Polarization in environmental donations – application to deforestation prevention donation

Dede Long Hongxing Liu Rodolfo M. Nayga Jr.

Professor and Chair

Rnayga@tamu.edu

Department of Agricultural Economics, Texas A&M University

Abstract

One common fund-raising strategy employed by non-profit organizations is through the provision of information to persuade potential donors. We theoretically and empirically analyze how information affects people's willingness to donate (WTD). Our theory suggests when people have different initial beliefs, new information leads to polarization through their understanding and rationalization of social norms. We provide empirical support using an online experiment, demonstrating that environmental and public health information leads to polarization in deforestation prevention donations. Being exposed to information opposite of individuals' existing beliefs reinforces their current opinions. Our results emphasize the implementation of information treatment calls for careful deliberation.

Keywords: environmental donation; polarization; deforestation; social norms; information treatment

Appendix materials can be accessed online at:
https://uwpress.wisc.edu/journals/pdfs/LE-99-1-Long_app.pdf

doi:10.3368/le.080921-0092R

Polarization in environmental donations – application to deforestation prevention donation

INTRODUCTION

While there are many reasons why people behave pro-socially (see Meier (2006) for a survey of the literature),[1] abundant literature in economics and psychology has repeatedly emphasized the importance of "nudges" in promoting pro-social behavior, that is, mechanisms that target cognitive heuristics and influence people's decision-making process without financially incentivizing them or restricting their choice alternatives (Thaler & Sunstein 2008). Many studies have examined the effect of default setting (i.e. pre-select a donation option as the default) (e.g. Andreoni & Payne 2013; Goswami & Urminsky 2016), social norms (i.e. approved choices and actions that most people follow in a community of society) (e.g. Bartke et al. 2017; Krupka & Croson 2016), and social comparison (i.e. providing information on how much a more/less generous donor has contributed) (e.g. Bartke et al. 2017; Croson & Shang 2008; Shang & Croson 2009) in charitable giving. However, the literature on how information affects donation behavior is relatively scarce.[2] Our study aims to fill the gap by theoretically and empirically investigating the impact of information on individuals' environmental donation decisions.

Understanding the effect of information is particularly critical in the realm of environmental donation for two reasons. As public goods, environmental resources are characterized by under-provision because people have incentives to free ride.[3] Non-profit organizations provide mechanisms to promote cooperation, which facilitates collective actions that address the insufficient provision of environmental resources. One common fund-raising strategy employed by these organizations is to inform and persuade potential donors through information. Given the fierce competition between charitable organizations, limited donor resources, and under-financing due to free-riding, evaluating whether information can be used to increase fundraising is crucial. Moreover, despite the scientific consensus of the likely causes and impacts of many environmental problems, much relevant information is unclear or unknown to the general public. More importantly, as demonstrated in a large body of economics and psychology literature, information may be interpreted differently by groups with different beliefs, leading to increasing divergence in public opinions and growing skepticism regarding environmental issues like climate change (see Hornsey et al. 2016 for a meta-analysis of belief in climate change; Birch 2020; Carmichael & Brulle 2017; Guber 2013; Unsworth & Fielding 2014). It is, therefore, important to examine the effect of information, particularly how information interacts with people's initial beliefs.

We first develop a theoretical model to predict the impact of new information on respondents' willingness to donate (WTD) to environmental programs. Our theoretical model shows that new information interacts with respondents' prior beliefs through their rationalization of social norms, which then affects donation behavior. The theoretical model leads to two testable hypotheses. First, respondents' WTD conforms to social norms and varies by their initial beliefs. Second, the new information affects respondents' WTD differently depending on whether it confirms or contradicts their initial beliefs.

We then empirically test these hypotheses through an application of deforestation prevention donation. Despite the widely documented ecosystem services provided by rainforests, deforestation continues to occur at an alarming rate, mostly in tropical forests in Latin America and Southeast Asia (Curtis et al. 2018). Forest degradation leads to rapid biodiversity loss and is responsible for 15 to 25% of global greenhouse gas emissions (Moutinho & Schwartzman 2005; WWF n.d.). In addition, deforestation is also the source of many threats to human health due to pathogen spillovers and outbreaks associated with land-use change and population increase in or beneath forests (Guégan et al. 2020). Recent studies have linked deforestation to the increasing severity and frequency of emerging infectious diseases over the past two decades (e.g. Daszak et al. 2000).[4] While the potential correlation between deforestation and infectious disease outbreaks has been recognized in the scientific community, the general public still lacks relevant information.

We implemented an online experiment with real stakes to test the impact of an information treatment. To alleviate potential hypothetical bias and payment incompatibility issues, we inform the respondents that two winners will be randomly picked out of all participants to receive a $100 bonus, and their WTD amount to the non-profit organization of their choice will be deducted from this bonus. To ensure trust, we provided the donation receipts to the respondents through email. Our results confirm the hypotheses in the theoretical model. We find that respondents' donation conforms to the (descriptive) social norm, which is measured by the expected average donation of others. We also show that the information treatment illustrating the potential correlation between deforestation and infectious diseases interacts with participants' pre-existing beliefs on whether deforestation is an issue and leads to polarization between groups. Specifically, the information treatment increases the donation amount in the group that agrees deforestation is a problem that needs to be addressed and decreases the donation in the disagree group. Taken together, our results show that while information is an important driver promoting people's environmental donation behavior, it can lead to polarization as an unintended consequence.

Our study contributes to three strands of literature. First, we contribute to the literature on the effect of an information treatment on donation behaviors by particularly focusing on the interactions between information and prior attitudes towards environmental issues (Grieco et al. 2018). Given the critical role of privation donations as a source of funding to provide environmental goods and services, our analysis provides important insight that organizations and institutions can leverage when eliciting private donations to combat under-provision issues of public goods.

Second, our findings add to the recent studies reporting that nudges have only limited effect (e.g. Giovanna et al. 2017) or cause backfiring effects and unintended consequences (e.g. Hagmann et al. 2019; Reijula et al. 2018). We demonstrate that being exposed to new information opposite of individuals' existing beliefs may reinforce their current opinions, leading to group polarization. Similar to previous studies documenting that additional information intending to promote donation may negatively impact the financial support towards environmental resources (Goff et al. 2017), our results further emphasize that the implementation of information treatment calls for careful deliberation and execution due to its interaction with individuals' prior beliefs.

Third, our study contributes to the broader discussion of polarization in beliefs and attitudes towards environmental issues such as climate change. One consistent finding in the literature is how people process information based on their own preexisting beliefs. Hornsey et al. (2016) conduct a meta-analysis on climate change beliefs and find values, ideologies, worldviews, and political orientation rather than education, gender, knowledge, or experience dominate people's belief in climate change. Additionally, many studies show that political biases affect how people interpret climate change information (e.g., Leiserowitz 2006) and argue that it may also be related to selective inattention to climate-related words (Whitman et al. 2018). Past work shows that climate change skeptics report greater justifications for not helping the victims after seeing information linking climate change to natural disasters (Chapman & Lickel 2016), our findings further confirm that the divide in beliefs affects how people take in new information and consequently impact their behaviors.

The rest of this paper is organized as follows. Section two describes the theoretical model. Section three presents the experimental design. Section four reports the data. Section five is the empirical model. Section six and seven present the estimation results, discussions, and robustness checks. Section eight concludes.

THEORETICAL FRAMEWORK

Inspired by Konow (2000) and Bejarano et al. (2021), we consider a utility maximization model with dissonance costs in environmental donation decisions. Participants understand that two of them out of all participants will be picked at random to receive a $100 bonus for participating in the study and can choose to donate a portion of the bonus to an environmental program. In addition to the chance of winning the $100, participants derive utility from donating money to non-profits aligning with their beliefs, and from donating more than what they consider the social norm to be. They obtain intrinsic utility from conforming to the social norm and thus want to maintain consistency between actions and the norm. However, when they behave differently from the social norm, they are incurring a dissonance cost,[5] which represents the costs due to shame or guilt associated with deviating from the group norm (Bejarano et al. 2021; Gawronski & Strack 2012; Kandel & Lazear 1992). The baseline utility function for a participant is as follows:

$$\mathrm{U}(\mathrm{x}_i, \hat{\mathrm{x}}_i, \alpha_i, \beta_i, \gamma_i, \varepsilon_i) = \mathrm{P}_i(100 - \mathrm{x}_i) + \alpha_i \mathrm{x}_i + \beta_i(\mathrm{x}_i - \hat{\mathrm{x}}_i) - \frac{\gamma_i}{2}(\hat{\mathrm{x}}_i - \mathrm{x}_i)^2 \qquad \text{Eq. [1]}$$

where *i* indicates individual *i*. P_i is the probability of winning the lottery;[6] x_i is the respondent's WTD; α_i is the belief parameter that shows how much they support or oppose the cause, β_i (> 0) is the comparison parameter that captures the additional utility/disutility from people feeling good or "bad" about themselves when comparing their own donation to the social norm ($\hat{x}_i$), and γ_i (> 0) the dissonance cost parameter representing the cost of deviating from the social norm. Note that these social norms ($\hat{x}_i$) are beliefs of each individual and, in our experiment, we use an incentive compatible bonus to make sure participants state their true beliefs in the follow-up question after stating their WTD.

Participants choose their donation level to maximize utility, which yields:

$$x_i^* = \underset{x_i}{\operatorname{argmax}}\, U_i = \hat{x}_i + \frac{\alpha_i + \beta_i - P_i}{\gamma_i} \qquad \text{Eq. [2]}$$

Therefore, for individuals who support the environmental cause or receive utility from behaving more generously (donating more money) than others ($\alpha_i + \beta_i > P_i$), their optimal donation is greater than the social norm: $x_i^* > \hat{x}_i$. On the other hand, for those who do not support the environmental cause or does not care much about how their donation compares to the average donation ($\alpha_i + \beta_i \leq P_i$): $x_i^* \leq \hat{x}_i$.

Substituting Eq. [2] into Eq. [1], we find:

$$\frac{\partial U_i}{\partial \hat{x}_i} = \alpha_i - P_i \qquad \text{Eq. [3]}$$

We define group *j* as those individuals who believe in the environmental cause ($\alpha_j > P_j$), we have $x_j^* > \hat{x}_j$, and $\frac{\partial U_j}{\partial \hat{x}_j} > 0$. That is, individuals in group *j* have an incentive to rationalize a higher amount of donation from others because deviating from the norm incurs utility losses. Similarly, we define group *k* as those individuals who do not support the environmental cause

($\alpha_k < P_k$), we have $\frac{\partial U_k}{\partial \hat{x}_k} < 0$, which means they have an incentive to rationalize a lower level of social norm to justify their lower donations, although some of them may be willing to donate more than the social norm depending on their utility from comparison (β_k).

Hypothesis 1: Without the information treatment, respondents' donations are proportional to the social norm: $x_i \sim \hat{x}_i$, but varies depending on their initial beliefs. The group (*j*) of participants who support the environmental cause ($\alpha_j > P_j$) have higher WTD than the group (*k*) that does not support the environmental cause ($\alpha_k \leq P_k$): $x_j > \hat{x}_j > x_k$.

When faced with the information treatment, participants may interpret the same information differently and choose to internalize what is consistent with their desired conclusions due to motivated reasoning, which represents a self-serving bias (Klayman & Ha 1987). The information treatment may also make the environmental cause salient and thus incentivize participants to reweigh their choices. Even though participants do not change their expectations of others' WTD ($\hat{x}_i$),[7] they use the new information to rationalize a new norm, which we refer to as the rationalized norm ($\tilde{x}_i$), to serve their own interests, based on their initial beliefs about the environmental cause. Previous studies have shown that people think that their beliefs are shared by others (e.g., Buchanan 2020), thus they can convince themselves that the rationalized norm is the true norm, although at a cost (Konow 2000). As a result, we predict a wider deviation from the social norm between these two groups when given new information. In other words, new information can lead to group polarization (Sunstein et al. 2017) and could cause backfiring effects in group *k* that does not believe the environmental cause (e.g. Hagmann et al. 2019; Reijula et al. 2018).

Thus, under the information treatment, participants' utility function can be written as:

$\widetilde{\mathrm{U}}(\hat{\mathrm{x}}_i, \tilde{\mathrm{x}}_i, \mathrm{x}_i, \alpha_i, \beta_i, \gamma_i, \theta_i)$

$$= \mathrm{P}_i(100 - \mathrm{x}_i) + \alpha_i \mathrm{x}_i + \beta_i(\mathrm{x}_i - \tilde{\mathrm{x}}_i) - \frac{\gamma_i}{2}(\tilde{\mathrm{x}}_i - \mathrm{x}_i)^2 - \frac{\theta_i}{2}(\hat{\mathrm{x}}_i - \tilde{\mathrm{x}}_i)^2 \qquad \text{Eq. [4]}$$

where comparison utility and dissonance cost depend on how far an individual's behavior deviates from the rationalized norm ($\tilde{\mathrm{x}}_i$). There is also a rationalization cost ($\theta_i > 0$) that participants incur when they rationalize a new norm.

Given Eq. [4], we use backward induction to solve for new optimal WTD:

$$\mathrm{x}_i^{*\prime} = \underset{\mathrm{x}_i}{\operatorname{argmax}}\, \widetilde{\mathrm{U}} = \tilde{\mathrm{x}}_i + \frac{\alpha_i + \beta_i - \mathrm{P}_i}{\gamma_i} \qquad \text{Eq. [5]}$$

We then plug $\mathrm{x}_i^{*\prime}$ into the utility function to find the optimal rationalized norm:

$$\tilde{x}_i^* = \underset{\tilde{\mathrm{x}}_i}{\operatorname{argmax}}\, \widetilde{\mathrm{U}} = \hat{\mathrm{x}}_i + \frac{\alpha_i - \mathrm{P}_i}{\theta_i} \qquad \text{Eq. [6]}$$

Group *j* that supports the environmental cause ($\alpha_j > \mathrm{P}_j$) has a higher rationalized norm $\tilde{x}_j^* > \hat{\mathrm{x}}_j$, while the other group, group *k*, that does not support the environmental cause, has a lower rationalized norm $\tilde{x}_k^* \leq \hat{\mathrm{x}}_k$.

Finally, we can find the relationship between the optimal WTDs with ($\mathrm{x}_i^{*\prime}$) or without (x_i^*) information as well as their relationship to the social norm ($\hat{\mathrm{x}}_i$).

$$\mathrm{x}_i^{*\prime} = \tilde{\mathrm{x}}_i + \frac{\alpha_i + \beta_i - \mathrm{P}_i}{\gamma_i} = \hat{\mathrm{x}}_i + \frac{\alpha_i - \mathrm{P}_i}{\theta_i} + \frac{\alpha_i + \beta_i - \mathrm{P}_i}{\gamma_i} \qquad \text{Eq. [7]}$$

$$\mathrm{x}_i^{*\prime} = \mathrm{x}_i^* + \frac{\alpha_i - \mathrm{P}_i}{\theta_i} \qquad \text{Eq. [8]}$$

Therefore, we find that $\mathrm{x}_j^{*\prime} > \mathrm{x}_j^* > \hat{\mathrm{x}}_j$ for group *j* that believes in the environmental cause ($\alpha_j > \mathrm{P}_j$), and $\mathrm{x}_k^{*\prime} \leq \mathrm{x}_k^*$ for group *k* that does not support the environmental cause ($\alpha_k < \mathrm{P}_k$).[8]

Hypothesis 2: Information treatment can induce group polarization when two groups have different beliefs. WTD of the group (*j*) that supports the cause will increase, while the WTD of the group (*k*) that does not support the cause will decrease: $x_j' > x_j > \hat{x}_j > x_k > x_k'$.

Our hypotheses can be summarized in Table 1.

[Table 1]

EXPERIMENTAL DESIGN

We design a donation experiment in which the information treatment is randomly assigned when asking for respondents' WTD to deforestation prevention programs. Our study is implemented online through a survey research firm. The survey research firm maintains research panels by recruiting study respondents through social media and other online communities, providing us a representative sample that mirrors the general population. Since participants do not contact the survey firm themselves, the recruitment method reduces possible selection bias. Our study was implemented between June 25 and August 4, 2020. It took each participant approximately 25 minutes to finish the experiment. The full survey is presented in Section A2 in the Appendix.

Payment Vehicle

Respondents are asked to state their willingness to donate some or all of a $100 bonus that will be given to two randomly chosen respondents at the end of the experiment.[9] The winners can donate some or all their bonus payments to the non-profit organization of their choice (out of three alternatives: Rainforest Alliance, Trees for the Future, and World Wildlife Fund). To ensure trust and remind respondents that actual payment will be collected, we create

GoFundMe campaigns for non-profit organizations so that donation funds are safely and automatically delivered. This also creates a public record verifying that the respondents' chosen donation actually occurred. Finally, we send the donation receipts to the participants through email. Overall, our novel study design ensures that the donation payment is real stakes and thus incentive compatible, which significantly improves the validity of treatment effects evaluations.

Real stakes are generally preferred since they can prevent social desirability bias, that is, respondents provide answers that are more socially desirable than their true attitudes or behaviors. We acknowledge our design is slightly different from a normal "real stakes" experiment given that a decision is probabilistically implemented. Because the probability of winning the bonus is low and the bonus amount is not high enough to guarantee a large expected value, our study design fits in between a "real stakes" and a "hypothetical stakes" experiment. Previous literature has shown that participants' behaviors differ between those who receive "hypothetical stakes" and "real stakes"(Buhren & Kundt 2015). However, such differences mainly affect the donation levels and have little impact on the treatment effects we are interested in, since the stakes are held constant across the treatments.

Experiment Content

To ensure a clear understanding of the donation mechanism and elicit accurate valuations, at the beginning of the experiment, we inform respondents that two out of all participants will be randomly selected to receive a bonus payment of 100 dollars sent to their PayPal accounts. We also provide detailed information on how to register for a free PayPal account (if they do not have one already) to receive the bonus. Following this information, we ask the subjects again whether they are aware that two survey participants will be selected at random to receive a bonus payment. Only those who answer yes will be allowed to remain in the survey and be asked for their PayPal accounts.

We then have the respondents read important background information on deforestation to contextualize them with the issue. We specifically provide the definition of deforestation and its negative impact. The background information reads:

> *"**Deforestation** refers to the process of clearing forested land on a large scale to allow timber production, expansion of agriculture, and the development of roads and urban infrastructure. It threatens the ability of our globe's forests, especially tropical rainforests, to continue providing valuable ecosystem services. These threatened or diminished services include flood prevention and erosion control, biodiversity preservation, and carbon sequestration. Deforestation also contributes directly to global warming and climate change. According to a recent estimate, deforestation is responsible for 10% of all global warming emissions."*

Following the background information and the randomized information treatment, we provide information on the three non-profit organizations, Rainforest Alliance, Trees for the Future, and World Wildlife Fund, including a description of the organizations' efforts on preventing deforestation and ask individuals for their WTD to deforestation prevention programs they choose among the three alternatives. We suspect that framing the WTD questions also affects individuals' donation behaviors, given that framing has been found to be a coordination device by impacting people's beliefs about the behavior of others (Fehr & Schmidt 2006). Following Capraro et al. (2019), we divide participants into three groups including a control group and test whether prompting them to think of the moral context of their action and make beliefs about norms salient have varying explanatory power of their donation behaviors. The first framing treatment, labeled as "personal framing treatment" reads as: "what do you *personally* think is the morally right thing to do in this situation?" The second framing treatment, labeled as "societal framing treatment" reads as: "what do you think your *society* considers to be the morally right thing to do in this situation?"[10]

After the WTD question, we ask respondents for their expected donations of other participants and demographic information. The expected donation serves as a measure of what the participants perceive as the descriptive social norm, as explained in the theoretical model section. To ensure incentive compatibility when eliciting expected donations, the respondent whose guess is the closest to the actual average donation from all respondents will receive a bonus payment of 10 dollars. We also collected other related information such as whether they or any family members own forest land, if they agree that deforestation is an urgent issue that calls for attention and exacerbates global warming and climate change, have prior knowledge that deforestation might contribute to the occurrence of pandemics, and have previously donated money to non-profit organizations or volunteered for social or environmental causes. As demonstrated in the theoretical models, participants' pre-existing beliefs of whether deforestation is a problem facilitates our analysis on whether their belief systems interact with the new information and thus change their donation behavior.

DATA

Our final survey sample consists of responses obtained from 1,200 randomly selected adult residents (i.e., above 18 years old) in the U.S. out of a total of 5,463 people who accessed the survey. A portion of the respondents is excluded for the following reasons. First, 364 respondents (6.67%) who are under 18 years old are excluded. Second, in the pre-screening consent question, respondents are asked: "Do you commit to carefully reading and providing your thoughtful and honest answers to the questions in this survey?” 3,214 (58.83%) respondents chose “I will not read carefully and provide my best answers”, while 122 (2.23%) chose “I can't promise either way.” These respondents did not pass the consent screening and are not allowed to proceed. As a result, 1,763 (32.27%) respondents who chose “I will read carefully and provide my best answers” remain in the sample. We want to note that respondents not consenting is a common phenomenon when social media and online forum outlets are used as survey recruitment channels. Responses are recorded if a participant has clicked the survey, but many lack the patience to answer the questions and thus indicate that they will not read the questions carefully.

Third, to further improve the data quality, we removed respondents who displayed evidence of poor attention and speeding during the survey. Those whose total response time is below a third of the median total response time (250 seconds) are excluded (495 observations (9.06%)). Forth, we removed 68 (1.24%) observations with missing values for the expected WTD, which is an important variable that measures the social norm in our study. After removing observations with missing values of expected WTD, the minimum total response time in the sample increased from 250 seconds to 494 seconds, suggesting that those missed questions may be speeding through the survey. Lastly, we balance the age and racial compositions across treatment groups to ensure data quality. After a certain age or racial group has reached the sampling quota in each information treatment group, respondents from these demographic groups are no longer included in the sample and their answers are not recorded.

Table 2 presents the demographics distributions of the survey respondents and the U.S. adult population. The z-scores obtained from one-sample proportion tests indicate that our survey sample’s gender and marital status distributions are similar to the general adult population. While our sample has lower shares of Hispanics and other races, the overall racial/ethnic composition is generally comparable to the national level. However, respondents in our sample tend to be older and are more likely to hold a bachelor's or graduate degree than the general population. We thus create sampling weights using the population level age, education, and income distributions as the target weights to correct for the non-representativeness. All models are then estimated based on the sampling weights.

[Table 2]

Table 3 below presents the summary statistics of other important attributes of the survey sample. Here we highlight several interesting observations. First, the amount participants expect others to donate, on average, is lower than their own WTD regardless of whether they receive information treatment or not. Specifically, the average expected donation of others is 37.32 dollars, while the respondent's own donation ranges from 39.51 dollars to 43.12 dollars on average, depending on the treatment group that they are in. This is consistent with the "Lake Wobegon effect" when people tend to think that they are more generous than average (Oxford Reference n.d.; Maxwell & Lopus 1994). Second, the average WTD is higher in the treatment group than in the control group. Third, the average expected WTD is similar regardless of information treatment status or whether participants agree/disagree deforestation is a problem, while it is the lowest among the disagree group. Fourth, most respondents (88.50%) agree that deforestation is a problem that calls for attention. However, only 56% of them have prior knowledge about the correlation between deforestation and the increase in occurrences of infectious disease outbreaks. Given the low level of awareness towards this information, educating the general public of the potential negative impact of deforestation on the spread of infectious diseases thus may significantly affect their WTD. Lastly, a large portion of respondents (74%) have donated money to non-profit organizations in the past.

Figure 1 further illustrates the differences between average WTD across information treatments and agree/disagree groups. As expected, the average WTD is the highest among participants who have received information treatment and agree deforestation is a problem, and the lowest among the group that has received the information treatment and disagrees deforestation is a problem.

[Table 3]

[Figure 1]

EMPIRICAL MODEL

Because the donation amount is censored with a lower bound $0 and an upper bound $100, we estimate the following Tobit model to evaluate factors determining respondent *i*'s WTD using the experiment data to verify the hypotheses predicted by the theoretical models in Eq. [1] and Eq. [4]:

$$WTD_i = \alpha_0 + \boldsymbol{\alpha_1 X_i} + \alpha_2 Info_i + \alpha_3 Personal\_Framing_i + \alpha_4 Societal\_Framing_i + \alpha_4 Donated\_Money_i + \alpha_5 Concern\_less_i + \alpha_5 Own\_Forest_i + \alpha_6 Agree\_Deforestation_i + \alpha_7 Know\_Infect\_Disease_i + \alpha_8 Expected\_WTD_i + \varepsilon_i, \quad \text{Eq. [9]}$$

where WTD_i denotes respondent *i*'s stated WTD. The vector $\boldsymbol{X_i}$ contains individual demographics, including age, gender, race, marital status, income, and education level, along with political party affiliations (i.e., Republican, Democrat, Independent, something else). $Info_i$ is a binary variable indicating whether respondent *i* receives the infectious disease information treatment. Similarly, $Personal\_Framing_i$ and $Societal\_Framing_i$ are binary variables implying whether an individual receives a personal framing or a societal framing, as explained in the experimental design section. Individuals' inclination towards charitable activities likely has an impact on their WTD, so we include $Donated\_Money_i$, to measure whether respondent i has previously donated money to non-profit organizations.

Empathetic individuals are more likely to make charitable donations (Batson & Shaw, 1991). To measure participants' empathy and altruism level, we ask respondents to use the scale from 1 (strongly disagree) to 5 (strongly agree) to indicate to what extent they agree or disagree with the following statements: "Despite how much money I have, I am concerned that there are people who have **less** money than me." $Concern\_less_i$ is included as a control that indicates the empathy/altruism level a subject has.

Given that the collected funds would be used to support deforestation prevention, we suspect that respondents who are forest owners or have family members who own forest land may have a higher WTD. As a result, we include variable Own_Forest_i to indicate if a respondent or another member of his/her family owns forest land. Preexisting knowledge regarding the possible correlation between deforestation and the spread of infectious disease is a factor differentiating individuals' WTD. The $Know\_Infect\_Disease_i$ binary variable implies whether respondent i knows previously that deforestation may lead to an increase in infectious diseases. Given the public good nature of deforestation prevention, individuals' expectation of how much money on average the other participants will donate is an important factor affecting a respondent's own WTD. As a result, we include $Expected\_WTD_i$ as a control variable.

Respondents' attitude towards deforestation and its impact is another important factor affecting their WTD. For instance, individuals who agree that deforestation is a problem that calls for attention are likely to donate a larger amount than their counterparts. In fact, we argue that their beliefs of whether deforestation is a problem divide them into a group that supports the environmental cause and a group that does not support the environmental cause, as predicted by our theoretical model. The binary variable $Agree\_Deforestation_i$ indicates respondents' beliefs on whether deforestation is a problem that needs to be addressed. ε_{ijt} is a stochastic error term.

RESULTS AND DISCUSSION

First we test the hypotheses derived from the theoretical model as presented in Table 1. Since donation amount is not normally distributed, we perform non-parametric Wilcoxon signed-rank tests and present the test results in Table 4. Note that all tests of significance are performed as one-tailed tests since the hypotheses derived in the theoretical model provide information on the directionality.

[Table 4]

The test results in the first row in Table 4 show that the median WTD is greater than the median expected WTD among the deforestation believer group (*j*), while the median WTD is less than the median expected WTD among the deforestation disbeliever group (*k*). Results in the second row demonstrate that the new optimal WTD after receiving the information treatment ($x_j^{*'}$) is greater than the optimal WTD without information treatment and the social norm (x_j^*).

Next, we estimate the empirical model presented in Eq. [9] using the experiment data to further examine the hypotheses. Table 5 below presents the Tobit model weighted estimation results, in which sampling weights are used to adjust for age, education, and income. The unweighted estimation results are presented in Appendix Table A1.

Column (1) in Table 5 presents the estimates based on the subsample without the information treatment to test hypothesis 1 derived from the theoretical model. Additionally, to test hypothesis 2 and examine whether and how the information treatment interacts with individuals' initial beliefs, the full sample is divided into subsamples based on respondents' beliefs towards deforestation. Columns (2) and (3) present these subsample estimates. Specifically, column (2) shows the results for the group of participants who do not agree that deforestation is a problem, whereas column (3) reports the results for participants who concur that deforestation is an environmental problem that calls for attention.

In our baseline model presented in Eq. [1], we predict that without information treatment, respondents choose to donate based on what they perceive as the descriptive social norm, which in our case, is what they expect other participants donate. Individuals' WTD and their expected WTD of others are highly correlated with a correlation of 0.61, and individuals' WTD increases as expected WTD becomes higher. In addition, the regression results in Table 5 column (1) further indicate that participants' expected average donation of other participants is positively correlated with their own donation. With a one-dollar increase in the expected donation of others, respondents' own donation increases by 0.89 dollars. We thus confirm the first part of our first hypothesis. That is, without the information treatment, respondents' donation is positively associated with the expected donation of other people.

People with different initial beliefs regarding an environmental issue behave differently when they make donation decisions. In our study, participants differ in their beliefs on whether they think deforestation is a problem that calls for attention. Without any information treatment, these two groups naturally diverge in their WTD because they place different values and importance on this environmental issue. Those who agree deforestation is a problem have a higher WTD on average than those who do not agree. Specifically, the median WTD among the support group is 36 dollars while it is 25 dollars within the other (do not support) group.

Together with the test results in Table 4, the first hypothesis is confirmed, demonstrating that without information treatment, respondents' donations are proportional to the social norm but vary depending on their initial beliefs. We acknowledge that it is possible people claim to believe in a norm that is closer to their own behavior so they can justify their decisions. However, our incentive compatible mechanism aligns people's beliefs of the social norm with what they state in the question, which alleviates this issue.

When faced with new information, people tend to internalize it with their own interpretations, which can be influenced by their personal beliefs and experiences, to avoid cognitive dissonance (Birch 2020; Klayman & Ha 1987). This self-serving bias can lead to polarization when groups have opposite initial beliefs. Hypothesis 2 states that, with information treatment, WTD of the agreeing group (*j*) that supports the cause will increase, while the WTD of the group (*k*) that does not support the cause will decrease. We examine the impact of the information treatment on these two groups that diverge in their beliefs on whether deforestation is a problem by stratifying the survey responses to two subgroups (Table 5 columns (2) and (3)).

The results of these subsample analyses confirm our hypothesis 2 and reveal that the information treatment has opposite impacts on groups with different initial beliefs regarding whether deforestation is a problem. Notably, the coefficient on the information treatment is negatively significant at the 10% level for people who disagree that deforestation is a problem, as shown in Table 5 column (2), but positive and significant at the 10% level in the agree group (Table 5 column (3)). In particular, the information treatment lowers the disagree group's average donation amount by 10.60 dollars, while it boosts the agree group's WTD by 4.50

dollars. These findings demonstrate that individuals process new information in a self-serving biased manner where they willingly believe reaffirming evidence but critically scrutinize disconfirming evidence. Concerningly, the reduction in WTD among the group that does not think deforestation is a problem is much greater than the increase in WTD within the agree group, which indicates a stronger backfiring effect and group polarization. There are two possible mechanisms through which the information treatment causes polarization. The first mechanism is reactance. Individuals who oppose the environmental cause may feel the information eliminates their freedom of decision-making, so they respond negatively by donating less. The second is related to creditability. Participants, particularly those who disagree with certain ideologies or government authority may become more skeptical and reluctant because they perceive the information as false.

In addition to testing our hypotheses, our empirical analysis also reveals several interesting findings through a full sample estimation without any stratification, as presented in Table 5, column (4). We find certain individual demographics significantly affect individuals' WTD for deforestation prevention. The coefficient estimates in Table 5 column (4) for almost all income levels are positive and highly significant, implying that higher-income individuals are willing to donate more. For instance, the average WTD of participants whose income is between $25,000 to $49,999 is 6.83 dollars higher than the baseline (those with income less than $25,000). The donation amount slowly increases as income becomes higher, and participants earning $150,000 to $199,999 donate additional 21.73 dollars on average, compared to the baseline. The estimate of the Democratic Party is also positively significant at the 10% level, which demonstrates that political party affiliation is an important factor determining individuals'

WTD, corroborating with findings in previous literature (Kotchen et al. 2013). Specifically, the average donation among Democrats is 4.82 dollars higher than the donation from Republicans.

We also examine the effect of the framing treatment. Recall that we have two, one personal framing treatment and one societal framing treatment. The coefficient estimate of the *personal* framing treatment is positive and significant at the 5% level in all models, while the coefficient of the *societal* framing treatment is not. Previous research finds that there is no significant difference between the two (Capraro et al. 2019). Our results, on the contrary, show that different framing treatments have heterogeneous effects. Individuals who have received a personal framing treatment asking them what they *personally* think is the morally right thing to do are willing to donate an additional 6.62 dollars compared with those who are in the control group, whereas the societal moral nudge that asks participants what they think their *society* considers to be the morally right thing to do does not influence respondents' WTD. Our finding confirms that a personal framing treatment serving as a moral reminder can be a cost-effective way to promote pro-environmental behaviors.

Other related characteristics influence participants' donation decisions as well. First, the coefficient of the binary variable indicating whether participants have donated money to non-profit organizations is positively significant at the 5% level. This suggests that previous donation behavior is positively correlated with respondents' WTD (Kessler & Milkman 2016). In particular, those who have donated to non-profit organizations before are willing to donate 5.69 dollars more than their counterparts. Moreover, as a proxy measure for empathy and altruism, the more the participants care about people who make less money than themselves, the higher their WTD is. The coefficient of almost all the empathy measurement levels, ranging from 3 (neutral) to 5 (strongly agree) are highly significant and positive at the 1% levels, demonstrating the importance of empathy and altruism in determining donation behaviors. For instance, individuals who strongly agree that they care about those who have less money than themselves are willing to donate 34.82 dollars more than those who strongly disagree with the statement. Furthermore, the positive coefficient on "know the link to pandemics" is statistically significant at the 10% level. This implies that participants with prior knowledge are willing to donate 4.98 dollars more than those without.

[Table 5]

ROBUSTNESS CHECK

It is possible that certain participants who are more inclined to take online surveys may be different from the average population and thus have different WTD, but it is unclear whether it affects our results and what direction the bias is. Additionally, since the deforestation belief question is asked after the WTD elicitation, it hinders our ability to measure how respondents' beliefs have changed. We acknowledge that there is a possibility that our treatment groups had differences with respect to respondents' prior beliefs towards deforestation. To investigate the robustness of our findings, we bootstrapped the results to observe the reliability of our findings across a larger number of samples. The procedure was performed as follows:

1. We subsampled 2,000 samples of *n* observations of our sample with replacement for each group.
    a. n = 126 for the disagreeing group.
    b. n =1,074 for the agreeing group.
2. The two weighted Tobit estimations were run for each of the new samples, logging key parameters and outcomes of each iteration.
3. We then calculate the bootstrap confidence intervals of our estimates.

In Table 6 below, we present the original and bootstrapping (2,000 replications) weighted estimation results for key variables. As shown in the table, the two sets of estimation results are similar. The 90% bootstrap confidence interval for the information treatment is (-23.650, -0.390) among the disagreeing subsample and is (0.134, 8.601) among the agreeing subsample. These results confirm that our key results are not necessarily a spurious product of the sample and are reliably reproduced across a larger number of repeated subsamples with replacement.

[Table 6]

Considering that a Tobit model comes with distributional assumptions, we have also estimated weighted and unweighted linear regression models without adjusting for $0 donations as a further robustness check of the treatment effect. The linear model estimation results (in Appendix Table A2) are similar to the results of the Tobit models, confirming that our treatment effects are robust.

CONCLUSIONS

In this paper, we develop an intuitive model to theoretically analyze the impact of information treatment on donation decisions. Our theory suggests that when people have different initial beliefs, new information can lead to polarization through people's understanding and rationalization of social norms. We then leverage a real-stake experiment to empirically explore how a new information treatment affects individuals' WTD to non-profit deforestation prevention programs. Since individuals have to actually pay for their elicited donation valuations, our survey design alleviates the hypothetical bias issue.

Our results indicate that new information does affect people's donation behavior. Specifically, an information treatment showing the possible correlation between deforestation and the spread of infectious diseases interacts with participants' existing belief systems and leads to group polarization. Such information lifts respondents' WTD among those who believe that deforestation is a problem that calls for attention while lowering the WTD among those who do not believe it. This result highlights the unintended consequences of providing information to potential donors and emphasizes the importance of a careful design of campaign information.

In addition, certain individual characteristics, including income, previous donation behavior, and empathy significantly affect people's WTD. Those who have previously donated to nonprofit organizations, are in higher-income groups, or are more empathic tend to donate more than their counterparts. We also find that having prior knowledge regarding the contribution of deforestation to infectious disease risks and a personal framing treatment asking respondents what they *personally* think is the right thing to do increases people's donations.

Collectively, these results demonstrate that information has the potential to influence environmental donation behaviors and can be used as cost-effective tools to promote prosocial actions. However, without careful design and execution, information treatment can lead to unintended consequences by increasing divergence in opinions and reinforcing self-serving biases. These results have significant implications for environment-related communications. Although difficult, it is better to target the audience and tailor the communications to improve their understanding of the information. Under certain circumstances, it may even be better to not provide additional information to avoid unintended consequences. Future research should test the robustness of our findings with different types of information since environmental donation decisions could be impacted differently depending on the type of information provided to people.

Additionally, within the group of disagreeing individuals, an information treatment may affect individuals differently. In other words, the information treatment effect is heterogeneous not only among the population, but also within the subsamples. Some disbelievers may contribute $0 regardless of the information, while some are affected by the information and choose to increase or decrease their donations. It is of great interest to provide some reasoning behind this and further examine such heterogeneity in future research. We also hope to extend our analysis to investigate the exact causes of polarization and identify effective ways of delivering information to mitigate polarization and bias, particularly on controversial environmental issues. Overall, non-governmental organizations and governmental agencies will benefit from considering these conclusions in eliciting private donations. Understanding the significant role new information plays and its interaction with individuals' in WTD formation is particularly crucial for policy design and implementation.

ACKNOWLEDGMENTS

We thank Grant H. West for his assistance of designing and conducting the online experiment. We are grateful to Sarah Jacobson, the editor, and two anonymous reviewers for comments that improved the paper.

REFERENCE

Alpizar, F., Carlsson, F., & Johansson-Stenman, O. (2008). Anonymity, reciprocity, and conformity: Evidence from voluntary contributions to a national park in Costa Rica. *Journal of Public Economics*, *92*(5–6), 1047–1060. https://doi.org/10.1016/j.jpubeco.2007.11.004

Andreoni, J. (1989). Giving with impure altruism: Applications to charity and Ricardian equivalence. *Journal of Political Economy*, *97*(6), 1447–1458.

Andreoni, J., & Payne, A. A. (2013). Charitable Giving. In *Handbook of Public Economics* (Vol. 5, pp. 1–50). Elsevier. https://doi.org/10.1016/B978-0-444-53759-1.00001-7

Bartke, S., Friedl, A., Gelhaar, F., & Reh, L. (2017). Social comparison nudges—Guessing the norm increases charitable giving. *Economics Letters*, *152*, 73–75. https://doi.org/10.1016/j.econlet.2016.12.023

Batson, C. D., & Shaw, L. L. (1991). Evidence for Altruism: Toward a Pluralism of Prosocial Motives. *Psychological Inquiry*, *2*(2), 107–122.

Becker, G. S. (1974). *A Theory of Social Interactions* (Working Paper No. 42; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w0042

Bejarano, H., Corgnet, B., & Gómez-Miñambres, J. (2021). Economic stability promotes gift-exchange in the workplace. *Journal of Economic Behavior & Organization*, *187*, 374–398.

Bénabou, R., & Tirole, J. (2006). Incentives and Prosocial Behavior. *American Economic Review*, *96*(5), 1652–1678. https://doi.org/10.1257/aer.96.5.1652

Birch, S. (2020). Political polarization and environmental attitudes: A cross-national analysis. *Environmental Politics*, *29*(4), 697–718. https://doi.org/10.1080/09644016.2019.1673997

Buchanan, J. A. (2020). My reference point, not yours. *Journal of Economic Behavior & Organization*, *171*, 297–311. https://doi.org/10.1016/j.jebo.2020.01.023

Buhren, C., & Kundt, T. C. (2015). Imagine being a nice guy: A note on hypothetical vs. incentivized social preferences. *Judgment and Decision Making*, *10*(2), 185+. Gale Academic OneFile.

Capraro, V., Jagfeld, G., Klein, R., Mul, M., & de Pol, I. van. (2019). Increasing altruistic and cooperative behaviour with simple moral nudges. *Scientific Reports*, *9*(1), 11880. https://doi.org/10.1038/s41598-019-48094-4

Carmichael, J. T., & Brulle, R. J. (2017). Elite cues, media coverage, and public concern: An integrated path analysis of public opinion on climate change, 2001–2013. *Environmental Politics*, *26*(2), 232–252. https://doi.org/10.1080/09644016.2016.1263433

Chapman, D. A., & Lickel, B. (2016). Climate Change and Disasters: How Framing Affects Justifications for Giving or Withholding Aid to Disaster Victims. *Social Psychological and Personality Science*, *7*(1), 13–20. https://doi.org/10.1177/1948550615590448

Croson, R., & Shang, J. (Yue). (2008). The impact of downward social information on contribution decisions. *Experimental Economics*, *11*(3), 221–233. https://doi.org/10.1007/s10683-007-9191-z

Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., & Hansen, M. C. (2018). Classifying drivers of global forest loss. *Science*, *361*(6407), 1108–1111. https://doi.org/10.1126/science.aau3445

Daszak, P., Cunningham, A. A., & Hyatt, A. D. (2000). Emerging Infectious Diseases of Wildlife—Threats to Biodiversity and Human Health. *Science*, *287*(5452), 443–449. https://doi.org/10.1126/science.287.5452.443

Fehr, E., & Schmidt, K. M. (1999). A Theory of Fairness, Competition, and Cooperation. *The Quarterly Journal of Economics*, *114*(3), 817–868.

Fehr, E., & Schmidt, K. M. (2006). Chapter 8 The Economics of Fairness, Reciprocity and Altruism – Experimental Evidence and New Theories. In S.-C. Kolm & J. M. Ythier (Eds.), *Handbook of the Economics of Giving, Altruism and Reciprocity* (Vol. 1, pp. 615–691). Elsevier. https://doi.org/10.1016/S1574-0714(06)01008-6

Festinger, L. (1962). *A Theory of Cognitive Dissonance*. Stanford University Press.

Fischbacher, U., Gächter, S., & Fehr, E. (2001). Are people conditionally cooperative? Evidence from a public goods experiment. *Economics Letters*, *71*(3), 397–404.

Gawronski, B., & Strack, F. (2012). *Cognitive Consistency: A Fundamental Principle in Social Cognition*. Guilford Press.

Giovanna, d'Adda, Capraro, V., & Tavoni, M. (2017). Push, don't nudge: Behavioral spillovers and policy instruments. *Economics Letters*, *154*(C), 92–95.

Goff, S. H., Waring, T. M., & Noblet, C. L. (2017). Does Pricing Nature Reduce Monetary Support for Conservation?: Evidence From Donation Behavior in an Online Experiment. *Ecological Economics*, *141*, 119–126. https://doi.org/10.1016/j.ecolecon.2017.05.027

Goswami, I., & Urminsky, O. (2016). When should the Ask be a Nudge? The Effect of Default Amounts on Charitable Donations. *Journal of Marketing Research*, *53*(5), 829–846. https://doi.org/10.1509/jmr.15.0001

Grieco, D., Lacetera, N., Macis, M., & Di Martino, D. (2018). Motivating Cord Blood Donation with Information and Behavioral Nudges. *Scientific Reports*, *8*(1), 252. https://doi.org/10.1038/s41598-017-18679-y

Guber, D. L. (2013). A Cooling Climate for Change? Party Polarization and the Politics of Global Warming. *American Behavioral Scientist*, *57*(1), 93–115. https://doi.org/10.1177/0002764212463361

Guégan, J.-F., Ayouba, A., Cappelle, J., & Thoisy, B. de. (2020). Forests and emerging infectious diseases: Unleashing the beast within. *Environmental Research Letters*, *15*(8), 083007. https://doi.org/10.1088/1748-9326/ab8dd7

Hagmann, D., Ho, E. H., & Loewenstein, G. (2019). Nudging out support for a carbon tax. *Nature Climate Change*, *9*(6), 484–489. https://doi.org/10.1038/s41558-019-0474-0

Hornsey, M. J., Harris, E. A., Bain, P. G., & Fielding, K. S. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. *Nature Climate Change*, *6*(6), 622–626. https://doi.org/10.1038/nclimate2943

Johansson-Stenman, O., & Martinsson, P. (2006). Honestly, why are you driving a BMW? *Journal of Economic Behavior & Organization*, *60*(2), 129–146. https://doi.org/10.1016/j.jebo.2004.08.006

Johnson, E. J., & Goldstein, D. (2003). Do Defaults Save Lives? *Science*, *302*(5649), 1338–1339. https://doi.org/10.1126/science.1091721

Kallbekken, S., Sælen, H., & Hermansen, E. A. T. (2013). Bridging the Energy Efficiency Gap: A Field Experiment on Lifetime Energy Costs and Household Appliances. *Journal of Consumer Policy*, *36*(1), 1–16. https://doi.org/10.1007/s10603-012-9211-z

Kandel, E., & Lazear, E. P. (1992). Peer pressure and partnerships. *Journal of Political Economy*, *100*(4), 801–817.

Kessler, J. B., & Milkman, K. L. (2016). Identity in Charitable Giving. *Management Science*, *64*(2), 845–859. https://doi.org/10.1287/mnsc.2016.2582

Klayman, J., & Ha, Y.-W. (1987). Confirmation, disconfirmation, and information in hypothesis testing. *Psychological Review*, *94*(2), 211.

Konow, J. (2000). Fair shares: Accountability and cognitive dissonance in allocation decisions. *American Economic Review*, *90*(4), 1072–1091.

Kotchen, M. J., Boyle, K. J., & Leiserowitz, A. A. (2013). Willingness-to-pay and policy-instrument choice for climate-change policy in the United States. *Energy Policy*, *55*, 617–625. https://doi.org/10.1016/j.enpol.2012.12.058

Krupka, E. L., & Croson, R. T. A. (2016). The differential impact of social norms cues on charitable contributions. *Journal of Economic Behavior & Organization*, *128*, 149–158. https://doi.org/10.1016/j.jebo.2016.05.005

Lake Wobegon effect. (n.d.). Oxford Reference. https://doi.org/10.1093/oi/authority.20110810105237549

Leiserowitz, A. (2006). Climate Change Risk Perception and Policy Preferences: The Role of Affect, Imagery, and Values. *Climatic Change*, *77*(1), 45–72. https://doi.org/10.1007/s10584-006-9059-9

Li, S., Hartemink, N., Speybroeck, N., & Vanwambeke, S. O. (2012). Consequences of Landscape Fragmentation on Lyme Disease Risk: A Cellular Automata Approach. *PLOS ONE*, *7*(6), e39612. https://doi.org/10.1371/journal.pone.0039612

MacDonald, A. J., & Mordecai, E. A. (2019). Amazon deforestation drives malaria transmission, and malaria burden reduces forest clearing. *Proceedings of the National Academy of Sciences*, *116*(44), 22212–22218. https://doi.org/10.1073/pnas.1905315116

Maxwell, N. L., & Lopus, J. S. (1994). The Lake Wobegon Effect in Student Self-Reported Data. *The American Economic Review*, *84*(2), 201–205.

Meier, S. (2006). *A Survey of Economic Theories and Field Evidence on Pro-Social Behavior* Working Papers 06-6, Federal Reserve Bank of Boston.

Moutinho, P., & Schwartzman, S. (2005). *Tropical deforestation and climate change*. Instituto de Pesquisa Ambiental da Amazônia ; Environmental Defense.

Olivero, J., Fa, J. E., Real, R., Márquez, A. L., Farfán, M. A., Vargas, J. M., Gaveau, D., Salim, M. A., Park, D., Suter, J., King, S., Leendertz, S. A., Sheil, D., & Nasi, R. (2017). Recent loss of closed forests is associated with Ebola virus disease outbreaks. *Scientific Reports*, *7*(1), 14291. https://doi.org/10.1038/s41598-017-14727-9

Olson, S. H., Gangnon, R., Silveira, G. A., & Patz, J. A. (2010). Deforestation and Malaria in Mâncio Lima County, Brazil. *Emerging Infectious Diseases*, *16*(7), 1108–1115. https://doi.org/10.3201/eid1607.091785

Reijula, S., Kuorikoski, J., Ehrig, T., Katsikopoulos, K., & Sunder, S. (2018). Nudge, Boost, or Design? Limitations of behaviorally informed policy under social interaction. *Journal of Behavioral Economics for Policy*, *2*(1), 99–105.

Rulli, M. C., Santini, M., Hayman, D. T. S., & D'Odorico, P. (2017). The nexus between forest fragmentation in Africa and Ebola virus disease outbreaks. *Scientific Reports*, *7*(1), 41613. https://doi.org/10.1038/srep41613

Schulz, J. F., Thiemann, P., & Thöni, C. (2018). Nudging generosity: Choice architecture and cognitive factors in charitable giving. *Journal of Behavioral and Experimental Economics*, *74*, 139–145. https://doi.org/10.1016/j.socec.2018.04.001

Shang, J., & Croson, R. (2009). A Field Experiment in Charitable Contribution: The Impact of Social Information on the Voluntary Provision of Public Goods. *The Economic Journal*, *119*(540), 1422–1439. https://doi.org/10.1111/j.1468-0297.2009.02267.x

Stadelmann, M., & Schubert, R. (2018). How Do Different Designs of Energy Labels Influence Purchases of Household Appliances? A Field Study in Switzerland. *Ecological Economics*, *144*, 112–123. https://doi.org/10.1016/j.ecolecon.2017.07.031

Sugden, R. (1984). Reciprocity: The Supply of Public Goods Through Voluntary Contributions. *The Economic Journal*, *94*(376), 772. https://doi.org/10.2307/2232294

Sunstein, C., Bobadilla-Suarez, S., Lazzaro, S., & Sharot, T. (2017). How People Update Beliefs about Climate Change: Good News and Bad News. *Cornell Law Review*, *102*(6), 1431–1443.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving Decisions about Health, Wealth, and Happiness*. Yale University Press.

Tiefenbeck, V., Goette, L., Degen, K., Tasic, V., Fleisch, E., Lalive, R., & Staake, T. (2018). Overcoming Salience Bias: How Real-Time Feedback Fosters Resource Conservation. *Management Science*, *64*(3), 1458–1476. https://doi.org/10.1287/mnsc.2016.2646

Unsworth, K. L., & Fielding, K. S. (2014). It's political: How the salience of one's political identity changes climate change beliefs and policy support. *Global Environmental Change*, *27*, 131–137. https://doi.org/10.1016/j.gloenvcha.2014.05.002

Whitman, J. C., Zhao, J., Roberts, K. H., & Todd, R. M. (2018). Political orientation and climate concern shape visual attention to climate change. *Climatic Change*, *147*(3), 383–394. https://doi.org/10.1007/s10584-018-2147-9

WWF. (n.d.). *Deforestation and Forest Degradation.* World Wildlife Fund. Retrieved April 27, 2021, from https://www.worldwildlife.org/threats/deforestation-and-forest-degradation

Zarghamee, H. S., Messer, K. D., Fooks, J. R., Schulze, W. D., Wu, S., & Yan, J. (2017). Nudging charitable giving: Three field experiments. *Journal of Behavioral and Experimental Economics*, *66*, 137–149. https://doi.org/10.1016/j.socec.2016.04.008

Figure 1. Average WTD by information treatment and agreeing/disagreeing groups

Table 1. Hypotheses for information treatment

	Agreeing Group j ($\alpha_j > P_j$)	Disagreeing Group k ($\alpha_k < P_k$)
No information treatment	$x_j^* > \hat{x}_j$	$x_k^* < \hat{x}_k$
Information treatment	$x_j^{*\prime} > x_j^* > \hat{x}_j$	$x_k^{*\prime} < x_k^*$

Table 2. Demographics distributions of the survey participants and the U.S. adult population

Variable	U.S. Population	Survey Sample	z-score	
Age				
18-24	9.09%	10.83%	2.27	*
25-34 (2)	13.79%	14.83%	1.47	
35-44 (3)	12.91%	17.50%	5.40	***
45-54 (4)	12.43%	17.92%	5.79	***
55-64 (5)	13.01%	17.25%	3.99	***
65+ (6)	16.33%	21.67%	3.59	***
Female	51.00%	52.80%	1.25	
Race				
White (1)	68.64%	67.10%	-1.15	
Black or African American (2)	13.81%	12.10%	-1.72	
Hispanic (3)	18.73%	12.50%	-5.53	***
American Indian or Alaska Native (4)	1.25%	1.00%	-0.79	
Asian (5)	6.68%	5.10%	-2.19	*
Native Hawaiian or Pacific Islander (6)	0.23%	0.20%	-0.23	
Other (7)	9.38%	2.00%	-8.77	***
Marital Status				
Single (1)	37.35%	37.30%	-0.04	
Married (2)	46.54%	45.80%	-0.52	

Divorced (3)	9.28%	12.00%	3.25	***
Widow(er) (4)	4.93%	4.90%	-0.04	
Education Level				
Some high school (1)	NA	2.00%	NA	
GED/High school diploma (2)	27.84%	16.30%	-8.92	***
Some college (3)	17.50%	18.10%	0.55	
Associate's degree (4)	10.10%	10.50%	0.46	
Bachelor's degree (5)	22.51%	32.50%	8.65	***
Graduate degree (6)	11.32%	20.80%	10.36	***
Income Level				
Less than $25,000 (1)	18.10%	18.60%	0.45	
$25,000 to $49,999 (2)	19.69%	23.70%	3.49	***
$50,000 to $74,999 (3)	12.59%	20.30%	8.06	***
$75,000 to $99,999 (4)	12.17%	13.00%	0.88	
$100,000 to $149,999 (5)	15.33%	14.60%	-0.70	
$150,000 to $199,999 (6)	7.98%	4.50%	-4.45	***
$200,000 or more (7)	10.25%	5.30%	-5.65	***

Notes: This table presents the demographics distributions for the survey sample and the U.S. adult population. The race/ethnicity composition data is obtained from the U.S. 2020 Census. Information for other demographics (i.e., education, race, and income) that has not been made available in the 2020 decennial census are obtained from the U.S. Census Bureau, Current Population Survey, 2020 are used. The z-scores are calculated from one sample proportional tests. Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 3. Survey sample summary statistics

Variable	**N of observation**	**Mean (or %)**	**Std. Dev.**
WTD (no info)	600	40.88	35.17
WTD (yes info)	600	42.4	35.65
Expected WTD of others (no info)	600	37.31	28.00
Expected WTD of others (yes info)	600	36.52	27.68
Expected WTD of others (Disagree deforestation is a problem)	126	35.64	30.97
Expected WTD of others (Agree deforestation is a problem)	1074	37.06	27.45
Expected WTD of others	1200	36.91	27.83
Concern – Less money (%)			
1	72	6	
2	69	5.8	
3	258	21.5	
4	289	24.1	

5	512	42.7
Organization choice (%)		
Rainforest Alliance	322	26.8
Trees for the Future	385	32.1
World Wildlife Fund	493	41.1
Own forest land (%)	169	14.1
Agree deforestation is a problem (%)	1074	89.5
Know link to Infectious Disease	497	41.4
Donated money previously	840	70

Notes: To measure how empathetic the survey participants are, we asked them to use the scale from 1(strongly disagree) to 5 (strongly agree) to indicate to what extent they agree or disagree with the following statements: "Despite how much money I have, I am concerned that there are people who have less money than me."

Table 4. Test results of the theoretical model hypotheses

	Agreeing Group j ($\alpha_j > P_j$)	Disagreeing Group k ($\alpha_k < P_k$)
No information treatment	$x_j^* > \hat{x}_j$ (V = 22797, one-tailed paired Wilcoxon signed-rank, p-value = 0.0077)	$x_k^* < \hat{x}_k$ (V = 235, one-tailed paired Wilcoxon signed-rank, p-value = 0.0627)
Information treatment	$x_j^{*\prime} > x_j^*$ (W = 66734, one-tailed unpaired Wilcoxon signed-rank p-value = 0.0574)	$x_k^{*\prime} < x_k^*$ (W = 936.5, one-tailed unpaired Wilcoxon signed-rank, p-value = 0.1320)

Table 5. Weighted Tobit models estimation results for WTD

Dependent Variable: WTD	(1)	(2)	(3)	(4)
	Without Information	Disagree deforestation is a problem	Agree deforestation is a problem	Full sample
Constant	-31.849**	-8.525	-42.208***	-42.592***
	(13.260)	(17.768)	(11.121)	(9.614)
Age	0.076	-0.186	0.146*	0.122
	(0.107)	(0.206)	(0.082)	(0.076)
Female	-1.295	1.115	0.509	0.962

	(3.280)	(5.306)	(2.420)	(2.207)
Black or African-American (2)	1.306	3.156	-4.599	-4.264
	(5.239)	(6.429)	(3.762)	(3.414)
Hispanic (3)	3.631	-17.503*	-2.902	-1.265
	(4.626)	(9.748)	(3.587)	(3.303)
American Indian or Alaska Native (4)	49.097**	8.097	29.170**	20.399*
	(20.923)	(17.413)	(12.575)	(11.362)
Asian (5)	-6.342		-5.257	-7.436
	(8.775)		(5.383)	(5.027)
Native Hawaiian or Pacific Islander (6)	-1.158		1.675	-0.392
	(14.884)		(14.619)	(14.206)
Other (7)	2.151		9.842	7.226
	(10.215)		(9.778)	(8.346)
Married (2)	-2.258		-5.176*	-5.091*
	(4.056)		(3.051)	(2.783)
Divorced (3)	4.405		0.210	-0.152
	(5.403)		(4.443)	(4.023)
Widow(er) (4)	11.073		2.667	2.343
	(8.445)		(5.913)	(5.528)
$25,000 to $49,999 (2)	-1.780	10.511	6.894*	6.832**
	(4.885)	(8.393)	(3.650)	(3.378)
$50,000 to $74,999 (3)	-1.509	5.765	5.143	4.664
	(5.493)	(9.299)	(4.222)	(3.883)
$75,000 to $99,999 (4)	16.304***	9.552	18.275***	17.762***
	(6.009)	(10.669)	(4.549)	(4.199)
$100,000 to $149,999 (5)	18.697***	23.511**	17.015***	17.994***
	(5.851)	(9.324)	(4.405)	(4.005)
$150,000 to $199,999 (6)	24.842***	24.025**	21.039***	21.726***
	(7.282)	(11.955)	(5.639)	(5.085)
$200,000 or more (7)	3.700	9.783	5.810	9.049*
	(7.153)	(8.954)	(5.723)	(4.930)
GED/High school diploma (2)	-15.650	-25.134*	0.467	-3.404
	(10.133)	(14.154)	(8.410)	(7.366)
Some college (3)	-7.558	-40.831**	-0.719	-5.917
	(10.404)	(17.753)	(8.626)	(7.600)
Associate's degree (4)	-11.390	-20.518	-0.463	-3.441
	(10.809)	(16.891)	(8.892)	(7.839)
Bachelor's degree (5)	-15.353	-36.477**	-1.022	-5.783
	(10.445)	(15.702)	(8.701)	(7.623)

Graduate degree (6)	-21.239*	-45.085***	-4.196	-10.105
	(10.888)	(16.496)	(9.159)	(7.951)
Democrat (2)	5.502	-1.502	4.891	4.822*
	(4.003)	(6.450)	(2.994)	(2.742)
Independent (3)	-3.729	10.565	-0.764	0.824
	(4.360)	(6.696)	(3.194)	(2.914)
Something else (4)	-14.401**	-7.027	-5.696	-6.527
	(7.238)	(14.455)	(5.214)	(4.868)
Information Treatment		-10.596**	4.495**	2.798
		(5.157)	(2.290)	(2.105)
Personal framing treatment	8.475**	13.205**	6.756**	6.615**
	(3.787)	(6.215)	(2.832)	(2.583)
Societal framing treatment	3.268	7.199	0.410	0.917
	(3.910)	(6.609)	(2.841)	(2.613)
Donated Money Previously	7.998**	4.227	6.252**	5.690**
	(3.571)	(6.182)	(2.704)	(2.455)
Concern_less2	23.498***	16.490	7.753	13.125**
	(8.973)	(10.449)	(7.281)	(6.119)
Concern_less3	38.388***	37.186***	18.068***	22.504***
	(7.187)	(8.858)	(6.021)	(5.083)
Concern_less4	38.198***	33.376***	27.143***	29.654***
	(7.157)	(9.350)	(6.026)	(5.094)
Concern_less5	40.306***	44.831***	31.253***	34.819***
	(6.929)	(9.176)	(5.825)	(4.930)
Own Forest	-0.990	0.709	-0.708	-0.259
	(4.904)	(6.683)	(3.718)	(3.327)
Deforestation is a problem	-5.884			2.932
	(5.027)			(3.515)
Know the link to infectious disease	6.409**	5.268	5.413**	4.984**
	(3.217)	(5.847)	(2.389)	(2.211)
Expected WTD of Other Participants	0.893***	0.843***	0.959***	0.957***
	(0.057)	(0.091)	(0.045)	(0.041)
AIC	4331.64	978.49	7704.38	8671.4
BIC	4498.72	1069.25	7893.59	8869.92
Log Likelihood	-2127.82	-457.24	-3814.19	-4296.7
Deviance	777.22	153.71	1406.62	1572.67
Total observations	600	126	1074	1200
Left-censored	98	33	145	178
Uncensored	413	83	747	830
Right-censored	89	10	182	192

Wald Test	432.37	257.98	671.07	826.21

Notes: This table presents the weighted Tobit models estimation results for no-information sample (column (1)), deforestation disbeliever sample (column (2)), deforestation believer sample (columns (3)) and full sample (column (4)). We create sampling weights using the population level age, education, and income distributions as the target weight to correct for the non-representativeness. We then estimate all models based on the sampling weights. Significance. codes: *p<0.1; **p<0.05; ***p<0.01. a. "Ethnicity" is not included in the estimations of column (2) since the deforestation disbeliever group (n = 126) does not have native Hawaiian population. Results do not change when all other ethnicity groups except native Hawaiians are included in the estimation.

Table 6. Original and bootstrapping (2,000 replications) subsample Tobit model weighted estimation results for key variables

	Disagree deforestation is a problem (*n* = 126)				Agree deforestation is a problem (*n* = 1074)			
	Original	Boot Bias	Boot Std. Err	Boot Median	Original	Boot Bias	Boot Std. Err	Boot Median
Info treatment	-10.596	-1.161	7.243	-11.577	4.495	0.066	2.569	4.623
Personal framing	13.205	0.051	10.234	13.347	6.756	-0.340	3.179	6.513
Societal framing	7.199	-0.389	10.065	6.815	0.410	-0.042	3.031	0.368
Donated money	4.227	0.855	8.916	5.071	6.252	0.005	2.987	6.321
Know the link to infectious diseases	5.268	1.328	9.019	6.242	5.413	-0.171	2.855	5.148
Expected WTD	0.843	-0.030	0.151	0.819	0.959	0.003	0.055	0.961

Notes: This table presents the key results obtained from the original and bootstrapping Tobit model weighted estimations for the disagreeing and agreeing subsample. The boot bias, boot std. error, and boot median are obtained from the bootstrapping estimation results.

[1] There are three main groups of models on why individuals have incentives to behave pro-socially. The first indicates that people have prosocial preferences because one's own utility depends on that of others, including pure altruism (Becker, 1974), impure altruism with a warm-glow motive (Andreoni, 1989), and inequality aversion are possible formulations of pro-social preferences (Fehr & Schmidt, 1999). The second group focuses on reciprocity, including conditional cooperation (Fischbacher et al., 2001) and true reciprocity (Sugden, 1984). The final group is based on the importance of social norms acceptance (Alpizar et al., 2008) and self-image concerns (Bénabou & Tirole, 2006).

[2] Many papers have focused on the effect of label information (Kallbekken et al., 2013; Stadelmann & Schubert, 2018) and presentation of information (Tiefenbeck et al., 2018) on consumer behaviors. The purpose of labels is to improve choices by providing information, which is not nudge per se. These studies also focus on consumer behaviors instead of prosocial donation behaviors.

[3] This is because each person benefits from everyone else's contribution, and each person's consumption does not diminish everyone else's consumption.

[4] A strong correlation has been identified between deforestation and habitat fragmentation and Ebola (Olivero et al. 2017; Rulli et al. 2017), malaria (e.g., MacDonald & Mordecai 2019; Olson et al. 2010), and Lyme disease (e.g., Li et al. 2012).

[5] Dissonance costs arise when people experience a discrepancy between their actions (in our case, donation decisions) and their beliefs (i.e., norms) (Festinger, 1962).

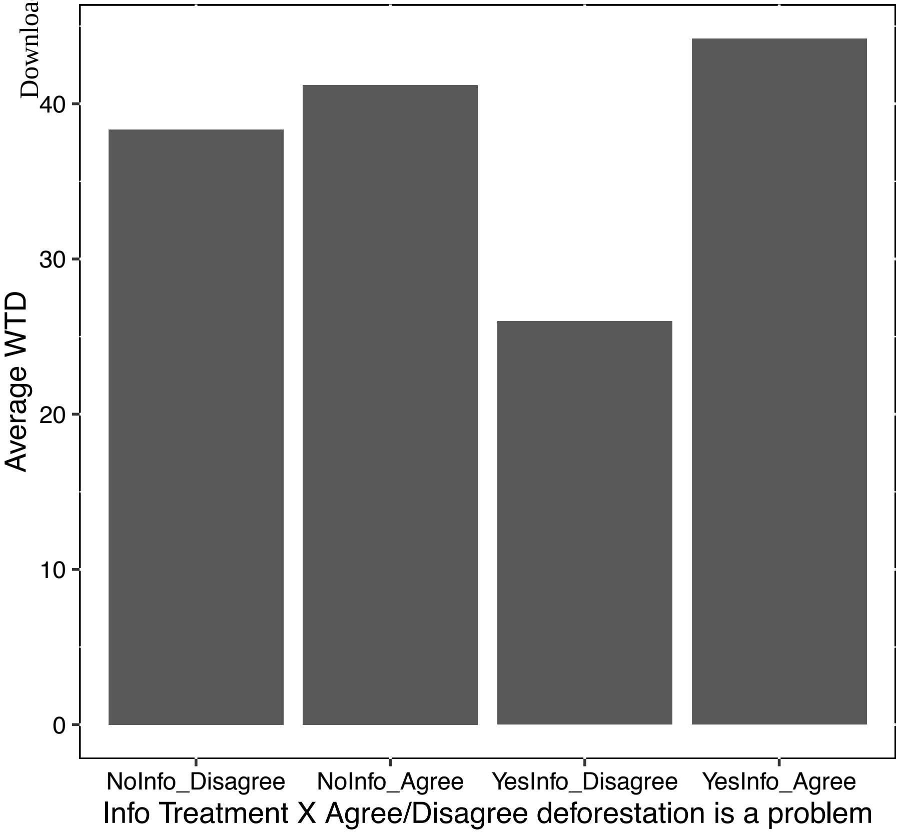
[6] Even though the true probability of winning the lottery is objective and does not vary among individuals, respondents may have different estimations of their chances of winning. We acknowledge that by not informing the participants the total number of participants, they may have a biased estimate of the chance of winning the probabilistic bonus. However, while our model more closely resembles the experiment design, our key results and predictions would remain unchanged under the assumption of common priors.

[7] This is because the belief of social norm ($\hat{x}_i$) is elicited using incentive compatible method and Wilcoxon rank sum test show that $\hat{x}_i$ does not vary among information treatment and control group (W = 64048, Wilcoxon rank sum test *p-value* = 0.3247).

[8] We can also define a subgroup l ($\alpha_l + \beta_l < P_l$) that is a subset of strong disbelievers with strong opinions against the cause, among group k ($\alpha_k \leq P_k$) of individuals that do not support the environmental cause. Based on Eq. [6] to [8], we find that subgroup l donates even less than the rationalized lower norm ($x_l^{*\prime} < \tilde{x}_l$) and less than without information treatment ($x_l^{*\prime} \leq x_l^* \leq \hat{x}_l$). Therefore, this group of individuals diverges further from group j after given the information, which drives the group polarization. This subgroup l corresponds to the disbelievers in the information treatment group in our experiment, who, after the information, still disagree that deforestation is a problem. We thank an anonymous reviewer for pointing this out.

[9] Respondents are provided a base compensation determined by the survey firm for participating the study.

[10] Both nudges are followed by the sentence "With this in mind, please enter the fraction of the 100 dollars that you would like to donate to preventing deforestation" to ensure that respondents understand that they are making the donation.


Average WTD
40
30
20
10
0
NoInfo_Disagree
NoInfo_Agree
YesInfo_Disagree
YesInfo_Agree
Info Treatment X Agree/Disagree deforestation is a problem