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Mapping charitable giving preferences from 3 million decisions worldwide

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Extended Abstract

In the United States alone, there are over one and a half million registered charities [1], which annually receive nearly half-a-trillion dollars in the United States alone [2], and many more worldwide. The scale and importance of charitable giving has provoked great academic interest, including studies on ways to increase the likelihood and size of donations [3] and why individuals may not give to charities that have the highest impact [4]. Such studies are commonly conducted in a 'one-off' manner and with limited variation in experimental stimuli [5]. They also often abstract away from personal relationships (e.g. duty to relatives) and their relevant influence on moral decision-making [6]. Further, experiments are commonly conducted among Western, Educated, Industrialized, Rich, and Democratic ('WEIRD') [7] populations. Together, this leaves us with a fragmented understanding of charitable giving.

Building on the growing field of experimental ethics, we created a charitable giving 'serious game' [8]. In this Internet game, participants are asked to make 10 dichotomous charitable-giving decisions. We deployed a multi-factorial design, which enabled the equivalent of thousands of 'one-off' experiments to be run. Decision scenarios were generated by co-varying eight factors. We deploy 300 levels (reflecting the number of recipients) for the effectiveness factor and between 2 and 8 levels for the remaining 7 factors. This is akin to running an experiment with tens of thousands of conditions. Scenarios were defined by elements of 'who' will receive the donation, 'where' the recipients are located, and 'what' is the charitable domain (Figure 1). Over 280,000 people from 200 countries and territories participated in the game, generating over 3 million decisions, some incentivized.

In addition to replicating some findings from the literature (e.g. identifiable victim effect, preference for younger people), our results reveal two key insights. First, we find that, above certain thresholds, the charity's effectiveness plays the dominant role, across cultures, in driving donation decisions, overshadowing all other effects tested (see Figure 2). Moreover, the preference for giving funds to self or a relative is the largest obstacle to giving effectively (i.e. benefiting the most recipients, and assuming equal benefit among recipients). To grasp the scale of the challenge, we compare the number of strangers that are needed to overwhelm preferences for oneself or relatives. Our model suggests that the difference between helping a stranger and giving to oneself (ΔP=0.155, se=0.002), is akin to the difference between helping one or three strangers (ΔP=0.159, se=0.003). Meanwhile, replacing a stranger with a relative (ΔP=0.334, se=0.002) results in the same effect size as replacing one stranger with six strangers (ΔP=0.354, se=0.003). Simply put, our results suggest that preferences for oneself or a relative could be overwhelmed by an opportunity to help 3 or 6 strangers, respectively. This suggests that while individuals may not always act in a utilitarian fashion, if enough strangers can be assisted, then preferences will shift towards helping strangers. This is consistent with a 'threshold effect' for utility overriding partiality.

Second, we identify heterogeneity in the effect size of different experimental factors, and assess which other experimental factors drive this. In the aftermath of the 'replication crisis' in psychological science, identification of heterogeneity of effects is especially important for both advancing scientific understanding and policy application [9]. Our approach for assessing heterogeneity can be thought of as a meta-analysis within our multi-factorial study. We subsetted the data to create 'imagined experiments' for each charitable 'who', 'where' and 'what' factor (Figure 3 (a)). In these 'imagined experiments', we extract scenarios with at least 30 participants per condition. In each 'imagined experiment', we fix different factors in donation decisions while allowing the main factor of interest to vary.

Consider the identifiable victim effect as an example. We generated 180 imaginary experiments and their respective average marginal probabilities for preferring to donate to an identified recipient over an unidentified counterpart. Consistent with a meta-analysis of 41 studies that found only small identifiable victim effects [10], the modal outcome was positive though approached zero. Perhaps surprisingly, in 26% of these 180 'imagined experiments' identifying a victim reduced the likelihood of them receiving a donation. This invites further exploration of what factors, if any, systematically drive heterogeneity for the identifiable victim and other main factors of interest for which we generated data. To do this, we generate causal trees [11]. In Figure 4 (b), we present a causal tree for the identifiable victim effect. This causal tree reveals that age is the most important factor in driving heterogeneity of identifiable victim effects among all of those that we experimentally vary.

Our findings paint a richer picture of human prosociality, and highlight the importance of large-scale, multi-factor experiments in understanding human prosociality.

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Figures

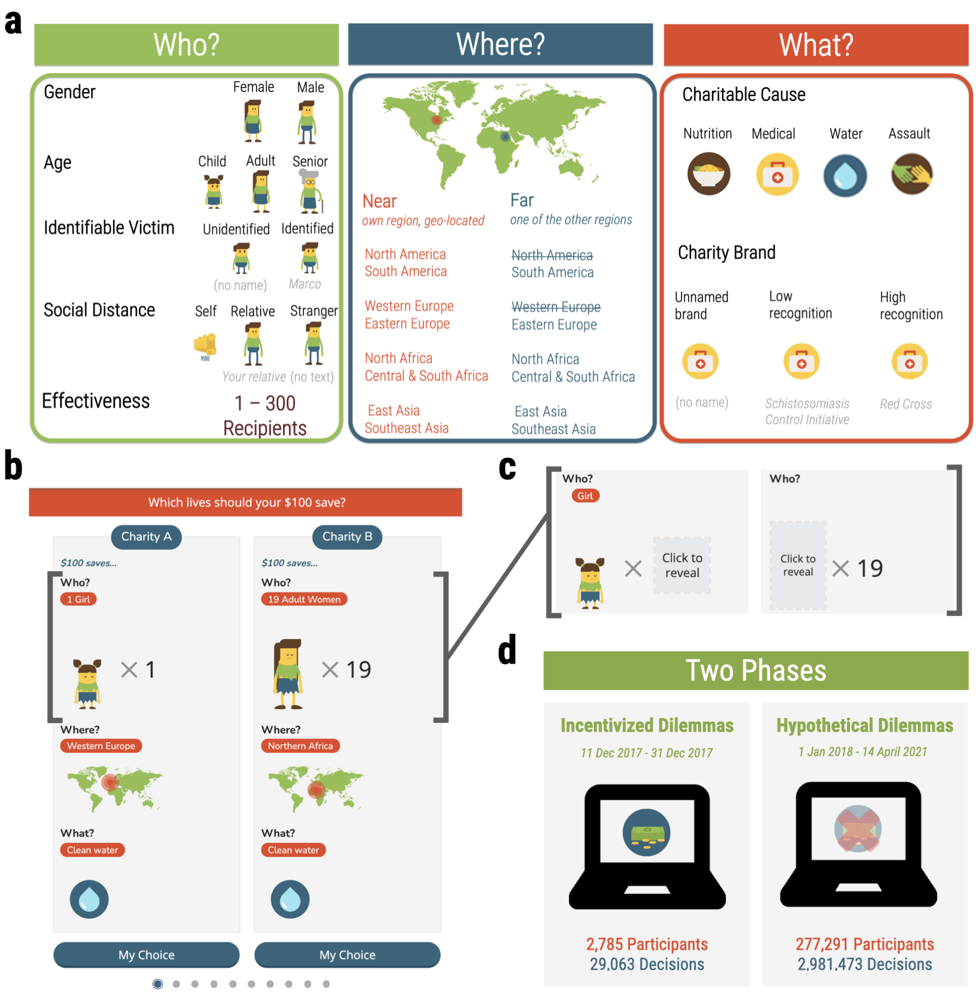

Figure 1: Design, interface, and incentivization phases. (a) Experimental design and factors. Each choice consists of three elements: 'who?' (describing recipients); 'where?' (describing the location of recipients), and 'what?' (describing the charitable domain and relevant charitable institutions). Each element consists of multiple factors (e.g., 'what' consists of 'charitable cause'' and 'charity brand' factors). Each factor consists of multiple levels (e.g., 'Age' factor consists of 'Child', 'Adult', and 'Senior' levels). Levels are presented randomly in two choices constituting each dilemma, an example of which is shown in the user interface. **(b)** My Goodness user interface. Participants are informed that they have $100 to donate and must choose between giving to Charity A or Charity B. In this example, Charity A would save the life of '1 Girl' located in 'Western Europe' by providing her with 'Clean Water' (left), while Charity B would save the lives of '19 Adult Women' located in 'North Africa' by providing them with 'Clean Water' (right). The prompt question is "Which lives should your $100 save?" **(c)** Deliberate Ignorance. In ~20% of scenarios, one or more pieces of information pertaining to the 'who', 'what' and 'where' of the charitable decision were obscured. Participants were informed that the obscured information could be revealed with a click, making it a largely costless exerciseess to reveal additional information. In this example, for the donation to Charity A, the number of girls that would be 'saved' by the donation is obscured. For Charity B, participants are informed that 19 people will be saved, though the age and gender of the recipients are obscured. **(d)** Two phases of the game. Initially we presented incentivized dilemmas where real money was used to implement all decisions by two randomly chosen participants. Subsequently, hypothetical dilemmas were presented wherein no real money was used. The website stated prominently when the decisions were incentivized.

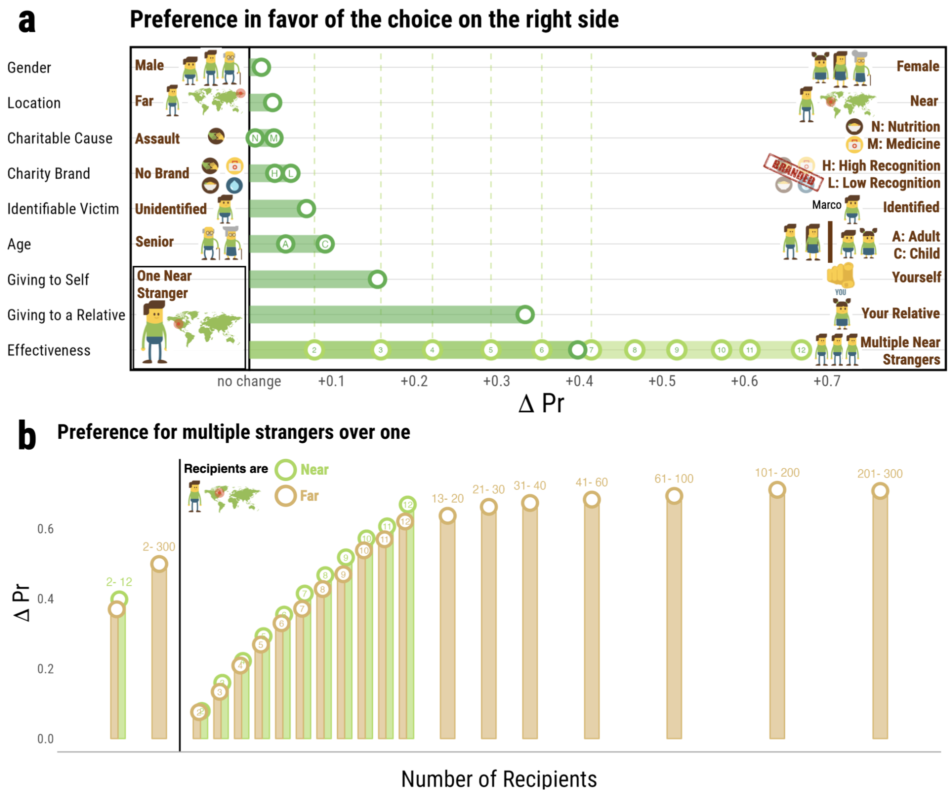

Figure 2. Global Preferences. (a) Average marginal component effect (AMCE) for each preference (n = 804,354). In each row, Δ Pr is the difference between the probability of donating to recipients possessing the attribute on the right, and the probability of donating to recipients possessing the attribute on the left, aggregated over all other attributes. For example, in the row labeled "identifiable victim", the probability of donating to a "Identified" recipient is 0.07 (se=0.002) greater than the probability of donating to an "Unidentified" recipient, while for "Gender", the probability of donating to female recipients is 0.01 (se=0.0006) greater than the probability of donating to male recipients. The 95% CIs of the means are omitted due to their insignificant width. The last row, labeled "Effectiveness", shows effect sizes for each number of stranger (i.e., not relatives or self) recipients (2 to 12) who are "Near" (i.e. in the same region as the participant) as compared to one near stranger; the effect size for 7 recipients overlaps with the mean effect of the attribute. The row "Cause" shows the effect of changing the cause from "assault" (helping recipients recover from an assault) to "N: Nutrition" (providing recipients with nutritious meals) or "M: Medicine" (providing recipients with medical help), which overlapped with water (not shown). The row "Charity Brand" shows the effect of adding a name to the charity that has either a "H: High Recognition" or "L: Low Recognition". The row "Age" shows the effect of replacing "Seniors" recipients (left) with an equal number of either "A: Adult" or "C: Child". Comparison in "Identifiable Victim" row is conditional on having one recipient on each side (one named recipient vs. one unnamed recipient). Comparisons in the rows "Giving to Self" and "Giving to a Relative" are conditional on having one near recipient on either side; this recipient is a stranger on the left side of both rows. **(b) Preferences for multiple strangers by location.** The marginal probabilities for giving to multiple 'near' and 'far' strangers numbering up to 12, and for giving to 13-300 'far' strangers, both relative to one stranger. The average effect (equal weight given to each number of recipients) of location of recipient is minimal over the range 2-12 strangers (near: 0.398 (se=0.002), far: 0.369 (se=0.010)). However, decomposition of this average location effect reveals that preference for giving to 'near' strangers increases with the number of recipients. With reference to 'far' strangers, a scope insensitivity for giving emerges; the change in probability of giving to one stranger, relative to giving to 2-300 strangers (equal weight given to each number or range of participants presented) is 0.499 (se=0.010).

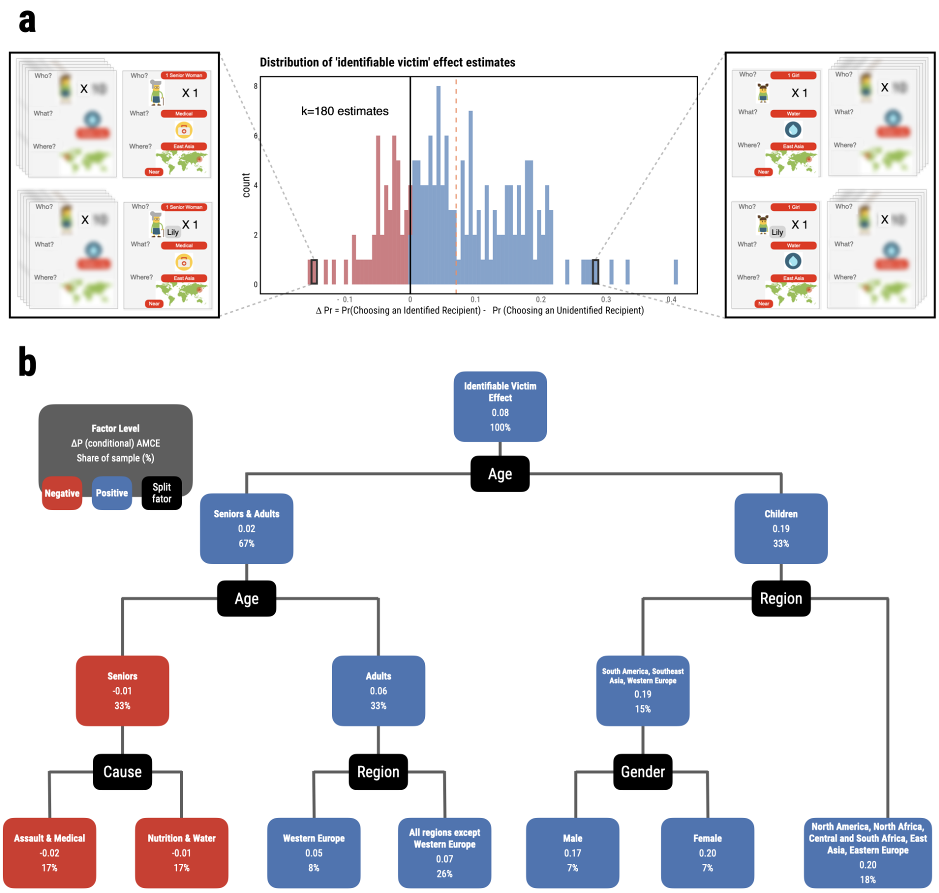

Figure 3. Estimate Distribution of effects for each factor. (a) Explanation of calculation for the identifiable victim effect on charitable giving. To generate a distribution of marginal probability of choosing an identified 'victim' (here, by simply giving a regionally-appropriate name to a charitable recipient) over an unidentified recipient. We first extracted scenarios in which there were at least 30 observations of identified and unidentified characters respectively for unique combinations of factors, other than charitable recipient identification. This marks what we describe as a series of 'imaginary experiments,' in which identification of the recipient is the factor that is varied. For each of these 'experiments' (k=180 for identifiable victim effect), we calculate the probability of choosing an identified and an unidentified character respectively. That is, for both the identified and unidentified character subsets of conjoint decisions, we calculate the probability of choosing the identified and unidentified characters respectively. Note that in expectation, the 'other' cards should not differ between the identified and unidentified character subsets. The difference between the probability of choosing an identified over an unidentified character is then calculated for each unique scenario. These marginal probabilities are then plotted as a distribution. The average marginal probability is marked with a vertical dashed line, here ~10 ppts. That is, there is a weak preference to give charity to identified characters relative to unidentified characters. For the scenario on the left-hand-side of the panel, which relates to an older woman located in the East Asia region (the same region as geo-located participants making this decision) who would receive funds from an unnamed medical charity, identifying the woman with a name ('Lily') reduced the probability of her being chosen to receive a donation by 15 percentage points. By contrast, the right-hand-side of the panel highlights a unique configuration of factors (also located in East Asia, who would receive a donation unnamed water (rather than medical) charity), in which the same identified character is 29 ppts more likely to be chosen over the unidentified equivalent. **(b)** Causal root tree for the identifiable victim effect. The most important experimental factors that causally drive variation in the identifiable victim effect. This causal tree reveals that the most important experimental factor driving heterogeneity of effects is age. Specifically, scenarios with children identified with a name amplifies the average effect effect size (i.e. ΔP=0.170 vs. ΔP=0.056), while identified adults diminish the average effect (ΔP=0.047). Moreover, identified seniors generate a negative effect (ΔP=-0.022). Among seniors and adults though not children, region and gender of recipient are the next most important factor driving heterogeneity of the main identifiable victim effect.