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ROBBING PETER TO PAY PAUL:
UNDERSTANDING HOW STATE TAX CREDITS IMPACT CHARITABLE GIVING

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ABSTRACT

Donations to charity are widely encouraged by policymakers through targeted tax incentives such as tax credits for contributions only to qualifying causes. We use a framed field experiment to test how the largest such program, Arizona's state income tax credit for donations to qualifying charities, affects donation decisions in a modified dictator game. In the experiment, we randomize whether subjects receive detailed information about the tax credit program prior to selecting potential recipients and completing the allocation task. We also vary the number of charities that subjects can select as recipients along with the (tax-credit) qualifying vs. non-qualifying composition of the choice set. We find that average giving is unaffected by the information provision and composition of the choice set. However, subjects direct significantly more funds towards qualifying charities when provided information about the tax program; an effect that is enhanced when subjects select multiple recipients from lists that contain a mixture of qualifying and non-qualifying organizations. Our results underline the importance of including a portfolio of choices when studying the impact of targeted incentives because this makes it possible to identify a central feature of our data: participants "rob Peter" (non-qualifying charities) "to pay Paul" (qualifying charities).

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To give away money is an easy matter and in any man's power. But to decide to whom to give it, and how large, and when, and for what purpose and how, is neither in every man's power nor an easy matter…. Aristotle

1. Introduction

Total giving to charitable organizations in the United States in 2017 exceeded $410 billion or approximately 2.1% of GDP. As nearly 80 percent of these dollars come from individual donors, there has been a tremendous amount of research on the primitives of the economics of charity and the relationship between charities and potential donors (see, e.g., List, 2011 or List and Price, 2012 for overviews of work in this area). To date, much of this work has focused on impacts of different fundraising techniques on both the number of donors and overall contribution levels to a given cause. While this literature has successfully documented the effectiveness of various fundraising strategies and identified ways for a given nonprofit to increase dollars raised, we know very little about whether and how increased giving to one charity impacts giving to others in the sector and the size of the overall "charitable pie." Do fundraising campaigns and tax incentives generate new dollars − increasing the size of the charitable pie? Or do such incentives prompt donors to reallocate funds amongst the causes they already support?

Such questions are of first-order importance given the prevalence of tax policies in the United States and Europe that include credits whose rates vary across causes or organizations within a cause.[1] As the charitable sector is comprised of millions of organizations competing for dollars from a finite set of budget constrained donors, we would expect that changes in giving to one organization should impact overall patterns of giving. What remains unknown is whether private dollars attracted via government policies (or other fundraising mechanisms) increase total contributions or simply prompt a substitution of funds across charities. It is this gap in the literature that our paper aims to fill.

To do so, we explore how a state level tax credit program impacts overall giving and the allocation of doantions across qualifying and non-qualifying causes. Specifically, we implemented a framed field experiment that embedded information about the nation's largest state income tax

[1] For example, both Italy and France have credit rates that vary across causes. In the United States, more than 30 states provide credits for contributions to a predetermined set of qualifying causes.

credit program for donations to charity – Arizona's *Credit for Contributions to Qualifying Charitable Organizations* – within a modified dictator game. The program is designed to encourage giving by providing a dollar-for-dollar state tax credit for donations to a predetermined set of qualifying causes.[2]

Participants in the experiment were recruited via Qualtrics to complete an on-line questionnaire (which included the modified dictator game) and were randomized into one of six treatments. The more than 900 participants in the experiment were adults living in the state of Arizona and were selected to reflect a random sample of this population. In the first-stage of the modified dictator game, subjects selected either one or two charities as potential recipients in a second stage dictator game. In the second stage, subjects determined how to allocate an $80 endowment amongst themselves and the charities selected in the first-stage. Prior agreement with the Arizona Department of Revenue ensured that receipts generated by the Qualtrics platform for charitable contributions by subjects in the experiment would be acceptable documentation for credits claimed on state income tax returns.

Experimental treatments varied along three main dimensions: (i) whether, prior to making the first stage decision, subjects were provided detailed information about the credit program and which organizations qualified for the credit; (ii) the number of potential recipients (one or two) that could be selected in the first-stage of the experiment; and (iii) whether the lists from which potential recipients were selected were comprised of only qualifying or non-qualifying charities or a mix of both types.

Our treatments were designed to isolate the effect of the tax credit program on four distinct outcomes of interest: (i) the likelihood of making a donation; (ii) the aggregate amount shared with the selected recipients; (iii) the likelihood and number of qualifying and non-qualifying organizations selected as recipients; and (iv) the allocation of donations across qualifying and non-qualifying organizations.

Results from our experiment highlight that information has no effect on either the likelihood a subject contributes or the aggregate amount shared with charity. However, awareness

[2] The program structure implies that donations up to the specified threshold are *free to the donor* since they reduce the individual's tax liability by the amount claimed.

of the charitable tax credit program does affect both the mix of qualifying and non-qualifying charities selected as potential recipients and the allocation of funds amongst a fixed set of qualifying and non-qualifying organizations. For example, in treatments where subjects are forced to select one charity of each type, information on the tax credit program causes an approximately eight percentage point increase in the fraction of contributions allocated to the qualifying cause. In treatments where subjects are free to select any mix of qualifying and non-qualifying charities as potential recipients, information on the tax credit program has an even greater effect on the allocation of funds across qualifying and non-qualifying causes due to changes in the composition of the donors' portfolios. In such instances, our information treatment leads to an approximately 23 percentage point increase in the likelihood that a subject selects two qualifying organizations and an approximately 12 percentage point increase in the fraction of contributions allocated to qualifying causes.

Our paper speaks to several distinct literatures. First and foremost, our paper speaks to the literature on competition amongst charities. Prior work in this area has focused on either (i) developing theoretical models to derive conditions under which competition amongst charities can lead to lower levels of public good provision (Rose-Ackerman, 1982; Scharf, 2014; Krasteva and Yildririm, 2016; Lange et al., 2017) or (ii) using experiments to understand how incentives to give to one cause impact the allocation of funds amongst a predetermined (fixed) set of causes (Null, 2011; Corrazini et al., 2015; Meer, 2017; Samek and Krieg, 2016; Ek, 2017; Cason and Zubrickas, 2019; Filiz-Ozbay and Uler, 2019; Halwell et al., 2019).[3] Our paper extends this work by separately identifying how incentives for giving to a subset of causes impact both the choice of causes included in the donor's portfolio and the resulting allocation of funds amongst causes within their portfolio. As charitable causes care *both* about the number of donors supporting their cause and dollars received, this is an important extension of prior work which has focused solely on the latter.

Second, our paper speaks to the literature on the role of government in the nonprofit sector. For example, there is a large literature exploring the effect of federal tax policy on aggregate giving

[3] A related body of work explores charitable giving in the aftermath of natural disasters and whether increased generosity following such events impacts aggregate patterns of giving in both the short- and long-run (Brown et al., 2012; Scharf et al., 2017; Deryugina and Marx, 2020). Results from this literature suggest that increased giving following such events does not crowd out giving to other causes or future donations.

(e.g., Feldstein and Clotfelter, 1976; Feldstein and Taylor, 1976; Clotfelter, 1980; Randolph, 1995; Auten and Joulfraian, 1996; Auten et al., 2002; Fack and Landais, 2010; Duquette, 2016).[4] The overarching aim of that work is to explore how federal tax policy and changes in the marginal tax rate impact aggregate giving – i.e., to recover the price elasticity of giving. Our paper differs from that work along two dimensions. First, we focus on state as opposed to federal tax policy. Given that more than 30 states have introduced tax incentives to promote giving, this is an important extension of prior work. Second, the policy we consider only changes the price of giving for a subset of charities as opposed to federal tax policy which applies to donations to all charitable organizations. In this regard, our paper is close in spirit to Duquette et al. (2018) who estimate the effect of state tax credits on aggregate patterns of giving and giving to targeted cause types. However, unlike Duquette et al. (2018) we are able to explore not only the effect of our policy on aggregate giving but also the allocation of funds across qualifying and non-qualifying organizations within a cause type. In doing so, we identify an alternate channel for the null effects found in Duquette et al. (2018) – the reallocation of funds amongst qualifying and non-qualifying organizations.

Finally, our paper contributes to the literature on inattention to taxes and tax incentives. For example, Chetty et al. (2009) develop a model of inattention and provide experimental evidence to explore how the salience of sales taxes impacts consumer purchases.[5] A related body of work examines the effects on labor supply of simple messages that educate consumers about non-linear tax incentives such as the Earned Income Tax Credit (Chetty and Saez, 2013) or Social Security benefits (Liebman and Luttmer, 2011). Our paper extends this literature by exploring the effect of such messages on actions that benefit others (charitable giving) as opposed to one's self. In this regard, our paper is closest in spirit to Gallagher and Muehlegger (2011) who compare the effect of sales tax waivers and tax credits on the purchase of hybrid cars.

More broadly our research contributes to a vast body of work exploring how simple messages (or nudges) that provide consumers information about misperceived or shrouded

[4] Our research also speaks to a related body of work exploring crowd-out and the impact of government expenditures on aggregate patterns of giving (e.g., Kingma, 1989; Payne, 1998; Ribar and Wilhelm, 2002; Andreoni and Payne, 2003, 2011; Hungerman, 2007; Andreoni et al., 2014).

[5] Similar findings are reported in Feldman and Ruffle (2015) who show that subjects in a laboratory experiment spend significantly more when facing tax-exclusive prices as opposed to tax-inclusive or tax-rebate prices.

attributes such as fuel efficiency (Allcott and Knittel, 2019), energy savings (Allcott and Taubinsky, 2015; Davis and Metcalf, 2016; Allcott and Sweeney, 2017), benefits of post-secondary education (Jensen, 2010; Barr and Turner, 2018), restaurant hygiene grades or calorie labels (Jin and Leslie, 2003; Bollinger et al., 2011), and truth-in-lending style disclosures (Seira et al., 2017) impact subsequent choices. Amongst this work, our study is closest in spirit to work exploring how donors respond to information contained in third-party ratings of charities (Figlio and Kenny, 2009; Brown et al., 2017; Adena et al., 2019). Our paper extends this earlier work by identifying the margins through which our informational nudge impacts giving to a particular cause and the allocation of dollars across causes.

2. Policy Background and Program Description

This section introduces the policy environment within which we embed our field experiment. We begin by describing various state level policies aimed at encouraging private contributions to charity. In doing so, we discuss how they could impact both the range of causes a donor supports and the allocation of funds amongst selected causes. We subsequently describe Arizona's policy which provides a dollar for dollar tax credit for contributions made to a set of qualifying organizations and how this policy has influenced aggregate patterns of giving in the state.

2.1. State income tax statutes to encourage contributions

In many countries, charitable contributions by individuals are subject to preferential tax treatment, often in the form of tax deductions for qualified contributions. For example, itemizing taxpayers in the U.S. can deduct donations from their taxable income, lowering their tax base and consequently their tax bill. In practice, this tax provision reduces the marginal cost of giving to $\$(1-\tau)$ per dollar contributed for the marginal tax rate, τ (Feldstein, 1975).

[Insert **Table 1** about here]

Like the federal government, many states have shown interest in encouraging charitable donations through the use of state-specific tax statutes. Bankman et al. (2018) name more than 100 state tax provisions aimed at encouraging donations by taxpayers. Table 1 provides an overview of key features of these programs. As noted in the table, programs differ in terms of the types of causes that are supported, the incentives provided for giving, and whether individuals,

corporations, or both types of donors have access to the tax incentives. More than thirty states allow taxpayers to donate out of their tax refunds, or to increase tax liabilities, directly on the tax forms by choosing qualified charities listed on the forms. Such "check-off programs" can influence donor behavior by reducing the cost of giving or by providing a credible signal of a charity's quality. An alternate policy to encourage giving is to extend federal deduction limits to allow for the additional deduction of state income tax for tax filers. More than fifteen states allow such deductions which serve to lower the price of giving.

Finally, more than 30 states provide some form of tax credit for contributions to qualified causes. Qualified causes cover a wide range of activities such as community development efforts, private school tuition programs, and private charities that provide local services (Bankman et al., 2018). Unlike deductions, which reduce the taxable income, credits directly reduce the income tax owed by a specified amount. A 50 percent tax credit, for example, implies that a $200 donation reduces the state income tax owed by $100. Currently, such programs provide tax credits between 20 and 100 percent of donations and may include caps on the total amount that can be claimed through the program.

2.2. Arizona's state income tax credit for charitable contributions

In this study, we focus on Arizona's *Credit for Contributions to Qualifying Charitable Organizations* which is the most generous of all state tax credit programs. We refer to the credit as Charitable Tax Credit (CTC) throughout this paper. The CTC was enacted in 1998 and provides a *one-to-one (or 100 percent) tax credit* for contributions to qualifying charities. This incentive structure implies that taxpayers can contribute to charity at *no cost* because giving reduces their state income tax burden by the amount given. The program thus allows taxpayers to redirect dollars from the general tax fund to a charity — or multiple charities — of their choosing.

[Insert **Figure 1** about here]

The CTC offers a tax credit for contributions up to $400 (single or head of household) or $800 (married filer) to qualifying charities. Charities must fulfill several criteria to qualify, which we summarize in Figure 1. Qualifying organizations must be certified with the Arizona Department of Revenue. A charity must also:

- be a registered 501(c)(3) organization or a designated community action agency that received community services block grant;
- provide services that meet immediate basic needs;
- serve Arizona residents who receive temporary assistance for needy families (TANF) benefits, are low income residents whose household income is less than 150 percent of the federal poverty level, or are chronically ill or physically disabled children;
- spend at least 50 percent of its budget on qualified services to qualified Arizona residents; and
- continue spending at least 50 percent of its budget on qualified services to qualified Arizona residents.[6]

For the 2018 tax year, more than 900 qualifying charities were registered with the Arizona Department of Revenue.[7]

Recent changes to the CTC have provided greater flexibility to donors. Donations can now be claimed in tax year t or tax year $t+1$ if they are made during tax year t or up until April 15 of tax year $t+1$. For example, a donation in March 2019 could be claimed on either the 2018 or 2019 tax return. Furthermore, taxpayers do not have to be itemizers to claim the credit; they simply must report their donations on Form 321 and include the form with the state income tax return.[8] Finally, unused credits can be carried forward for up to five consecutive years. Thus, if the allowable tax credit for an individual in year t exceeds their tax liability, the unused portion can be used in future tax years.

[Insert **Figure 2** about here]

Contributions claimed through the CTC have increased dramatically since the inception of the program in 1998. Figure 2 provides a visual depiction of the trends in the total value of donations claimed through the CTC and trends in aggregate giving to all registered 501(c)(3) charities in Arizona over the period 1998-2014. Values in the figure are normalized relative to the corresponding amount given in 1998. The left hand axis of the figure corresponds to the

[6] See https://azdor.gov/tax-credits/certification-qcos-and-qfcos for details.
[7] The Department of Revenue publishes the current list of qualifying charities on its website at https://azdor.gov/tax-credits/contributions-qualifying-charitable-organizations.
[8] Taxpayers must also report their donations on Form 301, *Nonrefundable Individual Tax Credits and Recapture*, which contains all available individual income tax credits for Arizona residents.

normalized value of contributions to all registered non-profits in the state of Arizona whereas the right hand axis of the figure corresponds to the normalized value of contributions claimed through the CTC.

Figure 2 higlights divergent trends in total tax credits and total contributions: while the total value of contributions claimed through the CTC has increased by a factor of 45 since the inception of the program, there has been little change in aggregate giving statewide over this same time horizon. Hence, while the introduction of the CTC appears to have had a great impact on giving to qualifying organizations, it has had no impact on overall giving to non-profits in Arizona. This poses an interesting question, where are the added dollars flowing to qualifying organizations coming from? Below we describe a field experiment designed to explore how the CTC impacts aggregate giving and the allocation of funds across cause types.

3. Experimental Design, Procedures, and Data

Our field experiment implements an allocation task that follows Eckel et al. (2005). Specifically, we utilize a modified dictator game where the recipient is a charitable organization selected from a predetermined list of causes. The modified dictator game proceeded in two stages. In the first stage, the subject was provided a set of chartiable organizations and asked to select either one or two organizations from this set as a recipient in the second stage allocation task.

The second stage was the allocation task. In the allocation task, subjects receive an endowment of $80 and are provided an opportunity to share any portion of the endowment with the organizations selected as recipients in the first stage. Figure 3 provides an example of the allocation task as observed by the subject. Importantly, the decision has consequences. Subjects are paid the amount they elect to keep to themselves and the chosen charities receive the shared allocation as a donation.[9]

[Insert **Figure 3** about here]

We vary three dimensions of the modified dictator game across experimental treatments. First, some subjects receive detailed information about the CTC, its history, and qualification

[9] As noted above, by prior arrangement with the Arizona Department of Revenue, receipts for contributions made through the experiment could be used by subjects to claim the tax credit when filing their state income tax return.

requirements for charities prior to selecting recipients in the first stage.[10] Second, we vary whether subjects are asked to select one recipient from a set of ten potential recipients or two recipients – one each from two distinct sets of five potential recipients. In treatments that provide information about the CTC, the lists explicitly indicate whether donations to a potential recipient would qualify under the CTC.[11] Third, in treatments where the subject selects two recipients, we vary the composition of the lists and the corresponding mix of qualifying and non-qualifying organzations that can be selected as recipients. In some treatments, subjects select recipients from one list that contains five qualifying organizations while the other list contains five non-qualifying organizations. In other treatments, both lists contain a mix of qualifying and non-qualifying organizations.

[Insert **Table 2** about here]

In total, the experiment consists of six treatments that we describe in Table 2. The six treatments are arranged in three pairs, where the only difference between groups within a pair is the provision of information about the CTC. The first two treatments, B and T1, have subjects select a single recipient from a list of ten charities before proceeding to the allocation task. In these treatments, the list from which subjects select the recipient organization contains five qualifying and five non-qualifying charities that are arranged in random order.[12] Subjects in treatment B were not provided any information about the CTC or whether donations to a particular organization qualified under this program. Subjects in T1, in contrast, were provided information about the CTC in the first stage of the experiment and, prior to selecting the recipient organization, observed whether or not donations to alternative recipients qualified for a tax credit under the CTC.

The remaining four treatments provide two lists of five charities each. In these treatments, subjects select one charity from each list as recipients in the allocation task. In treatments T2 and T3, subjects are "forced" to select a recipient of both types as one list contains only qualifying charities, while the second list is made up exclusively of non-qualifying charities. These treatments do not allow subjects to alter the number of qualifying and non-qualifying organzations selected

[10] We show an example of the information in Figure C1 in the appendix.
[11] Tables C1 and C2 in the appendix present all charities in the experiment.
[12] We chose the charities for this experiment from the published list of all qualifying charities and the universe of non-qualifying 501(3)(c) charities that operate in Arizona. The choice of charities for each treatment pair was based on the annual donations received and its cause. We obtained this information from the charity's 990 tax filings. Table C3 of the appendix presents the resulting charity lists and their combinations.

as recipients in response to information about the CTC. The only channel for response is an intensive margin adjustment – i.e., changes in the amounts allocated to a qualifying or non-qualifying organization.[13]

Our final two treatments are designed to allow adjustment along an additional margin as both lists in treatments T4 and T5 contain a mix of qualifying and non-qualifying charities. Subjects in these treatments are thus free to select zero, one, or two qualifying organizations as recipients and can adjust the number of qualifying organzations selected as recipients in response to information about the CTC. As a result, subjects in these treatments have two channels for response to information about the CTC; they can reallocate the amount allocated to a fixed mix of qualifying and non-qualifying recipients *and* they can adjust the number and mix of each type of organization selected as recipients.

This experimental design allows us to study the impact of the CTC on four dimensions of giving:

i. the likelihood of making a donation;
ii. the overall dollar amount given;
iii. the choice of charity recipient(s); and
iv. the allocation of donations across qualifying and non-qualifying organizations.

A comparison of B and T1 helps us understand whether knowledge of the tax credit affects the type of organization, qualifying or non-qualifying, selected as the recipient and the resulting amount donated. The remaining treatments are designed to explore whether and how information about the CTC impacts the allocation of dollars across qualifying and non-qualifying charities. T2 and T3 are designed to isolate how information about the CTC affects allocation of money across the two types of charities in the second-stage when the subject is "forced" to select one recipient of each type in the first-stage. T4 and T5 allow us to assess whether the CTC affects both the number of qualifying organizations chosen as recipients in the first stage along with the subsequent amounts donated to the different charity types in the second stage.

[13] The design of these treatments thus shares similarity with past experiments exploring how incentives for giving to a subset of potential recipients impact the allocation of funds amongst a fixed set of potential recipients (see, e.g., Null, 2011; Meer, 2017; Cason and Zubrickas, 2019; Filiz-Ozbay and Uler, 2019; Halwell et al., 2019).

3.1. Experimental Procedures – Survey Implementation

The experiment was embedded in a survey that was implemented in partnership with Qualtrics. Figure 4 summarizes the structure of the survey and the resulting experiment. As noted in the figure, every participant completed two question blocks in addition to the allocation task.

[Insert **Figure 4** about here]

The first block, which subjects see at the beginning of the survey, includes a consent form and basic demographics, such as gender, age brackets, and income brackets. Before seeing the questions, subjects had to consent to participation with their virtual signature, as required by IRB guidelines. The main purpose of the demographics questions was to elicit baseline characteristics that can be used to screen people and ensure that our sample is representative of the population of Arizona adults.[14]

After completing the allocation task, subjects saw a second block of questions that focused on auxiliary information about a subject's past charitable donations – i.e., past donations to each of the 20 charities included in our set of potential recipients, awareness of the CTC prior to the experiment, and tax credits claimed through the CTC and other state level programs. The second block of questions also included questions relating to basic tax morale and support for policies to redistribute income and support low-income families.. We use this information to ensure balance in factors that could impact response to our information treatments. The median time of completion for the survey was approximately eleven minutes.

We conducted the survey across two deployment waves that followed identical procedures and contained all six treatments. The first wave took place in December 2017 while the second wave was conducted in late April and early May of 2018. Our design thus allows us to study program impacts at different points of the tax year when the incentives provided by the CTC may be more or less salient.

To recruit subjects, we relied on Qualtrics' network of local panel providers, firms that curate lists of potential participants. We worked with one panel throughout the experiment to ensure that all participants were exposed to the same survey and payment procedures. This

[14] We excluded residents under the age of 18 because we are interested in behavior related to income tax filings.

approach allowed us to collect data uniformly and recruit a large sample of Arizona residents. The appendix provides more detail about the implementation of the experiment and our payment protocol.

Before proceeding, we should note that subjects had to meet three requirements to participate in our experiment: (i) they had to be members of the panel maintained by our partner; (ii) they had to be an Arizona resident of age 18 or older; and (iii) they had to consent to participation. The first criterion was necessary as invitations to participate in the survey are only sent to members of the panel via email. The second and third criteria were implemented based upon response to questions included in the first block of the survey – indiviudals could not begin the survey without consent and Qualtrics would end the survey should a respondent indicate that they were not a resident of Arizona or were under the age of 18. We further worked with Qualtrics to ensure that our subject pool was respresentative of the Arizona population along three dimensions: gender, age, and household income.[15]

3.2. Sample Size and the Allocation Across Cells

Based on power calculations following List et al. (2011), our experimental sample of 900 subjects across six treatment cells is designed to detect treatment effects of approximately one-third of a standard deviation. Table 3 provides an overview of the resulting sample by experimental treatment and wave. In total, we observe 904 completed surveys – 454 in the first wave and 450 in the second – and an additional 347 incomplete responses – 205 in the first wave and 142 in the second.[16]

[Insert **Table 3** about here]

As noted in the table, there was variation in the number of completed surveys both across treatments within a wave and across waves within a treatment. For example, the number of complete surveys in the first wave ranges from a low of 61 in treatment T5 to a high of 84 in treatment T4. We observe similar variability across waves for many of our treatments. For example, the number of complete surveys in treatment T5 increases by 10 between the first and

[15] Following Qualtrics' best practice, we implemented a quality check that excluded subjects who completed the survey in less than a third of the median completion time during the soft launch.
[16] Incomplete responses are surveys where the subject existed the survey after completing the allocation task but before completing the final block of survey questions.

second wave whereas the number of compete surveys in treatment T4 falls by 9 between the first and second wave.

Such imbalance is an artifact of using Qualtrics' software and sampling approach. Rather than ex ante randomizing subjects into treatments and directing them to treatment-specific landing pages, the Qualtrics software requires that subects are sent to a single landing page with randomization occuring as probabilistic assignment to a different version of the allocation task programmed as part of the survey. Hence, while we can control the likelihood a subject is assigned to a particular treatment, we cannot control the number of subjects that complete the allocation task in any given treatment.

This raises concern about selection effects and potential bias in our estimated treatment effects. We address these concerns by estimating a simple linear regression of the number of complete responses in each treatment/wave cell on binary indicators for an observation from an information treatment and observations from treatments that require subjects to select two recipients in the first-stage. Although we do observe fewer responses in our information treatments, the indicator on an information treatment is not significant at meaningful levels. Moveover, we find no difference in the number of responses for treatments with multiple recipients relative to those in treatements with a single recipient.

As a further test on selection effects, we perform a similar comparison for incomplete surveys. As noted in Table 3, we observe 347 such surveys in the data; 174 of which come from treatments that provide information on the CTC. Hence, amongst incomplete responses there is again no significant difference in the number of responses across information and no information treatments. Viewed in its totality, these analyses call into question concerns regarding differential selection based on treatment.

4. The Survey Data and Experimental Results

At the completion of each survey wave, we received a dataset from Qualtrics that included answers to every question in Blocks 1 and 2 of the survey, the charities selected as recipients in the first stage of the modified dictator game, and the subsequent allocations to the chosen recipients. In addition to data from the survey, Qualtrics provides auxiliary information such as treatment

assignment, the amount of time it took the respondent to complete the survey, a unique subject ID number, and the date and time the survey was completed.

To convert the raw data from Qualtrics into a usable sample, we followed a four step procedure for cleaning the data. First, we extracted information on the charities selected as recipients in the first stage of the modified dictator game and the subsequent allocations to each recipient. We augmented this data set to create outcome variables of interest such as the aggregate amount donated, the amount donated to qualifying and non-qualifying organizations, and indicators for the choice of qualifying organization from a mixed list. Second, we extracted answers from the demographic questions in the first block of the survey and select questions from the select block of the survey relating to awareness and use of the CTC prior to the experiment, tax morale, and whether or not the subject had donated to any of the twenty potential recipients in the past. Third, we created an indicator for the wave of the experiment and indicators for the experimental treatment to which the subject was assigned. Finally, we repeated the first and third steps for the set of incomplete responses and merged this with the data set generated in step one.[17]

Given the design of our experiment, there are two potential threats to identification and interprations of our findings that we would like to address before proceeding to the results section. First, subjects in the experiment may have a strong preference for select causes or a history of giving to particular organizations that could influence outcomes of the modified dictator game independent of treatment. For example, an individual may have a history of donating to the Arizona Community Foundation (a non-qualifying organization) or St. Mary's Food Bank (a qualifying cause) and thus select these causes as a recipient regardless of other organizations in the feasible choice set or information provided about these alterantives and the CTC. In this instance, we would tend to underestimate the effect of the information treatment and incorrectly infer that it has no impact on donor behavior.[18]

A second threat to identification relates to awareness and past use of the CTC amongst subjects in our experiment – a characteristic that is ex ante unobservable. As our treatment of

[17] We exclude the incomplete data in our primary analysis but include such responses in our supplementary analysis and for robustness checks.

[18] A similar concern would arise if we selected causes that nobody cared for and subjects select potential recipients in the no-information case at random. In this instance, however, it is not clear whether and how information about the CTC would impact the choice of recipient and subsequent allocations.

interest is information about the CTC and whether or not donations to a potential recipient would qualify for a credit under the program, one might expect that the effect of our intervention could depend on baseline knowledge of the CTC. If this is indeed true, imbalance in prior awareness of the credit program across treatments could compromise indentification and lead to biased estimates of our treatment effects.

We address these concerns using data from the second block of questions asking subjects: (i) whether or not they have given to each of the twenty potential recipient organizations in the past; (ii) whether or not they were aware of the CTC prior to the experiment; and (iii) whether they had claimed a tax credit through the CTC in the past. As described in the Appendix, we find no evidence that our results are driven by subjects observing and selecting charities that they have supported in the past. Moreover, we find that both awareness and use of the CTC prior to the experiment is balanced across treatments.[19] However, we control for such factors in our robustness checks and show that doing so does not impact the qualitative nature of our main findings.

Experimental Results

Table 4 provides summary statistics from our experiment. The upper panel of the table presents data on aggregate patterns of giving across our various experimental treatments. Specifically, the upper panel of Table 4 provides data on three metrics of interest: (i) the likelihood the subject donated to at least one of the selected recipients; (ii) the average contribution level; and (iii) the fraction of all dollars contributed that were given to a qualifying organization. In total, 81.4% of the subjects in our experiment donated to at least one of the selected recipients. The average donation in our experiment was $49.50 with approximately 59.3% of this amount allocated to qualifying causes.

[Insert **Table 4** about here]

The middle panel of Table 4 restricts attention to donations made to qualifying causes and summarizes four metrics of interest: (i) the number of qualifying causes selected as recipients in the first-stage; (ii) the likelihood that the subject donated to a selected qualifying

[19] Interestingly, we find that a large fraction of individuals who were aware of the CTC program elected not to claim a credit through that program, even though they had donated to a qualifying charity. Such behavior is consistent with results from Benzarti (forthcoming) who show that individuals are willing to forego substantial tax savings to avoid compliance costs.

cause; (iii) the number of qualifying causes that the subject donated to in treatments T4 and T5; and (iv) the average contribution to qualifying causes. In total, approximately 82% of our subjects selected at least one qualifying organization as a recipient in the first stage of the modified dictator game. Of these, 80.2% (592 out of 738) made a positive donation to the selected qualifying cause with an average gift of $29.33 to selected qualifying causes.

If we restrict attention to the final two treatments, T4 and T5, approximately 81% of the subjects (236 out of 291) select at least one qualifying cause as a recipient. Of these, approximately 51.3% (or 121 subjects) select two qualifying causes as recipients in the first stage. Amongst the 236 subjects who selected at least one qualifying cause, 80.5% (or 190) make a positive donation to at least one of the selected causes. Amongst the 121 subjects that select two qualifying causes, 79.3% make a positive allocation to both of the selected causes.

Impact of Information on Aggregate Pattern of Giving

We begin by exploring the effect of our information treatment on aggregate patterns of giving. Specifically, we explore the effect of information about the CTC program on two metrics of interest: (i) average contribution levels and (ii) the likelihood of making a donation. As summarized in the upper panel of Table 4, average contribution levels range from a low of $44.47 in treatment T1 to a high of $52.23 in treatment T4 and participation rates range from a low of 76.6% in treatment T1 to a high of 85.1% in our baseline treatment. If we restrict attention to a comparison across paired information and no-information treatments, our raw data suggest no discernable effect of information on either average gifts or the likelihood of giving.

To formally test the effect of our information treatment on average contributions we estimate a linear regression model of the form

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 M_i + \beta_3 T_i M_i + \gamma_t + \varepsilon_{it}$$

where: Y_{it} is the aggregate amount donated by subject i in wave t; T_i is an indicator that equals one if subject i participated in an information treatment; M_i is an indicator that equals one if subject i participated in a treatment with two recipients; and γ_t are wave fixed effects. Given prior evidence showing that demographic factors such as age, gender, and income are correlated with charitable donations, we augment our baseline specification to include indicators for: (i) female subjects; (ii)

subjects below age 35; (iii) subjects above age 65; (iv) subjects with reported annual income less than $50,000; and (v) subjects with reported annual income above $100,000.

The results from these models are presented in Table 5. As noted in the first column of the table, our information treatments have no discernable impact on the average amount donated in our experiment. Both the coefficient on the treatment indicator and the coefficient on the interaction of this indicator with the indicator for multiple-recipient treatments are statistically insignificant. For example, subjects in T1 give on average about $4.86 (or approximately 9.8 percent) less than do counterparts in our baseline treatment. However, this difference is not significant at any meaningful level. We observe similar effects when comparing the effect of information in treatments with multiple recpients – average donations in these treatments are approximately $0.17 lower than that observed in the corresponding no information treatments.

[Insert **Table 5** about here]

We observe qualitatively similar effects in column 2 which includes demographic controls although the magnitude of the differences increases. For example, when we include demographic controls, subjects in T1 give approximately $6.76 less than do counterparts in the baseline treatment – a difference that is marginally significant at the $p < 0.10$ level. In treatments with multiple recipients, average donations when subjects receive information about the CTC prior to the first stage give approximately $0.16 less than that observed in the corresponding no information treatments – a difference that is not significant at any meaningful level.

Before proceeding, we should note that the esimtates on our demographic controls are consistent with prior findings in the literature (e.g., List, 2004). Specifically, we find that: (i) women donate approximately $6.84 (or 13.8 percent) more to charity than do male counterparts; (ii) the elderly donate $5.80 (or 11.7 percent) more to charity than do middle aged counterparts; and (iii) those with annual household income below $50K donate approximately $9.43 (or 19.1 percent) less to charity than do counterparts with income in the $50-100K range. That our estimated demographic effects are consistent with prior findings is comforting and suggests that our sample is representative of the broader population – at least with regard to the determinants of giving.

We next explore the impact of our information treatments on the likelihood a subject makes a positive contribution. As noted in Table 4, this probability ranges from 76.6% in treatment T1 to to 85.1% in our baseline condition with little difference across our information and no information treatments. To formally test the effect of information about the CTC on the likelihood of giving to a selected cause, we estimate a series of linear probability models of the form

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 M_i + \beta_3 T_i M_i + \gamma_t + \varepsilon_{it}$$

where Y_{it} is a binary indicator that equals 1 if subject *i* in wave *t* shared a positive amount in the second stage allocation game and the remaining indicators identical to those described above. We again augment this baseline specification to include demographic controls for gender, age, and income.

Results from these models are presented in Table 6 and suggest that our information treatments had no discernable impact on the likelihood of giving. For example, as noted in the first column of the table, subjects in treatment T1 were actually 8.7 percentage points less likely to give than were counterparts in the baseline treatment – a difference that is marginally significant at the $p < 0.10$ level. Although we are unable to pinpoint the cause of this extensive margin effect, it drives the difference in average contributions across our baseline treatment and treatment T1.[20] We observe a less pronounced difference in treatments with multiple recipients. Subjects receiving information about the CTC in such treatments are approximately 0.6 percentage points less likely to give than counterparts in the corresponding no-information treatments – a difference that is not economically or statistically significant at any meaningful level.

[Insert **Table 6** about here]

The qualitative nature of our findings are unchanged when we add demographic controls. For example, as noted in column 2, subjects in treatment T1 are approximately 10.3 percentage points less likely to give than are counterparts in the baseline treatment – a difference that is marginally significant at the $p < 0.10$ level. If we restrict attention to treatments with multiple recipients, we observe no economically meaningful impact of information on the likelihood of giving. Subjects receiving information about the CTC in such treatments are approximately 0.4

[20] As noted in Table 4, there is no difference in the average conditional donation across our baseline ($57.71) and treatment T1 ($58.09).

percentage points less likely to give than counterparts in the corresponding no-information treatments.

Viewed in its totality, the empirical estimates in Tables 5 and 6 suggest a first result:

Result 1*: Information about the CTC has no impact on aggregate behavior. Both the likelihood of giving and average contributions are unaffected by our information treatment – particularly when subjects select multiple recipients in the first-stage.*

That our information treatment has no impact on average contribution levels in our experiment is consistent with the data patterns observed in Figure 2 which shows that the introduction of the CTC has had no discernable impact on aggregate patterns of giving statewide. Result 2 is also consistent with findngs from Duquette et al. (2018) who use data from the Panel Study of Income Dynamics and show that state tax credits for charitable contributions have no impact on overall donations. In what follows, we set forth to understand what drives this result. Perhaps information about the CTC program and available tax credits for giving to select causes has no impact on donor choice. Alternately, the aggregate statistics could be misleading if the impact of the CTC is that it leads to a reallocation of donations across qualifying and non-qualifying causes.

The Allocation of Funds across Qualifying and Non-Qualifying Charites

We next explore whether our information treatment leads subjects to shift donations from qualifying to non-qualifying charities. To do so, we first discuss summary statistics from Table 4. As noted in the table, the fraction of donations allocated to qualifying charities is greater in every information treatment than in its paired no information condition. For example, qualifying organizations in our baseline treatment receive approximately 60.5% of all donations. In the matched information treatment (T1), such causes receive approximately 65% of all donations. Moreover, when subjects are allowed to select two recipients, this difference is enhanced – there is an approximate 7.2 percentage point difference in the fraction allocated to qualifying charities across treatments T3 and T2 and an approximate 17.7 percentage point difference in the fraction allocated to qualifying causes across our final treatments T5 and T4.

To evaluate whether these differences are statistically significant, we estimate a series of linear regressions of the fraction of donations to qualifying charities on our various treatment indicators and demographic controls. We calculate the fraction of donations to a qualifying charity

as the amount allocated by subject *i* to qualifying charities divided by subject *i*'s aggregate donation and set this fraction to zero should subject *i* keep the $80 endowment for themself.[21] By construction, our dependent variable thus takes a value between 0 and 1.

Estimates for these models are presented in Table 7. As noted in the first column of the table, there is no difference in the average fraction allocated to qualifying causes across our baseline treatment and treatment T1 – the estimated coefficient on our indicator for an information treatment is negative but not statistically significant at any meaningful level. There is, however, a significant increase in the amount allocated to qualifying causes when subjects receive information about the CTC and select multiple recipients. The estimated coefficient on this interaction term is 0.153 suggesting that subjects in these treatments allocate approximately 15.3% more to qualifying causes than do counterparts in the corresponding no-information treatments – a difference that is significant at the $p < 0.05$ level.

[Insert **Table 7** about here}

The qualitative nature of these differences are unchanged when we add demographic controls. As noted in column 2 of Table 7, information has no impact on the fraction allocated to qualifying charities when subjects select a single recipient. However, information about the CTC leads to a significant increase in the fraction allocated to qualifying causes when subjects select multiple recipients.

Viewed in conjunction with the null effect of information on average giving, the estimates in Table 7 suggest a second result:

Result 2*: Providing subjects information about the CTC leads to a reallocation of donations towards qualifying causes but only when subjects select multiple recipients*.

Result 2 shares similarity with findings in Null (2011) who shows that changes in the relative price of giving leads to weak substitution between causes and a partial reallocation of donations from higher to lower priced causes. Result 2 also shares similarity with findings in Filiz-Ozbay and Uler (2019) that increases in the rebate rate for one charity relative to that of a substitute cause

[21] The qualitative nature of our findings remain unchanged if we instead calulate our dependent variable as the amount allocated to qualifying causes divided by the maximum possible donation – the subject's $80 endowment.

leads to a reallocation of funds amongst the two causes.[22] By design, subjects in our experiment should view qualifying and non-qualifying organizations as substitute causes so we should expect information about the CTC to cause a reallocation of donations towards qualifying causes.

For policy-makers and practitioners, Result 2 provides a potential explanation for the patterns of giving illustrated in Figure 2. The introduction of the CTC likely caused a reallocation of donations towards qualifying causes. Hence, there can be a dramatic increase in the amounts claimed through the CTC program with no change in aggregate patterns of giving statewide. For researchers, Result 2 highlights the importance of examining the effects of incentives not only on giving to the targeted cause but also on giving to other causes – i.e., it highlights the importancDe of modeling choice and testing behavior in a world with multiple charities or public goods.

Impact of Information on Charity Selection and Allocation

We next set forth to explore the various channels through which our information treatment impacts the allocation of funds amongst qualifying and non-qualifying causes. In doing so we examine the effects of information along two distinct margins: (i) the extensive margin – the selection of recipients in the first stage; and (ii) the intensive margin – the allocation of funds in the second stage.[23] In what follows, we restrict attention to the subset of treatments where subjects select multiple recipients as we do not observe significant differences in the allocation across the different cause types in treatments with a single recipient.

We begin by exploring the effect of our information treatment on the selection of recipients in the first stage of the modified dictator game. Recall that by design, subjects in treatments T2 and T3 were "forced" to select one recipient of each type. We thus focus our analysis on treatments T4 and T5 where subjects faced mixed lists and could select a "portfolio" of recipients that includes zero, one, or two qualifying causes. In doing so, we focus on three metrics of interest: (i) the likelihood of selecting at least one qualifying cause as a recipient; (ii) the likelihood of selecting

[22] Alternately, Filiz-Ozbay and Uler (2019) show that increases in the rebate rate for one charity leads to increased donations to both charities if the causes are complementary. Similar increases in aggregate giving are found in studies exploring the response of donors to new, but temporary, needs such as disaster relief (Brown et al., 2012; Scharf et al., 2017; Deryugina and Marx, 2020) or classroom projects in public schools (Meer, 2017).

[23] Figures A1 to A4 in Appendix A provide a graphic depiction of these outcomes and show that while there is no aggregate change in giving, our information treatment changes the type of charities subjects select and the allocation of funds across cause types.

at least one non-qualifying cause as a recipient; and (iii) the number of qualifying causes selected as recipients.

As noted in Table 4, our information treatment impacts the selection of both recipient types. For example, information about the CTC increases the likelihood of selecting at least one qualifying cause by approximately 6.9 percentage points (84.9 percent in T5 versus 78 percent in T4). In contrast, information about the the CTC reduces the likelihood of selecting at least one non-qualifying cause by 23.7 percentage points (45.5 percent in T5 versus 69.2 percent in T4).

Taken jointly, these differences lead to changes in the composition in the mix of cause types within the donors "portfolio" of seleced recipients. For example, whereas 47.2 percent of subjects (75 out of 159) in T4 select one cause of each type, this fraction falls to approximately 30.3 percent (40 out of 132) in the paired information treatment. In contrast, the number of subjects selecting two qualifying causes as recipients increases from approximately 30.8 percent (49 out of 159) in the no-information condition to more than 54 percent (72 out of 132) in the paired information condition.

To evaluate whether these differences are statistically significant, we estimate a series of linear probability models of the form

$$Y_{ilt} = \alpha + \beta T_i + \gamma_t + \mu_l + \varepsilon$$

where: Y_{ilt} equals one if subject *i* facing list *l* in wave *t* selects at least one cause of a given type as a recipient; T_i is indicator for subjects in our information treatment (T5); γ_t are wave fixed effects; and μ_l are list fixed effects.[24] We also estimate an augmented version of this basic model that includes demographic controls. Across all specfications, the coefficient of interest is β which captures the effect of our information treatment on the probability of selecting at least one recipient of the given type.

Estimates for these models are presented in Table 8. The first two columns examine the likelihood of selecting at least one qualifying cause as a recipient whereas the last two columns examine the likelihood of selecting at least one non-qualifying cause as a recipient. Empirical

[24] We estimate one model for the likelihood of selecting at least one qualifying cause as a recipient and another for the likelihood of selecting at least one non-qualifying cause as a recipient. Note that these two outcomes need not be isomorphic to each other as a subject can select two causes of a given type or one cause of each type.

results are largely consistent with the aggregate summary statistics. For example, subjects in an information treatment are approximately 6 percentage points more likely to select at least one qualifying cause as a recipient. However, this difference is not statistically significant at any meaningful level.

[Insert **Table 8** about here]

As noted in the last two columns of Table 8, our information treatment does have a significant impact on the likelihood of selecting at least one non-qualifying cause as a recipient. Subjects in treatment T5 are approximately 23 percentage points less likely to select at least one non-qualifying charity as a recipient than counterparts in the no-information condition (T4) – a difference that is statistically significant at the $p < 0.01$ level.

Viewed in conjuction, the above results suggest that information about the CTC influences the compostion of the "portfolio" of cause types selected by subjects. To formally evaluate this conjecture, we estimate the effect of our information treatment on the number of qualifying causes selected as recipients in the first stage of the modified dictator game. To do so, we estimate a series of linear probability models similar to those described above but where the dependent variable is an indicator if the subject selects a specific number – zero, one, or two – of qualifying causes. Results from this exercise are presented in Table 9.

[Insert **Table 9** about here]

The first two columns of the table present results for the probability that the subject selects no qualifying causes, the middle two columns present results for the probability that the subject selects one qualifying cause, and the final two columns the probability that the subject selects two qualifying causes. Results from the table are consistent with our raw data summary and suggest a significant change in the composition of a subject's "portfolio". Specifically, we find that subjects in our information treatment are more than 16 percentage points less likely to select a mixed portfolio that includes one qualifying and one non-qualifying charity – a difference that is statistically significant at the $p < 0.01$ level and robust to the inclusion of demographic controls. In contrast, we find that subjects in our information treatment are approximately 22.7 percentage points more likely to select a portfolio that contains *only* qualifying causes – a difference that is statistically significant at the $p < 0.01$ level and robust to the inclusion of demographic controls.

Estimates from Tables 8 and 9 suggest a third result:

Result 3: *Information about the CTC program and whether donations to a given cause qualify under the program influences the mix of cause types supported.*

We believe this result is novel to the literature and suggests a new channel through which incentives and competition amongst charities influence donor behavior – incentives lead donors to change the portfolio of causes they support.[25] For researchers, this reinforces the need to extend our models to include multiple charities and the choice of causes supported by a donor. The result also suggests the need to develop ways to measure the social benefits of donations to a given cause. From a social welfare perspective, incentives that lead to a reallocation of funds across causes within a sector is not necessarily a problem if the dollars are flowing from lower-valued to higher-valued causes.

For policymakers and practitioners, Result 3 should be viewed as a cautionary tale. Tax incentives and other policies designed to increase contributions to select causes can introduce an unintended consequence – increased contributions to targeted causes may come at the expense of support for and donations to other causes. As such, policymakers should take care when designing such programs and establishing criteria for inclusion. Such choices may implicity determine not only who gains from the program but also who loses once the program is enacted.

As a final metric of interest, we revisit the effect of our information treatments on the allocation of donations across qualifying and non-qualifying causes – the intensive margin effect. To do so, we restrict attention to the subset of subjects who donated to at least one cause and estimate the following linear regression model

$$Y_{ilt} = \alpha + \beta T_i + \gamma_t + \mu_l + \varepsilon$$

where Y_{ilt} is the fraction of subject *i*'s total contribution that is directed to qualifying causes and the remaining variables are identical to those described above. We estimate the model for two different pairwise comparisons – T2 vs. T3 and T4 vs. T5. The first comparison is akin to that explored in prior work (e.g, Null, 2011; Ek, 2017; Filiz-Ozbay and Uler, 2019; Halwell et al.,

[25] In many regards, this result shares similarity with prior theoretical work on competition amongst charities and how fundraising effort can influence the types of causes that a donor supports (see, e.g., Rose-Ackerman, 1982; Scharf, 2014; or Krasteva and Yildirim, 2016).

2019) which reports how incentives affect allocation of donations across a fixed set of cause types. The second comparison extends this prior work and captures the combined effect of changes in the composition of the donor's portfolio of causes and any changes in the allocation of funds across a fixed portfolio type. For each comparison, we estimate two different specifications, one that only includes treatment effects and the relevant fixed effects and a second that augments this baseline model to include demographic controls.

Results for these models are presented in Table 10 and suggest that information about the CTC programs leads subjects to increase the fraction of donations allocated to qualifying charities. For example, when subjects cannot adjust the mix of qualifying and non-qualifying charities selected as recipients, information provision causes an approximately eight percentage point increase in the amount allocated to qualified causes – a difference that is significant at the $p < 0.05$ level and robust to the inclusion of demographic controls. For perspective, the average amount donated in treatment T2 (the no information benchmark) is approximately $49.73. The estimated treatment effect thus corresponds to an increase of approximately $3.97 in the amount allocated to qualifying causes.

[Insert **Table 10** about here]

Such effects are enhanced when donors are allowed to both adjust the composition of their portfolios and reallocate funds within a fixed portfolio mix. As noted in the final two columns of the table, the effect of information provision on the share allocated to qualifying causes is an approximate 11.8 percentage point increase – a difference that is statistically significant at the $p < 0.05$ level and robust to the inclusion of demographic controls. For perspective, the average amount donated in treatment T4 (the no-information benchmark) is approximately $52.23. The estimated treatment effect thus corresponds to an increase of around $6.16 in the average amount donated to qualifying causes.

Viewed in its totality, the estimates in Table 10 suggest a fourth result:

Result 4: *Information about the CTC program causes a reallocation of funds amongst qualifying and non-qualifying causes; an effect that is enhanced when donors are allowed to adjust the composition of cause types supported.*

Result 4 highlights the two channels through which the CTC program likely impacts donor choice. For those donors who support both types of causes, the program leads to a shift in donations away from non-qualifying causes and towards qualifying causes. However, there is an additional effect that enhances such reallocation. For a subset of donors, the CTC leads to a change in the types of causes supported. Importantly, this helps explain why contributions claimed through the CTC program have grown exponentially with no discernable impact on overall giving in the state; the program proverbially robs Peter to pay Paul.

Robustness Checks

As a first robustness check, we estimate the effect of our information treatment on the likelihood of donating to a given cause type. To do so, we estimate a series of linear probability models of binary indicators for whether or not the subject donated to a given cause type on our indicator for subjects assigned to an information condition and both list (choice set) and wave of survey fixed effects. As in the prior section, we restrict the analysis to the subset of treatments where subjects select multiple recipients and estimate the model separately for our two pairwise comparisons of interest (T2 vs. T3 and T4 vs. T5).

Results from these models are presented in Tables B1 and B2 of the appendix and provide further insight into the channels through which information impacts the allocation of funds across cause types. For example, as noted in Table B1, information provision had a small, but statistically insignificant, impact on the likelihood of making a donation to a qualifying cause. Similarly, Table B2 provides evidence that information provision had a negative, but statistically insignificant impact, on the likelihood of donating to a non-qualifying cause in those treatments where subjects were "forced" to select one cause of each type. In contrast, information provision had a negative and statistically significant effect on the likelihood of donating to non-qualifying causes in situations where subjects were free to select any mix of qualifying and non-qualifying causes.

Viewed in conjuction with results from Tables 8-10, these results reinforce that information provision works through different channels across these two treatment types. In situations where subjects cannot adjust the mix of cause types supported, information provision works solely along the intensive margin – subjects shift a portion of what they would have otherwise given to non-qualifying causes to qualifying recipients. However, when subjects are free to adjust the mix of

cause types supported, information provision works predominantly through selection of causes – the extensive margin.

As a second robustness check, we expand our sample to include incomplete responses and rerun our various econometric models. These data are for responders who completed the first block of the survey and the donation decision but did not complete the second block of survey questions. The inclusion of such observations affords a way to check for potential selection effects and expand the power of our statistical tests.[26]

Results from these models are presented in Appendix B and provide qualitative support for our main findings. For example, estimates in Tables B3 and B4 reinforce Result 1 that information provision has no impact on either the probability of donating to a selected recipient or the average donation amount. Similarly, estimates in Table B5 provide support for Result 2 – information provision leads to an increase in the fraction allocated to qualifying causes but only in treatments where subjects select multiple recipients. Interestingly, however, the magnitude of this effect is reduced when we include incomplete responses – the estimated treatment effect with incompletes is approximately 4 percentage points (or 25 percent) lower.

We observe similar, albeit less pronounced effects, when examining the effect of our information treatments in the pooled sample on the likelihood of selecting a non-qualifying recipient and the number of qualifying charities selected in conditions across treatments T4 and T5. For example, as noted in Table B6, subjects receiving information about the CTC in the pooled sample are approximately 20 percentage points less likely to select a non-qualifying recipient – an effect that is approximately 10 percent lower than the effect in the subset of complete responses. Similarly, as noted in Table B7, subjects in the pooled sample are approximately 15.5 percentage points less likely to select only one qualifying charity and 20.3 percentage points more likely to select two qualifying causes when receiving information about the CTC prior to the first stage of the modified dictator game – effects that are both less pronounced than that estimated using the subset of complete survey responses.

[26] Recall that our second block of survey questions focused largely on tax morale and prior charitable donations. Such questions may have lead subjects to infer that the experiment was designed to measure altruism or generosity. As such, it is possbile that subjects who allocated less to selected causes in the second stage allocation game would disproportionally drop out of the survey while answering the second block of questions. If so, this would bias our sample of completed surveys in favor of more altruistic types. Ex ante, it is unclear whether and how this would impact our estimated treatment effects.

Finally, estimates in Table B8 provide support for Result 4; information provision leads to an increase in the fraction allocated to qualifying causes with this effect enhanced when subjects are allowed to adjust the mix of cause types selected as recipients. Again, both of these effects are less pronounced than when we restrict attention to the subset of complete surveys. However, the effects in the full sample remain statistically and economically significant.

Viewed in its totality, estimates from Appendix B highlight the robustness of our main results. While the point estimates are muted when we include incomplete responses, they remain economically and statistically significant.

5. Conclusions and Discussion

Policymakers frequently attempt to encourage donations to charity with special tax provisions such as income tax deductions and credits at the state level. A key feature of many such programs is that the provisions only apply for donations to select causes rather than any registered 501(c)(3) organization. We report an online field experiment around the largest such state program, Arizona's state income tax credit for donations to qualifying charities, to ascertain how awareness of the program affects overall giving and the allocation of donations amongst causes.

Our research questions were motivated by two trends in giving following the introduction of the CTC: (i) claims for contributions to qualifying causes increased nearly 50 fold since the program's inception; and (ii) aggregate contributions statewide remained fairly constant over this same time period. We designed our experiment to ascertain whether targeted tax credits increase aggregate patterns of giving or lead donors to reallocate donations amongst causes. Our design further allows us to separately identify the effect of targeted tax credits along two margins of interests – the types of causes a donor elects to support and the allocation of funds amongst selected causes.

Our experiment included a representative sample of more than 900 Arizona residents who completed an on-line survey that included a modified dictator game where the set of potential recipients were non-profit organizations in the state. Subjects in the experiment were randomized into one of six treatments that varied along three main dimensions: (i) the provision of detailed information about the CTC and whether donations to a given organization qualified for the credit under the program; (ii) the number of recipients that could be selected in the first-stage of the

modified dictator game; and (iii) whether the lists from which recipients were selected contained a mix of qualifying and non-qualifying causes or only one type of cause.

Empirical results from our experiment show that information provision has no impact on either the number of donors or the aggregate amount donated. However, information about the program does influence the allocation of funds amongst qualifying and non-qualifying causes but only when subjects select multiple recipients. Results from our experiment thus provide a potential explanation for the observed trends in giving in Arizona that motivated our experiment – the increased contributions to qualifying causes may be coming at the expense of donations to other, related causes and thus the program has had limited impact on aggregate giving statewide.

Exploring the mechanisms underlying the reallocation across cause type, we find that it reflects changes along both the intensive and extensive margins. When subjects are unable to adjust the mix of cause types supported, information about the CTC leads them to reallocate some of the money that they would have given to non-qualifying causes to increased donations to qualifying causes. When subjects are allowed to adjust the mix of cause types supported, information about the CTC reduces the likelihood of selecting non-qualifying causes and increases the likelihood of selecting qualifying causes.

Our findings should prove of interest for both researchers and policymakers alike. For policymakers, our results provide a cautionary tale and highlight an unintended consequence of policies designed to encourage giving to a subset of targeted causes. Increased donations to targeted causes may serve to crowd out donations to other causes and thus have limited impact on overall patterns of giving. It is thus important to consider such effects when designing targeted policies and to understand not only who would gain from the program but also who would lose if it were enacted.

For researchers, our results suggest the importance of extending our theoretical models and empirical analysis to consider multiple public goods. Specifically, we should extend our models to explore whether and how targeted incentives such as tax credits or fund-raising mechanisms used by individual charities influence the selection of causes a donor supports and the allocation of donations across causes. Moreover, our findings suggest the need to develop methods to measure the social benefit of dollars allocated to different causes because the main effect of targeted charitable tax credits is realocation across causes not increase in total donations.

Finally, it is important to note that our results are at odds with work exploring the response of donors to new, but temporary, appeals such as disaster relief or requests to fund classroom projects in public schools. Future work should explore why donors respond differently to such appeals than they do to changes in the incentives for giving to a pre-existing cause. In particular, future work should explore whether and why the immediacy of need and the impermanence of a request influences its impact on aggregate patterns of giving.

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Tables

Table 1: State Policies Encouraging Charitable Contributions

Policy Type	Description	States	Specific Causes	Itemizers Only
Full or Partial Credit	20-100% credit on state income tax up to specified threshold for charitable donations	12+	Yes	Yes/No
Check-off Program	Donations to approved funds out of tax refunds or liability directly on tax form	30+	Yes	No
Neighborhood Assistance Credit	Long-term support of local, community-based charities (usually corporate taxes)	12+	Yes	Yes
State Deductions	Extended limits or special rules for deduction of charitable contributions	15+	Yes/No	Yes/No
Tuition Credits	State scholarship programs for K-12; extracurriculars for public schools; 50-100% credit on state income tax	13	Yes	Yes/No

Notes: The table describes state-level tax statutes aimed at encouraging charitable donations. Programs include state income tax credits, tax deductions, and programs decreasing the transaction costs of giving. Most programs are restricted to specific causes or charities. Arizona's CTC is the only one-to-one tax credit for non-school donations to qualifying charities. Please note that some states do not levy corporate and/or individual state income tax, reducing the number of possible state tax statutes.

Table 2: Description of Treatments in the Experiment

Treatment	Charity Recipient(s)	Choice Set	Charity Types	Information about CTC and Eligibility
Baseline (B)	1	1 list of 10	mixed; 5 qualifying and 5 non-qualifying	No
Treatment 1 (T1)	1	1 list of 10	mixed; 5 qualifying and 5 non-qualifying	Yes
Treatment 2 (T2)	2	2 lists of 5	list 1: qualifying; list 2: non-qualifying	No
Treatment 3 (T3)	2	2 lists of 5	list 1: qualifying; list 2: non-qualifying	Yes
Treatment 4 (T4)	2	2 lists of 5	both lists mixed	No
Treatment 5 (T5)	2	2 lists of 5	both lists mixed	Yes

Notes: The table describes the six treatments of the experiment. Each subject was assigned to only one of the six treatments. Thus, it is a between subject design.

Table 3: Sample Sizes across Treatments in the Experiment

	Total	B	T1	T2	T3	T4	T5
Wave 1:							
Complete	454	79	76	80	74	84	61
Incomplete	409						
Useful Incomplete	205	40	28	31	37	28	41
Wave 2:							
Complete	450	82	69	82	71	75	71
Incomplete	361						
Useful Incomplete	142	21	28	23	19	30	21
Total:							
Complete	904	161	145	162	145	159	132
Incomplete	770						
Useful Incomplete	347	61	56	54	56	58	62

Notes: This table splits the sample by treatment and wave. We also categorize subjects as "Complete" when they finish the entire online survey. Subjects are categorized as "Incomplete" is they exit the survey without completing it fully. Among the Incomplete subjects, we categorize those who exit after having made the allocation decision as "Useful Incomplete". We do not have demographic information for subjects who did not complete the survey.

Table 4: Summary Statistics for the Pooled Sample

	B	**T1**	**T2**	**T3**	**T4**	**T5**	**Total**
All Decisions:							
Subjects	161	145	162	145	159	132	904
Subjects Donated	137	111	130	119	133	106	736
Pr(Donated)	85.1%	76.6%	80.2%	82.1%	83.6%	80.3%	81.4%
Fraction to Qualifying	60.5%	65.0%	51.4%	58.6%	52.8%	70.5%	59.3%
Fraction to Non-qualifying	39.5%	35.0%	48.6%	41.4%	47.2%	29.5%	40.7%
Mean Donation	$49.11	$44.47	$49.73	$50.95	$52.23	$50.30	$49.50
Conditional Mean	$57.71	$58.09	$61.98	$62.08	$62.44	$62.64	$60.79
Qualifying Charities:							
Can Select	0 or 1	0 or 1	1	1	0, 1 or 2	0, 1 or 2	
Subjects Selected Any	103	92	162	145	124	112	738
Subjects Selected One	103	92	162	145	75	40	617
Subjects Selected Two					49	72	121
Subjects Donated	87	70	127	118	102	88	592
Pr(Donated)	84.5%	76.1%	78.4%	81.4%	82.3%	78.6%	80.2%
Subjects Donated to One					64	30	
Pr(Donated to One)					51.6%	26.8%	
Subjects Donated to Two					38	58	
Pr(Donated to Two)					30.6%	51.8%	
Mean Donation	$29.70	$28.92	$25.57	$29.86	$27.58	$35.45	$29.33
Conditional Mean	$54.97	$59.91	$32.62	$36.69	$42.99	$53.18	$44.79
Non-Qualifying Charities:							
Can Select	0 or 1	0 or 1	1	1	0,1 or 2	0,1 or 2	
Subjects Selected Any	58	53	162	145	110	60	588
Subjects Selected One	58	53	162	145	75	40	533
Subjects Selected Two					35	20	55
Subjects Donated	50	41	122	100	89	45	447
Pr(Donated)	86.2%	77.4%	75.3%	69.0%	80.9%	75.0%	76.0%
Subjects Donated to One					61	29	
Pr(Donated to One)					55.5%	48.3%	
Subjects Donated to Two					28	16	
Pr(Donated to Two)					25.5%	26.7%	
Mean Donation	$19.40	$15.54	$24.16	$21.10	$24.65	$14.85	$ 20.20
Conditional Mean	$62.48	$54.98	$32.08	$30.59	$44.04	$43.56	$40.79

Notes: : Figures in the table represent summary statistics across the different treatments.

Tables: Estimates for Pooled Data

Table 5: Effect of Information Treatment on Donation

	Pooled	Pooled with Demographic Controls
1(Information Treatment)	-4.8603	-6.7569*
	(3.5652)	(3.5570)
1(Indicator for Treatment with Multiple Recipients)	1.7312	0.4358
	(2.9331)	(2.9171)
Information Treatment × Multiple Recipients Indicator	4.6883	6.5963
	(4.3992)	(4.3751)
1(Female)		6.8362***
		(2.1068)
1(Below Age 35)		-1.2378
		(2.7190)
1(Above Age 65)		5.7966**
		(2.5532)
1(Annual Income below $50,000)		-9.4282***
		(2.4667)
1(Annual Income Above $100,000)		-3.4799
		(2.5900)
Fixed Effects:		
Wave Fixed Effects	Yes	Yes
R^2	0.017	0.044
N	904	904

Notes: The dependent variable is the aggregate amount donated by an individual in each wave, pooled over treatments. Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table 6: Effect of Information Treatment on Participation (Likelihood of being a Donor)

	Pooled	Pooled with Demographic Controls
1(Information Treatment)	-0.0874*	-0.1031**
	(0.0450)	(0.0450)
1(Indicator for Treatment with Multiple Recipients)	-0.0328	-0.0428
	(0.0353)	(0.0351)
Information Treatment × Multiple Recipients Indicator	0.0818	0.0968*
	(0.0551)	(0.0549)
1(Female)		0.0889***
		(0.0261)
1(Below Age 35)		0.0514
		(0.0323)
1(Above Age 65)		0.0178
		(0.0319)
1(Annual Income below $50,000)		-0.0748**
		(0.0307)
1(Annual Income Above $100,000)		-0.0468
		(0.0322)
Fixed Effects:		
Wave Fixed Effects	Yes	Yes
R^2	0.010	0.029
N	904	904

Notes: The dependent variable is a binary indicator which takes the value 1 when a positive amount is allocated for donation, and 0 otherwise. Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table 7: Effect of Information Treatment on Fraction of Donation to Qualifying Charities

	Pooled	Pooled with Demographic Controls
1(Information Treatment)	-0.0582	-0.0707
	(0.0573)	(0.0574)
1(Indicator for Treatment with Multiple Recipients)	-0.1141***	-0.1246***
	(0.0436)	(0.0435)
Information Treatment × Multiple Recipients Indicator	0.1530**	0.1660**
	(0.0644)	(0.0645)
1(Female)		0.0388
		(0.0281)
1(Below Age 35)		0.0119
		(0.0357)
1(Above Age 65)		0.0635*
		(0.0343)
1(Annual Income below $50,000)		-0.0494
		(0.0327)
1(Annual Income Above $100,000)		-0.0504
		(0.0344)
Fixed Effects:		
Wave Fixed Effects	Yes	Yes
R^2	0.013	0.021
N	904	904

Notes: The fraction is defined as donation to qualifying charities over the total donation of a subject.This is closer to a measure of conditional giving to qualifying charities. For subjects who did not donate at all, we code the fraction as zero, while keeping them in the sample.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level.

Extensive Margin Effects : Charity Selection

Table 8: Effect of Information Treatment on Selecting a Qualifying/ Non-Qualifying Charity for T4 & T5

	Qualifying Charity	Qualifying Charity with Demographic Controls	Non-qualifying Charity	Non-qualifying Charity with Demographic Controls
1(Information Treatment)	0.0638	0.0596	-0.2269***	-0.2279***
	(0.0449)	(0.0450)	(0.0560)	(0.0561)
1(Female)		-0.0439		-0.0808
		(0.0467)		(0.0563)
1(Below Age 35)		-0.0611		0.1337*
		(0.0673)		(0.0741)
1(Above Age 65)		-0.0180		-0.0639
		(0.0524)		(0.0638)
1(Annual Income below $50,000)		-0.0090		0.0350
		(0.0596)		(0.0664)
1(Annual Income Above $100,000)		0.0567		0.0127
		(0.0547)		(0.0689)
Fixed Effects:				
List Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.022	0.037	0.117	0.139
N	291	291	291	291

Notes: This table includes T4 and T5 treatments only since these treatments allow the choice of more than one charity of similar type.
The dependent variable is a binary indicator which takes the value 1 when a qualifying(non-qualifying) charity is chosen, and 0 otherwise.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table 9: Effect of Information Treatment on Selecting a Specific Number of Qualifying Charities

	Chose Zero	Chose Zero	Chose One	Chose One	Chose Two	Chose Two
1(Information Treatment)	-0.0638	-0.0596	-0.1630***	-0.1683***	0.2269***	0.2279***
	(0.0449)	(0.0450)	(0.0563)	(0.0562)	(0.0560)	(0.0561)
1(Female)		0.0439		-0.1246*		0.0808
		(0.0467)		(0.0584)		(0.0563)
1(Below Age 35)		0.0611		0.0726		-0.1337*
		(0.0673)		(0.0797)		(0.0741)
1(Above Age 65)		0.0180		-0.0819		0.0639
		(0.0524)		(0.0634)		(0.0638)
1(Annual Income below $50,000)		0.0090		0.0260		-0.0350
		(0.0596)		(0.0683)		(0.0664)
1(Annual Income Above $100,000)		-0.0567		0.0694		-0.0127
		(0.0547)		(0.0710)		(0.0689)
Fixed Effects:						
List Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.022	0.037	0.052	0.079	0.117	0.139
N	291	291	291	291	291	291

Notes: This table includes T4 and T5 treatments only since these treatments allow the choice of more than one charity of similar type.
The dependent variable is an indicator which takes values between 0 and 2 indicating the number of qualifying charity/charities being selected.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Intensive Margin: Allocation of Dollars across Charity Types

Table 10: Effect of Information Treatment on Fraction of Donation to Qualifying Charities

	T2 vs. T3	T2 vs. T3	T4 vs. T5	T4 vs. T5
1(Information Treatment)	0.0800**	0.0793**	0.1177**	0.1164**
	(0.0318)	(0.0313)	(0.0497)	(0.0501)
1(Female)		0.0437		0.0422
		(0.0312)		(0.0510)
1(Below Age 35)		0.0815**		-0.0560
		(0.0369)		(0.0645)
1(Above Age 65)		0.1022**		0.0242
		(0.0432)		(0.0597)
1(Annual Income below $50,000)		-0.0656*		-0.0431
		(0.0362)		(0.0604)
1(Annual Income Above $100,000)		0.0002		0.0003
		(0.0413)		(0.0630)
Fixed Effects:				
List Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.033	0.071	0.047	0.054
N	307	307	291	291

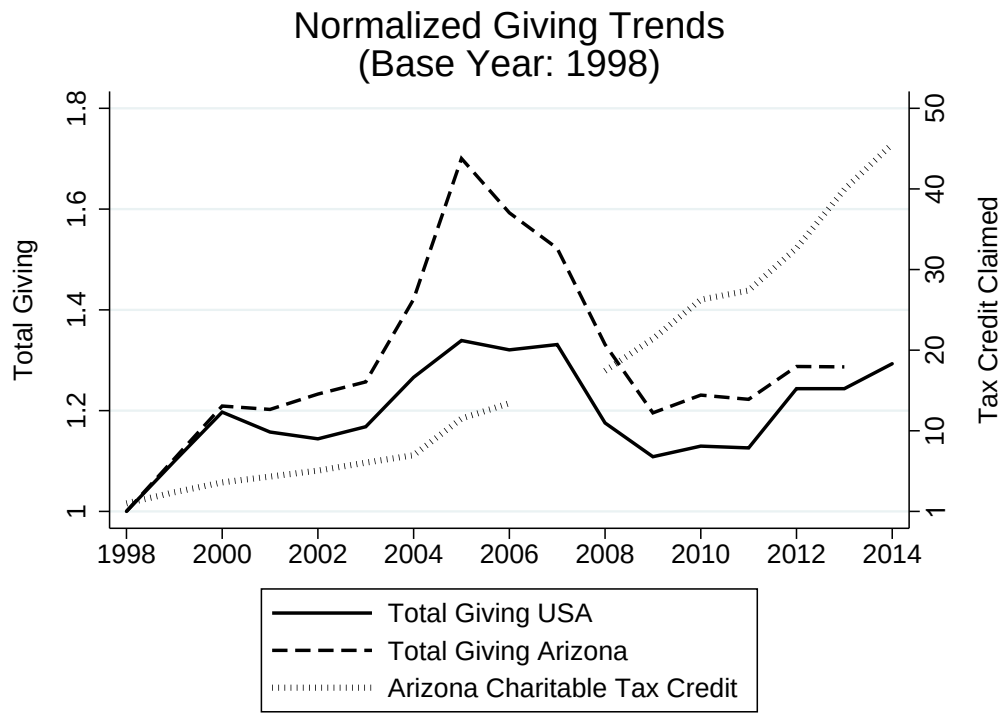
Notes: We consider treatments T2 to T5 here since subjects can allocate their endowment across two types of charities in these treatments.
The fraction is defined as donation to qualifying charities over the total donation of a subject. We consider only donors in this sample i.e. people who have made a positive donation.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Figures

Figure 1: Criteria for Qualifying Charities

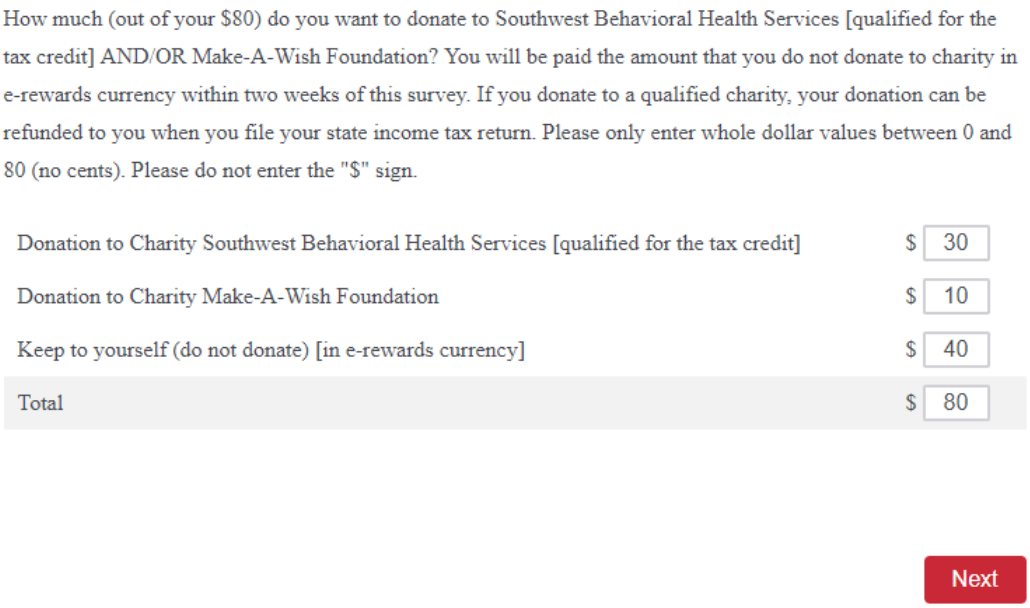
Notes: Overview of the criteria used by the Arizona Department of Revenue to dermine the qualifying status of charities for the CTC. Qualifying charities must meet all criteria and they must be registered with the Department of Revenue.

Figure 2: Charitable Giving Trends



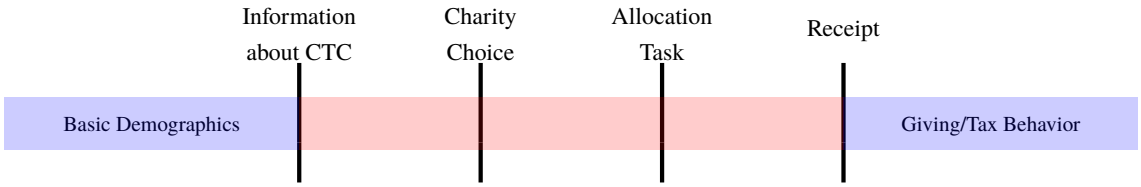
Notes: We plot giving in three categories from 1998 to 2015: (i) all giving to registered charities in the US; (ii) giving to registered charities in Arizona; and (iii) giving claimed through the CTC. All annual totals are normalized to giving in 1998 in the respective category.

Figure 3: Example Allocation Task with Two Charities



Notes: Example allocation task. Subjects receive an endowment of $80 and can freely allocate the amount between themselves and one or two charities that they chose on the previous page of the survey. The survey software indicates whether a charity qualifies for the CTC only in information treatments.

Figure 4: Overview of Timeline and Procedures in the Experiment



Notes: The experiment consists of three main phases. First, after consenting to participation, subjects answer basic questions about individual characteristics. Second, subjects face the randomized decision task, which include information about the CTC in some treatments, the choice of one or two recipient charities depending on the treatment, the allocation of the endowment between the subject and the recipient(s), and a receipt in case of a positive donation. Third, we ask subjects about their past donation behavior, knowledge and use of tax credits, and their tax filing behavior. The two question blocks are identical across treatments.

Appendix

Survey Design and Implementation: Added Detail

Our project progressed in five steps. First, we designed and developed the survey in Qualtrics' software. The final survey contains all components of the experimental design that we described in the previous section. Second, Qualtrics performed an internal quality control of the survey. This procedure ensured that the survey ran properly on different platforms and devices. Qualtrics also made sure that all questions follow current best-practice in survey design. After the quality control, Qualtrics conducted a "soft launch" with about ten percent of the target sample. The soft launch determined the expected survey duration, looked for unexpected technical difficulties, and allowed us to review the data format before the final rollout. Both waves of the experiment contained a soft launch.

Third, after a successful soft launch, Qualtrics opened the survey for the remaining sample. Recruitment was automated by the panel. The panel sent out a survey link to all registered members that met the criteria described above. Survey links were sent out in several sampling waves to ensure a representative sample based on the specific parameters – age, gender, and income – that we had specified. Members who chose to participate were subsequently assigned a unique and random identifier that we recorded in the data. Subjects could complete the survey on their preferred device at home or wherever they clicked on the link. If they exited the survey before completion, they could return to it at a later point. All decisions, including the allocation task, were automatically recorded by the software.

Fourth, Qualtrics performed several quality tests on the recorded decisions and shared the resulting data set with us. We received responses for all completed surveys and all surveys that were partially completed. Partial completions were from participants who exited the survey before the end and never returned to finish the remaining questions before the target sample was collected. Incomplete responses vary in terms of when the subject exited, although the majority of exists happened after the allocation task allowing us to use incomplete responses in some of our analyses.

Finally, we implemented payments to subjects and charities based on decisions in the allocation task. The experimental design includes two main forms of payment: (i) incentive payments based on the amount of the endowment not allocated to charities; and (ii) donations to

charities based on the subjects' decisions. These incentive payments were implemented in partnership with the panel provider and include a small show-up fee for completing surveys through the panel. Although many surveys do not include payments beyond the show-up fee, it is common to include additional payments for projects that include extraordinary survey elements, such as voice memos, videos, or diaries.

Our partner panel pays subjects in "e-Rewards currency", an online currency that can be used to purchase goods as well as gift cards from several retailers in an online portal.[1] While e-Rewards currency in not cash-equivalent, its many uses and familiarity of panel participants with the currency make it an attractive payment method. We thus relied on this existing infrastructure to pay subjects at the end of each wave of the experiment.[2]

To make payments to recipient charities, we developed a procedure that complied with the university's IRS compliance policies and the statutes of the CTC whereby the research team acted as an "umbrella organization" that directed donations to a qualifying charity on behalf of a donor.[3] To do so, we tallied the total contributions received by each charity in the experiment and created a separate invoice from the charity to Georgia State University for the donated amount. After receiving W-9 information from each charity, we set up a vendor profile and processed all donations which could be used by the charities to provide any service within the mission of the organization.

For subjects who shared their endowment with a selected recipient, our software provided receipts that were designed in collaboration with the Arizona Department of Revenue and could be used to claim the CTC. The receipts reinforce that a subject's decisions are consequential and impact not only immediate earnings, but also future tax liabilities should they donate to a

[1] See https://www.e-rewards.com/rewards.do for a list of all possible uses of e-Rewards. We show an example of current options as of April 2018 in Figure C3.
[2] At the end of each wave, we received the decisions for each subject using a random identifier. From this, we created a list of payments for each ID number based upon the amount kept by that subject in the allocation task. The panel provider used the ID number and list to distribute e-Rewards to the subjects.
[3] See https://www.azdor.gov/About/FAQs/CharitableTaxCredit.aspx for details. The CTC tax statute includes a provision for umbrella-type organizations: "Taxpayers may donate to a Qualifying Charitable Organization or Qualifying Foster Care Organization through an umbrella-type organization provided that the donation is designated to be directed to a Qualifying Charitable Organization or Qualifying Foster Care Organization that is certified by the Department."

qualifying cause.[4] The receipt summarizes the donation amount, the recipient charity or charities, information about the donor, and information about the research team. To match documentation provided by charities to their donors outside the study, we implemented a software feature that allows subjects to enter personal information, such as their name and address, in a textbox at the bottom of the receipt. Subjects were able to save the completed receipts locally as a PDF file or print it immediately for their tax records. As we did not want to record personally identifiable data, the software never recorded the entered information and required subjects to delete all information from the textbox before proceeding the next section of the survey.[5]

Threats to Identification

As noted in the main text, there are two potential threats to identification in our experiment. First, subjects in our experiment may have a strong preference for select causes or a history of giving to particular organizations that could influence allocations in our modified dictator game independent of treatment. Given that past donors are more likely donate and provide larger gifts than others, imbalance in the mix of qualifying and non-qualifying charities that subjects have supported in the past could bias our estimated treatment effect. A second threat to identification, centers around differences in baseline awareness of the CTC across treatments. As our treatment of interest is information about the CTC and whether donations to a potential recipient would qualify for a credit under the program, imbalance in awareness of the program could compromise identification and lead to biased estimates of our treatment effects.

We attempt to address the first concern using data from Table A1 which summarizes information from questions in the second block of the survey asking subjects whether or not they had given to each of the twenty potential recipient charities in the past. We use this data to generate three metrics of interest: (i) the number of past donations made to each of the twenty potential recipients; (ii) the number of past donations made to a charity that was included in subjects'

[4] We also provide receipts for donations to non-qualifying charities as such donations are eligible for federal tax deductions if the subject were to itemize. Figure C2 provides an example of the receipts that were provided to subjects.

[5] In practice, we required subjects to enter "0" in the textbox before proceeding to the next section. Any other content included in the textbox would prohibit the subjects from continuing with the survey. We described the process on the previous page of the survey and provided error messages detailing the necessary steps to continue should the subject fail to clear the textbox.

feasible choice set; and (iii) conditioned on observing a charity that they had supported in the past, the number of subjects who selected and gave to that charity in the experiment.

[Insert **Table A1** about here]

Table A1 highlights several patterns calling into question such concerns. First, as noted in the first column of the table, subjects in our experiment reported making 838 past donations to the set of charities included in analysis. More importantly, however, these donations were relatively split amongst qualifying and non-qualifying organizations; 455 or approximately 54.3% of the past donations were made to qualifying organizations with the remaining 45.7% going to non-qualifying organizations. Second, we observe a similar pattern if we restrict the analysis to past donations made to charitable causes included in the feasible set of potential recipients. In total, subjects in experiment reported 319 donations to organizations that were included in the set of potential recipients they observed in the first stage of the modified dictator game. Of these, approximately 61 percent (or 233) were donations made to qualifying organizations.

Finally, we can examine the extent to which past support for a charity impacts the likelihood that the subject selects that organization as a recipient in the experiment. As noted in the third column of Table A1, such organizations are selected as a recipient in the modified dictator game in approximately 48.5 percent (155 out of 313) of all such possible instances. Interestingly, if we split this analysis to focus on the selection of qualifying and non-qualifying organizations separately, we find that subjects are more likely to select a non-qualifying organization that they have supported in the past than they are to select a qualifying organization that they have supported in the past. Of the 86 instances in our data where a subject has the opportunity to select a non-qualifying organization that they have donated to in the past, this organization is selected half the time. In contrast, when a subject has the opportunity to select a qualifying organization that they have given to in the past, they only do so 43.8 percent of the time.

As an additional check, we estimate a series of linear probability models that examine if there is any correlation between a subject having made a past donation to (i) one of the twenty potential recipient organizations in our experiment and (ii) one of the ten organizations observed as part of their feasible choice set and indicators for the treatment to which the subject was assigned. Results from these models are presented in the final two columns of Table A3. As noted

in the table, there is no significant correlation amongst treatment assignment and our outcomes of interest.

Viewed in its totality, these data patterns suggest that subjects in our experiment cared about the causes selected as potential recipients in the experiment. However, there is no clear evidence that subjects cared more about qualifying organizations than non-qualifying organizations or vice versa. Furthermore, we find that past support for causes in our experiment is balanced across treatments.[6] Finally, there is no evidence that subjects are more likely to select a qualifying organization that they have given to in the past than they are to select a non-qualifying organization that they have supported in the past. Hence, subject's past preference towards a charity and observing those charities in the current choice set does not seem to drive behavior in our experiment. However, as described later, we control for such factors in our robustness checks and show that doing so does not change the qualitative nature of our findings.

A second threat to identification relates to awareness and past use of the CTC amongst subjects in our experiment – a characteristic that is ex ante unobservable. As our treatment of interest is information about the CTC and whether or not donations to a potential recipient would qualify for a credit under the program, one might expect that the effect of the intervention could depend upon baseline knowledge of the CTC. If this is indeed true, imbalance in prior awareness of the credit program across treatments could compromise identification and lead to biased estimates of our treatment effects.

We attempt to address this concern using data from questions in the second block of the survey asking subjects if they were (i) aware of the CTC program prior to the experiment and (ii) had claimed a credit through the CTC in the past. Table A2 summarizes the response to these questions by presenting the percentage of respondents within a treatment who answered that they were aware of the CTC prior to the survey (Columns 1 and 2) and, conditioned on being aware of the CTC, had claimed a credit through the program in the past (Columns 3 and 4). As noted in the first column of the table, almost forty of our subjects (348 out of 903) reported that they were unaware of the CTC prior to completing our survey. Importantly, however, we see no meaningful variation in this fraction across paired treatments. For example, there is 1.3 perecentage point

[6] Table A4 summarizes the raw data used to estimate these models.

difference in the fraction of subjects reporting that they were unaware of the CTC prior to the experiment when comparing our baseline treatment and treatment T1. While this difference is larger for the two remaining paired treatments (T2 vs T3 and T4 vs T5), neither is statistically significant using a two-sample test of proportions.

[Insert **Table A2** about here]

Interestingly, a significant fraction of subjects who were aware of the CTC prior to our experiment reported that they have not made any claims through the program. Of the subjects who reported that they were aware of the CTC prior to the experiment, approximately 35 percent (or 192 out of 555) have not made a claim through the program. Importantly, however, we see no significant differences in the proportion of such subjects across our paired treatments. For example, although there is an approximately 10 percentage point difference in this proportion across treatments T4 and T5, this difference is not statistically significant at any meaningful level.

As an additional balance test, we estimate a series of linear regressions exploring the correlation between our two outcomes of interest: (i) past awareness of the CTC and (ii) past claims through the CTC on indicators for the treatment to which the subject was assigned. Results from these regressions are presented in the first two columns of Appendix Table A3. As noted in the table, there is no significant correlation between treatment assignment and either outcome.

Viewed in its totality, data from Table A2 call into question concerns regarding bias relating to imbalance in prior awareness and use of the CTC across paired treatments. Moreover, data in the table suggest that there is a non-trivial fraction of our subjects who were unaware of the CTC program prior to our experiment. However, as described later, we control for such factors in our robustness checks and show that doing so does not change the qualitative nature of our findings.

Table A1: Past Donation Behavior and Current Choice by Charity in the Experiment

Charities	**# Who Donated to Charity in the Past**	**Had Previously Donated to Charity in Current Choice Set**	**Gave to charity Conditional on Past Donation**
Qualifying Charities:			
Arizona's Children Association	20	4	2
Community Food Bank	143	40	22
Phoenix Rescue Mission	45	22	10
Pima Council on Aging	4	4	1
Southwest Behavioral Health Services	7	6	2
Southwest Human Development	2	0	0
St. Mary's Food Bank	149	94	48
Teen Lifeline	8	6	4
Tucson Urban League	3	3	1
United Food Bank	64	54	22
Non-qualifying Charities:			
Arizona Community Foundation	15	3	0
Arizona Youth Partnership	41	4	1
Association for Supportive Child Care	12	2	1
Childhelp	19	0	0
Feed My Hungry Children	106	4	4
Food for the Hungry	45	10	1
Hospice of the Valley	56	20	13
Make-A-Wish Foundation	97	42	23
NARBHA	2	1	0
Pima Prevention Partnership	0	0	0
Total	838	319	155

Notes: This table summarizes information on past donations of subjects to the selected charities. It also provides information on the extent to which past donation to a charity impacts the likelihood of the same organization being chosen as a recipient in the experiment.

Table A2: Credit Awareness and Credit Claimed Before the Experiment

	Not Aware	Aware	Not Claimed	Claimed
B	38.5%	61.5%	37.8%	62.2%
T1	37.2%	62.8%	40.7%	59.3%
T2	47.5%	52.5%	36.5%	63.5%
T3	37.2%	62.8%	35.2%	64.8%
T4	31.4%	68.6%	30.3%	69.7%
T5	38.9%	61.1%	41.3%	58.8%

Notes: The credit awareness percentages in each treatment cell is out of the entire sample (903). However, the Credit Claimed percentages are out of the sample of those who were aware of the credit. We find one subject who did not answer this question since these were administered after the experiment. Thus, the total sample size in this case is 554, one less than the total number of subjects who are aware of the tax credit, 555.

Table A3: Balance of Observables

	Credit Awareness	Credit Claimed	Past Donation to Any Charity	Past Donation to Any Charity faced in the Choice Set
T1	0.0121	-0.0300	0.0313	0.0399
	(0.0556)	(0.0717)	(0.0573)	(0.0561)
T2	-0.0828	0.0440	0.0713	0.0265
	(0.0695)	(0.0893)	(0.0717)	(0.0694)
T3	0.0159	0.0525	0.0046	-0.0304
	(0.0684)	(0.0847)	(0.0705)	(0.0670)
T4	0.0917	0.1042	0.0206	-0.1029
	(0.0659)	(0.0817)	(0.0716)	(0.0672)
T5	0.0095	-0.0021	0.0536	-0.0583
	(0.0707)	(0.0891)	(0.0727)	(0.0683)
Fixed Effects:				
List Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.019	0.009	0.006	0.015
N	903	554	904	904

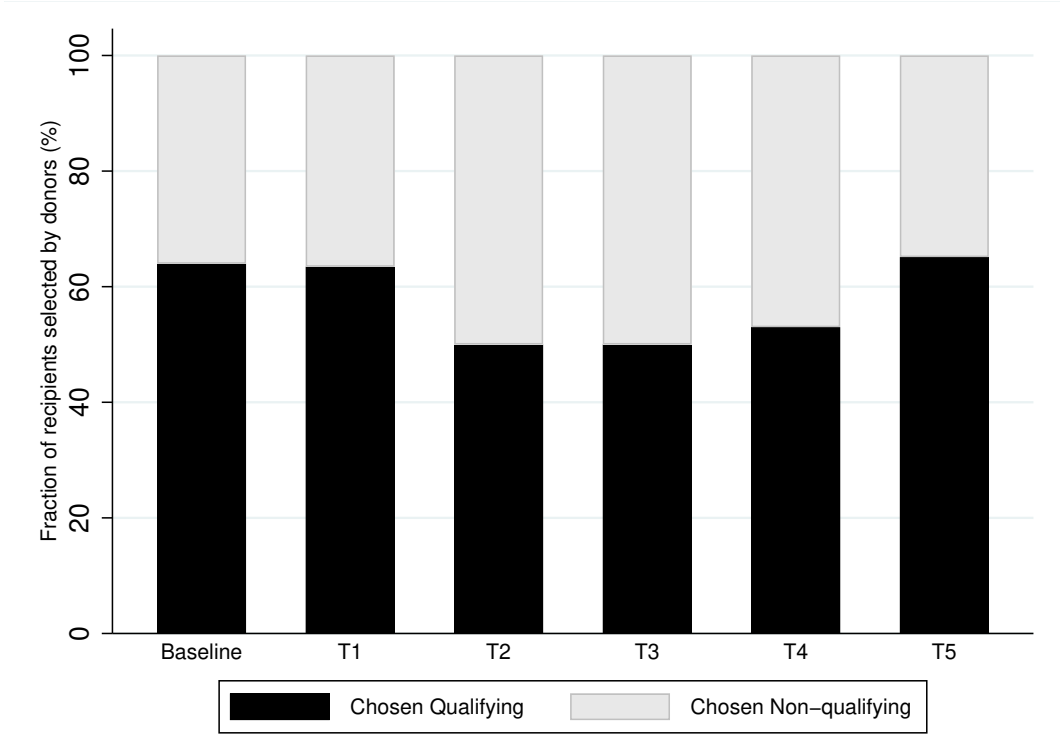
Notes: This table summarizes the balance of four characteristics that we record across the treatments. We regress the binary indicator variable of each characteristic on the indicator for the different treatments
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table A4: Past Donation Behavior and Current Choice

	Baseline	**T1**	**T2**	**T3**	**T4**	**T5**	**Total**
Sample Size (N)	161	145	162	145	159	132	904
Past Donation to any Charity (N)	71	69	80	63	77	68	428
Saw Past Charity in Choice set (N)	59	59	56	43	53	49	319
Donated to Past Charity (N)	24	28	28	23	28	24	155

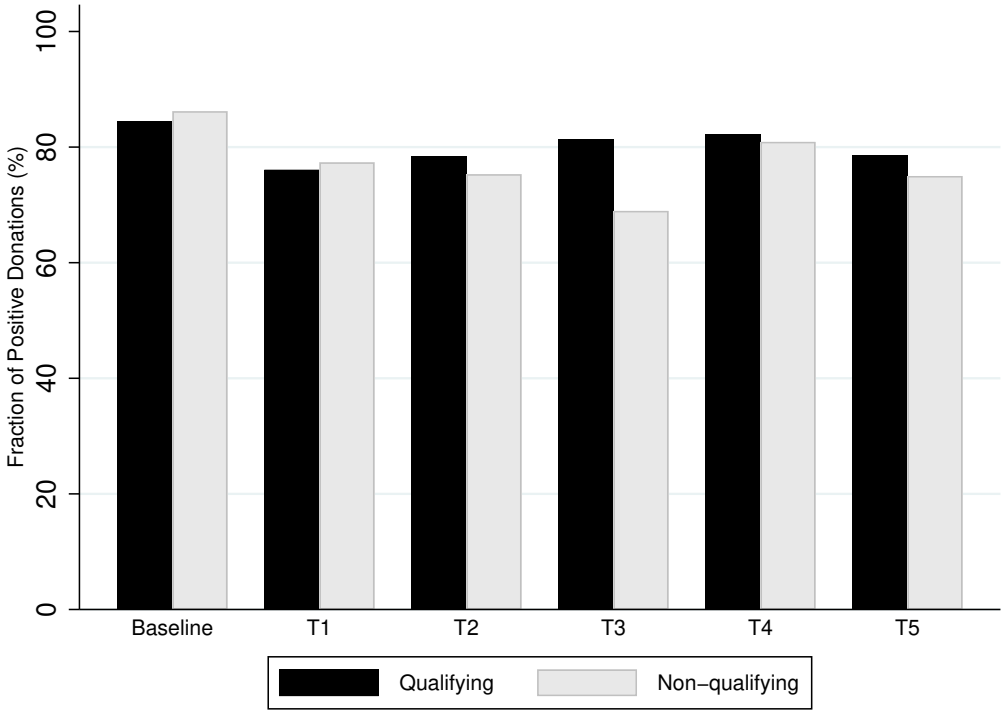
Notes: This table shows the link between past donations and the likelihood of donation to charities in the current choice set by treatments.

Figure A1: Fraction of Qualifying and Non-qualifying Charities Selected



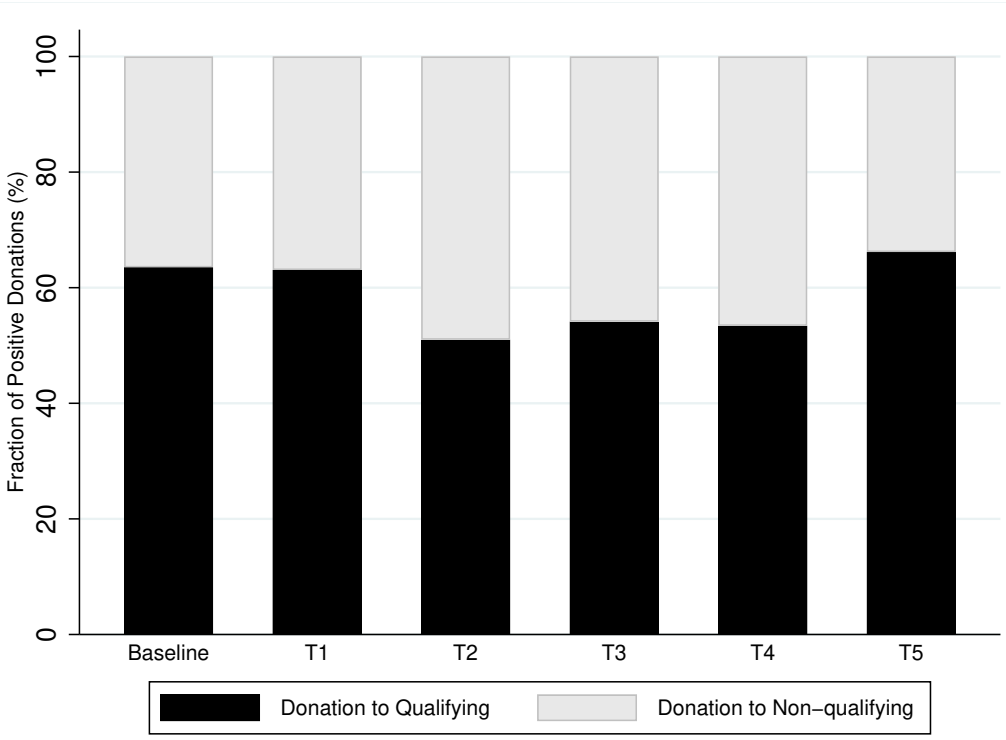
Notes: This graph shows the proportion of qualifying and non-qualifying charities selected in each treatment.

Figure A2: Propensity to Donate by Qualifying and Non-qualifying Charities



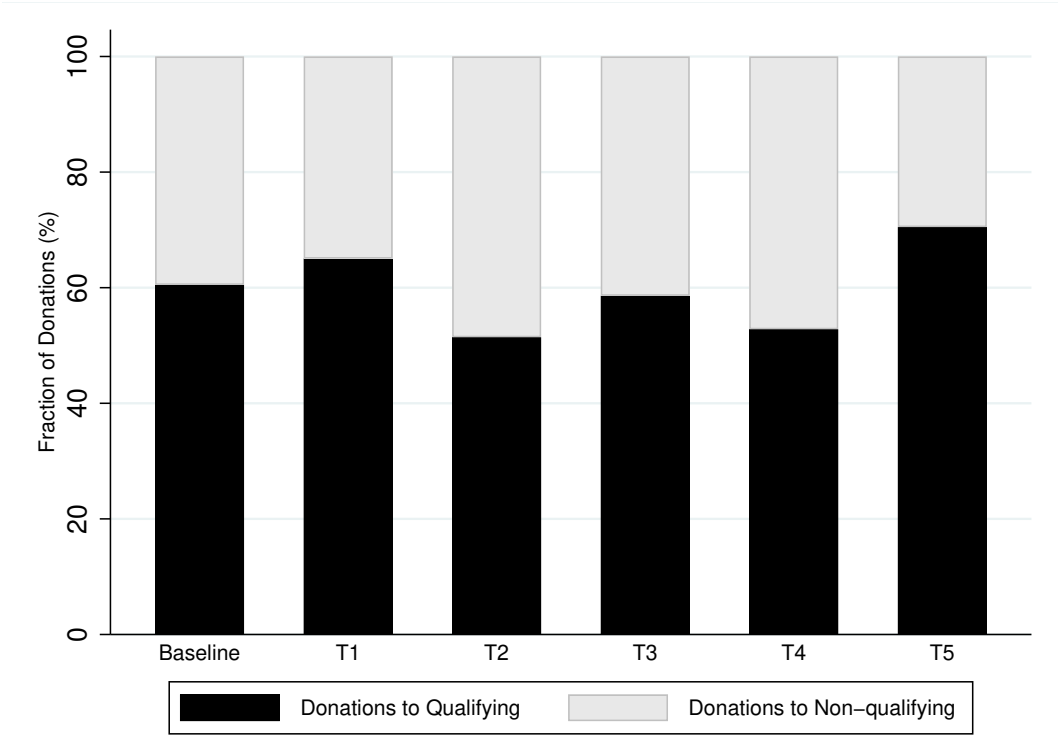
Notes: This graph shows the likelihood of donation to qualifying and non-qualifying charities in each treatment.

Figure A3: Fraction of Positive Donations Directed to Qualifying and Non-qualifying Charities



Notes: This graph shows the proportion of donations that went to qualifying and non-qualifying charities respectively out of the total number of donations.

Figure A4: Fraction of Total Donations (in $) Directed to Qualifying and Non-qualifying Charities



Notes: This graph shows the the fraction of their endowment subjects allocated to qualifying and non-qualifying charities on an average.

Appendix B: Robustness Checks

Table B1: Effect of Information Treatment on Making a Donation to a Qualifying Charity

	T2 vs. T3	T2 vs. T3	T4 vs. T5	T4 vs. T5
1(Information Treatment)	0.0340	0.0315	0.0269	0.0255
	(0.0455)	(0.0452)	(0.0559)	(0.0565)
1(Female)		0.0949**		0.0100
		(0.0463)		(0.0585)
1(Below Age 35)		0.1313**		-0.0224
		(0.0539)		(0.0778)
1(Above Age 65)		0.0847		-0.0234
		(0.0564)		(0.0662)
1(Annual Income below $50,000)		-0.0553		-0.0193
		(0.0540)		(0.0701)
1(Annual Income Above $100,000)		-0.0116		0.0232
		(0.0598)		(0.0711)
Fixed Effects:				
List Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.008	0.040	0.014	0.016
N	307	307	291	291

Notes: The dependent variable is the aggregate donation (in $) to a qualifying charity.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table B2: Effect of Information Treatment on Making a Donation to a Non-Qualifying Charity

	T2 vs. T3	T2 vs. T3	T4 vs. T5	T4 vs. T5
1(Information Treatment)	-0.0672	-0.0702	-0.2114***	-0.2109***
	(0.0514)	(0.0506)	(0.0571)	(0.0573)
1(Female)		0.1247**		-0.0100
		(0.0520)		(0.0586)
1(Below Age 35)		0.0680		0.1008
		(0.0627)		(0.0784)
1(Above Age 65)		-0.0626		-0.1155*
		(0.0663)		(0.0650)
1(Annual Income below $50,000)		-0.0530		0.0118
		(0.0595)		(0.0702)
1(Annual Income Above $100,000)		-0.0478		0.0186
		(0.0659)		(0.0696)
Fixed Effects:				
List Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.015	0.049	0.075	0.096
N	307	307	291	291

Notes: The dependent variable is the aggregate donation (in $) to a non-qualifying charity.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Appendix B : Robustness Checks with Inclusion of Incompletes

Note : The number of "useful incompletes" in our sample that we include for this analysis is 347. Thus the total sample size is 1251 (904+347). These are people who made the donation decision but dropped out before completing the experiment. We do not have demographic information for these people. Thus in column 2 with demographic controls we merely see the number of completes. This serves as a quick check to see whether including the incompletes in column 1 leads to results different from Column 2.

Table B3: Effect of Information Treatment on Donation

	Pooled	Pooled with Demographic Controls
1(Information Treatment)	-3.5697	-6.7569*
	(2.9481)	(3.5570)
1(Indicator for Treatment with Multiple Recipients)	3.4374	0.4358
	(2.4201)	(2.9171)
Information Treatment × Multiple Recipients Indicator	3.6869	6.5963
	(3.5960)	(4.3751)
1(Female)		6.8362***
		(2.1068)
1(Below Age 35)		-1.2378
		(2.7190)
1(Above Age 65)		5.7966**
		(2.5532)
1(Annual Income below $50,000)		-9.4282***
		(2.4667)
1(Annual Income Above $100,000)		-3.4799
		(2.5900)
Fixed Effects:		
Wave Fixed Effects	Yes	Yes
R^2	0.015	0.044
N	1,251	904

Notes: The dependent variable is the aggregate amount donated by an individual in each wave, pooled over treatments. Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table B4: Effect of Information Treatment on Participation (Likelihood of being a Donor)

	Pooled	Pooled with Demographic Controls
1(Information Treatment)	-0.0659*	-0.1031**
	(0.0348)	(0.0450)
1(Indicator for Treatment with Multiple Recipients)	-0.0179	-0.0428
	(0.0271)	(0.0351)
Information Treatment × Multiple Recipients Indicator	0.0640	0.0968*
	(0.0422)	(0.0549)
1(Female)		0.0889***
		(0.0261)
1(Below Age 35)		0.0514
		(0.0323)
1(Above Age 65)		0.0178
		(0.0319)
1(Annual Income below $50,000)		-0.0748**
		(0.0307)
1(Annual Income Above $100,000)		-0.0468
		(0.0322)
Fixed Effects:		
Wave Fixed Effects	Yes	Yes
R^2	0.011	0.029
N	1,251	904

Notes: The dependent variable is a binary indicator which takes the value 1 when a positive amount is allocated for donation, and 0 otherwise. Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table B5: Effect of Information Treatment on Fraction of Donation to Qualifying Charities

	Pooled	Pooled with Demographic Controls
1(Information Treatment)	-0.0326	-0.0707
	(0.0487)	(0.0574)
1(Indicator for Treatment with Multiple Recipients)	-0.1018***	-0.1246***
	(0.0370)	(0.0435)
Information Treatment × Multiple Recipients Indicator	0.1200**	0.1660**
	(0.0544)	(0.0645)
1(Female)		0.0388
		(0.0281)
1(Below Age 35)		0.0119
		(0.0357)
1(Above Age 65)		0.0635*
		(0.0343)
1(Annual Income below $50,000)		-0.0494
		(0.0327)
1(Annual Income Above $100,000)		-0.0504
		(0.0344)
Fixed Effects:		
Wave Fixed Effects	Yes	Yes
R^2	0.011	0.021
N	1,251	904

Notes: The fraction is defined as donation to qualifying charities over the total donation of a subject.This is closer to a measure of conditional giving to qualifying charities. For subjects who did not donate at all, we code the fraction as zero, while keeping them in the sample.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level.

Table B6: Effect of Information Treatment on Selecting a Qualifying/ Non-Qualifying Charity

	Qualifying Charity	Qualifying Charity with Demographic Controls	Non-qualifying Charity	Non-qualifying Charity with Demographic Controls
1(Information Treatment)	0.0474	0.0596	-0.2030***	-0.2279***
	(0.0400)	(0.0450)	(0.0464)	(0.0561)
1(Female)		-0.0439		-0.0808
		(0.0467)		(0.0563)
1(Below Age 35)		-0.0611		0.1337*
		(0.0673)		(0.0741)
1(Above Age 65)		-0.0180		-0.0639
		(0.0524)		(0.0638)
1(Annual Income below $50,000)		-0.0090		0.0350
		(0.0596)		(0.0664)
1(Annual Income Above $100,000)		0.0567		0.0127
		(0.0547)		(0.0689)
Fixed Effects:				
List Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.014	0.037	0.098	0.139
N	411	291	411	291

Notes: This table includes T4 and T5 treatments only since these treatments allow the choice of more than one charity of similar type.
The dependent variable is a binary indicator which takes the value 1 when a qualifying(non-qualifying) charity is chosen, and 0 otherwise.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table B7: Effect of Information Treatment on Selecting a Specific Number of Qualifying Charities

	Chose Zero	Chose Zero	Chose One	Chose One	Chose Two	Chose Two
1(Information Treatment)	-0.0474	-0.0596	-0.1555***	-0.1683***	0.2030***	0.2279***
	(0.0400)	(0.0450)	(0.0472)	(0.0562)	(0.0464)	(0.0561)
1(Female)		0.0439		-0.1246**		0.0808
		(0.0467)		(0.0584)		(0.0563)
1(Below Age 35)		0.0611		0.0726		-0.1337*
		(0.0673)		(0.0797)		(0.0741)
1(Above Age 65)		0.0180		-0.0819		0.0639
		(0.0524)		(0.0634)		(0.0638)
1(Annual Income below $50,000)		0.0090		0.0260		-0.0350
		(0.0596)		(0.0683)		(0.0664)
1(Annual Income Above $100,000)		-0.0567		0.0694		-0.0127
		(0.0547)		(0.0710)		(0.0689)
Fixed Effects:						
List Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.014	0.037	0.050	0.079	0.098	0.139
N	411	291	411	291	411	291

Notes: This table includes T4 and T5 treatments only since these treatments allow the choice of more than one charity of similar type.
The dependent variable is an indicator which takes values between 0 and 2 indicating the number of qualifying charity/charities being selected.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Table B8: Effect of Information Treatment on Fraction of Donation to Qualifying Charities

	T2 vs. T3	T2 vs. T3	T4 vs. T5	T4 vs. T5
1(Information Treatment)	0.0657**	0.0793**	0.1082***	0.1164**
	(0.0255)	(0.0313)	(0.0410)	(0.0501)
1(Female)		0.0437		0.0422
		(0.0312)		(0.0510)
1(Below Age 35)		0.0815**		-0.0560
		(0.0369)		(0.0645)
1(Above Age 65)		0.1022**		0.0242
		(0.0432)		(0.0597)
1(Annual Income below $50,000)		-0.0656*		-0.0431
		(0.0362)		(0.0604)
1(Annual Income Above $100,000)		0.0002		0.0003
		(0.0413)		(0.0630)
Fixed Effects:				
List Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.027	0.071	0.038	0.054
N	417	307	411	291

Notes: This table includes T4 and T5 treatments only since these treatments allow the choice of more than one charity of similar type.
The dependent variable is an indicator which takes values between 0 and 2 indicating the number of qualifying charity/charities being selected.
Robust standard errors are reported in parentheses.
*** denotes significance at the 1 percent level
** denotes significance at the 5 percent level
* denotes significance at the 10 percent level

Appendix C

Figure C1: Information about the CTC

Since 1998, Arizona offers a one-to-one state income tax credit for donations to qualifying charitable organizations. A one-to-one income tax credit means that your state income tax owed will be reduced by the entire amount you choose to donate to a qualified charity up to a threshold described below. In other words, your donations simply redirect tax dollars owed to the state from the general tax fund to a qualified charity of your choice. For example, if you choose to donate $X to a charity that is qualified for the state income tax credit, you can receive a refund of $X when you file your state income tax return. Donations to qualified charities are "free" for you if you claim the tax credit.

The credit program is called *Contributions to Qualifying Charitable Organizations* and allows taxpayers to claim a credit of up to $400 ($800) for an individual (joint) filer for contributions to qualified 501(c)(3) organizations serving particular causes certified by the Arizona Department of Revenue. Qualifying organizations are defined as follows:

An individual income tax credit is available for contributions to Qualifying Charitable Organizations that provide assistance to residents of Arizona who receive Temporary Assistance of Needy Families (TANF) benefits, are low income residents of Arizona, or are children who have a chronic illness or physical disability. In addition, a Qualifying Charitable Organization may be considered a Qualifying Foster Care Charitable Organization if it meets additional criteria in serving qualified individuals

A Qualifying Charitable Organization is a charity that meets ALL of the following provisions:

- *Is exempt from federal income taxes under Section a 501(c)(3) or is a designated community action agency that receives community services block grant program monies pursuant to 42 United States Code Section 9801.*
- *Provide services that meet immediate basic needs.*
- *Serves Arizona residents who receive temporary assistance for needy families (TANF) benefits, are low income residents whose household income is less than 150% of the federal poverty level, or are chronically ill or physically disabled children.*
- *Spends at least 50% of its budget on qualified services to qualified Arizona residents.*
- *Affirm that it will continue spending at least 50% of its budget on qualified services to qualified Arizona residents.*

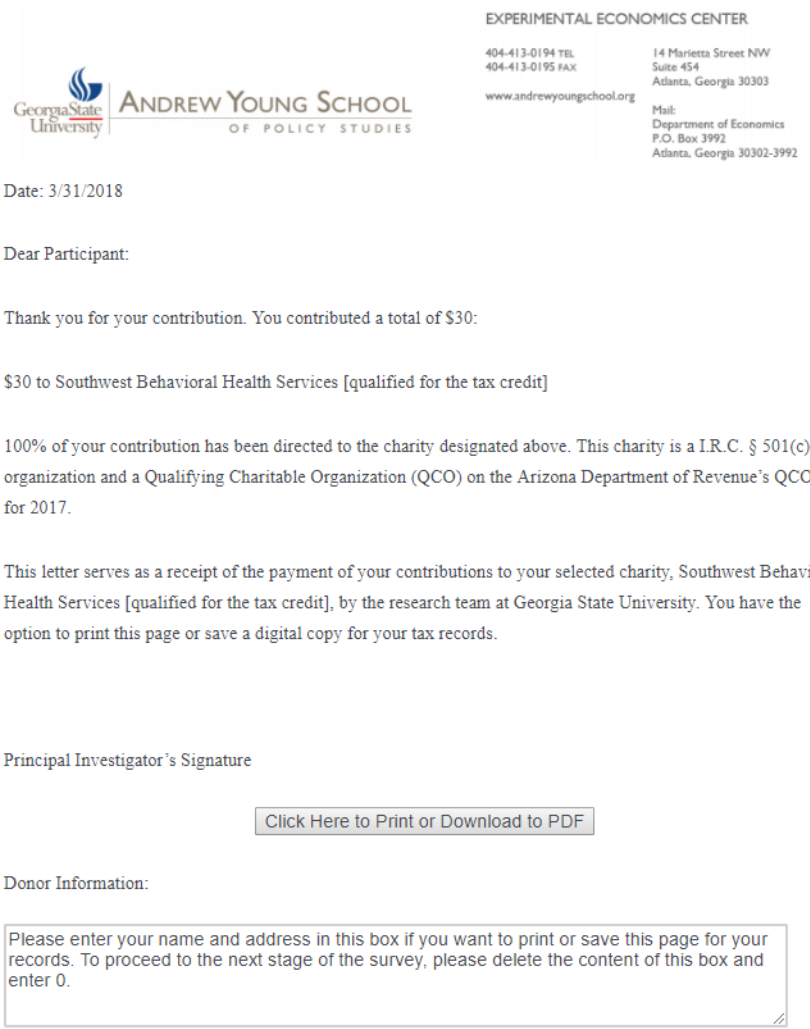
A charity must apply for and meet all requirements of the law to be considered as a Qualifying Charitable Organization. Approved charities' names are listed on the Department of Revenue's website.

You can obtain information about how to file the tax credit at www.azdor.gov or by typing "Arizona charitable giving tax credit" in the search engine of your choice.

Please look at the lists carefully and choose your preferred charitable organizations. It is entirely up to you how you determine your preferred charities; you can choose any charity you would like, regardless of how much you know about the charity or if you have donated to it in the past. The lists consist of both qualified organizations (**denoted with [qualified for the tax credit]**) and other charities that are not qualified for the income tax credit. If you give to a qualified organization, your contributions are eligible for the tax credit. Your chosen charity will be recorded by the survey software and will be the potential recipient in the allocation task of stage two.

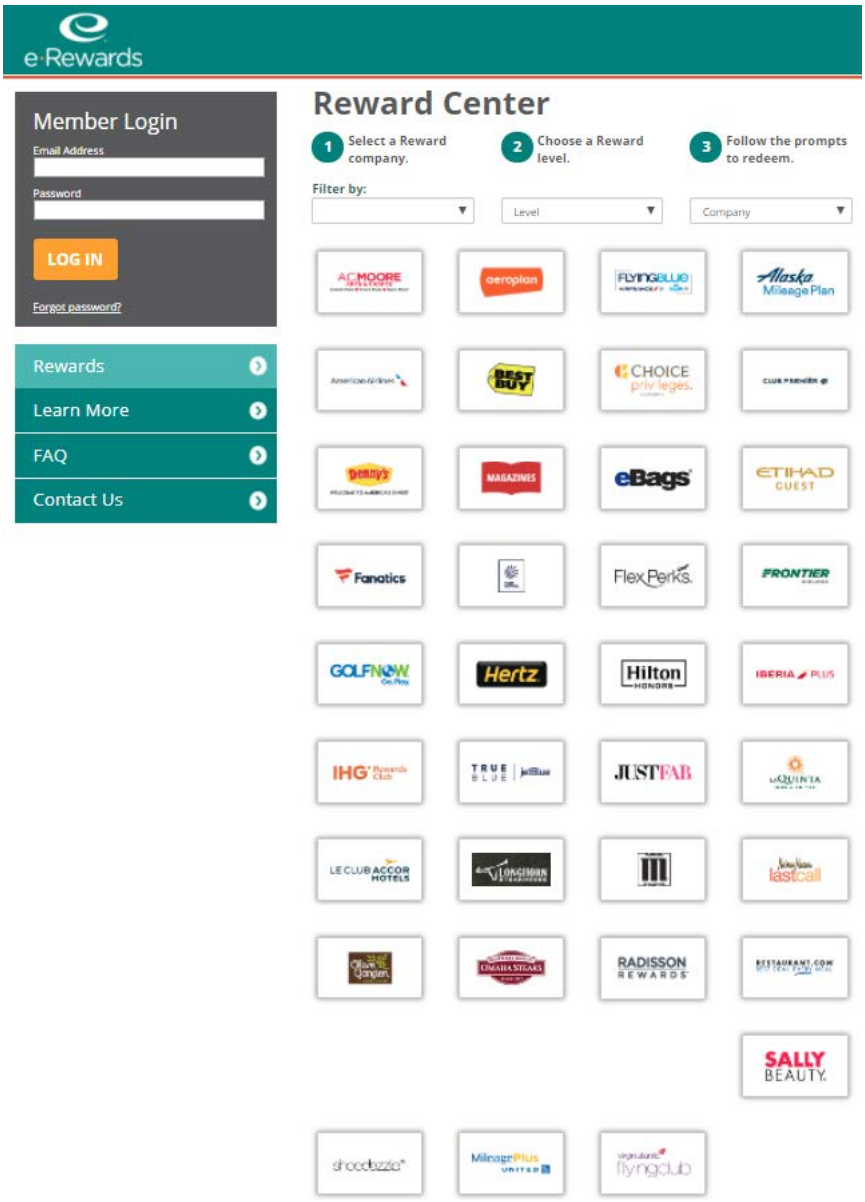
Notes: Subjects in treatments with information about the CTC see this information page before choosing a charity for the allocation task.

Figure C2: Example Receipt for Donation made to a Qualifying Charity



Notes: Example receipt for donations made to a qualifying charity. The text box at the bottom of the page allows subjects to enter their personal information. Before proceeding to the next page of the survey, subjects are forced to delete any personally identifiable data. A click on the button opens a standard print window that provides functionalities for saving a PDF locally or printing the receipt directly.

Figure C3: e-Rewards Currency Portal



Notes: Subjects received all show-up fees and payments based on their allocation decision in e-Rewards currency. e-Rewards can be used to purchase goods from online vendors.

Table C1: Charities in the Experiment, Part 1

Charity	Qualifies for the CTC	Mission Statement
Arizona Community Foundation	No	Lead, serve and collaborate to mobilize enduring philanthropy for a better Arizona.
Arizona Youth Partnership	No	Arizona Youth Partnership's mission is to partner with communities to cultivate healthy foundations for youth and promote strong families.
Arizona's Children Association	Yes	The mission of Arizona's Children Association is protecting children, empowering youth, and strengthening families.
Association for Supportive Child Care	No	Our mission is to enhance the quality of care for children in Arizona.
Childhelp	No	Childhelp exists to meet the physical, emotional, educational, and spiritual needs of abused, neglected and at-risk children. We focus our efforts on advocacy, prevention, intervention, treatment and community outreach.
Community Food Bank	Yes	We change lives in the communities we serve by feeding the hungry today, and building a healthy, hunger-free tomorrow.
Feed My Hungry Children	No	Feed My Hungry Children helps stand in the gap to provide the things that needy, hurting people may need to survive and become self-sufficient. Feed My Hungry Children's humanitarian projects are committed to helping children and their families around the world.
Food for the Hungry	No	Together we follow God's call responding to human suffering and graduating communities from extreme poverty.
Hospice of the Valley	No	Comfort and dignity as life nears its end.
Make-A-Wish Foundation	No	We grant the wishes of children with life-threatening medical conditions to enrich the human experience with hope, strength, and joy.
NARBHA	No	Managing integrated health care with a conscience. To be recognized as the innovative leader in managing superior behavioral health care.
Phoenix Rescue Mission	Yes	Providing Christ-centered, life-transforming solutions to persons facing hunger and homelessness.

Table C2: Charities in the Experiment, Part 2

Charity	Qualifies for the CTC	Mission Statement
Pima Council on Aging	Yes	Our mission is to provide dignity and respect for aging, and to advocate for independence in the lives of Pima County's older adults and their families, now and for generations to come.
Pima Prevention Partnership	No	Building partnerships with young people, families, and communities to improve their quality of life.
Southwest Behavioral Health Services	Yes	We inspire people to feel better and reach their potential. Through helping people discover their strengths, we improve our communities.
Southwest Human Development	Yes	Southwest Human Development strengthens the foundation Arizona's children need for a great start in life.
St. Mary's Food Bank	Yes	St. Mary's Food Bank serves to alleviate hunger through the gathering and distribution of food while encouraging self-sufficiency, collaboration, advocacy and education.
Teen Lifeline	Yes	To provide a safe, confidential, and crucial crisis service where teens help teens make healthy decisions together.
Tucson Urban League	Yes	The mission of the Tucson Urban League is to advance economic and social prosperity for African Americans and other underserved Tucson area residents by creating access to opportunity through advocacy, community partnerships, and programs and services.
United Food Bank	Yes	The mission of United Food Bank is to provide access to nutritious food for those who are without - by servicing as a community bridge between those who want to help and those who are in need.

Table C3: Charity Lists by Treatment

Subgroup 1	Subgroup 2
Pair 1: Baseline and Treatment 1	
Arizona Community Foundation	Arizona's Children Association
Hospice of the Valley	Arizona Youth Partnership
Make-A-Wish Foundation	Association for Supportive Child Care
NARBHA	Childhelp
Phoenix Rescue Mission	Community Food Bank
Pima Council on Aging	Feed My Hungry Children
Pima Prevention Partnership	Food for the Hungry
Southwest Behavioral Health Services	Teen Lifeline
Southwest Human Development	Tucson Urban League
St. Mary's Food Bank	United Food Bank
Pair 2: Treatment 2 and Treatment 3	
List 1	
Phoenix Rescue Mission	Arizona Youth Partnership
Pima Council on Aging	Association for Supportive Child Care
Southwest Behavioral Health Services	Childhelp
Southwest Human Development	Feed My Hungry Children
St. Mary's Food Bank	Food for the Hungry
List 2	
Arizona Community Foundation	Arizona's Children Association
Hospice of the Valley	Community Food Bank
Make-A-Wish Foundation	Teen Lifeline
NARBHA	Tucson Urban League
Pima Prevention Partnership	United Food Bank
Pair 3: Treatment 4 and Treatment 5	
List 1	
Hospice of the Valley	Arizona's Children Association
Pima Prevention Partnership	Arizona Youth Partnership
Southwest Behavioral Health Services	Childhelp
Southwest Human Development	Community Food Bank
St. Mary's Food Bank	Feed My Hungry Children
List 2	
Arizona Community Foundation	Association for Supportive Child Care
Make-A-Wish Foundation	Food for the Hungry
NARBHA	Teen Lifeline
Phoenix Rescue Mission	Tucson Urban League
Pima Council on Aging	United Food Bank

Notes: Subjects were randomly assigned to a treatment. Within each treatment, subjects were subsequently assigned to one of two subgroups that differed in terms of the charity list(s) from which subjects could choose the recipient(s) in the allocation task. Each treatment pair contained the same lists of charities.