

Enhancing Donor Agency to Improve Charitable Giving: Strategies and Heterogeneity

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Abstract

This research investigates whether charities can enhance fundraising effectiveness by increasing donors' sense of agency. This article introduces two strategies that allow donors to target individual charitable projects, either via the choice options (targeting-via-options) or via the suggested donation amounts (targeting-via-amounts). A large-scale field experiment involving more than 40,000 prospective donors manipulates the ability to control the allocation of the charity's resources and finds that enhancing donor agency boosts fundraising revenue by 42%. A causal forest analysis indicates significant donor heterogeneity with a subset of donors being three times more responsive to the opportunity to target their gift than the average donor. Inactive donors, clumpy donors (who exhibit uneven donation patterns) and donors who concentrate their gifts during the popular giving periods are less responsive to the interventions, while frequent, generous, and long-tenured donors are more responsive to them. Three experiments offer stronger internal validity regarding the manipulations and process evidence that agency and not emotion is responsible for the increased donation effects. An optimization analysis provides implications for how charities can leverage these insights to manage their fundraising campaigns to greater success.

Keywords: agency, charitable giving, causal forest, conditional average treatment effect, donation, field experiment, fundraising campaign optimization, machine learning, mediation, off-policy evaluation.

Donations are essential to charities. In the U.S., they account for almost 70% of charities' estimated \$470 billion in revenues (Giving USA). In line with the charitable giving literature that investigates how to boost donations (Bekkers and Wiepking 2011), we aim to improve fundraising effectiveness by increasing donors' sense of agency. By allowing donors to choose—or *target*—a specific charitable project, we offer them a greater sense of control over the allocation of the charity's resources. In line with agency theory (Bandura 1989), we propose that transferring agency from the charity to the donor should stimulate giving.

The positive effects of agency have been documented in several domains. For instance, allowing taxpayers to choose how the government should distribute its spending increases tax compliance (Lamberton, De Neve, and Norton 2018); encouraging people to vote for new products increases demand for those products (Fuchs, Prandelli, and Schreier 2010); and employees with more voice mechanisms are less likely to switch jobs (Spencer 1986). However, the benefits of agency could be more complex in a fundraising context. Depending on how it is implemented, enhancing donor agency may potentially generate emotional conflicts. For instance, asking donors to choose between two needy individuals (e.g., Frida versus Caroline) implies that they cannot help them both. In a recent study, Ein-Gar, Levontin, and Kogut (2021) found that offering choice reduces the generosity of donors. When donors allocate resources, they show a preference for distributing help because distribution (allocating help to multiple beneficiaries) feels procedurally fairer than concentration (allocating help to a single beneficiary) (Sharps and Schroeder 2019). Thus, enabling donors to target their gifts does not necessarily enhance fundraising effectiveness.

Charities can enhance donor agency in various ways. This article proposes two strategies that increase donors' agency by allowing donors to *target* a specific charitable project. The first strategy ("*targeting-via-options*") consists of presenting the choice options in a way that enables donors to *choose the option* that corresponds to the charitable project they want to

target. The second strategy (“*targeting-via-amounts*”) consists of coupling the suggested donation amounts to the charitable projects in such a way that donors can choose to donate the amount that is linked to the charitable project they want to target.

In a series of studies, including a field experiment involving more than 40,000 prospective donors, we show that targeting-via-options and targeting-via-amounts enhance donors’ sense of agency (Study 1a and 1b – lab studies) and consequently boost their donations (Study 2 – lab study). Together, these interventions increase the likelihood of donating and the average donation amount (Study 3 – field study), offering a 42% revenue increase. Finally, we show that the response to agency is highly heterogeneous across donors, and we demonstrate how charities can design effective fundraising campaigns accounting for donor heterogeneity. The Conditional Average Treatment Effects (CATE) estimated by causal forests (Wager and Athey 2018) reveal that many donors are insensitive to the interventions. In contrast, a small subset of donors is three times more responsive than the average donor. Inactive donors, clumpy donors (who exhibit uneven donation patterns) and donors who concentrate their gifts during the popular giving periods are less responsive to our interventions, while frequent, generous, and long-tenured donors are more responsive to them.

Our findings contribute to the literature in several ways. First, we show that enhancing agency by allowing donors to target a specific charitable project can be effective. We also show that our interventions are straightforward to implement in online (via call-to-action buttons) or offline (via money transfer forms) contexts. Second, we show that a preference for distributed helping (Ein-Gar, Levontin, and Kogut 2021; Sharps and Schroeder 2019) may be less general than previously anticipated. In contexts where prospective donors can choose between charitable projects—rather than needy individuals—increasing donors’ sense of agency can boost donations. Third, we explore donors’ heterogeneous responses to our interventions. Instead of cross-cultural differences (Fuchs, de Jong, and Schreier 2020) or

differences in income (Kessler, Milkman, and Zhang 2019), we find substantial heterogeneity based on past donation behavior.

We organize the remainder of the paper as follows. We first review the agency literature in the charitable giving context and make predictions about the effect of our interventions. We then present Study 1a and 1b to establish how targeting-via-options and targeting-via-amounts affect donors' sense of agency. Study 2 shows that a sense of agency mediates the relationship between targeting-via-options and targeting-via-amounts on the one hand and donations on the other. We continue with the field experiment that explores heterogeneity in donor responses. Finally, we end with a discussion, limitations, and recommendations. All codes and study materials are available on OSF.¹

Agency in Charitable Giving

Past research has proposed various strategies to increase individuals' motivation to donate (Bekkers and Wiepking 2011). For instance, Ariely, Bracha, and Meier (2009) distinguish intrinsic motives (e.g., pure altruism) from extrinsic and "impure" motives (e.g., donations stimulated by thank-you gifts or donating to increase reputation). A part of the literature argues that most donors do not calculate the expected benefit of their gifts but rather donate based on spontaneous affective reactions (Berman et al. 2018). For instance, identifiable victims evoke sympathy and move people to give because the victims invoke donors' affective system (Small and Loewenstein 2003). A single identified victim generates stronger feelings of distress among donors than a single unidentified victim or a group of victims (Kogut and Ritov 2005). Other framing effects, such as in-group or reference-dependent effects, create similar sympathy biases (Sudhir, Roy, and Cherian 2016).

We propose that increasing donors' sense of agency is another way to stimulate charitable giving (Heist and Cnaan 2018; Kessler, Milkman, and Zhang 2019). Acting with agency

¹ The R codes include the latent mediation, CATE estimation, BLP test, GATE analysis, partial dependence plots and off-policy evaluation. Weblink: https://osf.io/4nzsw/?view_only=d6fe47c83bd6493c8039b76bb1aa9ad0

means intentionally trying to achieve an outcome through one's actions (Bandura 2000; Bandura 1989; Bandura 2001). Sense of agency refers to the feeling of being in control (Metcalf and Greene 2007), controlling one's actions and, through them, controlling the external world (Haggard 2017; Haggard and Tsakiris 2009). None of the mechanisms of human agency are more central or pervasive than beliefs in one's own efficacy (Bandura 1982). Self-efficacy refers to a fundamental belief in one's ability to produce desired results. Several meta-analyses outside the charitable giving literature indicate that motivation and performance will be high if individuals believe they can produce desired outcomes (Bandura and Locke 2003). This fundamental relationship between efficacy beliefs, motivation, and performance has been documented in areas as diverse as work-related performance, psychosocial functioning, academic achievement, health functioning, and athletic performance (Bandura and Locke 2003). In a similar vein, we propose that enhancing donor's belief that they can control the external world through their actions will motivate them to donate. While our goal is not to test different theories or to apportion the variance among various accounts, we list four explanations for the positive effect of donor agency on giving.

First, enhancing agency allows *preference matching* by permitting individuals to select the charitable project they support the most. It makes economic sense for donors that the charity invests where they see fit (Berman and Small 2012). Investment decisions are more likely to match donors' preferences, making them more responsive to a request (Arora et al. 2008).

Second, the benefits of agency extend beyond the opportunity of merely matching personal preferences with available charitable projects. Research has established an effect on *choice evaluation* itself. When people perceive themselves as having exercised choice, they evaluate outcomes more positively, even if the available options were equally attractive or even incongruent with stated preferences (Langer 1975; Lefcourt 1973; Perlmutter and Monty 1977).

Third, agency may reduce *perceived uncertainty*, increasing donors' confidence that their gifts will be spent as they indicated. Less uncertainty can make donors more generous. For instance, people donate more to a victim that has already been determined than to a victim that is not determined yet (Small and Loewenstein 2003). The identifiable victim effect could be explained in view of the uncertainty related to the fate of victims (Jenni and Loewenstein 1997; Small and Loewenstein 2003). Identifiable deaths are usually certain to occur if action is not taken, whereas statistical deaths are probabilistic. Transferring agency to donors reduces the uncertainty regarding how their money will be spent, possibly contributing to the positive effect of agency on fundraising effectiveness.

Fourth, by enhancing agency over target, donors may assume they effectively solve a specific problem when they donate a particular amount to a well-defined charitable project. For instance, Fuchs, de Jong, and Schreier (2020) claim that donors who can earmark their contribution perceive their gift makes a *greater impact*, in accordance with the theory of impact philanthropy. An impact philanthropist prefers to target their contribution because targeting increases the perception that a financial gift is more effective. According to Duncan (2004, p.2161), "[...] sponsoring an individual child can increase a philanthropist's perceived impact because he or she gives the first, as well as the last, dollar to the child." Therefore, perceived impact can also contribute to the positive effect of agency on donations.

Predictions

We propose that "targeting-via-options" and "targeting-via-amounts" enhance donors' sense of agency. This sense of agency, in turn, enhances donation likelihood (*whether to donate*) and amount (*how much to donate*). Both interventions enhance donors' perceived control over the donation target because they enable donors to specify *which* charitable project to support (or not).

Figure 1 provides examples of both strategies. It is important to emphasize that, in all scenarios, donors have a basic level of autonomy: They can express *whether* they would like to donate and, if so, *how much* they would like to donate. For instance, in the upper-left example in Figure 1, donors can choose whether they would like to donate once or every month, and they can choose between various amounts (e.g., \$50, \$100, \$250). On top of that basic level of autonomy, our interventions enhance agency in two ways. First, in the upper-right example, donors can check the “U.S. United Way” radio button, the “International United Way” radio button, or the “Where help is needed most” radio button to target their donation. This is an example of targeting-via-options as the donor selects the radio button corresponding to the charitable project they want to target. Second, in the lower-left example, donors learn about three projects that are associated with three different suggested donation amounts (i.e., \$50 = food; \$150 = blankets; \$300 = face masks). Donors can target one of the projects (e.g., blankets) by selecting the amount (i.e., \$150) that is linked to a particular project. This is an example of targeting-via-amounts. Finally, the lower-right cell combines the two strategies. Donors can target their donation by clicking on one of the suggested donation amount buttons, where each amount is linked to a different charitable project (i.e., £22 = radios and education materials; £58 = nutrition packages; £106 = a hygiene kit).

---- Please insert Figure 1 about here ----

We now examine each intervention in more detail. Targeting-via-options consists of presenting choice options such that each choice option corresponds to a distinct charitable project. Suppose, for instance, a charitable request that raises funds for two mobility aids: wheelchairs and prostheses. Targeting-via-options can be done by presenting two choice options, one option with the label “wheelchair” and another with the label “prosthesis.” This approach enables donors to select the *option* that corresponds to the charitable project they want to support.

We predict that this choice of how their donation should be used increases donors' sense of agency for the following reasons. Targeting-via-options allows for preference matching (Berman et al. 2018), may reduce perceived uncertainty (Small and Loewenstein 2003) and may increase perceived impact (Fuchs, de Jong, and Schreier 2020). The alternative scenario would be to present a single choice option (e.g., labelled as "donate a wheelchair or prosthesis"). In this context, donors can no longer specify how their gift needs to be allocated across the charitable projects. The charity could decide to fund one project only, or both projects in varying proportions (e.g., 80/20; 30/70). Importantly, we predict that targeting-via-options will only stimulate giving if every choice option is associated with a *distinct* charitable project. Study 1a will show that merely offering multiple choice options but not linking them to distinct charitable projects (such as in Rifkin, Du, and Berger 2021) does not enhance donors' sense of agency. Targeting-via-options shares commonalities with the literature on unpacking (Tversky and Koehler 1994) and partition dependence (Fox, Bardolet, and Lieb 2005; Fox, Ratner, and Lieb 2005; Tannenbaum, Fox, and Goldstein 2013), because it effectively unpacks the "*whether to donate*" decision into a "*which charitable project to support*" decision.

The second intervention (targeting-via-amounts) consists of linking the suggested donation amounts to distinct charitable projects. Suppose, for instance, a charitable request that presents two suggested donation amounts (\$10 and \$15) to raise funds for two charitable projects (wheelchairs and prostheses). Targeting-via-amounts can be done by informing the donor that the charity needs \$10 for the prosthesis and \$15 for the wheelchair. Now, donors can specify how their donation should be used by choosing the *amount* that corresponds to charitable project they want to target (e.g., \$10 for a prosthesis), thus increasing their sense of agency. Targeting-via-amounts allows for preference matching (Berman et al. 2018), may reduce perceived uncertainty (Small and Loewenstein 2003) and may increase perceived impact

(Fuchs, de Jong, and Schreier 2020). In the alternative scenario where the suggested donation amounts (\$10; \$15) are mentioned but not linked to charitable projects (prosthesis; wheelchair), donating a suggested amount does not enable donors to specify how to use their gift. Importantly, we postulate that targeting-via-amounts only enhances donors' sense of agency if the charitable projects are coupled with distinct donation amounts.

In the case of identical suggested donation amounts (i.e., \$10 for a prosthesis; \$10 for a wheelchair), donors cannot specify how their donation should be used through the amount they donate. If a donor donates \$10 in response to a request where all projects cost \$10, the charity could fund one of the projects (but not necessarily the project that is favored by the donor) or both projects in varying proportions (e.g., 80/20; 30/70). Study 1b will show that merely linking an amount to a project does not significantly increase perceived control over the resource allocation process. Thus, the effect of targeting-via-amounts does not stem from providing information on how much each project costs and is therefore unrelated to providing more detailed information about charitable projects (Cryder, Loewenstein, and Scheines 2013). Targeting-via-amounts shares commonalities with the literature on mental accounting (Prelec and Loewenstein 1998; Thaler 1999) and coupling (Kamleitner and Hölzl 2009) because targeting-via-amounts creates an association between costs (i.e., the suggested donation amounts) and benefits (i.e., the charitable projects).

Heterogenous Responses to Agency

Although we hypothesize that enhancing donor agency will generally increase fundraising effectiveness, there are reasons to expect heterogeneous responses to our interventions. First, donors with limited time or resources may prefer to delegate their giving decisions to better-informed others (Butera and Houser 2018). Second, cultural values can influence how individuals react to agency. For example, earmarking a gift is less beneficial in cultures scoring lower on autonomy relative to embeddedness and lower on egalitarianism relative to

hierarchy (Fuchs, de Jong, and Schreier 2020). Third, Kessler, Milkman, and Zhang (2019) highlight the role of donors' income and social status in their response to agency. Wealth and power are associated with feelings of independence, autonomy and a stronger orientation towards agency (Rucker, Galinsky, and Magee 2018). Fourth, generous donors may have different donation motives than less generous ones, which can trigger different reactions to agency. For instance, Karlan and Wood (2017) show that making impactful donations matters more to large donors because "pure" donation motives (such as impact) may matter more for them than "impure" donation motives (such as warm glow). Relatedly, loyalty does not only affect the response to any solicitation request, but also affects the relative performance of different appeals (Karlan, List, and Shafir 2011). Overall, more engaged donors (e.g., loyal, generous, and active) should care more about the charity and be more motivated to express their choice and so be most responsive to our interventions to enhance sense of agency. Finally, donation habits may dampen responsiveness to particular charitable appeals. For instance, changing the suggested donation amounts affects infrequent donors differently relative to frequent donors (De Bruyn and Prokopec 2013). We expect that habitual donation patterns may make our interventions less effective as these routines might decrease donors' willingness to deviate from their typical donation pattern.

Study 1a: Targeting-via-Options

Study 1a has two goals. First, it tests that targeting-via-options effectively enhances donors' sense of agency. Second, and most importantly, we aim to rule out that the increased sense of agency comes from merely choosing between different options without determining the beneficiaries (Rifkin, Du, and Berger 2021).

Method

We randomly assigned participants from Prolific ($n = 304$; 48% women; median age = 24 years; all residing in countries with the euro as the official currency) to one of three

experimental conditions in a between-subjects design (targeting-via-options: high; low; pseudo). In all experimental conditions, participants had to evaluate a charitable request to provide mobility support to needy people. We mentioned the same two projects in all conditions (a prosthesis and a wheelchair, see stimuli in Web Appendix A). The high targeting-via-options condition presented two call-to-action buttons, one per project (“I would like to donate a prosthesis”, “I would like to donate a wheelchair”). The low targeting-via-options condition presented a single call-to-action button (“I would like to donate a prosthesis or a wheelchair”). The pseudo targeting-via-options condition presented two call-to-action buttons, one button associated with the two projects (“I would like to donate a prosthesis or a wheelchair”) and one button providing the opportunity to support the charity more broadly (i.e., “I would like to donate to NEWLIFE”). This condition has the same number of choice options as the high targeting-via-options condition but should not enhance perceived control over the resource allocation process. This condition is crucial because it rules out that the effect is due the number of choice options. Across all conditions, we randomized whether the prosthesis was mentioned first or second. We asked participants to inspect the information about the charitable request for 20 seconds and then measured their sense of agency (our dependent variable) with three items: “I feel that I can control how NEWLIFE will use my donation to support a specific project”; “I feel that I can choose how my donation will fund a specific project”; “I feel that I can target my donation to a specific project”; (alpha = .72 with 95% CI = [.65, .77]) on a 5-point scale with item labels “strongly disagree” (1); “somewhat disagree” (2); “neither agree nor disagree” (3); “somewhat agree” (4); “strongly agree” (5).

Results

Our focal prediction is that the high targeting-via-options condition increases participants’ sense of agency relative to the low and pseudo conditions. A GLM with the condition as predictor yields a significant effect ($F(2, 301) = 13.47, p < .001$), suggesting that sense of

agency differs across conditions. More specifically, the high targeting-via-options condition ($M = 4.02$; $SD = .79$) increases sense of agency relative to the low targeting-via-options condition ($M = 3.43$; $SD = .94$; $t(201) = 4.82$; $p < .001$) and relative to the pseudo targeting-via-options condition ($M = 3.58$; $SD = .77$; $t(199) = 3.99$; $p < .001$), while the low and pseudo conditions are not significantly different from each other ($t(202) = 1.25$; $p = .21$).

Figure 2 (left panel) summarizes the results.

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Discussion

This study shows that targeting-via-options increases participants' perceived control over the resource allocation process. Relative to the low and pseudo conditions, the high targeting-via-options condition offers the greatest perceived control over how funds are allocated. Most importantly, the results rule out that merely being able to choose between two options would enhance donors' sense of agency.

Study 1b: Targeting-via-Amounts

Study 1b has two goals. First, we test whether targeting-via-amounts (i.e., coupling different suggested amounts to distinct charitable projects) increases participants' sense of agency. Second, we aim to rule out that the increased sense of agency comes from merely providing more detailed information about the charitable projects (Cryder, Loewenstein, and Scheines 2013). We aim to show that the positive effect of coupling amounts to charitable projects disappears when the suggested amounts are identical.

Method

We randomly assigned participants from Prolific ($n = 304$; 47% women; median age = 25 years; all residing in countries with the euro as the official currency) to one of three experimental conditions in a between-subjects design (targeting-via-amounts: high, low, pseudo). In all experimental conditions, participants had to evaluate a charitable request to

provide mobility support to needy people. We mentioned the same two charitable projects in all conditions (a prosthesis and a wheelchair, see stimuli in Web Appendix B). In the high targeting-via-amounts condition, we coupled each charitable project to a different suggested donation amount (“prosthesis = €10”, “wheelchair = €15”), and we randomized whether the prosthesis (or wheelchair) was associated with the low (or high) amount. In the low targeting-via-amounts condition, we displayed the same suggested donation amounts (“€10”; “€15”) at the same location on the screen to hold the salience and the prominence of the suggested amounts constant across conditions. We displayed the same charitable projects (“prosthesis”, “wheelchair”), but we did not couple the amounts to the respective charitable projects. In the pseudo targeting-via-amounts condition, we coupled the distinct charitable projects to identical suggested donation amounts, and we randomized whether these amounts were low (“prosthesis = €10”, “wheelchair = €10”) or high (“prosthesis = €15”, “wheelchair = €15”). Across all conditions, we randomized whether the prosthesis was mentioned first or second. We asked participants to inspect the information about the charitable request for 20 seconds and then measured their sense of agency (our dependent variable) with the same three items and 5-point scale as Study 1a ($\alpha = .83$ with 95% CI = [.79, .87]).

Results

Our focal prediction is that the high targeting-via-amounts condition increases participants’ sense of agency relative to the low and pseudo conditions. A GLM with the condition as predictor yields a significant effect ($F(2, 301) = 12.15, p < .001$), suggesting that sense of agency differs across conditions. More specifically, the high targeting-via-amounts condition ($M = 3.76; SD = .95$) increases the participants’ sense of agency relative to the low condition ($M = 3.08; SD = 1.06; t(200) = 4.77; p < .001$) and relative to the pseudo condition ($M = 3.22; SD = 1.07; t(200) = 3.77; p < .001$), while the low and pseudo conditions are not significantly different from each other ($t(202) = .94; p = .35$). Figure 2 (right panel) summarizes the results.

Discussion

This study shows that targeting-via-amounts (i.e., coupling different suggested donation amounts to distinct charitable projects) affects donors' sense of agency. Participants indicate that coupling amounts to projects increases perceived control over how the funds will be used, relative to not coupling the projects to amounts or relative to coupling the charitable projects to identical amounts. This study rules out an explanation in terms of providing more detailed information (Cryder, Loewenstein, and Scheines 2013), such as the particular cost of a charitable project. The following study will test whether the enhanced sense of agency that stems from targeting-via-options and targeting-via-amounts stimulates donation behavior.

Study 2: Agency Process Evidence

Study 2 examines the mediating role of agency on the effect of targeting-via-options and targeting-via-amount on donation behavior. It also tests whether the manipulations may trigger alternative explanations in the form of emotions such as empathy, sympathy or compassion (Cryder, Loewenstein, and Scheines 2013; Small and Loewenstein 2003).

Method

We randomly assigned participants from Prolific ($n = 401$; 48% women; median age = 25 years; all residing in countries that have the euro as the official currency) to one condition of a two (targeting-via-options: high vs low) by two (targeting-via-amounts: high vs low) between-subjects full-factorial design. We used the same stimuli as in Study 1a and 1b (see Web Appendix C). In particular, we presented two call-to-action buttons, one per project ("I would like to donate a prosthesis", "I would like to donate a wheelchair") in the high targeting-via-options condition, but only a single call-to-action button ("I would like to donate a prosthesis or a wheelchair") in the low targeting-via-options condition. In the high targeting-via-amounts condition, we coupled the different charitable projects with distinct donation amounts, but we did not couple amounts and projects in the low targeting-via-amounts

condition. As in Study 1b, we displayed the suggested amounts at the same location in both conditions. We randomized the order of the projects such that a particular project (e.g., wheelchair) could be associated with the lower (€10) versus higher (€15) donation amount (in the high targeting-via-amounts condition) or such that a particular project could be mentioned first or last (in the low targeting-via-amounts condition). After inspecting the information about the charity (Newlife) for 20 seconds, participants had to indicate how much they would hypothetically donate to Newlife (our focal dependent variable). To avoid extreme responses, we required a numeric response between 0 and €30.

Following this, we assessed participants' sense of agency (our mediator) by asking them to what extent they agreed with three items ("I feel that I can control to which of the two causes I would like to donate to"; "I feel that I can choose one of the two causes by donating"; "I feel that I can target my donation to one of the two causes"; $\alpha = .80$ with 95% CI = [.74, .83]), with "strongly disagree" (1) and "strongly agree" (5) as anchors. In addition, we assessed participants' emotional response by asking to what extent they agreed with three items ("I feel sympathy for the people who will receive aid from NEWLIFE"; "I feel compassion for the people who will receive aid from NEWLIFE"; "I feel empathy for the people who will receive aid from NEWLIFE"; $\alpha = .77$ with 95% CI = [.73, .84]), with the same anchors as for agency. We counterbalanced the order of the agency and emotion measures. We standardized mediators and outcome (Pieters 2017).

Results

We first test the overall effect of our interventions on the donation amount using a regression with robust standard errors (SE) against heteroskedasticity (White 1980). As the interaction between the interventions is not significant ($p > .10$), we focus on the main effects. Targeting-via-options (total effect = .09, $p < .10$) and targeting-via-amounts (total effect = .17, $p < .001$) increase the amount donated. We then test whether the effects are mediated by one's

sense of agency and/or emotional response to the manipulation. To do so, we specified a Structural Equation Model (lavaan R package; Rosseel 2012) because the mediators are latent multi-item constructs. SEM is superior to conventional regression analysis when testing indirect effects as it accounts for measurement error (Pieters 2017; Preacher and Hayes 2008). We estimate the model with maximum likelihood with robust (Huber-White) SEs (Savalei and Rosseel 2022). The global fit indices suggest a good fit between the model and the underlying data (p -value $\chi^2 < .001$; CFI = .94, TLI = .90, RMSEA = .08, p -value $< .01$). Figure 3 reports the standardized coefficients and corresponding p -values and Web Appendix D contains details results per condition.

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The results show that the respondents' sense of agency significantly mediates the impact of the manipulations on the amount donated (i.e., indirect effect of targeting-via-options = .09, $p < .001$; indirect effect of targeting-via-amounts = .04, $p < .05$) with 48% ($p < .01$) of the total effect being mediated by sense of agency. Relative to the low targeting-via-options condition, high targeting-via-options boosts sense of agency ($a_1 = .33$, $p < .001$). Relative to the low targeting-via-amounts condition, high targeting-via-amounts enhances sense of agency ($a_2 = .13$, $p < .05$). Importantly, sense of agency increases the amount donated ($b_1 = .27$, $p < .001$).

We rule out a mediation via emotions (i.e., indirect effect of targeting-via-options = .01, $p > .10$; indirect effect of targeting-via-amounts = .00, $p > .10$). Neither manipulation affects emotions ($a_3 = .07$, $p > .10$ and $a_4 = .02$, $p > .10$). Note that respondents scoring higher on emotional items donate more ($b_2 = .16$, $p < .05$) but it is not driven by our manipulations. Finally, the conditional direct effects of targeting-via-options and targeting-via-amounts on the amount donated are $-.01$ ($p > .10$) and $.13$ ($p < .01$), respectively.

Discussion

This study shows that targeting-via-options and targeting-via-amounts increase charitable giving via enhanced agency and rules out a process in terms of an emotional response. We conclude that enhancing the perceived ability to control how donations are allocated across charitable projects can boost donations.

Study 3: Field Experiment

This final study has two goals. First, we aim to enhance the ecological validity of our research by showing the effects of our interventions on actual donations in a large field experiment. Second, we aim to investigate whether the effect is heterogeneous across donors by exploring the moderating role of past donation behavior (see next section).

Method

We cooperated with an international charity that manages a database of 40,893 donors, all included in the field experiment. All donors received an identical direct mail with a detailed description of the charitable projects. We randomly assigned donors to one condition of a two (targeting-via-options: high vs low) \times two (targeting-via-amounts: high vs low) between-subjects full-factorial design (see Web Appendix E). The charitable request described the same three charitable projects P1, P2 and P3 across all conditions,² and presented the same three suggested donation amounts (€48, €88 and €120) across all conditions. These specific amounts correspond to the marginal cost of every charitable project, as established by the charity.

In the high targeting-via-options condition, donors received three money transfer forms included in the envelope, together with the donation request. Those money transfer forms were labeled “for project P1”, “for project P2”, and “for project P3”. In the low targeting-via-options condition, donors received a single unlabeled money transfer form. The “donation

² A non-disclosure agreement prevents us from providing more details about these projects.

amount text box” on the money transfer form(s) was empty in all conditions. Donors could thus donate any amount. In the high targeting-via-amounts condition, we coupled each charitable project to one of the suggested donation amounts (“With 48 euros for project P1, 88 euros for project P2, or 120 euros for project P3, your help can make a difference”). In the low targeting-via-amounts condition, we mentioned the same suggested donation amounts but we did not couple them to the corresponding charitable projects (“With €48, €88, or €120, your generosity makes a difference”).

Data

We obtained data on the responses to the donation requests (incidence and amount) and past donation data for all solicited donors between 1990 and 2016. To leverage the richness of these data, we calculate the following donor covariates.

RFMC. Based on the RFMC framework (Zhang, Bradlow, and Small 2015), we calculate Recency (number of days between the start of the experiment and the last donation), Frequency (number of donations per year from 1990 up to 2016), Monetary value (donation amount per year from 1990 up to 2016) and Clumpiness. Following Zhang, Bradlow, and Small (2013), we measure Clumpiness as an entropy-like measure based on the inter-donation times, where higher values correspond to clumpier donation behavior. Clumpy donation patterns are characterized by extended periods of inactivity punctuated by short, intense donation bursts. Finally, we calculate three metrics for the Frequency and Monetary value times series: the *average over time*, the *standard deviation over time*, and the *time trend* (donor-specific regression slope). Overall, the RFMC metrics are good predictors of the future lifetime value of individuals (Zhang, Bradlow, and Small 2015).

Tenure. We measure donor tenure as the number of days between the first donation made to the charity and the start of the experiment.

YoY range. This variable captures recurring donation patterns from one year to the next. For each donor i and each month of the year, we calculate the minimum and maximum donation amount they have made across all years. From it, we calculate the range value for each *month* of the year: $range_{i,month} = \max_{year} amount_{i,month.year} - \min_{year} amount_{i,month.year}$. We sum all twelve values $\sum_{month=1}^{12} range_{i,month}$ such that a lower Year-Over-Year (YoY) range corresponds to smaller YoY variations in donation amounts, suggesting recurring monthly donation habits. This measure complements Clumpiness by exploring systematic monthly patterns from one year to another.

Share of past donations of €48, €88, or €120. We also consider whether the suggested amounts align with the donors' habits regarding how much they tend to donate to the charity. We calculate the fraction of past donation amounts corresponding to one of the suggested amounts in the current experiment.

Share of gifts in popular months. Some seasons such as the major holidays, are more popular than others for donations. In our data, popular months are May, November and December. We capture the percentage of contributions made by a donor during these popular months. A value of 100% indicates that donor made all his donations during popular months.

Number of gifts in February. Finally, we also capture whether the month during which the experiment took place (February) is a month where a donor typically makes a gift. This variable counts the number of past donations made in February.

Demographics. Finally, we have two binary variables: whether the prospective donor is an individual or a member of an organization and the donor's spoken language.

Table 1 provides an overview of the covariates per condition. We report the medians (and standard deviations into parentheses) for the continuous variables and the percentages per level for the categorical variables. We use pairwise permutation tests (Web Appendix F) to check the random assignment of donors across conditions. None of the covariates in Table 1

are significantly different between conditions. Note that 3,319 donors (equally spread across conditions) have missing values for some covariates, in which case statistics are computed on the non-missing values.

---- Please insert Table 1 about here ----

Descriptives

We start by describing the average donation across the conditions in the field experiment. The field experiment raised a total of €89,782 in gross revenues. The condition with the highest sense of agency (i.e., high targeting-via-options and high targeting-via-amounts) generated the highest donation revenue ($M = €2.57$ per request sent; $SE = .14$; $TOTAL = €26,277$), relative to the baseline condition (i.e., low targeting-via-options and low targeting-via-amounts), which raised the smallest amount ($M = €1.81$ per request sent; $SE = .11$; $TOTAL = €18,535$). The 42% increase is in line with the range of effects in the charitable giving literature on agency.³ The high targeting-via-options and low targeting-via-amounts condition generated $M = €2.30$ per request sent ($SE = .13$; $TOTAL = €23,538$) while the low targeting-via-options and high targeting-via-amounts condition generated $M = €2.10$ per request sent ($SE = .12$; $TOTAL = €21,432$). Web Appendix G details the specific amounts donated per condition.

Model Results

Following Kessler, Milkman, and Zhang (2019), we specified three regressions to decompose the effect of targeting-via-options and targeting-via-amounts on overall fundraising effectiveness (first regression) into their effects on donation likelihood (second regression) and conditional donation amount (third regression). Table 2 reports the results. In Column (1), we regressed the amount donated (€) by all donors and nondonors (i.e., we include zeros for donors who did not donate) on both variables. We used robust SEs (White

³ Kessler et al. (2019) found a treatment effect of 16% on total donations (see their Table 1, p.4052). Fuchs et al. (2020) found a cross-country treatment effect of 14% on willingness to donate (see their Table 2, p.4828).

1980) to account for heteroskedasticity (Breusch-Pagan test $p < .05$).⁴ For Column (2), we specified a linear probability model where the dependent variable captures whether the donor made a gift to the charity (0/1). Given the heteroskedasticity (Breusch-Pagan test $p < .10$), we again used robust SEs (White 1980). Finally, for Column (3), we regressed the donation amount conditional on donating. We thus excluded the nondonors and regressed the amount donated (€) on targeting-via-options and targeting-via-amounts for the 2,110 individuals who donated. In all three cases, we also specified an interaction effect between the manipulations. The overall specification is:

$$y_i = \alpha + \beta \text{Targeting_via_options}_i + \theta \text{Targeting_via_amounts}_i + \eta \text{Targeting_via_options}_i \times \text{Targeting_via_amounts}_i + \varepsilon_i \quad (1)$$

where y_i is one of the three outcomes of interest for donor i . $\text{Targeting_via_options}_i$ and $\text{Targeting_via_amounts}_i$ are 0/1 indicator variables denoting whether donor i is in the high targeting-via-options condition and in the high targeting-via-amounts condition. The interaction term captures a potential interaction between both variables. The coefficient η measures the difference-in-differences of the high targeting-via-options and high targeting-via-amounts request relative to the effect of targeting-via-options or targeting-via-amounts only. Figure 4 (Panel a) visualizes the mean fundraising revenues per contacted donor with +/- 1 SE bars and reports the total revenue in each condition. Figure 4 shows the probability of giving (Panel b) and conditional amount donated (Panel c) per condition and is described below.

---- Please insert Figure 4 and Table 2 about here ----

Looking at the overall effect on fundraising revenues (Table 2, Column 1), we find that both interventions positively impact donations. Targeting-via-options significantly ($p < .01$) increases fundraising revenues to €2.30 per request sent (i.e., €1.81 + €.49), representing a

⁴ As robustness check, we also used log-specification and results remain consistent.

27% increase (i.e., €49/€1.81) compared to the low targeting-via-option condition. Targeting-via-amounts marginally ($p < .10$) increases total donations to €2.10 per request sent (i.e., €1.81 + €0.28), which represents a 16% increase (i.e., €0.28/€1.81) compared to the low targeting-via-amounts condition. The interaction effect is not significant ($p > .10$)

These positive effects are in part due to an increase in donation likelihood (Table 2, Column 2 and Figure 4, Panel b). Given a donation rate of 4.7% in the baseline condition, targeting-via-options increases the probability of a donation with $\beta = .007$ ($p < .05$), or 14% (i.e., $.007/.047$) while targeting-via-amounts increases donation likelihood with $\theta = .01$ ($p < .10$), or 11% (i.e., $.005/.047$). Combined, targeting-via-options and targeting-via-amounts offer a donation rate of 5.38%.

Finally, we find somewhat weaker effects on the conditional donation amount (Table 2, Column 3 and Figure 4, Panel c). The baseline condition gives a conditional donation amount of €38.69. Conditional on a gift being made, targeting-via-options marginally ($p < .10$) increases the amount donated to €42.95 per request (i.e., €38.69 + €4.26), representing a 11% increase (i.e., €4.26/€38.69). Conditional on a gift being made, the effect of targeting-via-amounts is not significant ($\theta = 1.55$, $p = .53$). Combined, targeting-via-options and targeting-via-amounts give a conditional donation amount of €47.78. Again, we find no interaction effect ($p > .10$). In summary, both interventions boost fundraising revenues and do not interact with each other. This effect is due to an increase both in the donation likelihood and (to a lesser extent) donation amounts conditional of giving.

Heterogeneity in Treatment Effects

Overall, targeting-via-options and targeting-via-amounts increase donations. However, the aggregation may mask heterogeneous responses across donors (Karlan, List, and Shafir 2011; Sudhir, Fong, and Roy 2021). This section explores heterogeneity in treatment effects.

Method

We define the treatment dummy as $T_i = 1$ when a donor i receives the solicitation request that provides the *highest agency* (high targeting-via-options and high targeting-via-amounts) and $T_i = 0$ when donor i receives the solicitation request with the *lowest agency* (low targeting-via-options and low targeting-via-amounts).⁵ The potential outcomes $y_i(0)$ and $y_i(1)$ capture the donation (in €) made by a donor i respectively when $T_i = 0$ or 1. In reality, we only observe one of the two counterfactuals. The treatment effect conditional on the pre-treatment covariates X_i (see Table 1) is defined as

$$\tau(X_i) = E[y_i(1)|X_i] - E[y_i(0)|X_i] \quad (2)$$

This conditional average treatment effect (CATE) captures the expected change in donation when a donor characterized by X receives a request that provides a greater sense of agency. We estimate $\tau(X_i)$ using machine learning for causal inference (Chen et al. 2020; Yoganarasimhan, Barzegary, and Pani 2022). Compared to a typical moderation analysis, it can learn a flexible (nonparametric) estimate of the impact of a treatment variable on different groups of individuals. It designs an optimal policy that allocates individuals to a condition based on available covariates. Several estimation methods have been proposed. We use causal forests (Wager and Athey 2018) because the method offers consistent and asymptotically normal CATE estimates that enable valid confidence intervals. Like random forests, causal forests are ensembles of many trees. Each of them only uses a random subset of observations and variables. A key difference between causal forest and random forest lies in the loss function. Node splits in causal trees maximize the across-nodes heterogeneity in the *treatment effect* (not in the outcome variable). It assumes that donors ending in the same leaf have a homogeneous treatment effect. In addition, to ensure asymptotic normality, causal forest uses

⁵ Appendix I show that the results for each intervention separately are consistent with the main analysis.

honest trees, meaning that the data used to split the nodes are different from the data used to estimate the CATE at each node.

Causal forests have a key advantage over a regression model in which one would manually interact the treatment dummy with each pre-treatment covariate: The algorithm only retains the most impactful interactions and allows for flexible, nonparametric relationships between covariates and outcome of interest. It is ideal in large-scale field experiments like ours, where we observe many donor characteristics. We include all donor characteristics (Table 1) as pre-treatment covariates. We trained the causal forest on half of the donors and kept the other half aside as a holdout sample. To avoid that results would depend on a specific data split, we generated 1,000 splits and summarized results across splits (Ascarza 2018).⁶

Results

We interpret the results as proposed by Chernozhukov et al. (2020). First, we test for heterogeneity in the treatment effect. If the actual treatment effect is homogeneous, a model that allows for heterogeneous treatment effects would most likely overfit the data. We therefore need to confirm that the treatment effects are heterogeneous before interpreting the causal forest. Second, we compare treatment effects by heterogeneity quintiles identified by the causal forest. Third, we explore the relation between the predicted CATEs and the pre-treatment covariates. This step allows us to profile donors according to their responsiveness to the treatment. The detailed procedure is described in Web Appendix H.

Step 1: Test for Heterogeneity. We test for treatment effect heterogeneity based on the causal forest estimator using the Best Linear Prediction (BLP) test (Chernozhukov et al. 2020). This test determines whether the causal forest estimator is a good proxy for the true CATE or whether, in contrast, the causal forest predictions are uncorrelated with the true

⁶ We used the grf R package and optimized all hyperparameters including the fractions of observations and variables used to build a tree and to determine splits, the minimum number of observations per leaf and the maximum imbalance of a split using cross-validation. The final causal forest contains 4,000 trees.

CATEs and/or the treatment effect is homogeneous. The test consists of regressing the predicted CATE on the mean-centered X_i using a doubly robust estimator (that considers the propensity scores, see Eq. W3 and W4 in Web Appendix H) across all 1,000 data splits. The heterogeneity predictor loading parameter (see Eq. W2) is greater than zero (.74; $p < .01$), thus indicating significant heterogeneity in treatment effects. In addition, its 95% confidence interval (CI = [0.23, 1.23]) includes 1, suggesting that the causal forest estimator is a good proxy for the actual CATEs (i.e., it captures actual differences in the effectiveness of the treatment across donors).

Step 2: Group Average Treatment Effects (GATEs). We next explore how the treatment effect varies across donors. We group donors (in the holdout sample) in five quintiles based on their CATE predicted by the causal forest and estimate the GATE by quintile. The GATE is defined as $E[\hat{\tau}(X_i)|G_i]$ where G_i is an indicator of group membership. Q1 corresponds to the quintile with the smallest CATE, while Q5 corresponds to the largest CATE. Figure 5 reports the GATEs coefficient for each quintile (with ± 1 SE bars). The Average Treatment Effect (ATE) of €0.76 corresponds to the difference between €2.57 per request sent when $T_i = 1$ vs €1.81 when $T_i = 0$. The effectiveness of giving donors a greater sense of agency varies widely across donors. The most responsive quintile Q5 displays a GATE = €2.15 per request sent ($p < .001$). This response is about *three* times as large as the ATE. It is substantial considering that the *average* response to the highest agency request was already improving revenues by 42% compared to the lowest agency request. All other quintiles have a non-significant treatment effect ($p > .10$), indicating that many donors are, in fact, insensitive to the treatment.⁷ Confirming several studies on charitable giving behavior, aggregated results masked major heterogeneities (Karlan, List, and Shafir 2011; Kessler, Milkman, and Zhang

⁷ We ran two robustness checks. First, we divided the population into deciles (instead of quintiles). The top two deciles have a significant GATE, respectively €2.68 ($p < .001$) and €1.55 ($p < .05$), while all other deciles have a non-significant GATE ($p > .10$). Second, we divided the population into halves. The top half has a significant GATE of €1.04 ($p < .001$) while the bottom half has a non-significant GATE of €0.31 ($p > .10$).

2019). We note that the 95% confidence intervals of the differences in GATE between Q5 and any of the other four quintiles do not include zero. Therefore, the GATE in Q5 is significantly higher than in all other quintiles.

---- Please insert Figures 5 and 6 about here ----

Step 3: Partial Dependence Plots (PDP). We then explore the relationship between all pre-treatment covariates and the predicted CATEs across 1,000 holdout samples. Figure 6 plots these relations together with error bars (± 1 SE across the 1,000 splits).

RFMC. We discovered several meaningful variations in responsiveness based on donors' RFMC values. To begin, donors who show a more positive response to the higher-agency requests have donated more recently, donated more often, donated higher amounts and show a more positive trend in their donation patterns over time. This is in line with Karlan, List, and Shafir (2011) who found warm list donors to be more responsive to charitable appeals than cold list donors. Donors' attention is likely to play a role in this process—donors need to pay sufficient attention to the charitable request to notice the possibly greater sense of agency—but not only. Differences in giving motives can also contribute to these differences because large donors are more responsive to analytical effectiveness information (Karlan and Wood 2017) and because rich donors value agency more (Kessler, Milkman, and Zhang 2019). In addition, donors who exhibit clumpier donation patterns were less responsive to the higher-agency request than donors who spread their donations over time. 'Clumpy' donors exhibit donation activity phases that go from "hot, then cold, then hot again" (Zhang, Bradlow, and Small 2015). One explanation can be that it might be challenging to activate clumpy donors when they are in a cold phase. In contrast, regular donors tend not to experience cold phases and, as such, might be more responsive to our solicitation request.

Tenure. The higher-agency request was also more effective among the long-tenured charity donors, suggesting that loyalty positively influences the responsiveness to charitable appeals

(Karlan, List, and Shafir 2011). Long-tenured donors are more likely to care about the charity and be more motivated to express their choice.

YoY range. “Calendar” habits also play a role in donors’ responsiveness. Donors who donate the same amount every year in the same month (small YoY range) were less sensitive to the higher-agency request. One potential explanation could be that habits or routines might decrease donors’ willingness to deviate from their typical donation pattern. It might be harder to “move the needle” when donors have strong habits.

Share of past donations of €48, €88, or €120. Donor responsiveness to agency does not depend much on whether the suggested donation amounts (€48, €88, or €120) are amounts they have given in the past.

Share of gifts in popular months. This variable confirmed the role of habits. Donors who donate exclusively during popular months were less sensitive to the higher-agency request. The experiment occurred in February, outside a major holiday, possibly corresponding to a cold(er) phase for these donors.

Number of gifts in February., The response to our intervention was stronger for donors who tend to make more gifts in February, suggesting that these donors might be in a comparatively hot(ter) phase than the others.

Optimizing Fundraising Campaigns

Our analysis reveals that some donors respond more favorably when provided with a greater sense of agency. This section shows how a charity can leverage these insights to improve fundraising effectiveness. We consider two scenarios for illustrative purposes. In the first one, our starting point is the charity’s current approach of contacting *all* donors but rather than sending everyone the same request, our policy selectively assigns a higher-agency request or a lower-agency request based on the predicted CATEs. In the second scenario, our

policy determines how many donors to contact with a higher-agency request to maximize the net revenues of a campaign. We use *off-policy evaluation* to evaluate the expected return of each policy using the experiment data (Yoganarasimhan, Barzegary, and Pani 2022).

Scenario 1: What is the Best Mix of Lower-Agency vs. Higher-Agency Requests?

In each of the 1,000 holdout samples, we rank all donors in order of decreasing predicted CATE, such that $\hat{\tau}_{(1)} \geq \dots \geq \hat{\tau}_{(i)} \geq \dots \geq \hat{\tau}_{(N)}$. We then calculate the expected net revenues of a campaign that allocates the top $k\%$ of the donors to the higher-agency request and the bottom $(100-k)\%$ to the lower-agency request. For $k = 0\%, 1\%, \dots, 100\%$, we have

$$net\ revenues_k = N \sum_i \left(\frac{(1-T_i)1(\hat{\tau}_i < \hat{\tau}_{(k)})}{1-\hat{p}(X_i)} (y_i(0) - cost_0) + \frac{T_i 1(\hat{\tau}_i \geq \hat{\tau}_{(k)})}{\hat{p}(X_i)} (y_i(1) - cost_1) \right) \quad (3)$$

where $cost_0$ and $cost_1$ are the variable costs of sending a lower-agency, resp. higher-agency request. According to the charity, the baseline variable cost of contacting one donor is $cost_0 = \text{€}1$. To account for the administrative and logistic costs of keeping track of how funds should be distributed as well as for the constraints it puts on the charity's budget, we vary the variable cost of sending a higher-agency request between $cost_1 = \text{€}1, \text{€}1.5$ and $\text{€}2$ (+0%, +50%, +100%). Finally, we account for the fraction of cases where the randomly assigned treatment coincides with the proposed policy by scaling with the holdout predicted propensity scores $\hat{p}(X_i)$ (Hitsch and Misra 2018). We multiply by $N = 10,224$ to match the donor number to the size of the higher-agency condition.

Scenario 2: How Many Donors to Contact with a Higher-Agency request?

Similar to scenario 1, we rank donors but now, from highest to lowest holdout predicted donation amounts conditional on receiving a higher-agency request $\widehat{y_i(1)}$. We calculate the expected net revenues of a campaign that sends a higher-agency request to the top $k\%$ of the

donors. The bottom $(100-k)\%$ is not contacted. In line with Yadlowsky et al. (2021), the net revenues for $k = 0\%, 1\%, \dots, 100\%$ donors contacted are then given by⁸

$$net\ revenues_k = kN \sum_i \left(\frac{T_i 1(\widehat{y_i(1)} \geq y_{(k)}(1))}{\hat{p}(X_i)} (y_i(1) - cost_1) \right) \quad (4)$$

where kN accounts for the number of donors to be contacted. Based on (4), we can decide how many higher-agency requests to send. We call this policy “*higher agency + heterogeneity*” as it sends higher-agency requests and leverages donor heterogeneity by ranking donors using $\widehat{y_i(1)}$. We compare it with the default “*lower agency*” policy of the charity we collaborated with, which sends lower-agency requests ($T_i = 0$) to all donors and ignores donor heterogeneity. In addition, we also compare it to a “*higher agency*” policy that would send the higher-agency request ($T_i = 1$) to all donors without accounting for donor heterogeneity. Comparing the “lower agency” and “higher agency” policies quantifies the extent to which providing a greater sense of agency increases fundraising revenues. Comparing the “higher agency” and “higher agency + heterogeneity” policies quantifies the extent to which accounting for donor heterogeneity increases fundraising revenues.

Results

For each policy, we obtain a distribution of holdout net revenues across the 1,000 holdout samples $\{net\ revenues_{k,b}\}_1^{1000}$ that allow us to quantify the uncertainty. We compare policies using two-sided paired t-tests across the 1,000 values (Yoganarasimhan, Barzegary, and Pani 2022). Figure 7a and b show the average net revenues $(\frac{1}{1000} \sum_{b=1}^{1000} net\ revenues_{k,b})$ of each policy with error bands (± 1 SE across the 1,000 splits). In Figure 8b, error bands widen from left to right because the revenues are cumulative.

---- Please insert Figures 7a and 7b about here ----

⁸ Conditional means are obtained by $\widehat{y_i(1)} = E[y_i(1)|X_i] = \hat{y}_i + [1 - \hat{p}(X_i)] \hat{\tau}(X_i)$, with \hat{y}_i the holdout predicted amounts unconditional on the treatment which we predict using regression forests. Note that our donation context allows us to evaluate this policy because donors do not make a donor when not solicited.

In scenario 1 (Figure 7a), the horizontal axis is the % mix of donors receiving a higher-agency vs. lower-agency requests. Going from left to right shows the incremental revenues of offering more donors a higher-agency request rather than lower-agency request. When lower-agency and higher-agency requests are equally expensive (€1), the optimal mix is 100% higher-agency - 0% lower-agency requests, due to the fact that our data show no reactance to agency appeals (Figure 5). In addition, the top 20% of the donors in terms of largest CATE are responsible for 82.3% (95% CI = [81.8%; 82.9%]) of the incremental net revenues (i.e., €12,696 out of the €15,468) generated by a fundraising campaign that sends higher-agency requests rather than lower-agency requests. Benefits of providing agency decrease when higher-agency requests are more costly than lower-agency requests. In these cases, the optimal mix is approx. 20/80 with a net hold-out revenue of €11,727 (95% CI = [€11,634; €11,821]) when $cost_1 = €1.5$ and a net hold-out revenue of €10,580 (95% CI = [€10,484; €10,676]) when $cost_1 = €2$.

In scenario 2 (Figure 7b), the horizontal axis indicates the share of donors contacted with a higher-agency request. The figure shows the results for $cost_1 = €1$ (see Web Appendix J for €1.5 and €2). The net revenues of the “lower agency” and “higher agency” policies increase linearly as they ignore heterogeneity (donors ranked randomly). When contacting 100% of the donors, these policies respectively generate €8,234 (95% CI = [€8,161; €8,307]) and €15,466 (95% CI = [€15,379; €15,553]), after deducting the campaign cost of €10,224. This is a significant increase of €7,232 (95% CI = [€7,118; €7,346]; $p < .001$), i.e., 88% (for the *gross* revenues, the increase was 42%). The “higher agency + heterogeneity” policy ranks the most responsive donors first such that the revenue curve shows an inverted U. At its maximum (approx. half of the donors contacted), the policy offers €17,141 (95% CI = [€17,058; €17,223]) net holdout revenues. This is €1,675 (95% CI = [€1,647; €1,702]; $p < .001$) more,

i.e., 11%, than the “higher agency” policy that contacts *all* donors. Contacting more donors hampers the net revenues as the resulting donations no longer compensate for the contact cost.

General Discussion

From the charity management perspective, transferring agency to donors comes with challenges because it reduces the charity’s autonomy. It may lead to administrative and even humanitarian problems if donors target “sensational” emergencies (Evangelidis and Van den Bergh 2013). Given these challenges, transferring control to donors is only viable if the benefits (e.g., fundraising revenues) outweigh the costs (e.g., reduced autonomy). In this paper, we investigated the impact of two strategies, targeting-via-options and targeting-via-amounts, on donations in a large field experiment. We documented their underlying mechanism and heterogeneity in donor responses.

Theory Implications

Our research has theoretical implications. First, we show that enhanced control over *which* charitable project to target (through targeting-via-options and/or targeting-via-amounts) increases the donation likelihood and the donation amount. Prior research indicated that if donors allocate aid to multiple needy individuals, they prefer an equitable distribution across victims (Ein-Gar, Levontin, and Kogut 2021; Sharps and Schroeder 2019). In such cases, donating entails complex emotional trade-offs between being helpful vs. being fair and may undermine generosity. However, the donation decision is likely to involve a less intense emotional trade-off when choosing between charitable projects (e.g., wheelchair vs. prosthesis) rather than victims (e.g., Frida vs. Caroline). Therefore, the preference for distributed, rather than targeted, helping might be less general than anticipated (Sharps and Schroeder 2019). Rather than reducing generosity, we find that the ability to target a gift increases donations.

Second, our research contributes to the literature that sheds light into potential moderators when it turns to the overall positive role of agency. Prior research illustrated moderations in terms of demographic variables such as nationality (Fuchs, de Jong, and Schreier 2020) and income (Kessler, Milkman, and Zhang 2019), while we explored the moderating role of past donation variables that are readily available to any charity manager. We find that giving donors a sense of agency is not beneficial when these donors are less engaged with the charity or when they have strong donation habits or routines. Presumably, enhancing agency among individuals who are not very engaged is not an effective approach to re-activate those donors and thus, that other strategies may be needed to engage with less active donors.

Practical Implications

Our findings also yield practical insights for charities. First, both interventions are straightforward to implement in online (e.g., call-to-action buttons) and offline (i.e., money transfer forms) contexts. Most importantly, they increase fundraising effectiveness in the field by more than 40% and, in contrast to other mechanisms to increase fundraising effectiveness, we do not find countervailing effects on donation likelihood vs. amounts. This is a critical advantage for charities as some strategies to boost fundraising lead to self-canceling effects. For instance, suggesting a smaller donation amount typically increases donation likelihood, but often decreases the average donation amount. Conversely, suggesting a larger donation amount typically increases the average donation amount, but often reduces donation likelihood. Hence, some strategies, such as selecting defaults in charitable appeals, result in no net effect in fundraising revenue (Goswami and Urminsky 2016).

Second, we offer new insights into how different donor segments respond to charitable appeals. For instance, the more engaged donors, as captured by a longer tenure and/or larger, more recent, more frequent and less clumpy gifts were particularly responsive to our interventions. Charities can improve the effectiveness of their campaign by incorporating

these insights in deciding how to approach different donor segments. Notably, a differentiated approach is most beneficial when donors react in opposing directions to agency appeals.

Limitations and Future Research

Our research comes with limitations that might inspire future research. First, future research might consider other ways to enhance donor agency. Targeting-via-options is fundamentally different from prior research as we *force* donors to make a choice in the high targeting-via-options condition (i.e., the call-to-action buttons and money transfer forms were labeled with a project's name). Prior research allowed donors to *not* choose, e.g., by allowing donors to leave checkboxes corresponding to particular charitable projects unchecked (Kessler, Milkman, and Zhang 2019). The “checking a box” paradigm led to conflicting results. Fuchs, de Jong, and Schreier (2020) document strong effects on donation likelihood but negligible effects on donation amount, while Kessler, Milkman, and Zhang (2019) find no effect on donation likelihood but positive effects on donated amounts. Future research should explore when, why, and how different manipulations, such as drop-down lists or open entry boxes (Heist and Cnaan 2018) or tipping jars (Rifkin, Du, and Berger 2021), could trigger countervailing or additive effects on donation likelihood and amount. Decreasing agency by delegating the choice to algorithms or better-informed people (Berman and Small 2012; Butera and Houser 2018) may also be worth exploring given the heterogeneity we discovered.

Second, one could also explore whether a charitable project's attractiveness, perceived urgency, or importance moderate agency effects. The effect of our agency interventions is inherently tied to the nature of the charitable projects. For instance, if charitable projects are unattractive, the opportunity to control resource allocations may not stimulate donations. Moreover, if more attractive projects are coupled to excessively large suggested donation amounts, enhancing donor agency may not help either.

Third, the charity determined the suggested amounts in the field study based on marginal costs. These amounts might have nudged donors to give more than they had considered. Targeting-via-amounts might decrease the revenues of a charitable campaign if the suggested donation amounts were set below what people typically donate (Shang and Croson 2009). Further research should explore how the suggested amounts could alter our findings.

Fourth, the high targeting-via-options requests in Studies 2 and 3 offered more choice options than the low targeting-via-options requests. They may have triggered an obligation to donate, as not donating would mean rejecting a request two or three times. Also, the number of charitable projects was relatively small. Future research could explore whether more options dampen the effect of targeting-via-options by adding complexity.

Finally, the off-policy evaluation section ignored the uncertainty around the CATE predictions when ranking donors. Future research could consider whether and how to incorporate such uncertainty when prioritizing donors. For instance, should the charity prioritize donors with high but uncertain preferences for agency vs. low but more certain ones? Methods that specifically handle the exploration/exploitation trade-offs could provide a framework for fundraising campaign designs (Schwartz, Bradlow, and Fader 2017). We hope our results will encourage charities to leverage the heterogeneous benefits of agency in their fundraising activities.

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Table 1. Descriptive Statistics of Experimental Conditions in Study 3

	Low Targeting-via-Amounts		High Targeting-via-Amounts	
	Low Targeting- via-Options	High Targeting- via-Options	Low Targeting- via-Options	High Targeting- via-Options
<i>Number of requests sent by the charity</i>	10,224	10,224	10,221	10,224
RFMC variables				
Recency (in days)	255.00 (234.54)	250.00 (233.68)	250.00 (233.97)	248.00 (232.36)
Frequency: number of donations per year				
Average over time	.19 (.93)	.19 (.91)	.19 (.95)	.19 (.97)
Standard deviation over time	.48 (.93)	.48 (.93)	.48 (.97)	.48 (.95)
Time trend	.02 (.08)	.02 (.08)	.02 (.08)	.02 (.08)
Monetary value: total donation (in €) per year				
Average over time	5.33 (66.12)	5.48 (47.63)	5.56 (290.20)	5.48 (34.29)
Standard deviation over time	15.27 (294.80)	15.69 (115.74)	15.74 (1,497.61)	15.5 (75.06)
Time trend	.72 (11.50)	.73 (3.26)	.73 (61.69)	.73 (3.87)
Clumpiness	.59 (.27)	.60 (.27)	.59 (.27)	.59 (.27)
Other controls				
Tenure (in days)	2,485.00 (2,893.93)	2,485.00 (2,889.93)	2,490.00 (2,904.59)	2,559.50 (2,896.91)
YoY range	.00 (304.80)	.40 (451.85)	.50 (413.39)	.00 (203.38)
Share of past donations of €48, €88, or €120	.00 (.25)	.00 (.25)	.00 (.24)	.00 (.25)
Share of gifts in popular months	0.25 (0.28)	0.25 (0.28)	0.25 (0.28)	0.25 (0.27)
Number of gifts in February	.00 (2.18)	.00 (2.16)	.00 (2.23)	.00 (2.26)
Demographics				
Individual Company	97.10% 2.90%	97.09% 2.91%	97.21% 2.79%	96.99% 3.01%
Language A B	56.16% 43.84%	56.16% 43.84%	56.21% 43.79%	56.18% 43.82%

Notes: We report the medians (and standard deviations into parentheses) for the continuous variables. For the categorical variables, we report the percentages per level of the categorical variable. We tested for differences between conditions using permutation tests (10,000 permutations, Web Appendix F) with a Bonferroni correction for multiple testing and all *p*-values are greater than .10.

Table 2. Effect of Targeting-via-Options and Targeting-via-Amounts on Donations in Study 3

	(1) Amount Donated (€)	(2) Probability of Giving (%)	(3) Conditional Amount Donated (€)
Targeting-via-Options	.489*** (.173)	.007** (.003)	4.258* (2.414)
Targeting-via-Amounts	.284* (.166)	.005* (.002)	1.516 (2.430)
Targeting-via-Options x Targeting-via-Amounts	-.016 (.255)	-.005 (.004)	3.308 (3.366)
Baseline Condition Mean	1.813*** (.110)	.047*** (.002)	38.694*** (1.763)
<i>p</i> -value	.000	.085	.001
<i>N</i>	40,893	40,893	2,110

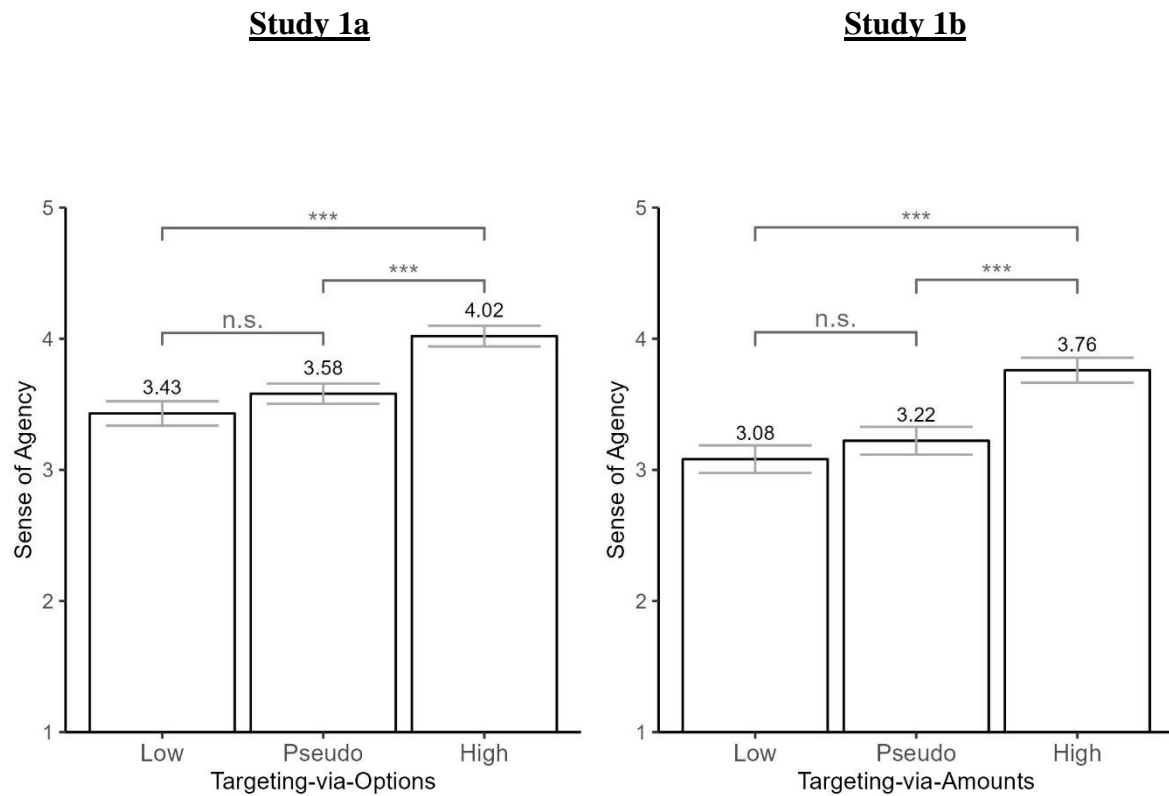
Notes: Estimates of the effect of targeting-via-options and targeting-via-amounts on (1) the total amount donated, (2) the likelihood of giving, and (3) the amount donated conditional on giving, with SEs into parentheses. The baseline condition is the low targeting-via-options, low targeting-via-amounts condition. Column (1) reports estimates for which the dependent variable is the total amount donated, including the zero donations. Column (2) reports estimates from a linear probability model in which the dependent variable indicates whether the individual has donated. Column (3) reports estimates when the dependent variable is the total amount donated only for the individuals who donated. For (1) and (2), we use and report White (1980) robust SEs. *, **, and *** indicate significant at the 10%, 5%, 1% respectively.

Figure 1. Strategies to Boost Donor Agency

	Low Targeting-via-Options <i>(no choice options associated with distinct projects)</i>	High Targeting-via-Options <i>(multiple choice options associated with distinct projects)</i>
Low Targeting-via-Amounts <i>(suggested donation amounts not linked to distinct projects)</i>	<p>Your Donation</p> <p>Thank you for supporting our lifesaving work.</p> <p>Your support plays a powerful role in our lifesaving work. We are grateful for the compassion you demonstrate through your loyal commitment to our patients around the world.</p> <p>For Doctors Without Borders, the ability to respond quickly to medical humanitarian emergencies is crucial to saving more lives. Unrestricted funds allow us to allocate our resources most efficiently and where the needs are greatest.</p> <div> <div>ONE-TIME</div> <div>MONTHLY</div> </div> <p>Increase the impact of your gift. Make it monthly.</p> <p>Please select your tax-deductible monthly gift amount below</p> <div> <div>\$10</div> <div>\$15</div> <div>\$30</div> <div>\$60</div> <div>\$90</div> <div>\$ OTHER</div> </div> <p>Minimum payment \$10.00.</p>	<p>HELP SOMEONE TODAY</p> <p>Your generous contribution will enable us to keep fighting for the health, education and financial stability of every person in your community and around the world.</p> <p>Use my donation to support:</p> <p> <input type="radio"/> A U.S. United Way <input checked="" type="radio"/> An International United Way <input type="radio"/> Where help is needed most </p> <p>Nigeria</p> <p>Selecting a location will direct you to additional information about donating.</p> <div> <div>1 Amount</div> <div>2 Details</div> <div>3 Payment</div> </div> <div> <div>US\$25</div> <div>US\$50</div> <div>US\$100</div> <div>US\$300</div> <div>US\$600</div> <div>US\$1,000</div> <div>US\$2,500</div> <div>\$ 0.00</div> </div> <p><input type="checkbox"/> Please Make This A Recurring Monthly Contribution</p>
High Targeting-via-Amounts <i>(suggested donation amounts linked to distinct projects)</i>	<p>DONATE TODAY: SAVE A LIFE</p> <p>Vulnerable children need you more than ever.</p> <p>Right now, children are growing up against the backdrop of hunger, conflict and natural disasters. Your gift today can help make change that protects the lives of children, families and their communities.</p> <ul style="list-style-type: none"> \$50 - can provide enough food to keep 3 children from going hungry for a month \$150 - can wrap 30 warm, cozy blankets around children affected by conflict \$300 - can provide 150 face masks to refugee health workers on the front lines <p>Join us today and make change for children.</p> <div> <div>1. CHOOSE YOUR GIFT TYPE</div> <div>MONTHLY</div> <div>ONE-TIME</div> <div>2. CHOOSE YOUR GIFT AMOUNT</div> <div> <div>\$15</div> <div>\$25</div> <div>\$35</div> <div>\$50</div> <div>\$75</div> <div>\$100</div> <div>OTHER</div> </div> </div>	<div> <div>I would like to donate:</div> <div>£ 22</div> <div>£ 58</div> <div>£ 106</div> <div>£ Other</div> <div>A SINGLE DONATION OF</div> <div>£22</div> <div>COULD PROVIDE FIVE CHILDREN WITH RADIOS AND EDUCATIONAL MATERIALS</div> </div> <div> <div>I would like to donate:</div> <div>£ 22</div> <div>£ 58</div> <div>£ 106</div> <div>£ Other</div> <div>A SINGLE DONATION OF</div> <div>£58</div> <div>COULD PROVIDE NUTRITION PACKAGES FOR 20 PREGNANT WOMEN AND ADOLESCENT GIRLS</div> </div> <div> <div>I would like to donate:</div> <div>£ 22</div> <div>£ 58</div> <div>£ 106</div> <div>£ Other</div> <div>A SINGLE DONATION OF</div> <div>£106</div> <div>COULD PROVIDE A HYGIENE KIT TO 20 FAMILIES, INCLUDING SOAP AND OTHER ESSENTIALS</div> </div>

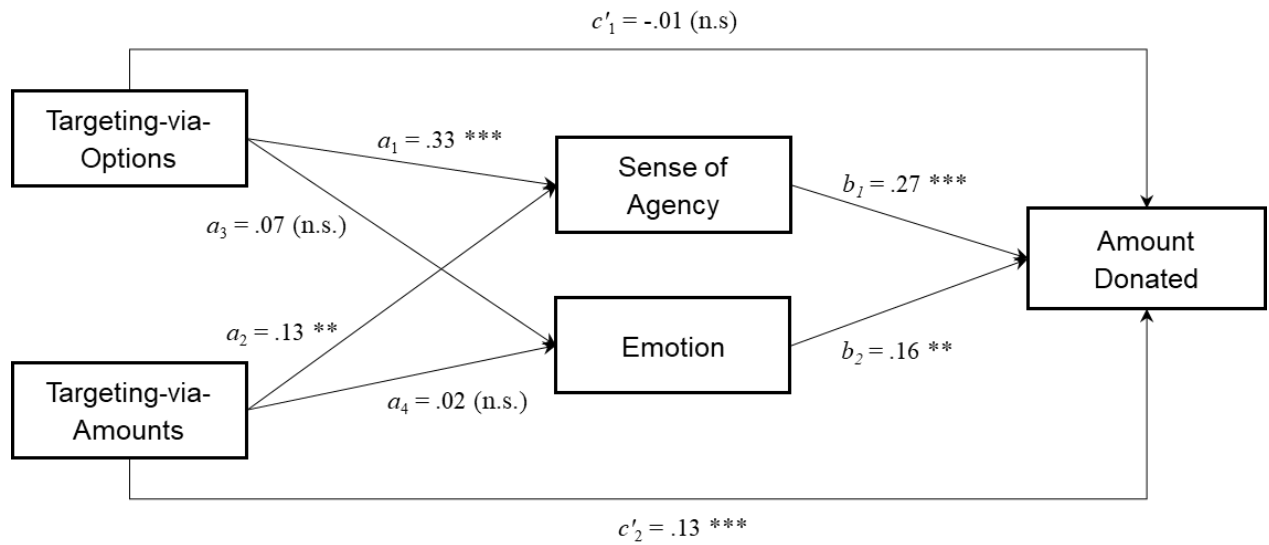
Notes: Examples of real fundraising requests that illustrate the targeting-via-options and targeting-via-amounts interventions.

Figure 2. Sense of Agency Across Conditions in Study 1a and Study 1b



Notes: Participants' sense of agency (scale 1-5) in Study 1a (left panel) and Study 1b (right panel). Error bars = +/- 1 SE. Means are reported above each bar.

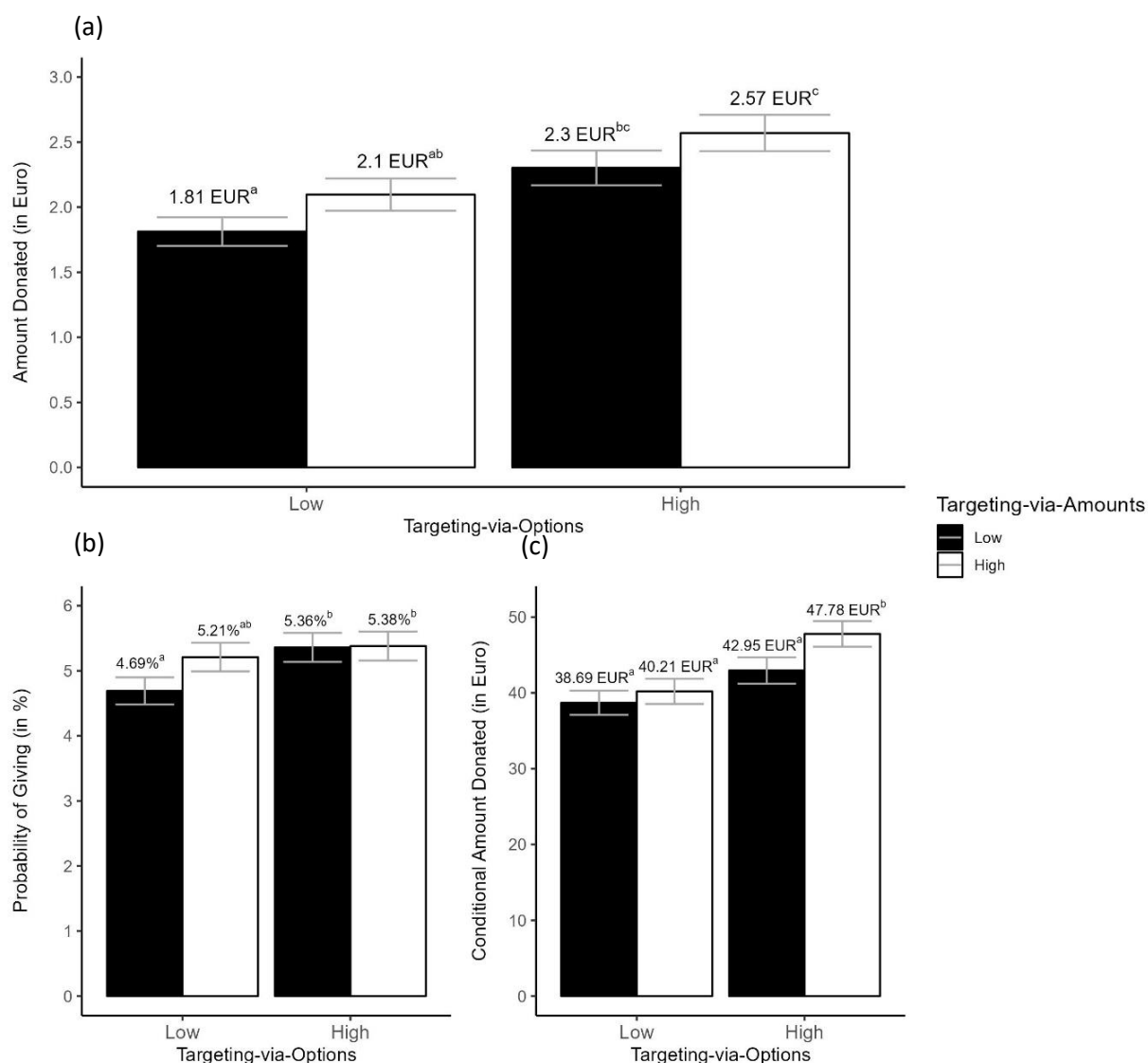
Figure 3. Mediation via Sense of Agency in Study 2



		<i>Total Effects</i>
Targeting-via-Options	→ Amount donated	0.09 *
Targeting-via-Amounts	→ Amount donated	0.17 ***
		<i>Indirect Effects</i>
Targeting-via-Options	→ Sense of agency → Amount donated	0.09 ***
Targeting-via-Amounts	→ Sense of agency → Amount donated	0.04 **
Targeting-via-Options	→ Emotion → Amount donated	0.01 (n.s.)
Targeting-via-Amounts	→ Emotion → Amount donated	0.00 (n.s.)
		<i>Proportion Mediated</i>
Via Sense of Agency		48.24% ***
Via Emotion		5.20% (n.s.)

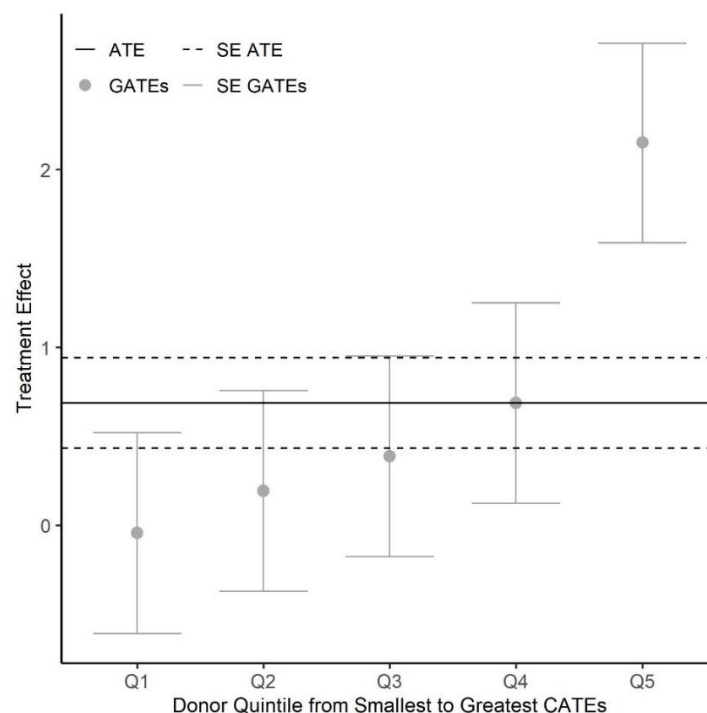
Notes: Structural equation model with “sense of agency” and “emotion” as latent mediating constructs. Standardized coefficients are shown. We use White (1980) robust SEs. *, **, and *** indicate significance at the 10%, 5%, 1% respectively.

Figure 4. Amount Donated, Probability of Giving and Amount Donated Conditional on Giving per Condition in Study 3



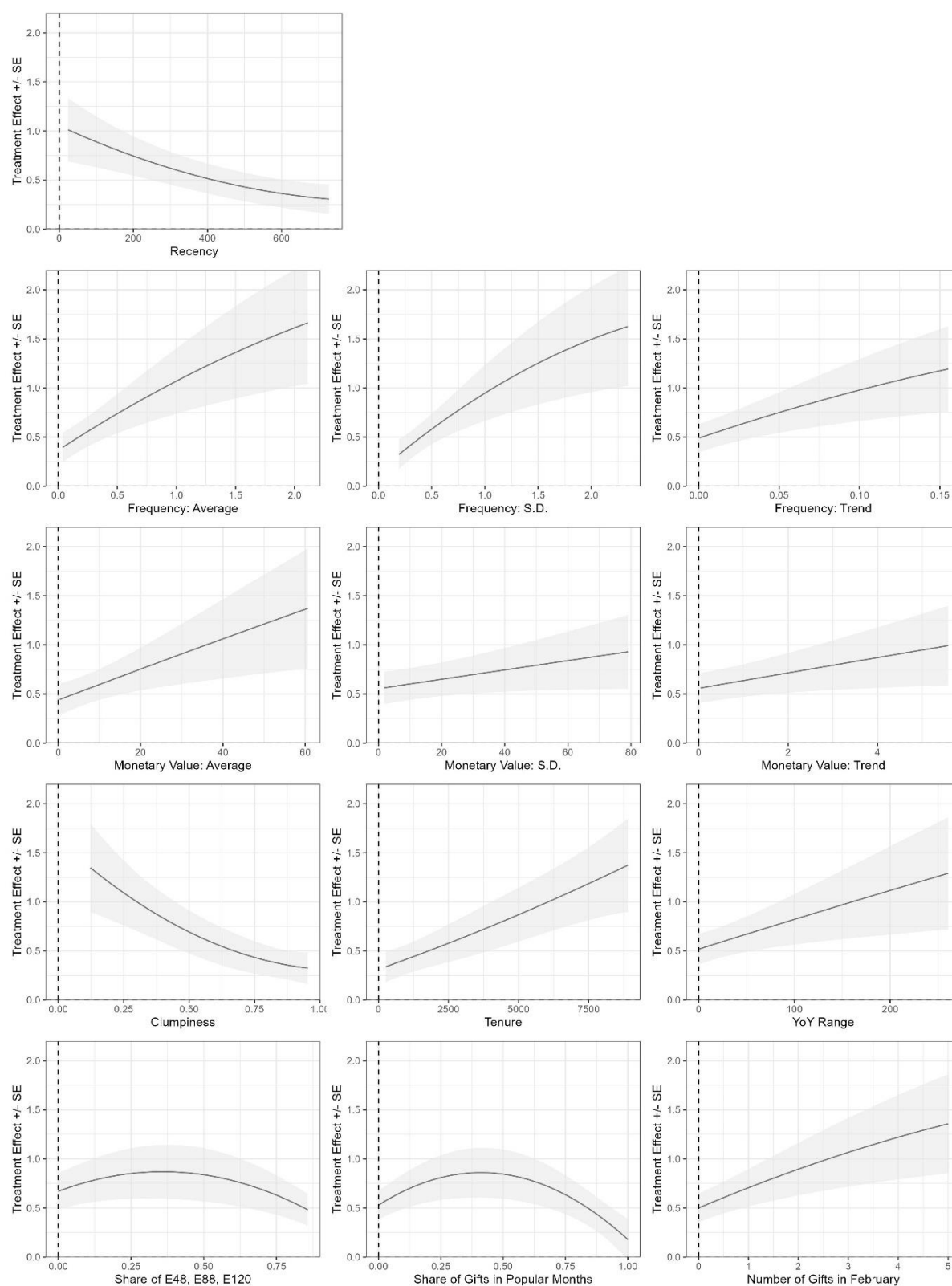
Notes: The chart reports the mean amount donated in €/request (top panel), the probability of giving in % (bottom left panel) and the mean amount donated conditional on giving in € (bottom right panel) for the four conditions in Study 3. Error bars = +/- 1 SE. We tested for differences between conditions using permutation tests (Web Appendix F). Values in a panel without a common superscript (a, b, c) are significantly different from each other at the 5% significance level. For example, in panel (a), 1.81 EUR is statistically different from 2.57 EUR and 2.30 EUR but is not statistically different from 2.10 EUR.

Figure 5. Group Average Treatment Effects by Donor Quintile in Study 3



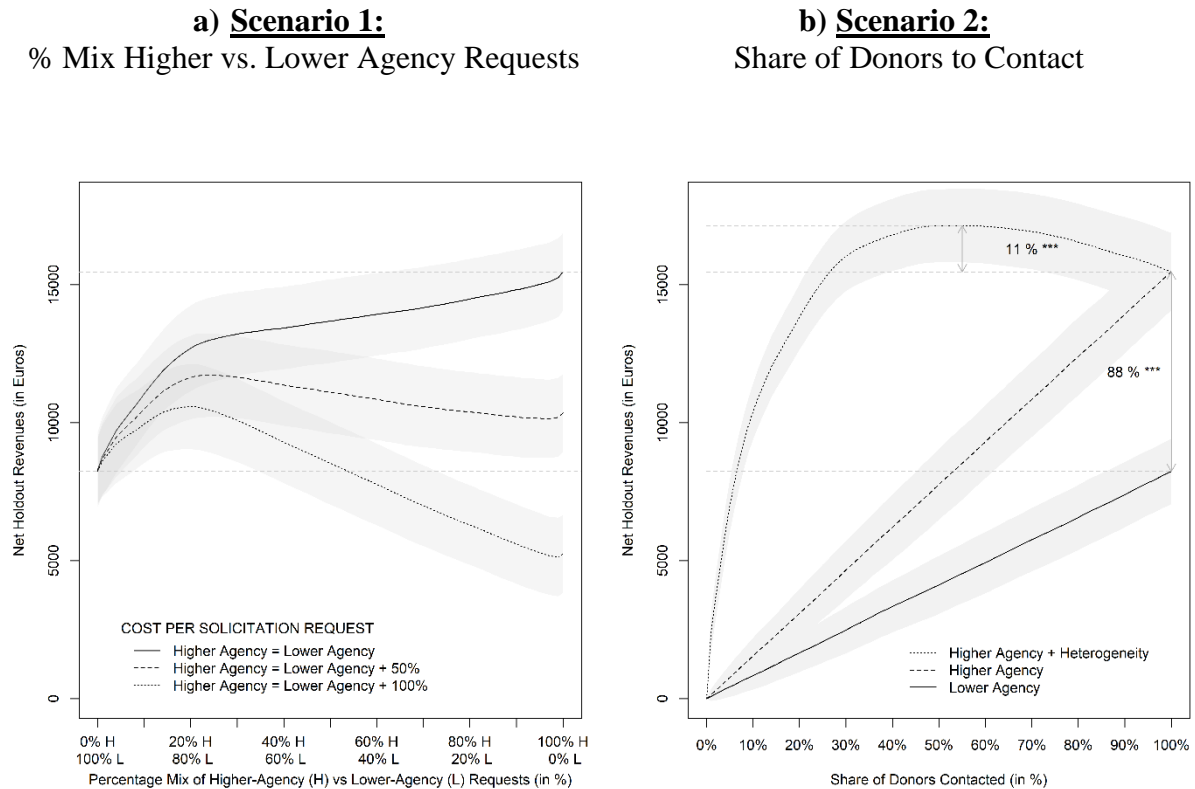
Notes: Group Average Treatment Effects (GATEs) in €/request (grey dots) of a higher agency request compared to a lower agency request per donor quintile (Q1-Q5). Q1 (resp. Q5) is the quintile with the lowest (resp. greatest) CATE. Error bars = +/- 1 SE across 1,000 data splits. The solid horizontal line is the Average Treatment Effect (ATE) estimate across donors; the horizontal dashed lines +/- 1 SE.

Figure 6. Partial Dependence Plots in Study 3



Notes: Partial dependence between each pre-treatment covariate (x-axis) and the predicted CATEs (y-axis), averaged across all 1,000 holdout samples +/- 1 SE (shaded grey areas).

Figure 7. Off-Policy Evaluation in Study 3



Notes: Net holdout revenues in € (y-axis) of various campaigns +/- 1 SE (shaded grey areas). In Figure 7a, the horizontal axis is the percentage mix of donors receiving a higher-agency request (H) and a lower-agency request (L). In Figure 7b, the horizontal axis is the share of donors contacted. We assume a cost of €1 for a lower-agency request. The cost of a higher-agency request varies in Figure 7a between €1 (solid line), €1.5 (dashed line) or €2 (dotted line), while it is set to €1 in Figure 7b (see Web Appendix J for other costs). In Figure 7b, a share of 100% corresponds to 10,224 contacted donors (the number of donors in one condition). The black dotted line corresponds to the “Higher agency + heterogeneity” policy, the black dashed line to “Higher agency” policy and the solid black line to the “Lower agency” policy. Arrows indicate differences in net holdout revenues between policies. *, **, and *** indicate significant at 10%, 5%, 1% respectively.

WEB APPENDICES

Enhancing Donor Agency to Improve Charitable Giving: Strategies and Heterogeneity

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These materials have been supplied by the authors to aid in the understanding of their paper.
The AMA is sharing these materials at the request of the authors.

WEB APPENDIX A. STIMULI STUDY 1A


Condition 1: High Targeting-via-Options Condition

<p>NEWLIFE supports vulnerable people by providing them with a prosthesis or a wheelchair. Please consider helping people with a reduced mobility by clicking one of the buttons below.</p>	
<p>I would like to donate a prosthesis</p> 	<p>I would like to donate a wheelchair</p> 

Condition 2: Low Targeting-via-Options Choice Condition

<p>NEWLIFE supports vulnerable people by providing them with a prosthesis or a wheelchair. Please consider helping people with a reduced mobility by clicking the button below.</p>
<p>I would like to donate a prosthesis or a wheelchair</p> 



Condition 3: Pseudo Targeting-via-Options Condition

<p>NEWLIFE supports vulnerable people by providing them with a prosthesis or a wheelchair. Please consider helping people with a reduced mobility by clicking one of the buttons below.</p>	
<p>I would like to donate a prosthesis or wheelchair</p> 	<p>I would like to donate to NEWLIFE</p>



Note: The order of the charitable projects (prosthesis, wheelchair) was counterbalanced.

WEB APPENDIX B. STIMULI STUDY 1B



Condition 1: High Targeting-via-Amounts Condition

NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating.	 = €10
	 = €15



Condition 2: Low Targeting-via-Amounts Condition

  NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating.	€10
	€15

Condition 3a: Pseudo Targeting-via-Amounts Condition (low amount)

















NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating.	 = €10
	 = €10

Condition 3b: Pseudo High Targeting-via-Amounts Condition (high amount)

NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating.	 = €15
	 = €15

Note: The order of the charitable projects (prosthesis, wheelchair) was counterbalanced.

WEB APPENDIX C. STIMULI STUDY 2

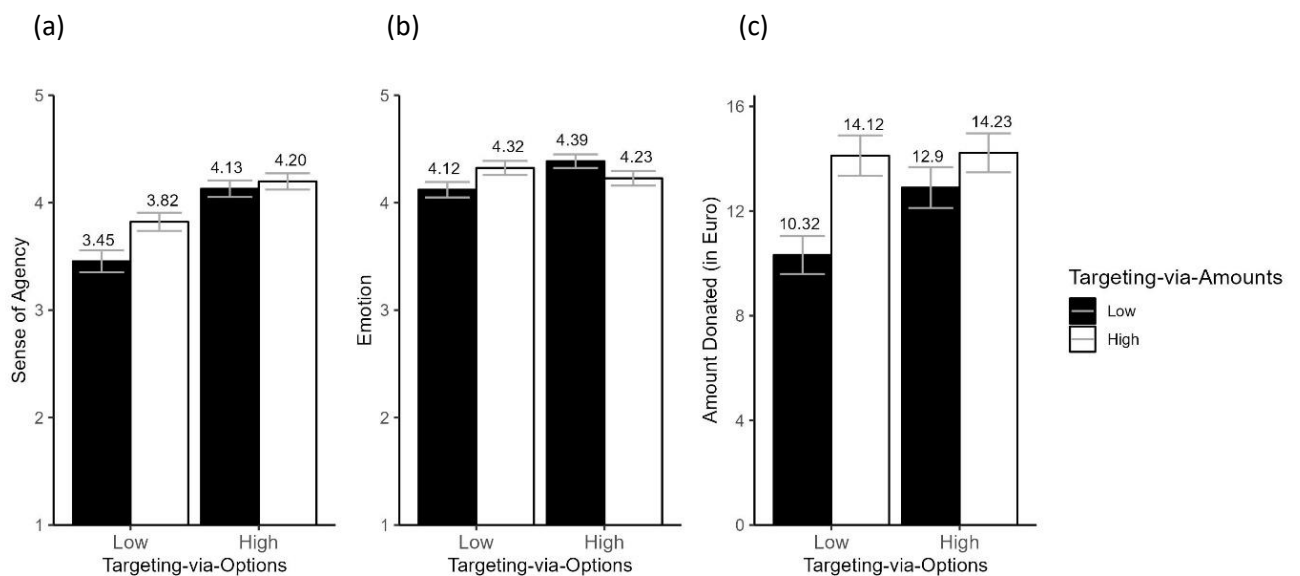
	<i>Low Targeting-via-Options</i>	<i>High Targeting-via-Options</i>
<i>Low Targeting-via-Amounts</i>	<div>   <p>NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating by clicking the button below.</p> <p>€10</p> <p>€15</p> </div> <div> <p>I would like to donate a prosthesis or a wheelchair</p>   </div>	<div>   <p>NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating by clicking one of the buttons below.</p> <p>€10</p> <p>€15</p> </div> <div> <p>I would like to donate a prosthesis</p>  </div> <div> <p>I would like to donate a wheelchair</p>  </div>
<i>High Targeting-via-Amounts</i>	<div> <p>NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating by clicking the button below.</p>  = €10  = €15 </div> <div> <p>I would like to donate a prosthesis or a wheelchair</p>   </div>	<div> <p>NEWLIFE supports vulnerable people with a reduced mobility. It can provide a prosthesis or a wheelchair to people in need. Please consider donating by clicking one of the buttons below.</p>  = €10  = €15 </div> <div> <p>I would like to donate a prosthesis</p>  </div> <div> <p>I would like to donate a wheelchair</p>  </div>

Note: The order of the charitable projects (prosthesis, wheelchair) was counterbalanced.

WEB APPENDIX D. RESULTS STUDY 2

This Web Appendix contains the detailed results per condition of Study 2. Panel (a) reports the participants' mean sense of agency per condition (scale 1-5). Panel (b) reports participants' mean emotion per condition (scale 1-5). Panel (c) reports the participants' mean hypothetical amount donated per condition (in €). Each panel has +1/-1 SE error bars. Means are reported above each bar.

Figure WD.1. Sense of Agency, Emotion and Amount Donated in Study 2



WEB APPENDIX E. STIMULI STUDY 3

This Web Appendix shows an anonymized version of the solicitation request per condition for Study 3. We remove the real project names and altered the request in the way that preserves the anonymity of the charity we collaborated with. We also used the pseudo “NEWLIFE” to preserve anonymity.

Low Targeting-via-Options

One money transfer form is included in the envelope. The amount box is left empty.

Handtekening(en)

OVERSCHRIJVINGSOPDRACHT 02

Bij invulling met de hand, één HOOFDLETTER of cijfer in zwart (of blauw) per vakje

Geweeste uitvoeringsdatum in de toekomst

Bedrag EUR CENT

Rekening opdrachtgever (IBAN)

Naam en adres opdrachtgever

Rekening begunstigde (IBAN)

BIC begunstigde

Naam en adres begunstigde

Mededeling

High Targeting-via-Options

Three money transfer forms are included in the envelope. They are respectively labelled “for Project P1”, “for Project P2”, “for Project P3”. All amount boxes are left empty.

Handtekening(en)

OVERSCHRIJVINGSOPDRACHT 02

Bij invulling met de hand, één HOOFDLETTER of cijfer in zwart (of blauw) per vakje

Geweeste uitvoeringsdatum in de toekomst

Bedrag EUR CENT

Rekening opdrachtgever (IBAN)

Naam en adres opdrachtgever

Rekening begunstigde (IBAN)

BIC begunstigde

Naam en adres begunstigde

Mededeling

for [project P1]

Handtekening(en)

OVERSCHRIJVINGSOPDRACHT 02

Bij invulling met de hand, één HOOFDLETTER of cijfer in zwart (of blauw) per vakje

Geweeste uitvoeringsdatum in de toekomst

Bedrag EUR CENT

Rekening opdrachtgever (IBAN)

Naam en adres opdrachtgever

Rekening begunstigde (IBAN)

BIC begunstigde

Naam en adres begunstigde

Mededeling

for [project P2]

Handtekening(en)

OVERSCHRIJVINGSOPDRACHT 02

Bij invulling met de hand, één HOOFDLETTER of cijfer in zwart (of blauw) per vakje

Geweeste uitvoeringsdatum in de toekomst

Bedrag EUR CENT

Rekening opdrachtgever (IBAN)

Naam en adres opdrachtgever

Rekening begunstigde (IBAN)

BIC begunstigde

Naam en adres begunstigde

Mededeling

for [project P3]

Low Targeting-via-Amounts

<p>NEWLIFE LOGO</p> <p>Prospective donor name Prospective donor address</p> <hr/> <p>Support vulnerable people with NEWLIFE!</p> <p>Date</p> <p>Dear [Prospective donor name],</p> <p>NEWLIFE has been active since 19xx supporting vulnerable people all over the world.</p> <p>Drawing on our long experience in helping vulnerable people, we have deployed teams to distributes various types of aids such as [Project P1], [Project P2] and [Project P3].</p> <p>At the back of this letter, you will find all the details of these three projects.</p> <p>You too can act now!</p> <p>With 48 euros, 88 euros, or 120 euros your generosity will make the difference!</p> <p>On behalf of our beneficiaries, I sincerely thank you,</p> <p>John Doe General Director NEWLIFE</p>	<p>NEWLIFE LOGO</p> <p>Support vulnerable people with NEWLIFE!</p> <p>Project P1 detailed description</p> <p>Project P2 detailed description</p> <p>Project P3 detailed description</p> <p>With 48 euros, 88 euros, or 120 euros your generosity will make the difference!</p>
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High Targeting-via-Amounts

<p>NEWLIFE LOGO</p> <p>Prospective donor name Prospective donor address</p> <hr/> <p>Support vulnerable people with NEWLIFE!</p> <p>Date</p> <p>Dear [Prospective donor name],</p> <p>NEWLIFE has been active since 19xx supporting vulnerable people all over the world.</p> <p>Drawing on our long experience in helping vulnerable people, we have deployed teams to distributes various types of aids such as [Project P1], [Project P2] and [Project P3].</p> <p>At the back of this letter, you will find all the details of these three projects.</p> <p>You too can act now!</p> <p>With 48 euros for Project P1, 88 euros for Project P2, or 120 euros for Project P3 your generosity will make the difference!</p> <p>On behalf of our beneficiaries, I sincerely thank you,</p> <p>John Doe General Director NEWLIFE</p>	<p>NEWLIFE LOGO</p> <p>Support vulnerable people with NEWLIFE!</p> <p>Project P1 detailed description</p> <p>Project P1 = 48 euros</p> <p>Project P2 detailed description</p> <p>Project P2 = 88 euros</p> <p>Project P3 detailed description</p> <p>Project P3 = 120 euros</p> <p>Your generosity will make the difference!</p>
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WEB APPENDIX F. PERMUTATION TEST

This Web Appendix describes the procedure for significance testing in Table 1. Permutation tests are nonparametric. They can test for differences in any statistic, e.g., medians, proportions and means. Unlike parametric tests, the test makes no distributional assumption. Given our 2 x 2 between-subject design, the samples are unpaired and assumed independent of each other.

We test the null hypothesis that a value of a statistic (e.g., the median in Table 1) of x in one condition equals the value of the same statistic of x in another condition

$$H_0: \text{statistic}(x)_{i \in k} = \text{statistic}(x)_{i \in l},$$

for $k, l = 1, \dots, 4$, with $k \neq l$, one of the four conditions using pairwise permutation tests (Richter and McCann 2007). The test is implemented in the rcompanion package.

The test consists of:

- (1) generating B samples $\mathcal{D}_1, \dots, \mathcal{D}_B$ of the original data $\mathcal{D}_0 = (x_i)_{i=1, \dots, n}$ by randomly assigning all observations to one of the four conditions,
- (2) for each \mathcal{D}_b , take the differences in statistic between conditions

$$\text{statistic}(x)_{i \in k} - \text{statistic}(x)_{i \in l}$$

- (3) and count the proportion of $\mathcal{D}_1, \dots, \mathcal{D}_B$ where the difference is as large as the difference on the original data \mathcal{D}_0 (in absolute value for the two-tailed test). We use this probability to reject or not the null.

The code is available on OSF at

https://osf.io/4nzsw/?view_only=d6fe47c83bd6493c8039b76bb1aa9ad0.

References:

Richter, S. J., & McCann, M. H. (2007). Multiple comparison of medians using permutation tests. *Journal of Modern Applied Statistical Methods*, 6(2), 6.

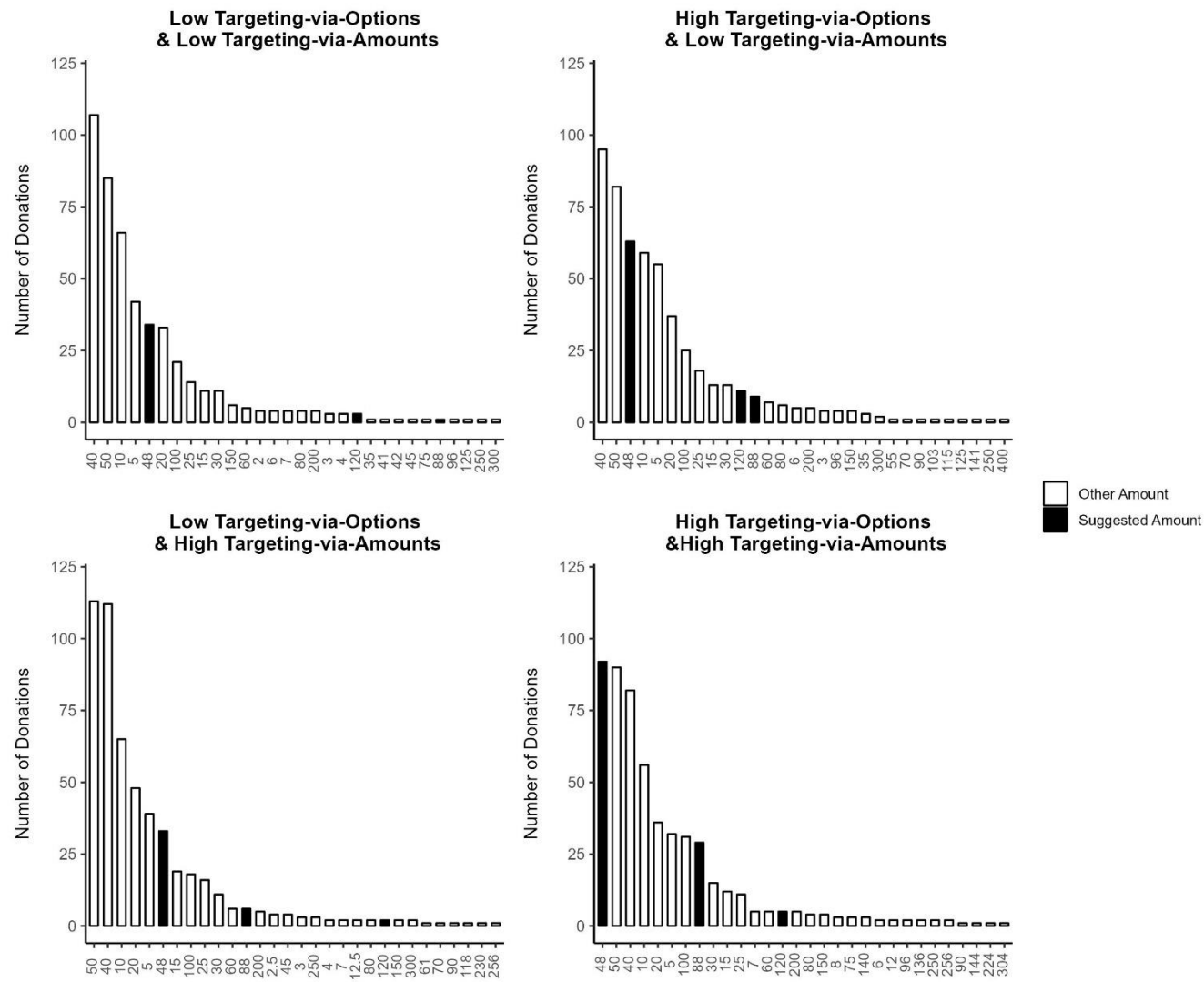
WEB APPENDIX G. DONATION AMOUNTS (STUDY 3)

To gain deeper insights into the donation amounts gifted to the charity in the field study (Study 3), we provide an overview of the most prevalent gifts in Figure WG.1 and report the number of donations of a given amount for every condition. The figure shows that our interventions trigger qualitatively different contributions, suggesting that the requests affect not just how *much* people give but also, to some extent, *what* donors give. We observe a shift in the occurrence of suggested amounts across conditions. In addition, one of the most prevalent donated amounts is €40, which is the minimum amount that needs to be donated to turn a financial contribution into a tax-deductible expense. Many of the donations are a chronically accessible value (Desmet and Feinberg 2003), such as banknote denomination (i.e., powers of ten, their doubles, and their halves). In our experiment, it corresponds to €1, 2, 5, 10, 20, 50, 100, and 20. These “prominent amounts” (Converse and Dennis 2018; Whynes, Philips, and Frew 2005) represent 51% of all donation amounts.

References:

- Converse, Benjamin A. and Patrick J. Dennis (2018), "The Role of “Prominent Numbers” in Open Numerical Judgment: Strained Decision Makers Choose from a Limited Set of Accessible Numbers," *Organizational Behavior and Human Decision Processes*, 147, 94-107.
- Desmet, Pierre and Fred M. Feinberg (2003), "Ask and Ye Shall Receive: The Effect of the Appeals Scale on Consumers' Donation Behavior," *Journal of Economic Psychology*, 24 (3), 349-76.
- Whynes, David K., Zoë Philips, and Emma Frew (2005), "Think of a Number... Any Number?," *Health Economics*, 14 (11), 1191-95.

Figure WG.1: Prevalence of Donation Amounts across Conditions in Study 3



WEB APPENDIX H.
TECHNICAL DETAILS ON CAUSAL ML INFERENCE BASED ON
CHERNOZHUKOV ET AL. (2020)

This Web Appendix summarizes the methodology by Chernozhukov et al. (2020) to make valid inference on several key *features* of the CATE. We refer the reader to their original article for technical details and formal proofs. The approach can be used with any CATE estimator as it does not require any strong assumption of the properties of this estimator. Here, we explain how we use it with the causal forest estimator.

The procedure treats the CATE predictions (obtained from the causal forest) as proxies that serve in place of the true CATE. It works in high-dimensional randomized control trials where the propensity score is known and bounded away from zero or one. Under the assumption of strong ignorability, the outcome y (e.g., donation amount) can be written as

$$y = b_0(X) + s_0(X)T + U, \text{ with } E[U|X, T] = 0 \quad (\text{W1})$$

with $b_0(X)$ the baseline conditional average (e.g., conditional mean donation amount when $T_i = 0$) and $s_0(X)$ the CATE of treatment T given X , the set of pre-treatment covariates.

Chernozhukov's procedure focuses on estimating key *features* of the CATE function (rather than attempting to get consistent estimation and uniformly valid inference on the CATE itself) using weighted regression analyses (see below) that use the CATE predictions to create an orthogonalized variable together with an orthogonalized treatment indicator. To avoid overfitting and achieve validity, the approach consists of repeatedly and randomly splitting the data in two samples (usually of equal size). The first sample, called *auxiliary* sample, is used to fit the causal forest using T , X , and y . The model is then used to generate holdout CATE predictions on the second sample, called the *main* sample. These predictions are proxies used for post-processing and make inference on the three features of the CATE. In the paper, we use 1,000 splits to ensure the stability of our results.

Best Linear Predictor (BLP)

Following Chernozhukov et al. (2020), the BLP of the CATE function $s_0(X)$ based on the proxy $S(X)$ is given by

$$\text{BLP}[s_0(X)|S(X)] = \beta_1 + \beta_2(S(X) - E[S(X)]) \quad (\text{W2})$$

where $\beta_1 = E[s_0(X)]$ is the average treatment effect (ATE) and the second parameter $\beta_2 = \text{Cov}(s_0(X), S(X))/\text{Var}(S(X))$ is called heterogeneity predictor loading parameter as it captures any additional heterogeneity in treatment effects. It captures how well the proxy $S(X)$ approximates $s_0(X)$ with $\beta_2 = 1$ when $S(X)$ is a perfect proxy for $s_0(X)$, and $\beta_2 = 0$ if $S(X)$ is uncorrelated with $s_0(X)$ and/or the treatment effect is homogenous, $s_0(X) = s_0$. Thus, rejecting the hypothesis that $\beta_2 = 0$ means that there is both heterogeneity in treatment effect and the CATE predictions are correlated the true CATE. The parameters β_1 and β_2 can be estimated using Weighted Least Squares (WLS) on the main sample using the proxies $B(X)$ and $S(X)$ that were previously estimated on the auxiliary sample,

$$y_i = \alpha_0 + \alpha_1 B(X_i) + \alpha_2 S(X_i) + \beta_1(T_i - p(X_i)) + \beta_2(T_i - p(X_i))(S(X_i) - E[S(X_i)]) + \varepsilon_i, \quad (\text{W3})$$

Given the propensity score $p(X_i)$, the weights are the inverse of the variance of T_i ,

$$\text{weight}(X_i) = \left(p(X_i)(1 - p(X_i)) \right)^{-1} \quad (\text{W4})$$

Sorted Group Average Treatment Effects (GATEs)

The second feature estimated by the Chernozhukov's procedure is the average treatment effect of non-overlapping groups of units (e.g., donors) as sorted and categorized by their predicted CATEs. The sorted GATEs are given by $E[s_0(X)|G_k]$ where G_k indicates membership to group k , $k = 1, \dots, K$ with groups sorted from smallest to largest treatment effects. The GATEs parameters γ_k can be estimated using WLS on the main sample using the proxies $B(X)$ and $S(X)$ that were estimated on the auxiliary sample,

$$y_i = \alpha_0 + \alpha_1 B(X_i) + \alpha_2 S(X_i) + \sum_{k=1}^K \gamma_k (T - p(X)) 1(i \in G_k) + \varepsilon_i \quad (\text{W5})$$

with the weights defined as in (W4) and $1(i \in G_k)$ indicating whether i belongs to group k . One can test for treatment effect heterogeneity by testing $\gamma_1 = \dots = \gamma_K$.

Partial Dependence Plots (PDPs)

Partial dependence plots visualize the relationship between a pre-treatment covariate and the predicted treatment effect $S(X)$ (Friedman 2001). For each covariate X , we regress the proxy on the pre-treatment covariate allowing for a quadratic function,

$$S(X_i) = \alpha_0 + \alpha_1 X_i + \alpha_2 X_i^2 + \varepsilon_i. \quad (\text{W6})$$

We then plot the predicted values across the complete range of X , averaged across the 1,000 splits, together with the SEs across the 1,000 splits.

Accounting for Uncertainty

For all three features described above, Chernozhukov et al. (2020) account for the *estimation* uncertainty and the *splitting* uncertainty induced by randomly partitioning the data. Inference is based on the medians of p -values and medians of confidence intervals across all data splits, and then adjusts their nominal confidence level to account for the splitting uncertainty. The final confidence level is $(1 - 2\alpha)\%$ and the adjusted p -value is twice the median of the split-dependent p -value. Chernozhukov et al. (2020) show that the estimators are normally distributed conditional of the sample split and under mild regularity conditions.

The original code is available in the GenericML package. Our adapted version can be found on OSF: https://osf.io/4nzsw/?view_only=d6fe47c83bd6493c8039b76bb1aa9ad0.

Reference

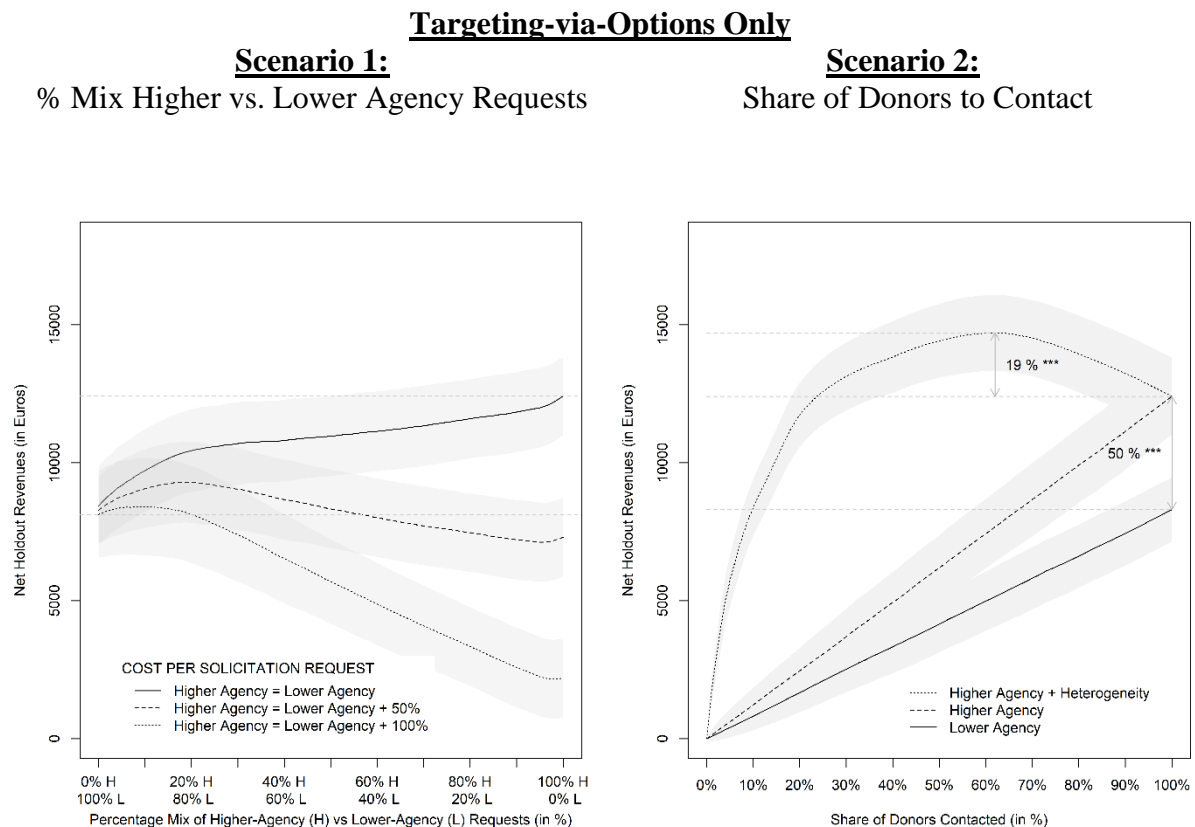
- Chernozhukov, V., Demirer, M., Duflo, E., and Fernández-Val, I. (2020), "Generic Machine Learning Inference on Heterogenous Treatment Effects in Randomized Experiments," *arXiv preprint arXiv:1712.04802*.
- Friedman, J.H. (2001), "Greedy Function Approximation: A Gradient Boosting Machine," *Annals of Statistics*, 29 (5), 1189–1232.
- Welz M., Alfons, A., Demirer, M. and Chernozhukov, V. (2022), "GenericML: Generic Machine Learning Inference." *R package version 0.2.2*. URL: <https://CRAN.R-project.org/package=GenericML>.

WEB APPENDIX I.
OFF-POLICY EVALUATION FOR ALTERNATIVE SPECIFICATIONS OF THE CAUSAL FOREST IN STUDY 3

We used two alternative specifications of the causal forest estimation that investigate the CATEs of each strategy to enhance sense of agency separately. For the first one, we re-specify the treatment variable as $T = 1$ in the high targeting-via-options condition and $T = 0$ in the low targeting-via-options condition. For the second one, we re-specify the treatment variable as $T = 1$ in the high targeting-via-amounts condition and $T = 0$ in the low targeting-via-amounts condition. We follow the same steps as for the main analysis and use the same two scenarios and values for the cost.

Results are consistent with the main analysis. Figure WI.1 shows the results of the two scenarios of the off-policy evaluation when focusing on a single treatment rather than combining them. As indicated in our main analyses, targeting-via-options has a large effect (50%, $p < .001$, top panels) on holdout revenues. The effect of targeting-via-amounts is also significant but somewhat smaller (27%, $p < .001$, bottom panels). In both cases, accounting for donor heterogeneity offers additional gains in net holdout revenues of, respectively 19% ($p < .001$) and 21% ($p < .001$).

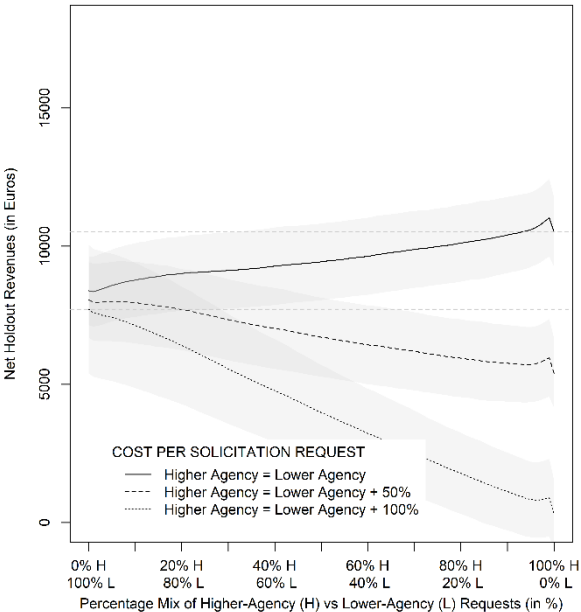
Figure WI.1: Off-Policy Evaluation for Targeting-via-Options Only and Targeting-via-Amounts Only



Targeting-via-Amounts Only

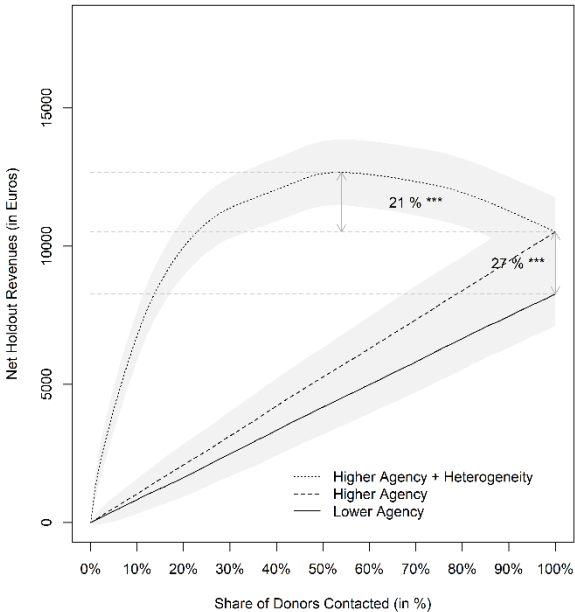
Scenario 1:

% Mix Higher vs. Lower Agency Requests



Scenario 2:

Share of Donors to Contact



WEB APPENDIX J.
OFF-POLICY EVALUATION UNDER ALTERNATIVE COSTS OF AGENCY APPEALS IN STUDY 3

This Web Appendix provides the full results of the off-policy evaluation under scenario 2 when the cost of a higher-agency request is $cost_1 = €1.5$ and $cost_1 = €2$. Results for $cost_1 = €1$ are reported in the paper.

Results in Figure WJ.1 highlights the importance of accounting for heterogeneity when the cost of contact increases. The higher the cost of contacting donors, the greater the value of selectively choosing a subset of donors to ensure the effectiveness of the fundraising campaign. Results also confirm that the prediction models are doing a good job at capturing heterogeneity between donors such that the most responsive donors are prioritized over the less responsive ones (inverted U shape).

Figure WJ.1: Off-Policy Evaluation for $cost_1 = €1.5$ (left panel) and $cost_1 = €2$ (right panel)

