characteristics within a single screen, or what we define as *saliency at the screen-level*.

Measuring the Saliency of Beneficiaries Characteristics

In a theory of choice under salience, consumer choice responds disproportionately to variation in attributes of the goods available to them. Not because of the underlying value of these attributes, but because of how distinctive these attributes are from other attributes of the good (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 how easily they can pick up unique characteristics of beneficiaries from any given screen? For instance, donors might donate to a beneficiary if he is the only breadwinner among the presented options, making this beneficiary stand out among other beneficiaries in the same screen. On the other hand, he might not favor a beneficiary for being a breadwinner if multiple beneficiaries in the screen share this trait.

To that end, we define our measure of saliency, as the probability that a donor encounters a salient beneficiary-characteristic, at the *screen-level* (*% saliency*). We construct the data in four steps. First, within each screen, for each beneficiary, we code

donor-sessions in which a donor makes exactly one donation in screen A but more than one donation in screen B.

an indicator that equals one if a beneficiary is the only individual in that screen with a particular characteristic. Consider a breadwinner beneficiary, beneficiary #3. who first appears in a {*non-breadwinner, non-breadwinner, breadwinner*} screen for donor A, and next appears in a {*breadwinner, breadwinner, breadwinner*} screen for donor B. Beneficiary #3 is coded as having a salient breadwinner characteristic only in donor A's screen. Second, for each beneficiary(-screen), we sum up the number of characteristics for which they might have appeared to be salient.[26] Third, we construct the *% of salient beneficiary characteristics at the screen-level*, by summing up the previous value across all beneficiaries and dividing by the total number of possible characteristics in a screen. Fourth, we take the average of this across all screens. This gives us a measure of *screen-level saliency* at the donor-session level.

Intuitively, we investigate if donors respond disproportionately to the saliency of particular characteristics of a given beneficiary, given the characteristics of all other beneficiaries displayed to them in the same screen. We are able to do so given that the characteristics of beneficiaries both *within and across screens*, across all screen-sizes, are as-good-as-random. Hence, we continue to estimate equation (1) with OLS, and regress screen-level % saliency on indicators for 3- and 8-beneficiary screens. This allows us to test if (i) our treatment assignment induces differences in the probability of screen-level salient characteristics and (ii) Assuming that *% saliency* affects donation outcomes only-through differences in screen-size, measure the extent to which earlier results on cross-screen donation behavior are driven by differences in *% saliency* in an IV analysis.

Column (1) of Table 5 shows that donors in 3-beneficiary screens encounter beneficiaries that are 9p.p. more likely to have a salient characteristic This is nearly 5 times the incidence of saliency in 10-beneficiary screens. Instrumenting for *% saliency* using our assignment to screen-sizes, Column (2) estimates that a 1% increase in *% saliency* leads to a 0.001 increase in # of donations over total beneficiaries seen. We can interpret this coefficient in two ways. First, multiplying 0.001 by the coefficient on the 3-beneficiary screens in Column (1) implies that moving from a 3-beneficiary screen to 10-beneficiary screen leads to a 0.009 (9.753*0.001) increase in donations, a 40.9% increase relative to a 10-screen size mean of 0.022. Second, we can divide the size of this coefficient by that of Column (3) in Table 2. Slightly more than half of the observed increase in donations (0.009/0.017), can be attributed to differences in *% saliency*.

[INSERT TABLE 5 HERE]

In summary, our analysis demonstrates that saliency plays a significant role in shap-

[26] Out of an exhaustive set of 19 characteristics including all deservingness characteristics defined later in Section 5.1.

ing donor behavior on our online donation platform. Donors are more likely to respond to beneficiaries with salient characteristics, particularly when fewer options are presented per screen. The IV analysis also highlights that a significant portion of the observed increase in donations can be attributed to differences in saliency.

5. Within-Donor Analysis

5.1. Within-Screen Donation Behavior: Impact of Display Order and Perceived Beneficiaries' Deservingness

Taken together, our results suggest that smaller screen-sizes lead to higher proportion of beneficiaries receiving donations, and higher donations per beneficiary, through inducing greater donor effort and decreasing choice overload. A natural, policy-relevant question to ask is then whether platforms and policy-makers who wish to further direct donations towards a particular cause or individual might be able to do so, holding screen-size constant. In this section, we estimate donations at the 52,086 donor-beneficiary dyad level with donor-session FE to leverage our beneficiary displays within and across screen-sizes, to investigate two possible determinants of within donor-session donation behavior. We show that, firstly, display order and, secondly, deservingness are key policy-relevant parameters that could potentially be leveraged to achieve higher donations.

Beneficiary Display Order: Dipping Behavior

So far, our results suggest that donors employ a heuristic thinking process: a smaller screen size induces donors to spend more time deliberating and seeking information on beneficiaries. Their decision-making processes under the smallest screen 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, might be 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-beneficiary sets receive a disproportionately larger share of donations than those placed in the middle.

This result is mirrored in how the likelihood of donors giving is influenced by the sequence with which beneficiaries are displayed to donors in a given screen 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 screen size treatments. 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 screen-size treatment, this beneficiary would appear as the third beneficiary at the bottom of the third screen viewed by a potential donor. In an 8-beneficiary (10-beneficiary) screen size treatment, this ninth beneficiary would be the first (the penultimate) beneficiary on the second (first) screen. 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 screen is higher than that in larger screen-sizes.

In Table A.6, we regress our donation indicator on dummies for our screen-size treatment, across all screen sizes (Column (1)), to the first set of beneficiaries a donor encounters - the first three in a 3-beneficiary screen, the first eight in an 8-beneficiary screen, and the first 10 in a 10-beneficiary screen (Column (2)) - or the first three, eight, or ten beneficiaries in the sequence of beneficiaries regardless of screen size (Columns (3)-(5)). For example, in a 3-beneficiary screen size, the first eight beneficiaries (1–8) are captured by the first two screens and the top two beneficiary cards in the third screen that a donor encounters. However, in an 8-beneficiary (10-beneficiary) screen, these first eight beneficiaries are presented in the first screen. Overall, our results suggest that a donor viewing a 3-beneficiary screen is more likely to donate to a beneficiary than a donor viewing a 10-beneficiary screen, particularly for cards in the screens immediately following the first (i.e., to the fourth individuals onward rather than to the first 1–3 individuals that they encounter).[27]

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 4, we plot the proportion of beneficiaries receiving donations against their sequential display order within a given screen. In the context of a 3-beneficiary screen, 1 - 3 would indicate the order position of a beneficiary in that screen. Thus, for example, the dot on the graph for the 3-beneficiary screen at the order position 1, 2, or 3 represents

[27]Table A.7 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 screen size and higher donation likelihood remains, and additional fixed effects increase the precision of some coefficients.

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 screen size treatment. 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 screens. The proportion of beneficiaries receiving donations declines from beneficiaries positioned first in each screen to those positioned subsequently until a certain point, after which it rises again. The effect is most pronounced for beneficiaries in the middle of the screen. Specifically, beneficiaries placed in the 5th position in the 8- and 10-beneficiary screen size and those in the 2nd position in the 3-beneficiary screen size 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 screen size.[28]

[INSERT FIGURE 4 HERE]

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 screens and the least attention to those in the middle. In other words, donor attention dips as they move sequentially down a screen and recovers as they near the end of a screen.[29] This suggests that policy-makers or online platforms that seek to maximize donations towards certain individuals or causes, should place these alternatives either towards the start or end of the platform's display screen.

Beneficiary Characteristics: Perceived Deservingness

Smaller screen sizes lead to higher donations by lowering information overload. What characteristics of beneficiaries, however, does lower information overload allow donors to concentrate on? The context of COVID-19 induced losses suggest that *deservingness* might be a key characteristic of interest. To answer this, we analyze the effect of beneficiary characteristics on donation outcomes, utilizing the display of beneficiary cards from our database. We conduct a within-donor-session analysis by running regressions at the beneficiary-dyad level and including donor-session fixed effects. This allows us to study, holding donor identity constant, which beneficiaries a donor is more likely to donate to.

[28] We explore this pattern further using regression analysis, and the results are shown in Table A.8. 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.

[29] 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.

We proceed in three steps. First, we use survey data submitted by donors who participated in our follow-up survey to understand what beneficiary characteristics are considered, by donors, to be key markers of deservingness. Second, we construct measures of deservingness from hand-coding beneficiary characteristics, and textual analysis. Third, in a within-donor-session analysis, we regress donation outcomes on these measures to understand how relative deservingness of beneficiaries drives donor behavior.

Donor Survey

Table A.9 reveals that the most common reason donors cite for making a donation is the "beneficiary needs my donations" (*deservingness*), with 58% of donors stating this as their primary motivation.[30] This leads to the question: who do donors view as most deserving? Table A.9 summarizes donor response and finds, in descending order, beneficiaries who are breadwinners (with either children or elderly dependents) (86%); individuals in persistent poverty (85%); those hit by unforeseen circumstances outside of the beneficaries' control such as disasters, illnesses', or job loss (82%); and female beneficiaries (69%), as the *most* deserving of donations. Conversely, beneficiaries with low educational attainment (53%); from neighborhoods similar to the donors' own (56%); those sharing the same religion (49%); or ethnicity (42%) are perceived as the *least* deserving.[31]

Measuring Deservingness

We hand-code beneficiary narratives to obtain a complete set of *all* potential beneficiary characteristics that donors might consider as markers of deservingness. To ensure accuracy, and to mirror donors' reading of beneficiary narratives during the donation process, we task two Indonesian research assistants with manually reading through each narrative.[32] Following donor survey responses, hand-coded characteristics include whether a beneficiary is a primary breadwinner, based on keywords indicating financial responsibility for his/her family, including children, parents, or siblings. We also create indicator variables for occupational sector, gender, religious identity, and regional location. In addition, we measure the length of each narrative.[33]

We illustrate this process in Appendix Table A.1. For Beneficiary #5, a former drink shop attendant: "I lost my job because the drink shop where I work is closed. My

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

[31]Even fewer donors state that they would donate to beneficiaries who have already received donations (34%) and those who are younger (32%).

[32]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.

[33]We also measure the presence of additional donation request details such as the specified amount of money needed; the duration of need; social media presence; and e-payment channel options.

wife recently gave birth, I need help to buy my child's needs.", we assigned a value of 1 to "Breadwinner/has dependent(s)", "Breadwinner/mentions dependent child(ren)", and his occupational sector is classified as "hospitality, retail, and food service". In contrast, for Beneficiary #8: "My office closed in July ... I deepen my design and illustration and copywriting skills, building updated portfolios to get freelance opportunities", we assigned a value of 0 to "Breadwinner/has dependent(s)", and "Breadwinner/mentions dependent child(ren)", and his occupational sector is classified as "art and creatives".

Within-Donor Analysis: Empirical Specification

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

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

For donor session i seeing beneficiary j in the k-th screen, with l indexing beneficiary's order within the screen and $Characteristics$ is a vector of beneficiary characteristics inferred from beneficiary narratives. As above, 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. We additionally control for donor-session fixed effects, ϕ_i. Hence, 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 donor–session fixed effects ϕ_i. Hence, we interpret β_3 as the effect on the probability of receiving a donation (or a higher donation amount).

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 shocks*, *demographics*, and *donations received from other donors*. Full regression results are presented in Table 6. Here, we focus on Figures 5 and 6, where we display selected coefficient estimates.[34]

[INSERT TABLE 6 HERE]

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

[INSERT FIGURE 5 AND 6 HERE]

Figures 5 and 6 show that beneficiaries who are primary breadwinners are more likely to receive a donation and obtain larger donations. This is consistent with donors' self-reported responses. Next, we consider *occupational sector* and *economic shocks*. For example, teachers (or those who are education workers) are considered more deserving than cafe workers. Using beneficiaries in the hospitality industry as the baseline, Table 6 and Figures 5 and 6 show that those in the education sector are 1.3 pp more likely to attract donations and receive USD 0.18 more in donation value. In contrast, we find little evidence that individuals experiencing *economic shocks* are more likely to receive donations. The coefficient estimate for *retrenchment* is statistically insignificant in any of the regressions.

We interpret these results as suggesting that breadwinners are consistently perceived as being more deserving of donations. In addition, context-specific beneficiary occupations can also matter as a measure of deservingness. Teachers were particularly hard hit by the COVID-19 pandemic given that Indonesian schools were closed for one of the longest duration in the world. In contrast, *economic shocks*, despite donors' self reported preferences, had a possibly lower impact on donor behavior given nearly all workers had their income sources cut off, given restrictive, large-scale movement controls throughout Indonesia.

Last, we consider three other plausible proxies for deservingness: beneficiary narrative length (in 50-word increments); requested donation amount; and the duration for which beneficiaries ask to be funded. Figure 5 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. In contrast, neither the requested donation amount nor its duration have any effect. This suggests that extended narratives could further enhance donors' perception of deservingness.

Textual Analysis: Keyness Statistics and Latent Semantic Scaling

Thus far, we have relied on hand-coded measures of deservingness. To corroborate this, we employ textual analysis to classify and construct a deservingness index specific to each beneficiary narrative by using *Keyness Statistics* and *Latent Semantic Scaling* (LSS) (Zollinger, 2022). In our context, this method analyzes beneficiary narratives to approximate the most salient information that donors focus on when making donation decisions, revealing their motivations. Figure 7 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. These results align closely with hand-coded narratives. Keywords positively associated with donations are those related to beneficiaries with child dependents or affiliations with the education sector.

[INSERT FIGURE 7 HERE]

From keyness statistics, we use *latent semantic scaling* (LSS) to compute a composite score for each beneficiary narrative (henceforth, *deservingness index*). We rescale the LSS statistic for each narrative to take a value between 0 to 1. 0 indicates the highest similarity to words appearing in narratives *least* likely to receive donations. 1 indicates the highest level to words appearing in narratives *most* likely to receive donations.[35] We then include the index as a regressor in our regression analysis.

Table 7 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 potentially important control variables. In Table 7, Column (1) shows that a beneficiary narrative with a higher deservingness index is more likely to receive a donation and this significance remains (Columns (2) - (3)) when we add additional control variables. We find similar results for donation amounts in Columns (4) - (6).

[INSERT TABLE 7 HERE]

Together, these results validate our hand-coded measures and show that perceptions of deservingness matter, above and beyond all other beneficiary characteristics. Importantly, they provide novel empirical evidence for the accountability principle (Konow, 1996, 2000): donors are more likely to donate to beneficiaries whose neediness corresponds with factors he cannot reasonably influence or change in the short run through his or her own effort. Our setting also allows us to provide a direct test of *which* notions of perceived deservingness are *comparatively* more important in altruistic decisions when donors are presented with a full menu of beneficiaries.

5.2. In-Group Bias

Beyond display order and deservingness, an alternative explanation for donors' charitable behaviors is that of in-group biases. It is possible that donors give generously 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

[35] The methodology of our textual analysis is detailed with examples in Appendix B

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.[36]

We test for the effect of group ties on donation by pairing our beneficiary data with demographic information about our donors from our ex-post-donor survey. We run these regressions at the beneficiary-dyad level. This part of our analysis uses a smaller subset of data, owing to the fact that our donor information is limited to potential donors who chose to leave their emails on the *Bagirata* platform and also independently completed our donor survey. As noted previously, the survey was decoupled from the donation process to minimize the possibility that reduced anonymity could discourage potential donors from making donations In this context, we are able to match donors in 78 sessions with 1,283 beneficiaries, giving us a sample of 2,396 observations.

We illustrate our coding process using narratives in Appendix Table A.1, which originally contains beneficiaries' names and locations. In the table, personal identifiers have been replaced with numbers for anonymity. For example, Beneficiary #5 has a first name that is a masculine Javanese word and a surname that is an Arabic word, our assistant coded his name as both masculine and Muslim. Furthermore, as this beneficiary resides in Central Java, an area with a predominantly ethnic Javanese population, we coded his ethnicity as Javanese, which is concordant with information from his name. Similarly, because 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.[37]

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

[36]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).

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

donor and beneficiary district. The shorter physical distance between donors and beneficiaries in this case would mean that they have shared environments, which could activate in-group bias.

Across regressions, we find evidence of in-group bias in terms of female gender identity and, to a smaller extent, ethnic identity. Table 8 presents the full results. For donation indicators, coefficient estimates on the concordance indicators for female gender identity are statistically different from zero. We find similar results for the regression with donation amounts as the outcome variable. In comparison, the coefficients for all other concordance variables are statistically indistinguishable from zero except for ethnicity alignment which is marginally significant at the 10% level in donation indicator regression.

[INSERT TABLE 8]

These results provide novel evidence broadly complementary to that of Fong and Luttmer (2009) who, in studying charitable giving to victims of Hurricane Katrina, show that donors who feel closer to their own racial group give substantially more to victims of their own racial group. We introduce a novel finding by showing that the activation of in-group bias in altruistic settings is highly context-dependent and can be attenuated by the *nature* of disasters. First, our weak results on ethnic identity concordance could potentially be explained by the fact that COVID-19 was a global public health disaster that, arguably, affected all individuals equally, regardless of ethnic identity. In contrast, Hurricane Katrina was a more localized disaster that affected "poorer" individuals who were predominantly Black. Hence, in our context, ethnic identity biases might have been less central in donors' decision-making processes. Second, and in contrast, our strong results on female identity concordance suggest an interactive effect between gender in-group bias and deservingness. Female donors were more likely to consider female beneficiaries to be more deserving of donations. In contrast, male donors, despite survey responses, were not more likely to do so.

6. Conclusion

This paper documents that donors are susceptible to choice overload in the context of online charitable giving in a developing country. Beneficiaries randomly assigned to and displayed in a 3-beneficiary (8-beneficiary) screen-size are 1.7 pp (0.9 pp) more likely to receive a donation, and on average, donation amounts received are 16 US cents (14 cents) larger than in a 10-beneficiary screen size. We hypothesize that the higher donation rates possibly arise from the smaller screen sizes enabling the donor to provide greater attention to each beneficiary both within and across screens, 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.

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

Last, we believe that our findings have important implications for thinking about the ways to optimize altruistic behavior above and beyond those associated with disaster response. In particular, given the significant reduction in transaction costs on online donation platforms, our findings suggest that policy makers could play a valuable role in overseeing and guiding these online platforms to help minimize donor fatigue and reduce the potential de-personalization of donation experiences (Andreoni and Payne, 2013). Our findings also offer the tantalizing possibility that small adjustments in choice architecture could be used to attenuate attention bias and increase individual empathy towards altruistic causes that society at large might deem to be important.

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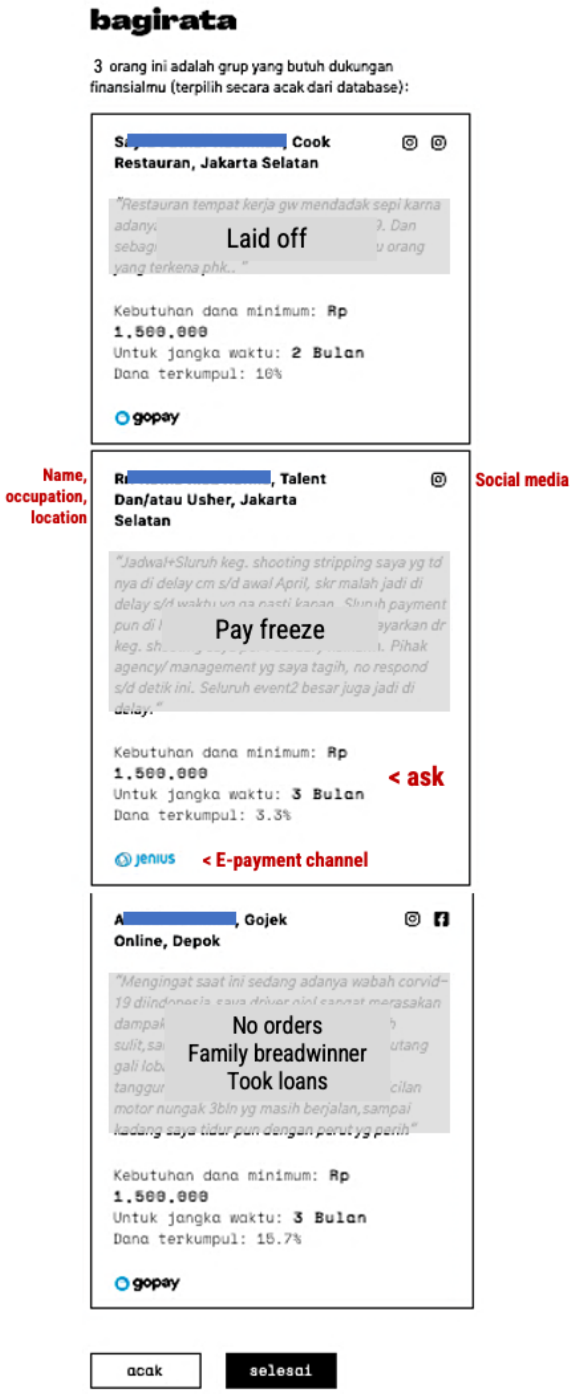
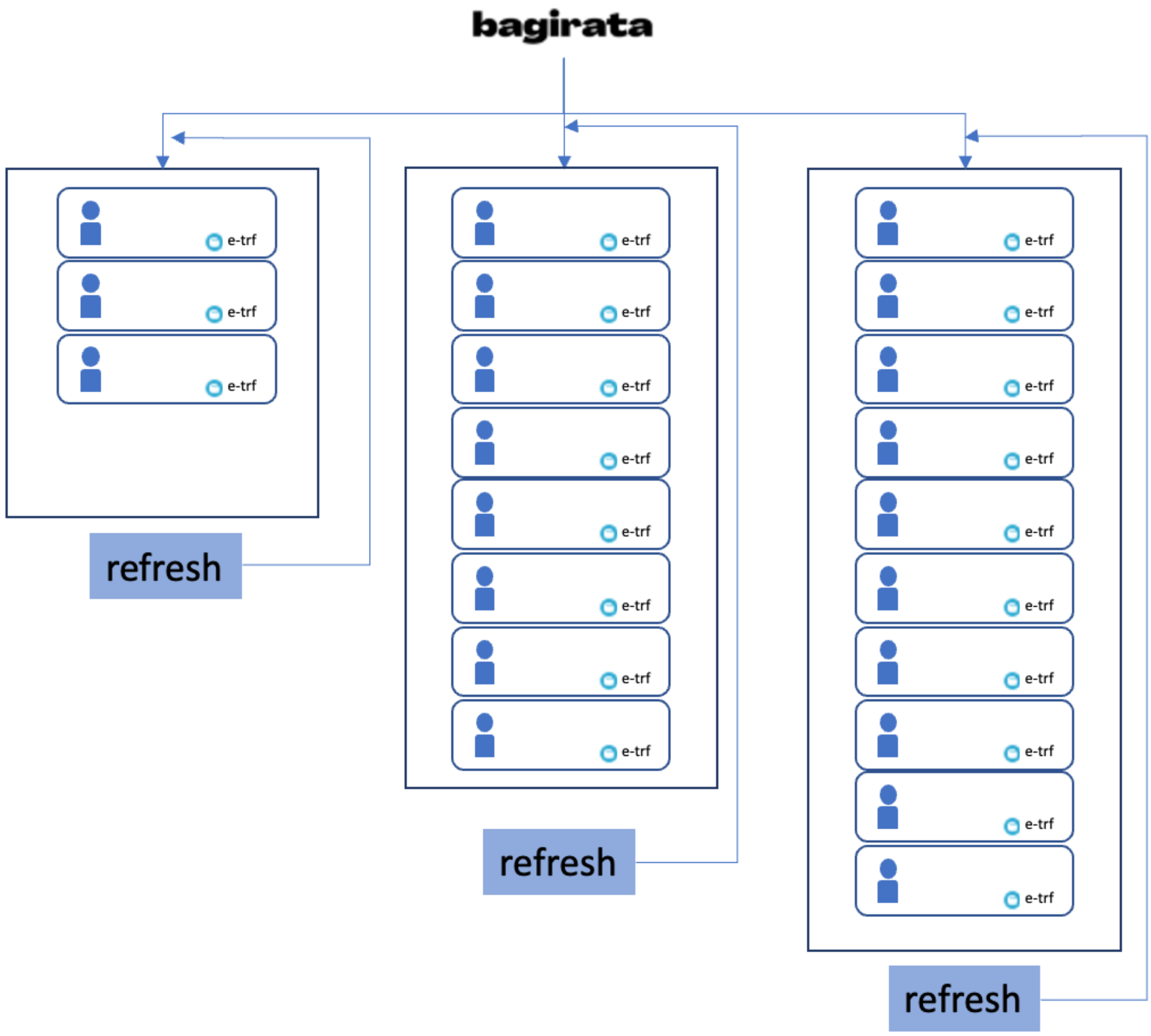
Figure 1: Set of Beneficiary Cards Presented to Donors on the Platform



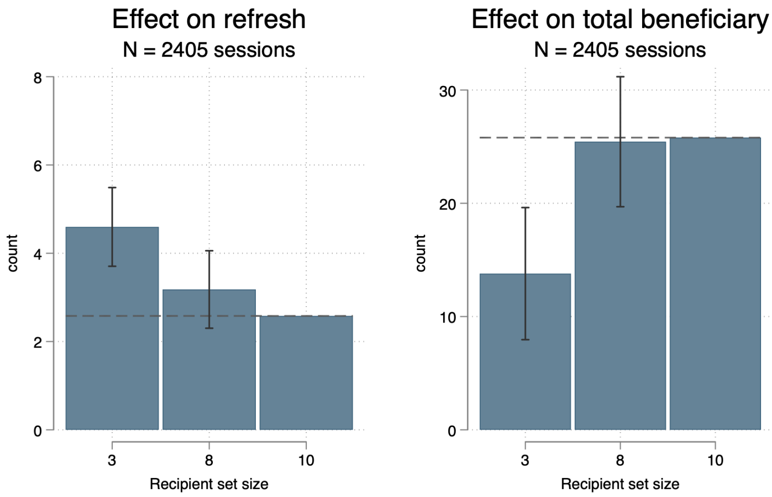
Note: An example of a set of beneficiary cards that potential donors encounter on the *Bagirata* platform. In this example, the donor was randomly assigned to view sets of three beneficiaries at a time. The randomization of the choice set size and the random selection of beneficiaries from the database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

Figure 2: Schematic of Randomization Procedures for Platform Visitors



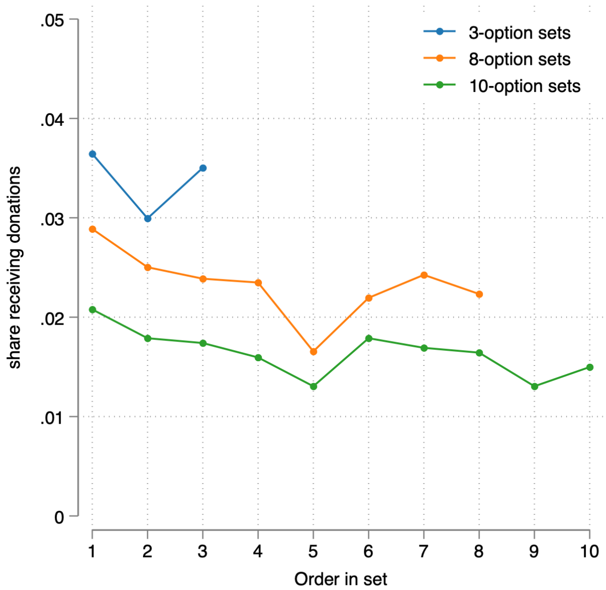
Note: Schematic of randomization procedures for platform visitors. Visitors are randomly assigned with equal probability to one of our three treatment groups, which present sets of 3, 8, or 10 beneficiaries. This randomization scheme is maintained throughout the duration of a web session, which typically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

Figure 3: Effects of Choice Set Size on Potential Donor Behavior and Total Choice Exposures



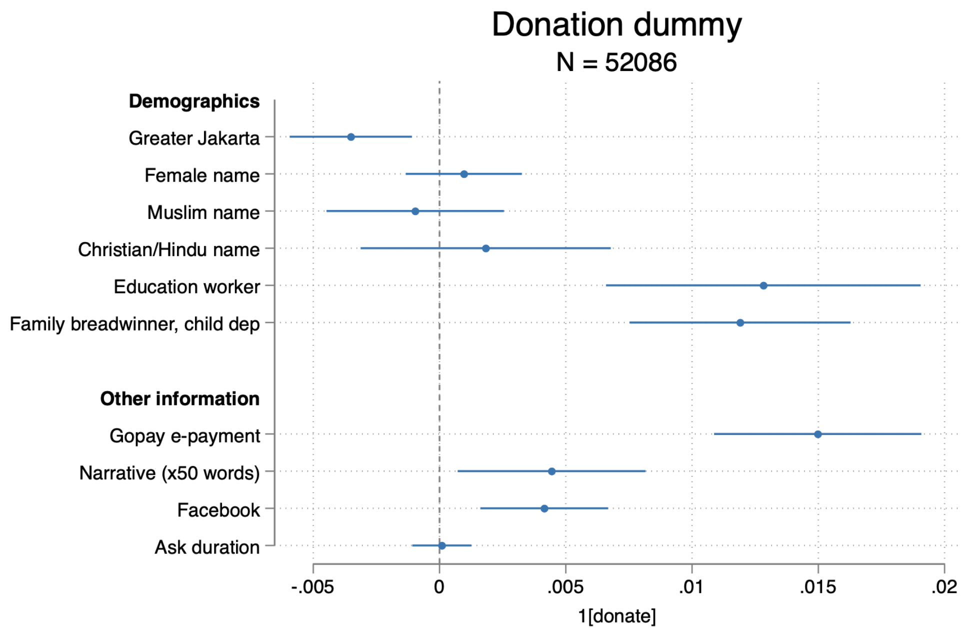
Note: Charts plot the mean for the control group (set of 10) plus the coefficients for the treatment groups (sets of 3 or 8). Coefficients from equation (1). Groups are assigned randomly. The sample consists of donor sessions from Oct 2020 to Jun 2021, excluding outlier donors. Whisker for each bar indicates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

Figure 4: Donation Rate for Beneficiaries, by Position in a Set



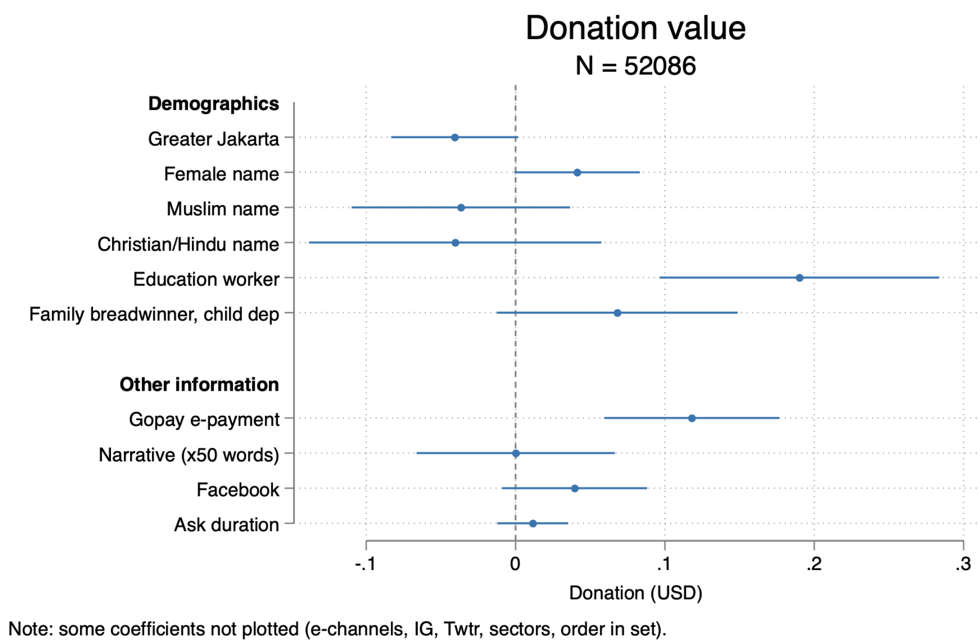
Note: Order in set refers to placement of cards within each set, in descending/sequential order. Number 1 thus is the topmost display for all three treatment groups, with number 3 at the bottom for the 3-beneficiary treatment arms. Numbers 8 and 10 refer to the bottom display in the 8- and 10-beneficiary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

Figure 5: Effects of Beneficiary Characteristics on Donation Indicator



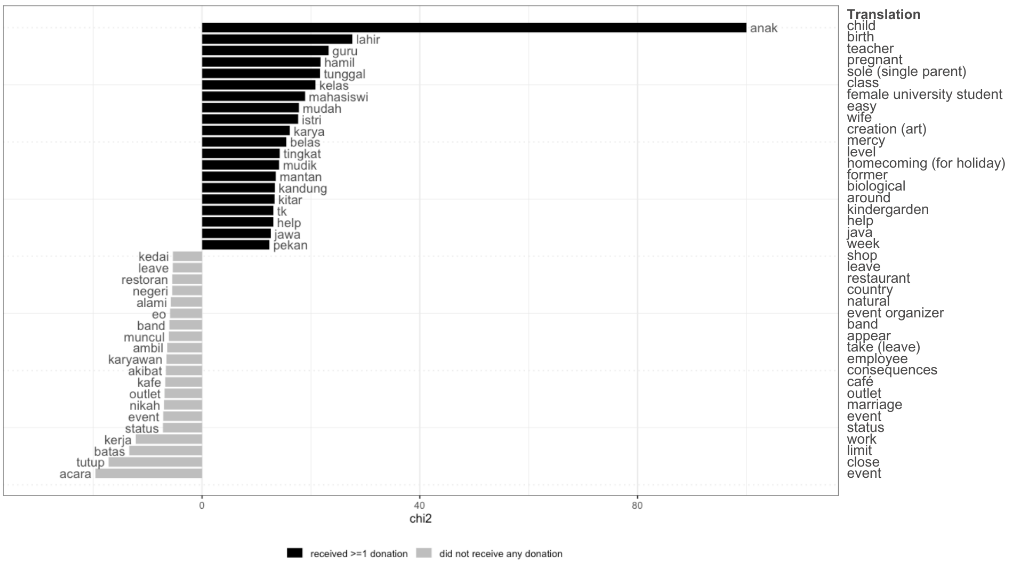
Note: Chart plots coefficients from $Y_{ijkl} = \alpha_2 + \beta_2 Characteristics_j + DonorFE_i + \varepsilon_{1,ijkl}$. Range for each coefficient indicates the 90% confidence interval.

Figure 6: 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 7: Keyness Statistics on Donor Behavior: Characteristics of Beneficiaries Who Received a Donation versus Those Who Did Not



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

Table 1: Summary Statistics of Platform Users

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

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

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

Table 2: Impact of Screen Size on Donation Outcomes

	(1) 1(Donate)	(2) Total # of Donations	(3) # of donations over total seen	(4) Average donations per beneficiary seen (USD)
3-opt sets	-0.002	0.043	0.017***	0.162**
	(0.019)	(0.070)	(0.005)	(0.066)
8-opt sets	0.016	0.166*	0.009**	0.146**
	(0.019)	(0.089)	(0.004)	(0.072)
Constant	0.172***	0.421***	0.022***	0.217***
	(0.013)	(0.045)	(0.003)	(0.033)
Observations	2405	2405	2405	2405

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

Table 3: Impact of Screen Size on Search Behavior

	(1) Average deliberation time per benef. card (minute)	(2) Continue search after last donation	(3) Refresh button action (times)	(4) Total beneficiary exposure (cards)	(5) Donate in first screen	(6) Donate after first screen	(7) Did not stop after first donation
3-opt sets	0.924**	0.024	2.017***	-12.009***	-0.172***	0.162***	0.130**
	(0.366)	(0.046)	(0.510)	(2.571)	(0.060)	(0.055)	(0.060)
8-opt sets	0.170	0.009	0.600	-0.362	0.072	-0.090	-0.008
	(0.153)	(0.043)	(0.474)	(4.009)	(0.056)	(0.058)	(0.058)
Constant	0.753***	0.158***	2.580***	25.799***	0.619***	0.626***	0.453***
	(0.104)	(0.031)	(0.217)	(2.166)	(0.041)	(0.041)	(0.042)
Observations	426	426	2405	2405	426	426	426

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

Table 4: Impact of Screen Size on Number of Donations Per Screen

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

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

Table 5: Impact of Screen Size on Saliency (OLS and IV)

	(1) % Salient	(2) # of donations over total seen IV	(3) Average donations per beneficiary seen (USD) IV
3-opt sets	9.753***		
	(0.100)		
8-opt sets	0.940***		
	(0.040)		
% Salient		0.001***	0.011
		(0.000)	(0.007)
Constant	2.888***	0.021***	0.251***
	(0.025)	(0.004)	(0.054)
Observations	2405	2405	2405

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

Table 6: 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 7: *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 8: In-Group Bias: Regression of Donation Indicator and Value on Alignment of Donor–Beneficiary Characteristics

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

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

A. Appendix Tables and Figures

Table A.1: Sample of Appeals

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

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

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

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

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

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

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

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

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

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

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

Table A.6: Impact of Choice Set Size on Donation Indicator, Selected Sample Regression

	(1) All	(2) Only first set	(3) 1-3	(4) 1-8	(5) 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.7: Impact of Choice Set Size on Donation Indicator, Various Fixed Effects

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

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

Table A.8: 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.9: Platform Users' Self-Declared Reasons for Charitable Donations

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

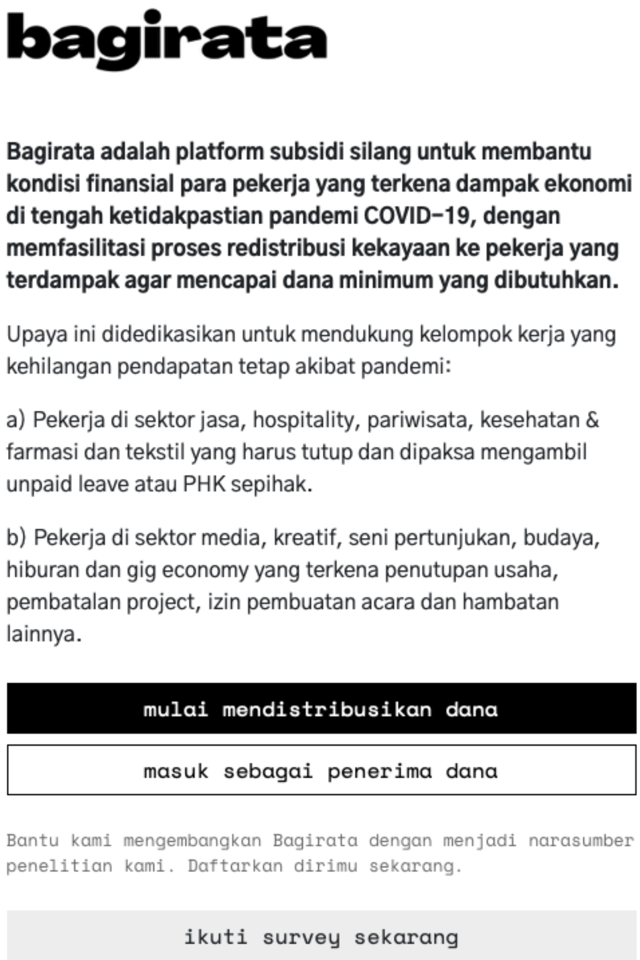
Notes: Survey responses from Oct 2020 to July 2021.

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

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

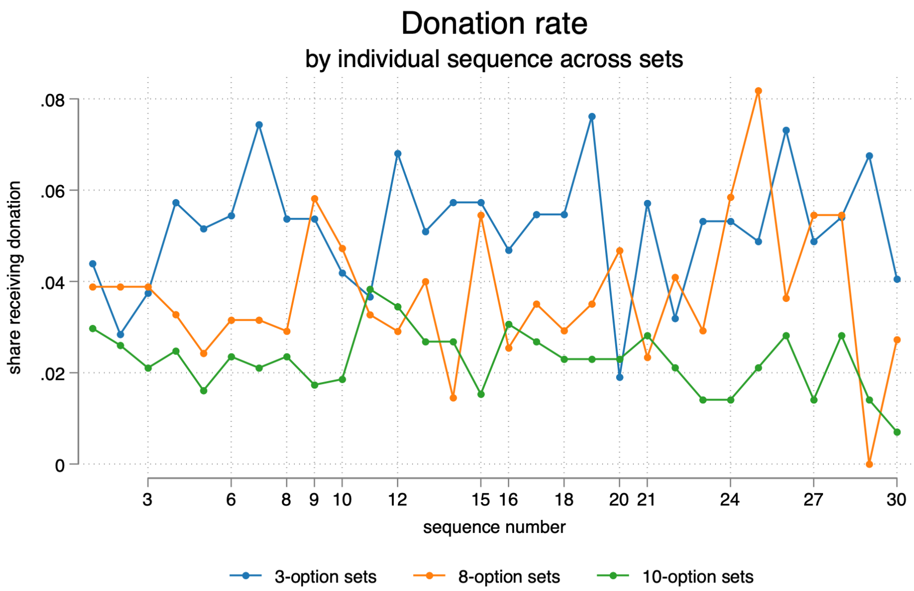
Notes: Regression of the donation outcomes on beneficiary's donation progress (% of asked donation amount received so far from other donors). The observation unit is a donor–beneficiary dyad. Standard errors are clustered at the donor and session levels and displayed in parentheses. * $p < 0.1$, ** $p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

Figure A.1: Landing Page of the Platform



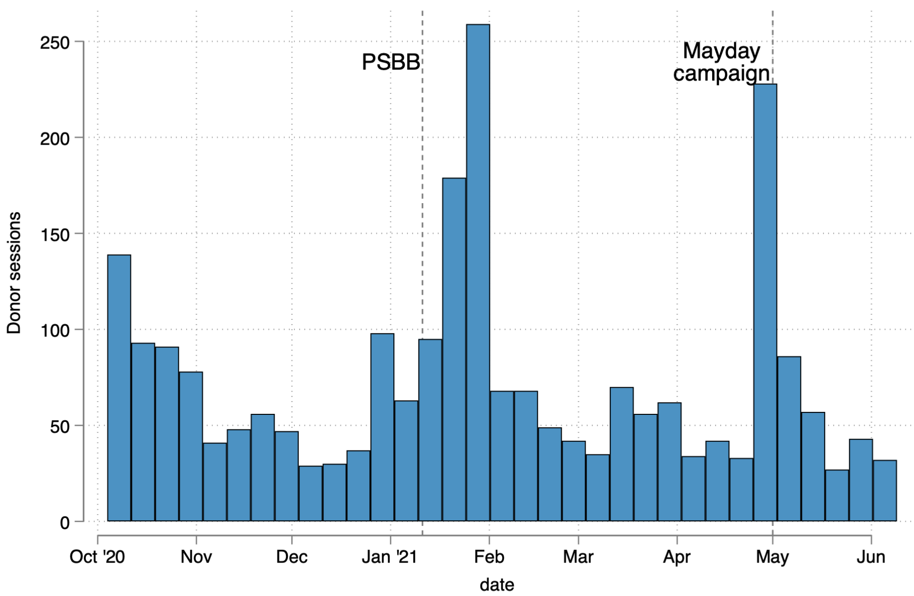
Note: This is the first page that potential donors see upon entering the *Bagirata* website.

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 7, 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 1 presents the seed words utilized in the computation, based on the keyness statistics.

Table B.1: Top 10 Keywords: Keyness Statistics

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

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

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

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

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

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

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

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

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

Table B.2: Notes on pre-registration

Pre-registration at OSF	Implementation comment
Hypotheses We aim to test the following hypotheses: 1. The more the number of potential beneficiaries displayed to donors, the lower the donors' probability of donating. 2. The higher the number of existing donors who have already donated to a beneficiary, the lower a potential donor's incentive to help the beneficiary. 3. The larger the sum of donations that a beneficiary has already secured, the lower a potential donor's incentive to help the beneficiary. 4. Potential donors exhibit in-group favoritism, preferring to donate to beneficiaries who share some identity similarity (e.g., religion, location, gender, etc.)	Hypothesis 1 test is reported in Table 5 Hypothesis 2: N/A. Experiment for this hypothesis was scrapped from implementation by the partner. Hypothesis 3 tests are reported in Table A.9. Hypothesis 4 tests are reported in Table 10.
Study Design We will conduct an online experiment amongst the Indonesian population using Bagirata's platform. Our primary tool will be a randomized number of potential beneficiaries and the beneficiaries shown, the number of other donors who have donated, and the amount of donation that has been collected so far out of the targeted donation amount. There will be four main treatments in the experiment. 1. Donors are presented with three recipients at a time upon their visit to the website. 2. Donors are presented with eight recipients at a time upon their visit to the website. 3. Donors are presented with ten recipients at a time upon their visit to the website. 4. Donors are presented with a menu/choice set of randomly selected beneficiaries of varying characteristics ranging from gender composition, occupation, social status, and other salient characteristics. In this treatment, donors would see ten recipients at a time upon their visit to the website. 5. Donors are presented with information similar to Treatment 1, and also, they are provided with information on the number of other donors who have donated to the same beneficiaries. 6. Donors are presented with information similar to Treatment 1, and also, they are provided with information on the magnitude of donations that beneficiaries have received so far.	Treatments 1-2-3 were implemented as planned. In our analysis, we used treatment 3 as the control treatment, because it was the arm that was originally implemented prior to the introduction of the experiment. Treatment 4 is implemented by randomly selecting beneficiaries from the beneficiary list. The implementation departs from the planned design by instead crossing this with treatments 1-2-3 (instead of only treatment 3). Treatment 5 were scrapped from implementation. Treatment 6 were instead uniformly provided to all potential donors (in all treatments). We did not field a follow-up phone survey due to funding limitations. However, we were able to conduct an online survey to a subset of our sample to collect demographics data and corroborate donation activities.

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