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Can Charitable Appeals Identify and Exploit Belief Heterogeneity?

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Can Charitable Appeals Identify and Exploit Belief Heterogeneity?

Abstract

Charitable fundraisers frequently announce giving by others, and research shows that this can increase donations. However, this mechanism may not put information about peers to the most efficient use if it is costly to inform individuals who are indifferent to peer actions or causes some individuals to give less. We investigate whether a simple mechanism without incentives can predict heterogeneity in charitable responses to peer decisions. We elicit beliefs about donations in a baseline solicitation, and in subsequent solicitations we randomly assign information about others' donations. We find that elicited beliefs are often logically inconsistent and that many subjects fail to update beliefs when treated. However, elicited beliefs can predict heterogeneous treatment effects if individuals are engaged and the information is salient.

JEL-Codes: D010, D640, A130.

Keywords: charitable, donation, norm, social preferences, peer effects, experiment.

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1 Introduction

Charitable giving has garnered attention from researchers seeking to uncover the nature of social preferences or to address the under-provision expected due to a donation's positive externality. One influential group of these studies has built a body of evidence that individuals increase their donations when informed of high levels of giving by others (Hermalin, 1998; List and Lucking-Reiley, 2002; Vesterlund, 2003; Potters et al., 2007; Alpizar et al., 2008; Martin and Randal, 2008; Shang and Croson, 2009; Huck and Rasul, 2011; Bekkers, 2012; Karlan and List, 2012; Smith et al., 2013; Huck et al., 2015; Kessler, 2017; Klinowski, 2020; van Teunenbroek and Bekkers, 2020). This pattern arises for both large and small stakes, as experiments involving donations of \$4 or less have also found that such giving responds positively to the average donated by others (Drouvelis and Marx, 2020) and the percentage of others donating (Frey and Meier, 2004; Heldt, 2005). The average effect of such information might, however, mask considerable heterogeneity if donors differ in their preferences or beliefs. If this is the case, incorporating information about others' giving into a charitable solicitation could be wasteful or even counterproductive.

Whether a fundraiser can improve on the average treatment effect of providing such information depends on whether heterogeneity can be predicted. Charities regularly engage in and can pay considerable amounts for data about donors in what is sometimes called "prospect research." Such research typically examines markers of wealth and past donation patterns to identify donors who might have the capacity and willingness to make generous donations. We consider an alternative form of donor research that gauges individuals' beliefs about others' donations. If beliefs can be elicited at minimal cost to the fundraiser and the prospect, and if donations depend on these beliefs, then information treatments can be targeted

towards those who would have positive treatment effects.

Our study tests whether collecting a small amount of information about beliefs in one solicitation can allow a fundraiser to predict and take advantage of donor belief heterogeneity. To do so, we employed a short survey following one solicitation and then randomly assigned information in later solicitations. Each solicitation invited subjects to donate some of their earnings from completing a survey for another study. In the baseline solicitation, we elicited subjects' beliefs about amounts donated by others and about the amount they themselves would donate if they knew that the average donation of others was \$0.50 or \$1. We elicited these beliefs without providing incentives for accuracy, thereby testing whether fundraisers can reasonably collect predictive information in their campaigns. We elicited beliefs about three statistics of baseline donations: the mean, the share of subjects making any donations, and the share donating \$1 or more. We found dispersion in beliefs about each statistic, with a number of subjects overestimating and underestimating each.

We then conducted experiments to test for heterogeneity in treatment effects of information about others' baseline donations. As we described in our pre-registration, the quantity of interest was not the average treatment effect but whether the information collected in the baseline solicitation predicts treatment effect heterogeneity. Our three treatments each informed subjects about one of the statistics of baseline donations. We elicited beliefs again after the experimental solicitation to check whether the treatments shifted beliefs from their baseline value towards the value shown in the treatment. After assessing this, we test whether donations change in the same direction as beliefs about others' behavior.

Results of our first experiment were mixed. The treatment that revealed the mean donation significantly shifted beliefs about that mean towards the provided value. However, any treatment effect on donations did not differ significantly be-

tween these those with high versus low beliefs at baseline, and it did not depend on whether the subject reported beliefs about their own donations that indicated they would give more. The treatments that revealed the shares of subjects donating more than zero or at least \$1 had little effect on beliefs about these statistics.

In a second experiment, we made the share-donating treatment more salient. Speculating that its effects on beliefs had been minimal because subjects missed the information, we amended the treatment by placing the information near the beginning of the solicitation in bold text. This version of the treatment shifted beliefs towards the value provided. Donations did not change along with beliefs in the full sample, though we document that more than half of all subjects reported impossible combinations of baseline beliefs, such as a nonzero mean donation with zero percent donating. If we treat this as an attention check and restrict the sample to subjects with logically consistent baseline beliefs, then we find that treatment effects differ significantly by baseline beliefs, with treatment shifting donations in the same direction as beliefs. The restricted sample also gives a larger point estimate for the mean-donation treatment, with a magnitude consistent with extant estimates of the effect of beliefs on donations.

We conclude that it would be possible but likely difficult for charities to identify and exploit belief heterogeneity. More than half of our subjects report beliefs that are logically inconsistent and therefore not reliable in predicting how they will respond to treatment. Among those treated with information, two thirds or more appear to not see the information, even after efforts to increase its salience. Such lack of attention by potential donors would limit a fundraiser's ability to use belief heterogeneity to increase donations. However, the sizable donation responses to changes in beliefs about others' donations suggest that fundraisers could profitably exploit belief heterogeneity among donors who have a stronger connection with the charity and hence might be more attentive and accurate in the belief elicitation

stage.

In examining whether individuals attempt to follow the donation patterns of others, our study was similar to the literature on “conditional cooperation” in public goods games. In a review of research with public goods games, Chaudhuri (2011) discusses a bevy of studies finding that half or more of their subjects are conditional cooperators whose contributions are increasing in the contributions of others, typically by slightly less than dollar-for-dollar (e.g. Keser and Van Winden, 2000; Fischbacher et al., 2001; Kurzban and Houser, 2005; Gächter, 2007; Kocher et al., 2008; Fischbacher and Gächter, 2010; Kessler et al., 2020; Croson, 2007; Kumru and Vesterlund, 2010). In the public goods game, conditional cooperation may be due to reciprocity, but Bardsley and Sausgruber (2005) also find an effect of informing subjects about the amounts given by a group other than their own, thereby identifying conformity that may also occur in giving to charity.

There are several reasons that information about others’ donations might affect one’s own giving decision. The donations of others might signal charity quality (Glazer and Konrad, 1996; Vesterlund, 2003; Andreoni, 2006; Potters et al., 2007; Bracha et al., 2011), but we have minimized this factor in our experiment by allowing donors to choose from a list of charities and not informing them about which charities others chose. Individuals may donate amounts similar to others to improve their image or social status (Andreoni and Bernheim, 2009; Ariely et al., 2009; Kumru and Vesterlund, 2010) or because they feel social pressure (DellaVigna et al., 2012; Andreoni et al., 2017), particularly when peers are soliciting the donations (Meer, 2011; Meer and Rosen, 2011; Castillo et al., 2014, 2017). In our experiment, we give subjects no reason to think that anyone other than the researchers will observe their donation.

van Teunenbroek et al. (2020) conduct a systematic review of 35 studies and propose factors that may determine whether social information affects donations.

The factors that they propose included perceptions of social norms. Social norms are rules for appropriate behavior (Elster, 1989; Ostrom, 2000; Krupka and Croson, 2016). They should be commonly recognized, but incentive-compatible elicitation has shown heterogeneity in beliefs about what others consider appropriate (Krupka and Weber, 2013; Drouvelis et al., 2019). We considered adherence to an uncertain social norm to be the most likely reason for a treatment effect in our setting.

Finally, we note that our study reflects recent interest in targeting treatments among heterogeneous donors. Cagala et al. (2015) study how to target a gift-exchange treatment, while Adena and Huck (2019) propose matching gifts with thresholds that are personalized to each potential donor. Both of these papers employ heterogeneity in past donations, whereas our paper studies heterogeneity according to elicited beliefs about one's own and others' donations.

The paper proceeds as follows. Section 2 describes the design and results of the baseline solicitation and elicitation. Section 3 presents the first experiment, and Section 4 presents the second. Section 5 concludes.

2 Baseline Solicitation

The baseline solicitation and survey captured variation in donations and reported beliefs. This section describes how we elicited these and provides descriptive analysis that motivated the choices in the experimental design.

2.1 Design and Procedures

We conducted our study using Prolific (www.prolific.co), a web-based platform for recruiting participants, and oTree (Chen et al., 2016). We restricted our sample to be of US nationality, and 80 percent of our sample is nationally representative in

terms of age, sex, and race.¹

Subjects were recruited to complete a survey on judicial politics (Garcia, 2020). Prolific users who met our selection criteria saw a link for this survey and the description “This study on court-case decisions pays \$4 (£3.05) and will take approximately 20 minutes.” In this way, subjects earned income through a task unrelated to donating.² The baseline solicitation and those in each experiment followed variants of the same survey task. The consent screen explained that “If you complete the survey, you will be paid \$4, which is the sum of the \$1 shown on Prolific and \$3 to be paid as a bonus.” Base payments on Prolific cannot be donated in a way that researchers can observe, but by paying \$3 of the \$4 as a bonus, we were able to give subjects the option of donating any portion of the \$3.

The solicitation occurred after subjects had completed the survey, and it was unannounced as in checkout campaigns and other charitable solicitations. The text read “Thanks, you’re almost done! When you finish, you will be paid a \$3 bonus. Would you like to donate some of your bonus to one of these charities fighting the COVID-19 pandemic? These are some of Charity Navigator’s highest-rated charities.” Subjects were then able to select from the following list of charities that we collected from a web page in which the charity evaluator Charity Navigator listed highly rated charities fighting the effects of the coronavirus pandemic.³ Below this list were two lines of text: “How much of the \$3 bonus would you like to donate?

¹With some uncertainty about the number of subjects who would provide complete responses, we initially collected a nationally representative sample of 309 subjects before discovering that the Prolific feature for adding subjects does not allow nationally representative samples to be increased by less than 300 subjects at a time.

²Previous research has demonstrated that donation responses may vary depending on whether income is earned or unearned (Cherry et al., 2002; Cherry et al., 2005; Harrison, 2007; Kroll et al., 2007; Erkal et al., 2011; Reinstein and Riener, 2012; Carlsson et al., 2013; Tonin and Vlassopoulos, 2017; Drouvelis et al., 2019; Drouvelis and Marx, 2020).

³The charities (and total donated to each across all sessions) were Save the Children (\$184.36), CDC Foundation (\$83.45), National Foundation for Infectious Diseases (\$57.50), Matthew 25: Ministries (\$52.00), United Way Worldwide (\$45.11), and Give Directly Inc. (\$42.50). Because the choice of charity was not a topic of inquiry, we chose not to randomize the order so that the screen was identical for subjects.

_____ You will receive a receipt for this tax-deductible donation.”

The solicitation was followed by the belief-elicitation screen. Text at the top stated “Please answer these final questions to help us learn a bit more about donations in Prolific surveys.” The questions were as follows

- How much of the \$3 bonus do you think other participants donate on average?
\$_.____
- How much of the \$3 bonus do you think you would donate if
 - You knew that others gave \$0.50 on average? \$_.____
 - You knew that others gave \$1.00 on average? \$_.____
- Out of 100 people, how many do you think donate? ____
- Out of 100 people, how many do you think give \$1 or more? ____

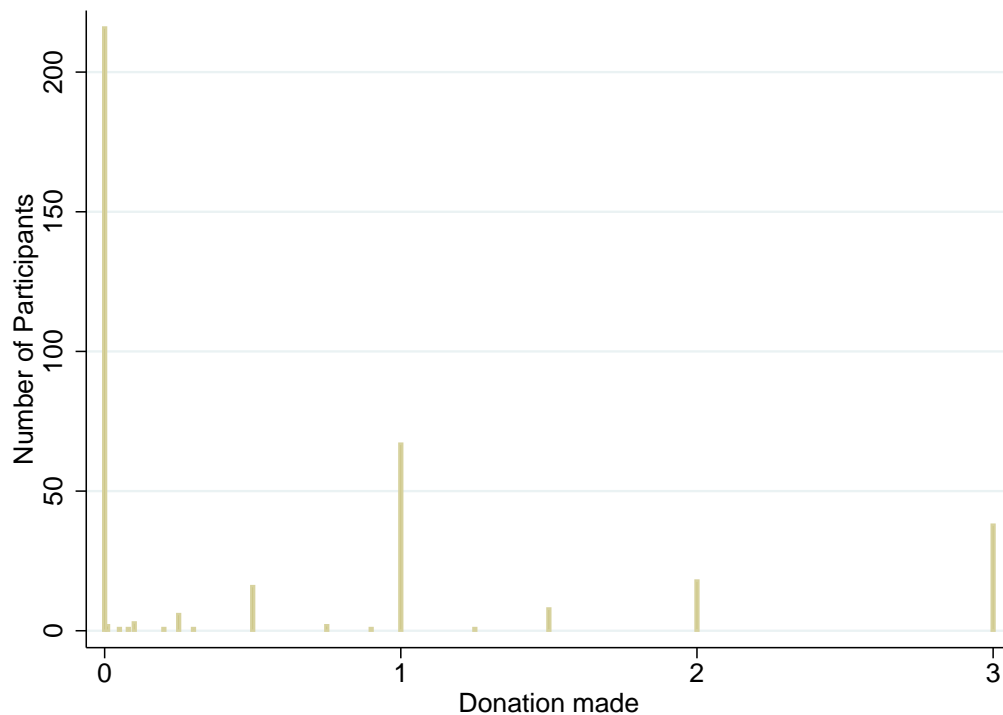
This screen of questions always followed the solicitation so that all subjects knew what solicitation the questions were regarding, and they were appeared as listed here in the order we thought most intuitive. A key component of our design is that we purposefully did not incentivize responses to these questions. Our choice reflected a desire to mimic a realistic tool for a fundraiser to use, recognizing that it would be unusual to incentivize accurate prediction within a fundraising interaction in the field. Responses to these questions in our study should therefore contain inaccuracies or biases that are similar to those in data that a charitable organization would collect.

In total, we collected data from 382 individuals. Of these, 51 percent identified as female and 65 percent as white. One benefit of using Prolific was the dispersion of subject ages: 40 percent were ages 18 to 34, 33 percent ages 35 to 54, 26 percent ages 55 to 74, and 2 percent 75 or over.

2.2 Results of Baseline Solicitation

Figure 1 shows the distribution of donations made. The maximum amount that subjects could donate was \$3, which was the decision made by 9.9 percent of subjects. The modal donation was \$0, while the second most popular choice was \$1. On average, donations were equal to \$0.64 (s.d. = 0.96), which is line with results from similar donation experiments. Subjects often chose round numbers or increments of \$0.50, though there are some who chose smaller fractions.

Figure 1: Distribution of baseline donations

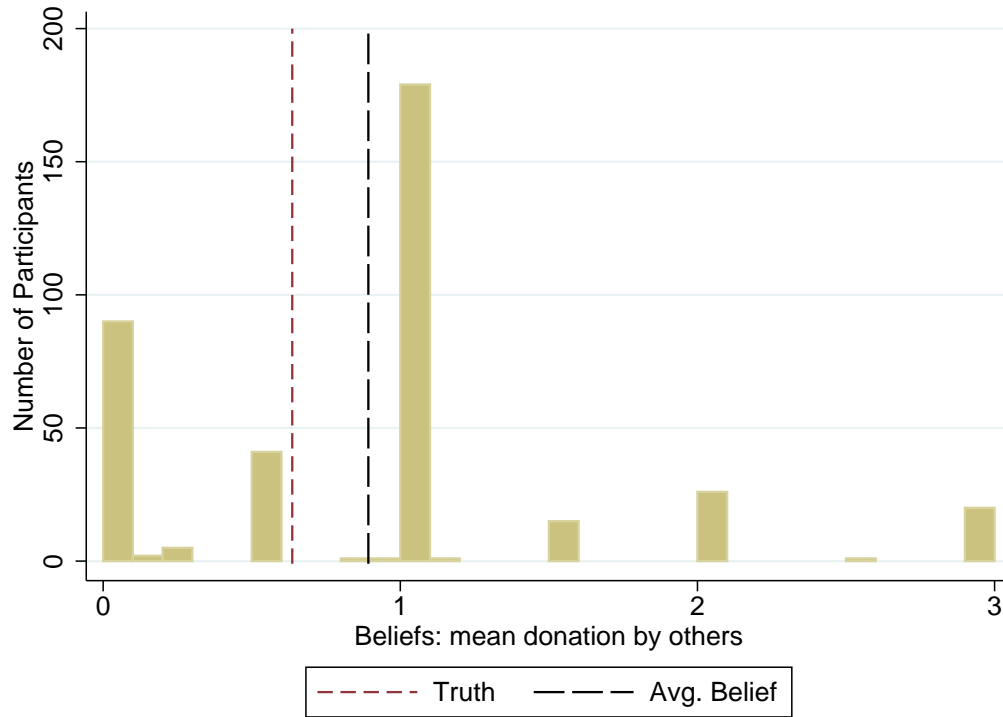


Notes: N = 382. Bin width = 0.1. Mean = \$0.64.

Figure 2 displays the distribution of beliefs about the mean of others' donations. We found that subjects expect others to donate a bit more than they actually do (average = \$0.89, s.d. = 0.75). Subjects' own donations were positively correlated with their beliefs about the average of others' donations ($\rho = 0.34$; $p < 0.001$). Causality here could run in either direction, with subjects wanting to give an amount

similar to what they think others give, or with subjects stating beliefs that justify their donation choice. Our experiments attempted to examine causality by randomly assigning information about the giving of others.

Figure 2: Baseline beliefs about mean donation



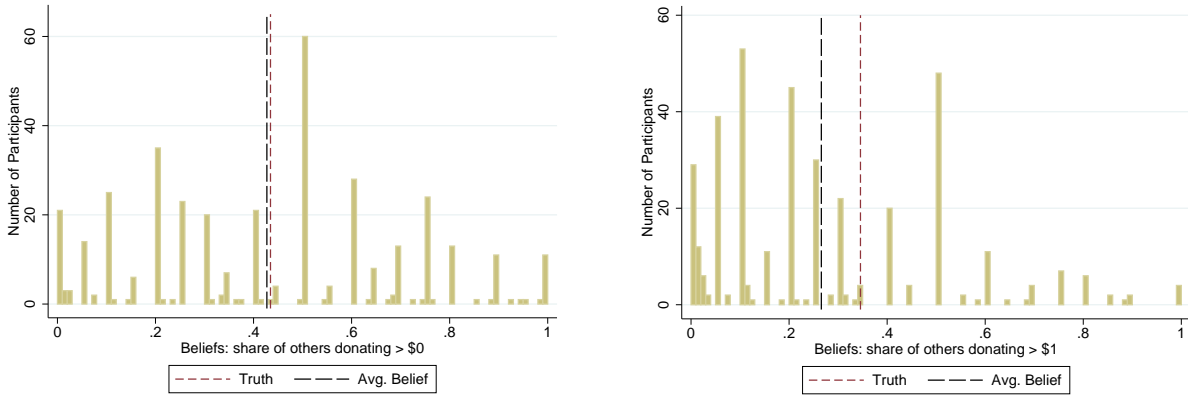
Notes: Bin width = 0.1.

It is worth noting the discrete nature of the responses in Figure 2. The most common belief was that other subjects give exactly \$1 on average, and other multiples of \$0.50 were common choices. “Heaping” at round numbers has been observed in many contexts (Barreca et al., 2011), and in our context there are few round numbers to choose from. Here, heaping could be due to low precision in subjects’ beliefs.

Figure 3 displays the distribution of beliefs about the share of others donating particular amounts. We constructed these shares by dividing subjects’ responses to the “Out of 100 people” questions by 100. The first panel of the figure shows subjects’ beliefs about the number of individuals making a positive donation. Here

the average belief (0.427) was very close to the truth (0.434) that we observed in the data. The most common response was a belief that 50% of others donate a positive amount. The second panel of Figure 3 shows beliefs about the share donating \$1 or more. Here the average belief (0.27) somewhat underestimated the true share of subjects who give \$1 or more (0.35).

Figure 3: Beliefs about share of others donating threshold amounts
 Donate > \$0 Donate ≥ \$1



Notes: Bin width = 0.01.

Comparing the subjects' beliefs about each of the donation statistics, we found that the majority of subjects report logically inconsistent beliefs. Let b_i^{avg} , b_i^0 , and b_i^1 denote, respectively, the reported beliefs of subject i about the average donation, share donating, and share donating \$1 or more. It is logically inconsistent for a subject to hold beliefs with any of the following properties: $b_i^1 > b_i^0$, $b_i^{avg} < 0.01b_i^0$, $b_i^{avg} > 3b_i^0$, $b_i^{avg} < 1b_i^1$, or $b_i^{avg} > 3b_i^1 + 0.99(b_i^0 - b_i^1)$. We found that 238 subjects (62 percent) reported beliefs that were not logically consistent. This fact provided suggestive initial evidence that unincentivized beliefs are imprecise and would be difficult to exploit to increase donations. We could have treated this as an attention check and dropped subjects reporting beliefs that are not consistent with each other, but it could be that any one of these subjects' beliefs is predictive, and the three treatments in our design each test for heterogeneity related to a particular be-

lief. We therefore invited subjects with logically inconsistent beliefs to participate in the experiments, but we estimate each regression with and without these subjects included.

The other baseline questions asked subjects how much they would donate conditional on particular values of donations by others. We found that only 49 subjects (13 percent) report that they would donate more if others donate \$1 than they would if others donate \$0.50. These self-proclaimed conditional donors (similar to “conditional cooperators” in the public goods literature) reported distributions of beliefs that were similar to those who reported that their donations are not conditional on those of others: across the three belief measures, the largest difference in means between the two groups was 0.019, and the largest difference in absolute error was 0.028. The similarity in the two groups’ belief distributions offered the opportunity to test whether self-proclaimed conditional donors do in fact respond more to information about the giving of others.

3 Experiment 1

3.1 Design of Experiment 1

Our primary randomized trial took place during the last week of August 2020. We invited all participants from the baseline solicitation. Subjects were again asked to decide how much to donate from the \$3 fixed bonus they received. The list of selected charities was identical to the ones available at baseline, and we asked the same questions about beliefs following the donation decision in the experiment, allowing us to estimate treatment effects on beliefs.

Our experiment was designed to answer the following research questions:

R1. Do reported hypothetical conditional donations predict the effect of information about the average donation of others?

R2. Do reported beliefs about the donations of others predict the effect of information about:

R2a) the average donation?

R2b) the share of individuals donating?

R2c) the share of individuals donating \$1 or more?

Our design randomized information between subjects. In the control group (denoted by CG) subjects made their donation decisions without being provided any information about giving behavior in the baseline solicitation. In our treatments, we accompany the solicitation of subject i with information about past donations from the first wave. The “Average Donation” treatment (T^{avg}) stated that “Participants in our last Prolific survey donated an average of \$.64.” The “Share Donating” treatment (T^0) stated that “43% of participants in our last Prolific survey made a donation.” The “Share Donating \$1+” treatment (T^1) stated that “35% of participants in our last Prolific survey donated \$1 or more.” These were the true statistics, and hence we do not employ deception.

We distributed subjects between treatment arms so as to address question **R1** and question **R2**. Research question **R1** relates to heterogeneity in reported hypothetical conditional donations. We used the elicited hypotheticals to define $\Delta hypo_i$ as the predicted treatment effect of learning the average of others’ donations. We calculated this using a linear combination of the hypothetical donations conditional on others’ donations of \$0.50 and \$1 to approximate the response to the information that the average was \$0.64. Only 87 subjects reported that their donation would change, i.e. that $\Delta hypo_i \neq 0$. We therefore split all of these subjects between CG and T^{avg} , with the remaining subjects distributed across the four treatment arms.

To promote balance across treatment arms and enhance precision for our heterogeneity analyses, we utilized stratification in our randomization. We stratified based on the sign of four variables: $\Delta hypo_i$, b_i^{avg} , b_i^0 , and b_i^1 . Because only 13

subjects have $\Delta hypo_i < 0$, we did not further subdivide them using the other variables. Because subjects with $\Delta hypo_i > 0$ are assigned to either CG or T^{avg} , we did not subdivide them based on b_i^0 , or b_i^1 . We created a separate category for subjects with $b_i^{avg} = 0$. Then, to the extent that we could do so without reducing the count within strata to single digits, we further subdivided strata into “high” and “low” groups based on whether their b_i^0 (which was the most accurate belief on average) was above or below the median for their stratum. We assigned subjects in each stratum as evenly as possible across treatment arms and then as needed assigned any additional subject to arms in the following order: Control, then “Average Donation,” and then “Share Donating \$1+.”

Appendix Tables A.1 and A.2 describe the randomization. Appendix Table A.1 details the stratification and displays the number of subjects in each stratum. The only single-digit strata contain exactly four subjects, allowing one to be assigned to each treatment arm. In recognition of the small strata, we follow the recommendation of de Chaisemartin and Ramirez-Cuellar (2020) to cluster standard errors at the stratum level. Appendix Table A.2 shows tests of balance across treatment arms in baseline donations, beliefs, and demographics. None of the coefficients in either panel are statistically significant, nor are any of the F tests of joint significance.

3.2 Estimation

Our goal was to estimate heterogeneous effects across subject types. This necessitates a more complicated estimating equation than what one would use to estimate the average treatment effect. We therefore pre-registered our design in the AEA Registry prior to the experiment. We estimate separate equations for the different types of elicited variation that might predict treatment effects.

To answer question **R1**, we restrict the sample to subjects assigned to either the control group (C) or the “Average Donation” treatment (T1). We estimate the

following regression:

$$Y_i = \alpha + \beta_1 T_i^{avg} + \beta_2 pos\ hypo_i + \beta_3 T_i^{avg} * pos\ hypo_i + \epsilon_i \quad (1)$$

We consider two types of outcomes Y_i : the change in individual i 's belief between the baseline solicitation and the experiment, and the change in the individual's donation. In equation (1), we estimate these outcomes as a function of the treatment dummy variable T_i^{avg} and an indicator $pos\ hypo_i = 1 \{ \Delta hypo_i > 0 \}$ for subjects for whom we should see a positive treatment effect according to their hypothetical donations conditioning on the amount given by others. In this regression, the constant (α) gives the average value of the outcome among those who are in CG and *do not* report hypothetical donations greater than their baseline donation. Similarly, β_2 gives the average value of the outcome among those who are in CG and *do* report hypothetical donations greater than their baseline donation. Coefficient β_1 gives the effect of treatment among CG, while β_3 gives the size of the treatment effect among T_i^{avg} relative to CG. We test whether $\beta_3 = 0$ to assess whether subjects' beliefs about their own donations are predictive of treatment effects.

To answer the three parts of question **R2**, we estimate three regressions. In each, we restrict the sample to the control group and a single. We then estimate the following regression:

$$Y_i = \alpha + \beta_1 T_i^X + \beta_2 f(b_i^X) + \beta_3 T_i^X * b_i^X + \epsilon_i \quad (2)$$

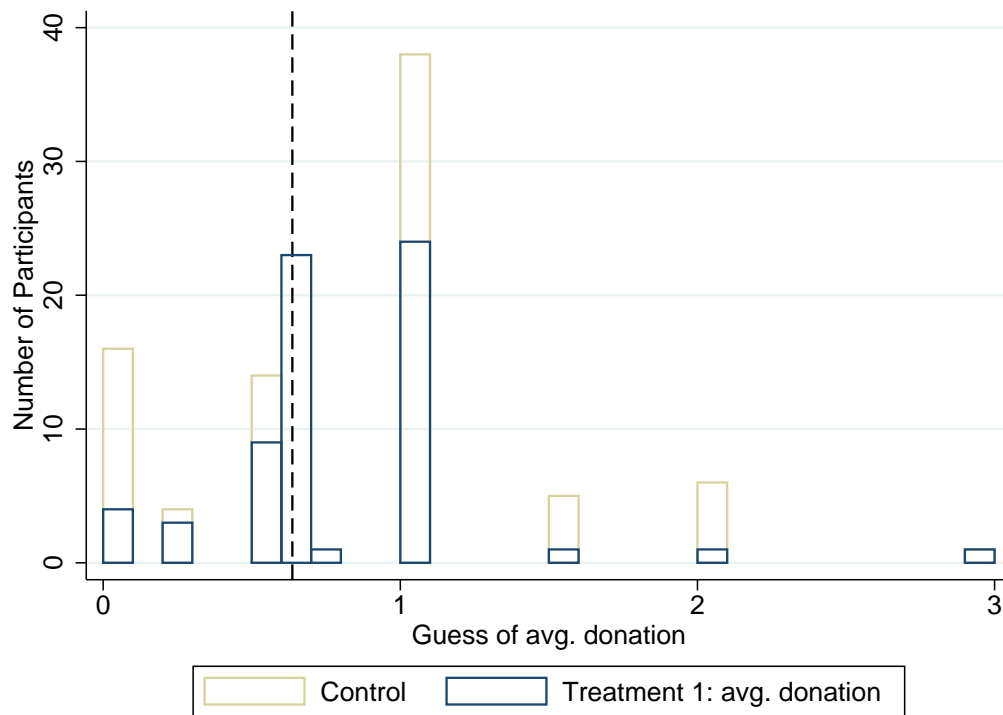
In equation (2), we estimate outcome Y_i as a function of the treatment dummy variable TX_i , an indicator for receiving treatment $X \in \{avg, 0, 1\}$, and the corresponding belief variable b_i^X . The control variable b_i^X captures any differential trends, such as if subjects who were optimistic on the day of the baseline solicitation systematically give less in the experiment, regardless of treatment. For the function $f(b_i^X)$ we employ a full set of randomization-strata dummy variables, which control for

baseline beliefs more flexibly than would a parametric (e.g. linear) control. The coefficient of interest is β_3 , which captures relative treatment effects. If elicited beliefs are predictive, then we would expect information about the true value of the statistic to have a positive (negative) effect on those whose baseline beliefs were below (above) the truth, i.e. we would expect $\beta_3 < 0$.

3.3 Results of Experiment 1

Figure 4 shows the density of beliefs, elicited after the experiment, about the average donation. Among subjects who were treated with the information that the previous average donation was \$0.64, 34 percent reported beliefs strictly between 0.6 and 0.7. No subjects in the control group report such values. The figure also shows that the treatment reduces the likelihood of other values throughout the distribution that subjects would have entered if not for treatment.

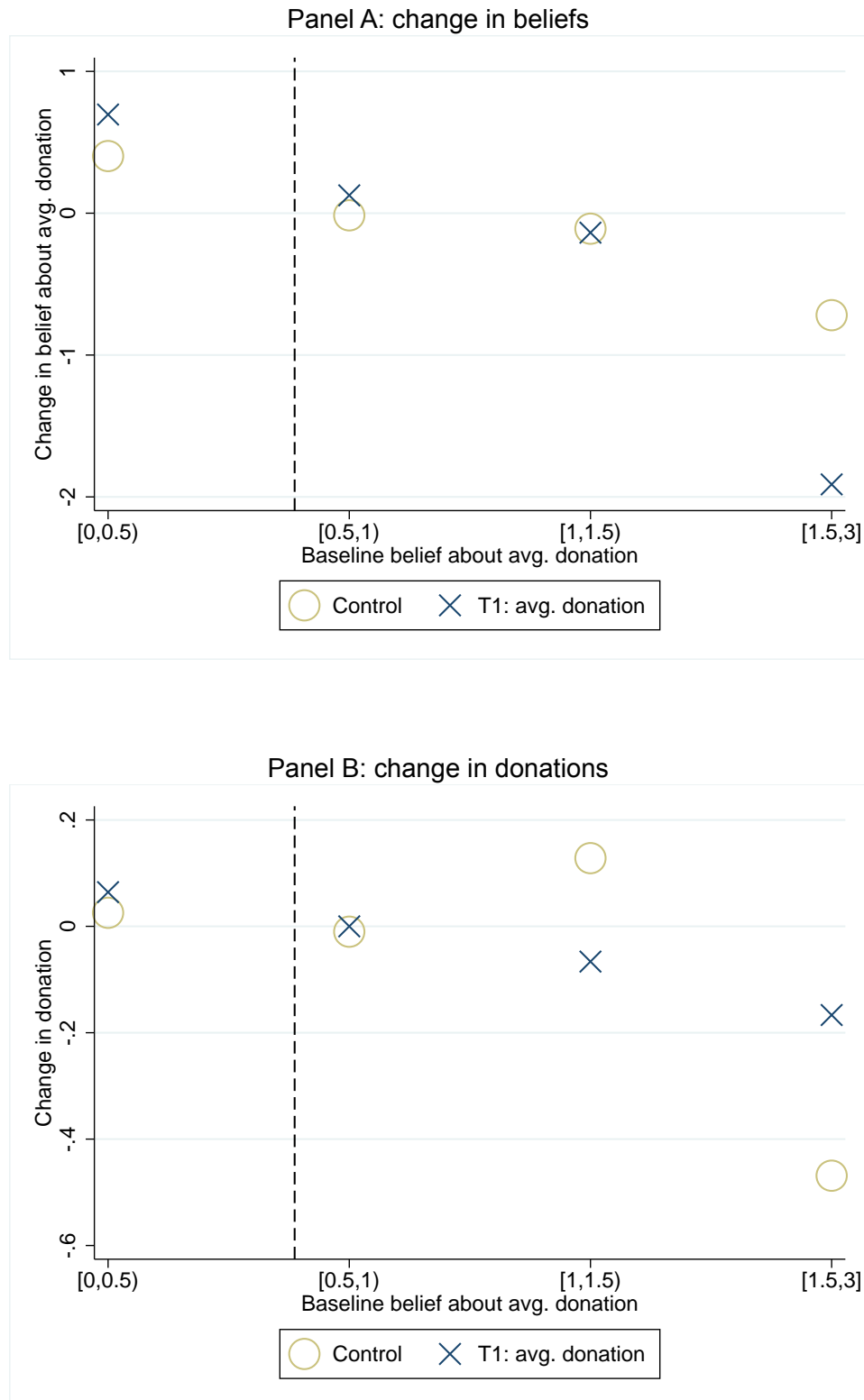
Figure 4: Beliefs after Experiment 1: average donation



Notes: N = 151. Bin width = 0.1. Dashed vertical line indicates mean baseline donation, which was reported to the treatment group.

Figure 5 shows the essence of the estimation strategy. Panel A of the figure plots the change from baseline beliefs to post-experiment beliefs as a function of baseline beliefs and treatment. The x axis is binned to group subjects by ranges of baseline donations. The downward sloping pattern among the control group demonstrates mean reversion, as those with low baseline beliefs increased towards the mean and those with high baseline beliefs decreased towards it. This regression to the mean suggests that initial beliefs were not firmly held. The expected effect of treatment was to increase regression to the mean, or rather to the baseline mean donation of \$0.64. It was therefore expected that the change in beliefs among those with a low value would be more positive for the treatment group than the control group, while the opposite would be true at high baseline levels, and this is what we observe in the figure.

Figure 5: Effects of average-donation treatment



Notes: N = 151. Dashed vertical line indicates baseline average donation.

Panel B of Figure 5 describes heterogeneity in treatment effects on donations. In Panel B, the outcome variable is the difference between a subject's donation before and after the experiment. For subjects whose baseline guess was that the average donation was less than \$1.50, treatment shifts donations in the same direction in which it shifted beliefs. In contrast, CG subjects with higher baseline beliefs reduced their donations by more than \$0.40, on average, while there was less reduction among the T^{avg} group. This weakens the connection between elicited beliefs and donations. We note that 18 of the 22 subjects with a baseline belief of \$1.50 or more had logically inconsistent beliefs. Higher values may reflect subjects who entered their beliefs about the mean conditional on donating rather than the unconditional mean. In our regression analysis, we examine how results change when we drop subjects whose elicited beliefs are logically inconsistent.

Appendix Figure A.1 shows that the share-donating treatments had less effect on the distributions of relevant beliefs. In both the treatment and control groups there is wide dispersion, with beliefs spanning the full range from 0 to 1. Treated subjects are more likely to report values near the value stated in the treatment but by a small amount. For T_i^0 , the treatment group is only 4.3 percentage points more likely to appear in the bin containing the treatment value of 0.43 ($p = 0.085$). Thus, it appears that fewer than 5 percent of subjects absorbed the information provided through the treatment, and the effect is even smaller for T_i^1 .

Regression results appear in Table 1. In each panel of the table, we display the coefficient of interest from estimates of equation 1 (columns 1-2) or equation 2 (columns 3-8). We estimate each regression with the full experimental sample and then dropping subjects who reported beliefs that were not logically consistent with each other.

Panel A shows estimated effects of each treatment on the relevant belief. We first test whether treatment effects of T^{avg} on beliefs depend on whether a subjects'

reported conditional donations imply a treatment effect on donations ($pos\ hypo_i$ in equation 1). We find such heterogeneity in the full sample (column 1) but not among subjects with internally consistent beliefs (column 2), suggesting that both variables proxy for subject attentiveness. Subjects with $pos\ hypo_i = 1$ are 19 percent more likely to have logically inconsistent beliefs ($p = 0.013$). Recall that these are subjects who reported hypothetical donation amounts that were different from the amount they had just donated.

The remaining columns of Panel A of Table 1 test for heterogeneous effects by baseline beliefs about others' donations. Columns (3) and (4) show that T^{avg} *did* have the expected effect of shifting beliefs about the average donation, in particular causing a relative reduction among those who reported a higher value at baseline. Columns (5) through (8) show that the other treatments, T^0 and T^1 , did not significantly shift beliefs towards the truth in either the full sample or subsample. We would therefore not expect these treatments to cause a relative change in donations either.

Table 1: Results of Experiment 1

Panel A: beliefs								
Change in belief about:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Avg. donation		Avg. donation		Share >0		Share 1+	
$T^{avg} * 1\{\text{hypothetical}>0\}$	0.47 (0.18)**	0.06 (0.14)						
$T^{avg} * \text{Baseline belief: avg.}$			-0.65 (0.15)***	-0.65 (0.14)***				
$T^0 * \text{Baseline belief: >0}$					-0.09 (0.10)	0.05 (0.16)		
$T^1 * \text{Baseline belief: 1+}$							-0.03 (0.10)	-0.10 (0.10)
Observations	151	57	151	57	100	42	110	41
R-squared	0.04	0.03	0.19	0.15	0.01	0.01	0.05	0.06
Drop logically inconsistent		X		X		X		X

Panel B: donations								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T^{avg} * 1\{\text{hypothetical}>0\}$	-0.00 (0.21)	-0.51 (0.62)						
$T^{avg} * \text{Baseline belief: avg.}$			0.06 (0.10)	-0.30 (0.28)				
$T^0 * \text{Baseline belief: >0}$					-0.04 (0.44)	-0.43 (0.36)		
$T^1 * \text{Baseline belief: 1+}$							0.06 (0.34)	-0.37 (0.45)
Observations	151	57	151	57	100	42	110	41
R-squared	0.00	0.03	0.00	0.02	0.00	0.01	0.00	0.01
Drop logically inconsistent		X		X		X		X

Notes: All regressions include the uninteracted heterogeneity variable and treatment variable in addition to their displayed interaction. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel B of Table 1 tests for heterogeneous effects on donations. No coefficients are statistically significant. To assess whether they are economically significant, we consider the estimates in columns (3) and (4) because we found that T^{avg} significantly shifted b_i^{avg} . Comparing magnitudes between panels, we find that in the full sample (column 3), each \$1 increase in perceived beliefs by others only increased

a subject's own donation by \$0.09 ($=0.06/0.65$). In the subsample (column 4), each \$1 increase in perceived beliefs by others increased a subject's own donation by \$0.46 ($=0.30/0.65$). Among those reporting logically consistent beliefs, then, the estimated effect-size ratio is similar to the values of 0.52 to 0.55 found in the incentivized experiment of Drouvelis and Marx (2020). A potential explanation for the stronger response in column (4) is that the new treatment induced accurate beliefs among subject whether or not their baseline beliefs were meaningful, which would imply that the change in beliefs was only meaningful for those who reported meaningful beliefs at baseline. However, standard errors are too large to draw strong conclusions.

In summary, no treatment had effects that could be usefully predicted from baseline heterogeneity. Only the average-donation treatment shifted beliefs as expected, and the ensuing effects on donations only had the expected sign in a small subsample that appears to have been relatively attentive. Even in this subsample, elicited hypothetical donations were not predictive of the donation response to the average-donation treatment, and the other treatments did not shift the relevant beliefs as expected. It was therefore important that we measured changes in beliefs, which could be viewed as a manipulation check that determined that treatment did not affect beliefs as expected for many subjects. If we had assumed an effect on beliefs and only measured changes in donations, then we might have drawn the unwarranted conclusion that changing beliefs about the giving of others does not affect giving.

4 Experiment 2

Our first experiment failed to reveal predictable heterogeneity in treatment effects. While the findings would be consistent with beliefs having no second-stage effect

on donations, we cannot conclude that there is no second stage because the treatments mostly did not have a predictable first-stage effect on beliefs. We therefore decided to run a second experiment that tested whether making the information from one of the treatments more salient would have a greater effect on reported beliefs. If so, then future research could employ a larger sample to test whether the salient treatment also has effects on donations.

4.1 Design of Experiment 2

For maximum power, Experiment 2 employed a single treatment and control. We selected one of the treatments that had not significantly altered reported beliefs, namely the sentence “43% of participants in our last Prolific survey made a donation.” Rather than appearing in between the charity options and the field for donation amount, in this experiment this sentence appeared on the line after the first line that said “Thanks, you’re almost done! When you finish, you will be paid a \$3 bonus.” The sentence was in bold font and followed by the same content as in Experiment 1, starting with “Would you like to donate some of your bonus...” Appendix Figure A.2 provides a screen shot of the share-donating treatment in each experiment. We updated the AEA experiment registry before launching the second experiment.

Subjects were selected from the sample that had completed the baseline survey. Sample inclusion and stratification were determined by the baseline belief about the share of others donating. We excluded subjects whose reported belief was equal to zero and those who had entered a share from 0.4 to 0.59. The latter exclusion removed subjects whose baseline beliefs were already close to the truth. Subjects were then grouped by baseline-belief bins of $(0, 0.2)$, $[0.2, 0.4)$, $[0.6, 0.8)$, and $[0.8, 1]$. The potential subjects in each bin were randomly divided between treatment and control groups. Both versions of the survey were opened on December 21 and

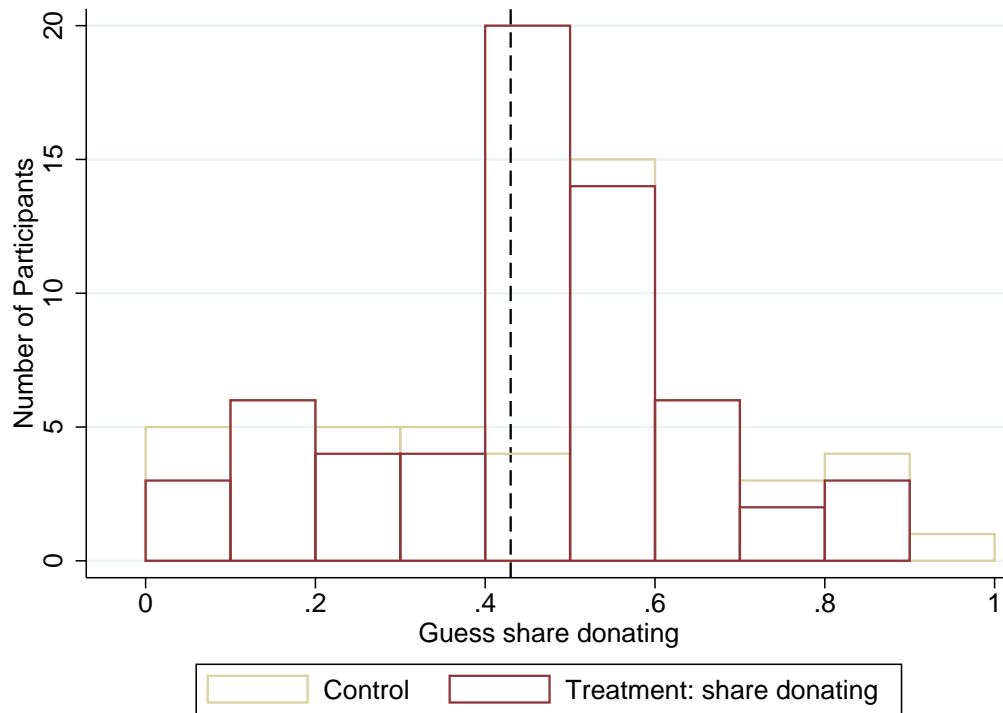
closed on December 31, at which time 54 members of the control group and 62 members of the treatment group had completed Experiment 2.

Other procedures were similar to Experiment 1. The solicitation again followed a political science survey experiment. The list of selected charities was identical to the list in the baseline solicitation and Experiment 1. Among the questions that followed the solicitation, we removed those that asked how much the subject would donate based on amounts of donations by others, and we retained the questions about statistics of others' donations.

4.2 Results of Experiment 2

Figure 6 shows that the more salient information treatment increased the odds of subjects reporting a belief close to the value of 43 percent provided in the treatment. The treatment increased the probability of a subject reporting a belief $b \in [0.4, 0.5)$ by 24 percentage points ($p < 0.01$). Even so, 69 percent of subjects continue to report beliefs outside of this bin, and there is no increase in the adjacent bins. Thus, it appears that subjects who respond to the information continue to be in the minority.

Figure 6: Beliefs after Experiment 2



Notes: N = 115. Bin width = 0.1. Dashed vertical line indicates baseline share donating.

Regression results appear in Table 2. The outcome in columns (1) and (2) is the change in a subject's belief about the share of others donating (relative to that subject's belief in the baseline survey). The coefficient of interest has the expected negative sign, with treatment causing subjects with higher (lower) beliefs at baseline to revise these down (up) towards the value of 43 percent that was provided in the treatment. Indeed, both estimates are more negative than those in the first experiment. The heterogeneous effect on beliefs is significant at the 0.05 level for the full sample and the 0.1 level for the subsample whose baseline beliefs were logically consistent. We conclude that increasing the salience of the treatment improved its effectiveness, at least for some subjects.

Table 2: Results of Experiment 2

	(1)	(2)	(3)	(4)
Change in:	Belief		Donation	
T^0 * Baseline belief: >0	-0.17 (0.06)**	-0.28 (0.11)*	-0.04 (0.17)	-0.33 (0.08)**
Observations	116	46	116	46
R-squared	0.02	0.02	0.01	0.00
Drop logically inconsistent		X		X

Notes: All regressions include a dummy variable for treatment and dummy variables for each of the randomization strata bins of baseline beliefs. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Columns (3) and (4) of Table 2 display estimated effects on donations. For the full sample, there is no predictably heterogeneous treatment effect, much as in the first experiment. However, when we restrict the sample to subjects with logically consistent baseline beliefs, we find a statistically significant effect with the expected negative sign. As with the results of T^{avg} in the first experiment, it appears that the new treatment induced accurate beliefs among both subject types and so the change in beliefs was only meaningful for those who reported meaningful beliefs at baseline. Unlike the effects of T^{avg} , the heterogeneity in the treatment effect of the salient version of T^0 is statistically significant, despite the smaller sample size.

We assess the magnitude of the effect by comparing the estimates for beliefs and donations. We find that for each one-percentage-point decrease in a subject's perceived share of others making a donation, the subject's own donation falls by 1.2 ($= 0.33/0.28$) cents. To compare the estimate to that from T^{avg} , we estimate the regression in column (4) but with the outcome the change in belief about the average donation by others. The estimate of interest from the interaction term is -0.29 ($p = 0.007$). In other words, a subjects donation responds by \$1.14 ($= 0.33/0.29$) for each \$1 change in perceived average donations by others.

Thus, there appears to be scope for charities to exploit belief heterogeneity. For each subject, we can calculate the predicted effect of applying the 1.2 cents-

per-percentage-point effect size to the difference between 0.43 and the subject's baseline belief. Averaging these predicted effects across all subjects, we find that convincing all subjects that 43 percent of others donate would *reduce* the \$0.70 average baseline donation by \$0.02. In contrast, if the treatment were only applied to the subjects whose baseline beliefs were below the truth, it would nearly double their average donation, from \$0.32 to \$0.61. However, this calculation assumes that the treatment effect on beliefs is perfect and that the effect on donations is the same for all subjects as what we estimate for subjects with consistent baseline beliefs. Our research shows that these assumptions are unrealistic and that charities would likely need to find better ways to identify and treat beliefs to exploit belief heterogeneity for more than moderate gain.

5 Conclusion

Our experiment tests whether beliefs about one's own giving and that of others, elicited without incentives, predict how a person's giving responds to information treatments. Our baseline survey found sufficient dispersion in beliefs to test whether they are informative of treatment effects. Our experiments showed that information about others' donations affected a minority of subjects' beliefs, with non-salient versions of share-donating-amount treatments having no significant effect, but that when effective these treatments shifted beliefs from the baseline value very close to what subjects were told. This implied an increase in the belief for some subject and a decrease for others, and we test whether treatment affect donations in the same direction as beliefs. We find a null result for the full sample, most likely because many subjects reported baseline beliefs that were not meaningful. When restricting to subjects who reported logically consistent baseline beliefs, we obtain estimates that are larger in absolute value and statistically significant for the heterogeneous

effect of the salient share-donating treatment on donations.

Our mixed results highlight the question of when and where it would be most likely that a charity could elicit beliefs that would predict heterogeneous effects of information about others' donations. Our setting is a solicitation for a small donation following a transaction, similar to those of purchasers outside of a supermarket (Andreoni et al., 2017) or sellers on eBay (Elfenbein et al., 2012). Subjects are therefore likely less engaged than a charity's "warm list" of past donors would be and perhaps more like the "cold list" of potential new donors. Consistent with this, Bekkers (2012) finds that similar treatments are only effective when potential donors are asked to estimate others' generosity just before the solicitation. Future research might test, then, whether beliefs are more predictive when solicited from a charity's warm-list donors. Regardless of the setting, our study demonstrates the importance of conveying the information about others' donations in a clear and salient way.

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Appendix

Table A.1: Randomization strata

hypo_effect	rel_belief_avg	rel_belief1	rel_belief0	subjects
neg	n/a	n/a	n/a	13
pos	neg	n/a	n/a	17
pos	pos high	n/a	n/a	10
pos	pos low	n/a	n/a	32
pos	zero	n/a	n/a	15
zero	neg	neg	neg	19
zero	neg	neg	pos	13
zero	pos high	neg	n/a	11
zero	pos high	pos high	pos	14
zero	pos high	pos low	pos	22
zero	pos low	neg high	neg	24
zero	pos low	neg low	neg	33
zero	pos low	neg high	pos	22
zero	pos low	neg low	pos	13
zero	pos low	pos high	pos	14
zero	pos low	pos low	pos	36
zero	zero	neg high	neg	32
zero	zero	neg low	neg	33
zero	zero	neg	pos	4
zero	zero	pos	pos	4

Notes: Table displays the number of subjects in each of the randomization strata defined by the variables shown in the top row. Variable “hypo_effect” shows the sign of the hypothetical effect of the “Average Donation” treatment (T1), as described in the text. Variable “rel_belief_avg” shows whether the subject’s belief about the average donation was positive relative to the truth, negative relative to the truth, or zero. Variables “rel_belief_belief0” and “rel_belief_belief1” show whether the subject’s belief was positive or negative relative to the truth for, respectively, the share of subjects who donate and the share of subjects who donate \$1 or more. In all columns, “n/a” indicates a distinction that is not applicable because we do not incorporate it into the stratification. In addition to positive (“pos”) or negative (“neg”), we split strata into “high” or “low” where possible, indicating those above or below the median value of the variable.

Table A.2: Balance tests

Panel A: Subjects in estimation of heterogeneity by hypothetical change in donation

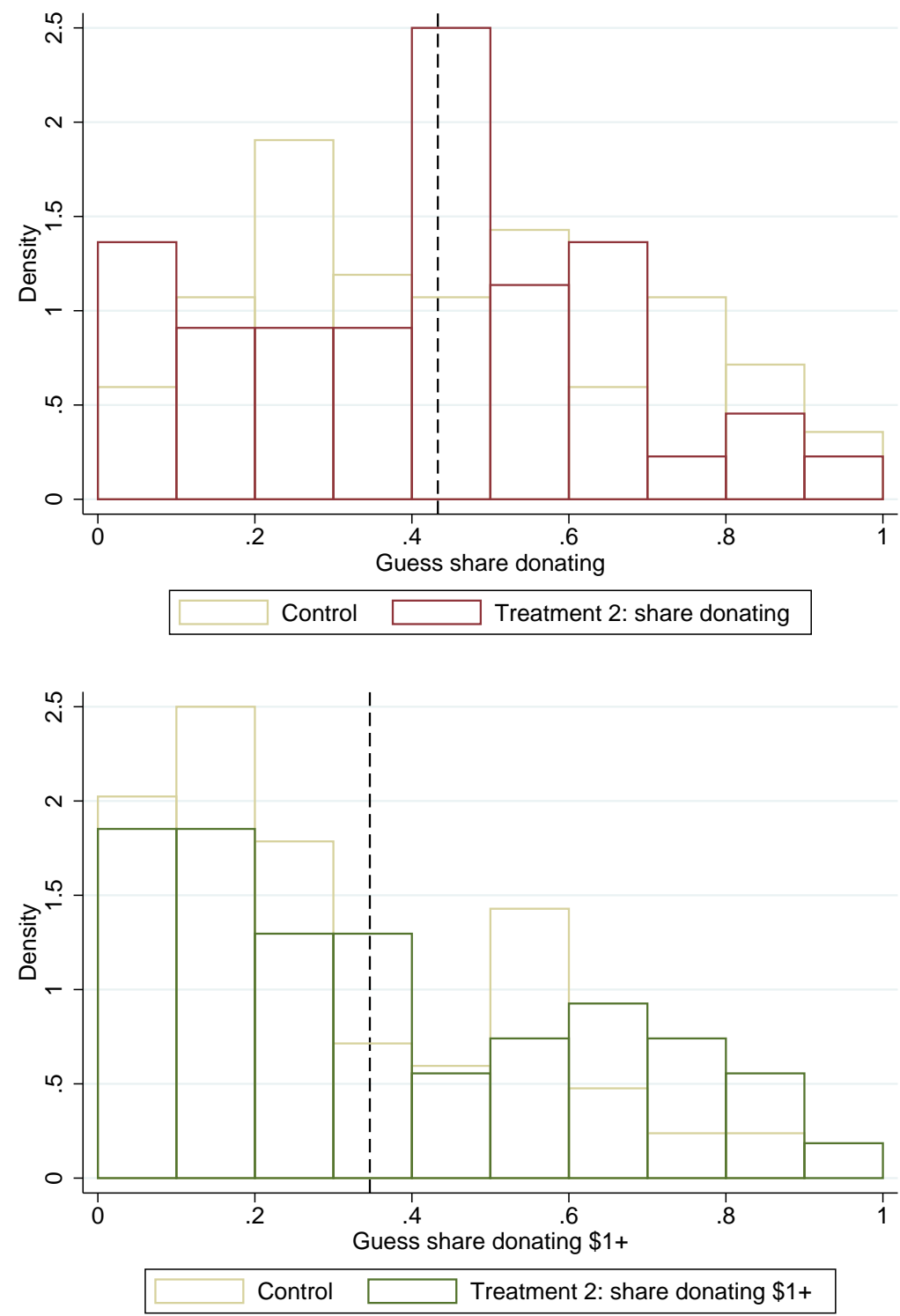
	(1) donation	(2) delta hypo	(3) belief1	(4) belief2	(5) belief3	(6) female	(7) age	(8) U.S.-born	(9) student
T1: Average Donation (N=117)	-0.113 (0.114)	0.00336 (0.0635)	-0.0223 (0.0947)	-0.0388 (0.0349)	-0.0185 (0.0290)	-0.102 (0.0643)	-2.071 (2.060)	0.0411 (0.0459)	-0.0378 (0.0523)
Constant	0.594 (0.0839)***	0.144 (0.0461)***	0.913 (0.0679)***	0.448 (0.0247)***	0.273 (0.0204)***	0.581 (0.0445)***	41.72 (1.482)***	0.831 (0.0338)***	0.226 (0.0377)***
Observations	241	241	241	241	241	241	240	241	241
R-squared	0.004	0.000	0.000	0.005	0.002	0.010	0.004	0.003	0.002

Panel B: Subjects in estimation of heterogeneity by beliefs

	(1) donation	(2) belief1	(3) belief2	(4) belief3	(5) female	(6) age	(7) U.S.-born	(8) student
T1: Average Donation (N=75)	-0.105 (0.147)	0.0333 (0.123)	-0.00545 (0.0458)	0.000488 (0.0379)	-0.116 (0.0806)	-3.425 (2.674)	0.0199 (0.0520)	-0.00388 (0.0617)
T2: Share Donating (N=69)	0.199 (0.171)	-0.0152 (0.127)	-0.0236 (0.0447)	0.00299 (0.0389)	-0.0769 (0.0826)	-1.376 (2.863)	0.0106 (0.0541)	0.0692 (0.0678)
T3: Share Donating \$1+ (N=72)	0.135 (0.165)	-0.0423 (0.121)	-0.00841 (0.0465)	0.00385 (0.0387)	-0.105 (0.0818)	2.145 (2.747)	0.0562 (0.0485)	-0.00820 (0.0623)
Constant	0.638 (0.109)***	0.900 (0.0827)***	0.438 (0.0313)***	0.262 (0.0265)***	0.570 (0.0561)***	45.04 (1.940)***	0.873 (0.0377)***	0.177 (0.0433)***
Observations	294	294	294	294	294	293	294	294
R-squared	0.014	0.001	0.001	0.000	0.009	0.015	0.005	0.006
p-value, test of joint significance	0.233	0.946	0.959	1	0.469	0.209	0.652	0.660

Notes: Table displays balance in subject baseline characteristics across treatment arms. Some subjects do not report their age to Prolific. Panel B reports the p-value of an F test that coefficients on all three treatment indicators are zero.

Figure A.1: Beliefs after Experiment 1: share donating threshold amounts



Notes: N = 144 in Panel A, 154 in Panel B. Dashed vertical lines indicate relevant statistic from baseline donation.

Figure A.2: Screen shots of solicitation page with share-donating treatment

Experiment 1

Thanks, you're almost done! When you finish, you will be paid a \$3 bonus.

Would you like to donate some of your bonus to one of these charities fighting the COVID-19 pandemic? These are some of Charity Navigator's highest-rated charities.

- ☐ Save the Children - <https://www.savethechildren.org/> - Medical services
- ☐ Matthew 25: Ministries - <https://m25m.org/> - Relief supplies: health & medical
- ☐ Givedirectly Inc. - <https://www.givedirectly.org/> - Relief supplies: community support & services
- ☐ CDC Foundation - <https://www.cdcfoundation.org/> - Cross-categorical
- ☐ United Way Worldwide - <https://www.unitedway.org/> - Funding local organizations
- ☐ National Foundation for Infectious Diseases - <https://www.nfid.org/> - Education & awareness

43% of participants in our last Prolific survey made a donation.

How much of the \$3 bonus would you like to donate?

 \$

You will receive a receipt for this tax-deductible donation. If you do not want to donate, enter a zero in the box.

Next

Experiment 2

Thanks, you're almost done! When you finish, you will be paid a \$3 bonus.

43% of participants in our last Prolific survey made a donation.

Would you like to donate some of your bonus to one of these charities fighting the COVID-19 pandemic? These are some of Charity Navigator's highest-rated charities.

- ☐ Save the Children - <https://www.savethechildren.org/> - Medical services
- ☐ Matthew 25: Ministries - <https://m25m.org/> - Relief supplies: health & medical
- ☐ Givedirectly Inc. - <https://www.givedirectly.org/> - Relief supplies: community support & services
- ☐ CDC Foundation - <https://www.cdcfoundation.org/> - Cross-categorical
- ☐ United Way Worldwide - <https://www.unitedway.org/> - Funding local organizations
- ☐ National Foundation for Infectious Diseases - <https://www.nfid.org/> - Education & awareness

How much of the \$3 bonus would you like to donate?

 \$

You will receive a receipt for this tax-deductible donation. If you do not want to donate, enter a zero in the box.

Next