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JACKPOT FOR GOOD:
CAN LOTTERY MATCHES INCREASE CHARITABLE GIVING?

Amelia Ahles
Joanna Lahey
Marco A. Palma

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ABSTRACT

This study investigates the effectiveness of donation matching gift schemes using lotteries for increasing charitable giving relative to deterministic matches of equivalent or higher expected value and a no-match control. We recruit 1,402 online participants and randomly assign them to one of seven conditions: No Match (Control), and two sets of matching schemes of varying equivalent expected values: EV=1 (1:1 Deterministic Match, 1:10% of 10 tokens, and 1:1% of 100) and EV=0.5 (2:1 Deterministic Match, 1:1% of 50 tokens and 1:0.5% of 100), where one token is $0.50. Participants complete three 10-token allocation decisions for hunger-related charities with one allocation randomly selected for realization. The 1:1 Match significantly increases giving by 15.7% compared to No Match. We find that matching schemes with a small probability of a very large amount (1% and 0.5% of 100) elicit significantly higher rates of giving compared to No Match (Mann-Whitney p=0.019 and p=0.096 respectively) and do not statistically differ from the 1:1 Match (Mann-Whitney p=0.976 and p=0.622 respectively). Our results suggest nonprofits can use matching gift donations more efficiently through lottery matching donation schemes while increasing downstream donations.

Amelia Ahles
Oklahoma State University
amelia.ahles@okstate.edu

Joanna Lahey
Texas A&M University
The Bush School
and NBER
jlahey47@gmail.com

Marco A. Palma
Texas A&M University
mapalma@tamu.edu

A randomized controlled trials registry entry is available at https://www.socialscienceregistry.org/trials/13266

1 Introduction

Understanding key drivers of charitable giving is important for nonprofit organizations and their beneficiaries. Roughly $2 to $3 billion is donated annually in the United States alone under matching schemes, in which a lead donor matches subsequent individual charitable donations by a rate up to a predefined amount to increase total donations.[1] For example, the 1:1 deterministic match is a popular mechanism for fundraising, where for every $1 donated a third-party "matches" the donation with an additional $1. This type of matching scheme has generally been found to be an effective mechanism for increasing donations compared to no-matching (Karlan and List, n.d.; List 2011; Vesterlund 2016). Matching gifts increase donations from downstream donors by encouraging them to perceive their individual donations going further and increasing the impact of their individual contribution (Huck and Rasul 2011; Karlan, List, and Shafir 2011). While previous work finds that 1:1 matching ratios effectively increase charitable donations compared to no matching gifts (Karlan and List, n.d.; List 2011; Vesterlund 2016), investigations into the effects of larger matching ratios (1:2 and 1:3 matches, where for every $1 donated a third party donates $2 or $3) (Karlan and List, n.d.) or equivalent rebates (Eckel and Grossman 2003; Davis and Millner 2005; Vesterlund 2016) find no significant increases in donations compared to 1:1 matches. Matching ratios below 1 (ex. 2:1, where for every $2 donated a third party donates $1) do not increase donations compared to no-matching (Karlan, List, and Shafir 2011). Previous results suggest that charitable organizations cannot generate increased efficiency gains in individual donations by using matches smaller than 1:1.

This lack of donor responsiveness to smaller matching ratios suggests the potential for a behavioral intervention to investigate lottery matching gift schemes on donations. More specifically, we are interested in determining if a lottery matching scheme, with its lure of a high reward (albeit at a low probability — including expected value rewards below the 1:1 matching equivalent), can motivate donors to increase contributions while lowering the cost

1. Source: https://doublethedonation.com/matching-gift-statistics/

to charities compared to the gold-standard 1:1 match. Lotteries are popular despite being economically irrational for risk averse individuals, with their low probabilities of winning and low payout ratios (even compared to other forms of gambling). There are several theories as to why people engage in lotteries, but there is no clear consensus among researchers. Ariyabuddhiphongs (2011) provides a review of current psychological and economic theories such as the theory of judgment under uncertainty, cognitive theory of gambling, and the theory of demand for gamblers. Given the widespread use, familiarity, and fascination of the general public with lotteries, we incorporate this concept into the charitable giving matching literature.

Lotteries have been investigated in a variety of domains with mixed results. For public goods contributions, the use of lottery incentives (Fabbri, Barbieri, and Bigoni 2019; Naritomi 2019; Goette and Stutzer 2020) and lottery prizes (Morgan 2000; Lange, List, and Price 2007) are generally effective. Lotteries (or raffles) have long been used to finance public good contributions and have shown to be more effective than deterministic (or known) payments, particularly when the prize is large and valued (Morgan 2000; Morgan and Sefton 2000). However, alternative domains such as lotteries to encourage survey responses (Singer and Ye 2013; Halpern et al. 2011), education outcomes (Levitt, List, and Sadoff 2016), and health care (Volpp et al. 2017) have generally found lotteries ineffective. In these previous studies, the lottery prize is awarded to the *donor*; a key contribution of our framework is the prize is awarded as a match to the *nonprofit organization* for individual contributions.

This study investigates two relatively unexplored questions about the impacts of matching gift schemes on charitable giving. We assess if a low-probability, potentially high-reward lottery matching gift influences individual charitable donations to (1) increase individual donations and (2) extend the use of matches to increase fundraising goals. We conduct an online experiment with a sample of 1,402 general population participants to investigate the effects of uncertain donation matches (lottery matches) at two different expected values compared to no matching and a standard 1:1 match. We implement seven conditions: *"No*

Match" (Control), and two sets of 3 matching conditions (1 deterministic and 2 lottery matches) for expected values of 1 and 0.5. Participants are endowed with 10 tokens ($5.00) and asked to complete three allocation decisions (Eckel and Grossman 2003, 2006; Charness and Holder 2019; Deck and Murphy 2019) for hunger-related charities, with one allocation randomly selected for realization.

Consistent with previous findings, deterministic 1:1 matching increases contributions by 0.70 tokens ($0.35) over *No Match*, an increase of 16% off the *No Match* base of 4.46 (Mann-Whitney[2] $p = 0.032$). Similarly, we find that deterministic matches with a lower Expected Value (EV) (*2:1*) do not significantly differ from *No Match* (MW $p = 0.830$). Additionally, lottery matches with a 1% chance of 100 tokens (implying a 1:1 probabilistic match) produce donations that are significantly larger than *No Match* (MW $p = 0.019$) and not statistically different than the deterministic 1:1 Matching (MW$p = 0.976$). Crucially, we also find that the lottery match with a 0.5% chance of 100 tokens (implying a 2:1 probabilistic match) also produces higher donations than the no-match (MW $p = 0.096$) and no different than the deterministic 1:1 matching (MW $p = 0.622$). Based on these results, we conduct back-of-the-envelope calculations to investigate if nonprofits can leverage *1%* and *0.5% of 100* lottery matches to extend pledged matching caps to increase donations. Our calculations find a *1%* and *0.5%* of $100 lottery match can increase donations by 19% and 216% respectively without increasing the pledged match cap. Therefore, we conclude lottery matches with a low probability of a large jackpot can raise funds statistically indistinguishable from deterministic 1:1 matches thus extending the use of matches to increase fundraising goals.

We see this paper as having three key contributions. First, we are the first to our knowledge to explore the effect of lottery matches on donations when the lottery prize goes to the charity rather than to the donor.[3] Second, we explore the effects of uncertain matches in which the participant is certain that their donation will go to the charity, but there

2. Mann-Whitney (hereafter MW) tests the hypothesis that two independent samples are from populations with the same distribution (Wilcoxon 1945; Mann and Whitney 1947).

3. We discuss a concurrent working paper, Higgs (2025), below.

is only a chance that a match will follow. Third, we demonstrate that lottery matching mechanisms with lower expected values can extend matches in fundraising campaigns to increase fundraising goals for no additional match cost to nonprofit organizations.

2 Literature Review

While 1:1 matches are effective, individual donations are not sensitive to the magnitude of matching ratios when matches are greater than 1; larger matches (1:2 and 1:3) do not increase contributions beyond the 1:1 match (Karlan and List, n.d.). Smaller matches (3:1) decreased donations when combined with high example suggested donations (ex. $75), but had no effect on donations when combined with a lower example suggested donation (ex. $25) in a natural field experiment (Karlan, List, and Shafir 2011). While deterministic matching rations lower than 1 have not been shown to increase donations over no-match, it is possible that lottery incentives with low expected values but substantive jackpots could increase donations because, the predictions of prospect theory suggest that people will be insensitive to smaller probabilities when the jackpot is large.

Why agents choose to participate in lotteries, which are gambles with actuarially unfair odds with low probabilities of winning (sometimes several million to one) for a large jackpot but an expected value much smaller than the lottery ticket purchase price has been highly studied (Friedman and Savage 1948; McCaffery 1994; Clotfelter and Cook 1990; Griffiths and Wood 2001; Ariyabuddhiphongs 2011). Prospect theory suggests that people overweight small chances of winning the lottery (Kahneman and Tversky 1979; Tversky and Kahneman 1992), and potentially focus on the size of the jackpot (Peel 2010). Other theories suggest a consumption value of playing (Burger et al. 2020), with perhaps disproportionate utility from lottery winnings (Friedman and Savage 1948). Theories about “longshot bias”[4] suggest individuals favor skewness, not risk, in horse betting (Golec and Tamarkin 1998) and lottery

4. A gambling behavior where bettors prefer positive skewness of potential returns (i.e., a low probability of a high return) over higher expected returns (i.e, high probability of a low return).

tickets (Garrett and Sobel 1999). However, a later laboratory study by Grossman and Eckel (2015) suggests while preferences for skewness may impact risky decision-making, there is evidence of probability weighting impacting participants choices, with larger maximum payoffs (jackpots) appearing to drive participant preferences towards skewed lotteries.

Individuals may treat lotteries differently when the lottery benefits another rather than themselves, although this has not been studied in the context of lottery matches to charities. For example, previous research on risky decision-making finds the responsibility of decision-making for others reduced loss aversion (Andersson et al. 2016), which suggests lotteries may be even more attractive in donation settings. However when risky decisions impose externalities on others, De Oliveira (2021) finds no evidence that individuals increase risk taking to benefit others. Studies investigating how uncertainty and risk impact excuse-driven risk preferences (Exley 2016; Palma and Xu 2019) in charitable giving find that when tradeoffs exist between self and charity, people are risk averse to a charity's risk and risk seeking to self risk, serving as an excuse to not give, which suggests lotteries could be less attractive in our setting.

Classical investigations into competitive fundraising mechanisms such as lotteries provide winnings to the *donor* and thus behave like standard lotteries in gambling theory. These investigations have found that lottery (raffle) tickets and auctions are generally effective at increasing donations compared to voluntary contribution mechanisms (VCM). This literature has spurred a large literature on competitive fundraising mechanisms including lotteries and auctions (Morgan and Sefton 2000; Morgan 2000; Davis et al. 2006; Lange, List, and Price 2007; Andreoni and Payne 2013; Vesterlund 2016; Carpenter and Matthews 2017; Duffy and Matros 2021).

We have been only able to find one other published study that tests a lottery bonus framework where the bonus is given to the charity rather than to the participant (Deck and Murphy 2019). However, their focus is to determine whether different incentives change the choice of *which* charity to give to, not whether the lottery match itself increases donations.

They find increases in giving based on match bonuses are primarily driven by reallocating funds away from match-ineligible charities to match-eligible charities (Deck and Murphy 2019).

A concurrent working paper, Higgs (2025), also looks at uncertain charitable giving matches in a different framework. The main differences between his empirical study and ours is that first, he explores smaller match jackpots between 1 and 2 (instead of 1 and 100), and second, his participants make 13 decisions for the same charity (instead of 3 of the same decision, once for each charity), and thus can compare their choices internally. Unlike previous literature, he finds that a 2:1 deterministic match is preferred to a 1:1 deterministic match, which may be an artifact of his survey design allowing direct comparisons. Linear regressions in the paper suggest increasing donations with increased probability of a match, which is consistent with our findings, although our sample universes are different. Two innovations in his paper are a two-sided model and his exploration of participants' behavior based on how they change the size of their donations given certainty of matches ("match lovers," "match haters," and "match ignorers"). We view this paper as complementary to ours.

3 Experimental Design

This study investigates the effects of lottery matching gift schemes on individual contributions to charitable donation. We implement seven between-subject treatments, shown in Table 1, to investigate how an uncertain lottery match impacts an individual's charitable donation.

The *No Match* serves as our baseline control and has no match. We also implement three treatments with an expected value of one token. That is, if one token is donated by a participant, then, on expectation, an additional "bonus" one token will be donated to the charity. The difference between the treatments is that in the *1:1 Match*, the donation is

Table 1: Experimental Treatments

Treatment	Description	EV	N
No Match	No donation match		209
1:1 Match	Donate 1 Token, guaranteed organization donation of 1 Token	1	199
1:10% of 10 Tokens	Donate 1 Token, 10% chance organization donation of 10 Tokens	1	204
1:1% of 100 Tokens	Donate 1 Token, 1% chance organization donation of 100 Tokens	1	196
2:1 Match	Donate 1 Token, guaranteed organization donation of 0.5 Token	0.5	209
1:1% of 50 Tokens	Donate 1 Token, 1% chance organization donation of 50 Tokens	0.5	197
1:0.5% of 100 Tokens	Donate 1 Token, 0.5% chance organization donation of 100 Tokens	0.5	188

*Note each token is worth $0.50

guaranteed, whereas in the *1:10% of 10 tokens*, for every 1 token donation, the matching gift is probabilistic with a 10% chance of 10 bonus tokens. Similarly, the *1:1% of 100 tokens* provides a 1% chance of 100 bonus tokens matching. The remaining three treatments follow the same pattern but with an expected value of 0.5. That is, the deterministic match is *2:1*, if one token is donated by the participant, then an additional bonus of half of a token will be provided to the charity as a match. Similarly, in the lottery matches, there is a *1% of 50 token* and a *0.5% chance of 100 token* match, respectively.

The treatments are structured to answer two questions. First: Can lottery matching increase charitable giving at a similar rate as the *1:1 Match*? Second, if so: Can lottery matching increase individual contributions when the organization match has an EV of less than 1? By focusing on lottery matching treatments where EV$\leq$ 1 compared to the common 1:1 match, we can determine if there are effective matching schemes that either (1) increase donation amounts from individuals (lotteries with EV=1) or (2) extend fundraising campaign goals without increasing matching funds (lotteries with EV<1).

3.1 Theoretical Predictions

The extant theory motivating literature on charitable giving preferences using matching gift schemes assumes donors derive utility from donation to charity (e.g., see Becker 1974; Andreoni 1989, 1990, 2006; Andreoni and Payne 2013; Hungerman and Ottoni-Wilhelm 2021; Vesterlund 2016). Matches thus lower the price, in terms of foregone individual consumption, by providing part of the total donation amount received by the charity (Andreoni and Payne 2013). We start with a standard model for charitable giving, adding in the lottery match. We assume an individual donor i maximizes the utility derived from the consumption of private goods (c_i) and how much the charity receives in donations, R_i, which is the sum of the individual's "checkbook" charitable donations (g_i) and any subsequent matches. As per usual, total income $y_i = c_i + g_i$.

We use a simplified CES utility function to capture risk preferences, but, in order to make the math more tractable, remove the $(1/\gamma)$ exponent term that captures social preferences, given that our focus is not social preferences.[5] Thus: $U_i(c_i, R_i) = ac_i^\gamma + (1-a)R^\gamma$ where $a\epsilon[0,1]$ is the selfishness parameter, and γ captures risk aversion with $0 < \gamma < 1$ indicating risk aversion.[6]

We introduce a probabilistic match in which the charity always gets the initial individual donation g_i, but there is some probability, p, that the charity gets an additional matched donation which is λ (the jackpot) times g_i (the individual donation).[7]

Then the expectation of U_i is:

$$E[ac_i^\gamma + (1-a)R^\gamma] \tag{1}$$

$$= ac_i^\gamma + (1-a)E[R^\gamma] \tag{2}$$

$$= ac_i^\gamma + (1-a)E[pR_{win}^\gamma + (1-p)R_{lose}^\gamma] \tag{3}$$

$$= ac_i^\gamma + (1-a)p(g_i + \lambda g_i)^\gamma + (1-a)(1-p)(g_i^\gamma) \tag{4}$$

5. Feldman and Vargas (2023) provide a more general framework that allows for a fuller separation between risk and social preferences. Their more general model nests Andreoni and Miller (2002) and thus will yield similar predictions for our set-up.

6. γ also includes preferences for smoothing payoffs between own consumption and donations to charity, again we refer you to the excellent Feldman and Vargas (2023) model exploring the tradeoffs between risk and social preferences.

7. In our experiment the decision on whether to give g would be decided for each additional dollar rather than being decided on the entire donation at one time.

Taking the partial derivatives w.r.t. c_i and g_i s.t. $MRS = 1$.

$$\frac{\partial E[u_i]}{\partial c} = \gamma a c_i^{\gamma-1} \tag{5}$$
$$\frac{\partial E[u_i]}{\partial g} = (1-a)p\gamma(g_i + \lambda g_i)^{\gamma-1}(1+\lambda) + (1-a)(1-p)\gamma g_i^{\gamma-1} \tag{6}$$

$$MRS = \frac{\frac{\partial E[u_i]}{\partial g}}{\frac{\partial E[u_i]}{\partial c}} = \frac{(1-a)\gamma[p(g_i)^{\gamma-1}(1+\lambda)^{\gamma-1}(1+\lambda) + (1-p)g_i^{\gamma-1}]}{\gamma a c_i^{\gamma-1}} = 1 \tag{7}$$

$$\frac{(1-a)[p(g_i)^{\gamma-1}(1+\lambda)^{\gamma-1}(1+\lambda) + (1-p)g_i^{\gamma-1}]}{a c_i^{\gamma-1}} = 1 \tag{8}$$
$$a c_i^{\gamma-1} = (1-a) g_i^{\gamma-1}[p(1+\lambda)^{\gamma} + (1-p)] \tag{9}$$
$$c_i = [(\frac{1-a}{a})^{\frac{1}{\gamma-1}}(p(1+\lambda)^{\gamma} + (1-p))^{\frac{1}{\gamma-1}}]g_i \tag{10}$$

plug in $y_i = c_i + g_i$

$$y_i - g_i = [(\frac{1-a}{a})^{\frac{1}{\gamma-1}}(p(1+\lambda)^{\gamma} + (1-p))^{\frac{1}{\gamma-1}}]g_i \tag{11}$$
$$y_i = g_i[(\frac{1-a}{a})^{\frac{1}{\gamma-1}}(p(1+\lambda)^{\gamma} + (1-p))^{\frac{1}{\gamma-1}} + 1] \tag{12}$$
$$g_i^* = \frac{y_i}{(\frac{1-a}{a})^{\frac{1}{\gamma-1}}(p(1+\lambda)^{\gamma} + (1-p))^{\frac{1}{\gamma-1}} + 1} \tag{13}$$

If $\gamma < 1$ is positive, indicating risk aversion, then giving increases with λ and p. Thus theoretical predictions for our proposed treatments would follow expectations for a risk-averse utility maximizer, indicate certain matches and larger jackpots (λ) are preferred comparatively to *No Match* and smaller jackpot lotteries. We would predict certain *1:1 Matches* will raise the greatest donations, followed by treatments with equivalent expected values but lower match probability (*1:10% of 10* and *1:1% of 100*). Continuing the same theoretical predictions for treatments of lower expected values (EV=0.5), we predict more certain matches will raise more funds compared to *No Match*, but less than certain matches with higher expected values (i.e., *1:1 Match*). Within our treatments where EV=0.5, we can predict the deterministic *2:1 Match* will raise the most donations, and *1:1% of 50*, *1:0.5% of 100* will exhibit smaller donations compared to *2:1 Match* and matches of larger expected value. Therefore for all treatments, the theoretical predictions would follow a downward trend from largest to smallest donations as: *1:1 Match, 1:10% of 10, 1% of 100, 2:1 Match, 1:1% of 50, 1:0.5% of 100,* and *No Match*.

If we consider adding in prospect theory, the math is the same, except p is replaced with $\pi(p)$ where $\pi(p) = \frac{p^\alpha}{(p^\alpha+(1-p)^\alpha)^{\frac{1}{\alpha}}}$

Thus:

$$g_i^* = \frac{y_i}{(\frac{1-a}{a})^{\frac{1}{\gamma-1}}(\pi(p)(1+\lambda)^\gamma + \pi(1-p))^{\frac{1}{\gamma-1}} + 1} \tag{14}$$

The key insights here are: when p is small, $\pi(p) \approx \pi(p+\varepsilon)$ for all small ε, however $1-p$ will be large when p is small so $\pi(1-p) \not\approx \pi(1-p+\varepsilon)$, so the $(\pi(1-p))$ term is important. But when λ, the jackpot, is large enough, this term swamps the $\pi(1-p)$ term. Thus: when p is small and λ is large, utility maximizers will treat gambles with the same jackpot but different (small) probabilities similarly.

In the context of our lottery match treatments, this addition means that a utility maximizer would view treatments with the same large jackpots ($\lambda = 100$) and different small probabilities similarly. For our treatments we would predict the *0.5%* and *1%* of 100 token lottery treatments will raise similar amounts of donations to each other and will raise more money compared to smaller jackpot treatments (e.g., *1:10% of 10* and *1:1% of 50*).

3.2 Experimental Procedures

We conduct an online experiment using panelist from Forthright Access (forthrightaccess.com). The institutional review board (IRB) at Texas A&M University approved the procedures, and the study is pre-registered with the American Economic Association's registry for randomized control trials (AEARCTR-0013266). Participants begin the online experiment by reviewing the consent form, instructions, and passing two attention checks to ensure they pay close attention to the instructions. Participants who fail one attention check receive a warning. Participants who fail both attention checks are disqualified and removed from the study.[8] We implement a decision allocation task (sometimes referred to as a modified dictator game), a standard method of elicitation in charitable giving literature (Charness and Holder 2019; Deck and Murphy 2019; Eckel and Grossman 2003; Eckel, Sinha, and Wilson 2023) to elicit charitable donations. In line with Deck and Murphy (2019) participants make multiple (3) independent decisions and one decision is randomly selected for realization. We select three highly reputable 501(c)(3) nonprofit organizations working on hunger issues: Feeding America, Meals on Wheels, and Action Against Hunger. The charities and descriptions given to participants are reported in Table 2. All three charities have a four out of four rating by Charity Navigator, which is a 501(c)(3) nonprofit charity assessment organization that evaluates charitable organizations based on financial stability, adherence to best practices for accountability, transparency, and results reporting.

In each independent decision allocation task, participants are endowed with 10 tokens, with each token worth \$0.50, and allocate the 10 tokens between themselves and the charity. Each decision allocation task includes the name of the charity and the brief description provided in Table 2 at the top of the allocation page. An example of what participants see is available in Figure A1. Participants view the three charity allocations in random order to control for any order effects. After all three allocation decisions, participants complete a survey to measure the reputation perceptions of the charities, charitable giving behavior, 9-point self-reported altruism scale (Manzur and Olavarrieta 2021), German Socio-Economic Panel Study (SOEP) risk aversion measure (Richter et al. 2017). In addition, for participants

8. Our study experienced a 9.4% dropout rate:1,568 surveys started, 1,402 completed, 166 removed (156 incomplete and 10 unqualified), which is low compared to estimated distribution of attrition rates of 15-30% reported by Stantcheva (2023). Dropouts on average seem to be more likely to be female (58% compared to the stratified 50%), older (53 compared to 46), and without children under 18 (84% compared to 71%).

Table 2: Charities & Descriptions Provided in Experiment

Charity	Description
Feeding America	Feeding America is a United States–based non-profit organization that is a nationwide network of more than 200 food banks that feed more than 46 million people through food pantries, soup kitchens, shelters, and other community-based agencies.
Meals on Wheels	Meals on Wheels America is the community-based organization dedicated to providing nutrition and helping to eliminate isolation among the elderly. It supports more than 5,000 communities across the United States.
Action Against Hunger	Action Against Hunger is a global humanitarian organization which originated in France and is committed to ending world hunger. The organization helps malnourished children and provides communities with access to safe water and sustainable solutions to hunger.

in a lottery matching treatment, we elicit their interest in knowing the lottery's resolution.

After the survey, participants receive information about the charity that is randomly selected for realization (Figure A2). Additionally, participants in the lottery match treatments are subsequently directed to spin a digital lottery wheel (Figure A3) to determine the matching outcome. After participants observe the match outcome, they are informed about the total payments to themselves and the charity and exit the experiment.

3.3 Subjects

We recruit 1,402 general population participants using Forthright Access. Forthright Access is a research-grade, fully-managed online panel of 100% US-based participants. Forthright uses a multi-step verification process to vet and verify all participants' information before they participate in our research. Participants are randomly assigned to one treatment at the beginning of the study. As recent literature has pointed to weaknesses in balance tests (e.g., Deaton and Cartwright 2018; Briz, Drichoutis, and Nayga Jr 2017; Ho et al. 2007; Moher et al. 2010; Mutz and Pemantle 2015), we report standardized differences (Imbens and Rubin 2016; Imbens and Wooldridge 2009) of observable characteristics in Table 3 to check for effective randomization of participants across treatments. Based on Cochran and Rubin's (1973) heuristic that the standardized difference should be less than 0.25, we can conclude our sample is well randomized.

We base preliminary power calculations on Charness and Holder's (2019) reported average contribution, sample size, and standard error for the total no-matching and total matching groups to estimate effect size ($|d = 0.487|$). Based on effect size, we estimate for a power of 0.80 we will need a sample size of 69 subjects per cell. To investigate any potential gender differences given our modeling framework incorporating risk, we pre-registered our plan to stratify by gender for 14 total cells (2x7).

Table 3: Standardized Differences Between Treatments for Observable Characteristics

	No Match vs.						1:1 Match vs.				
	1:01	1:10% of 10	1:1% of 100	2:01	1:1% of 50	1:0.5% of 100	1:10% of 10	1:1% of 100	2:01	1:1% of 50	1:0.5% of 100
Female	0.0531	0.0429	0.0322	0.1536	0.0476	0.0846	0.096	0.0854	0.2071	0.1007	0.1379
Age	-0.1214	-0.0611	-0.1847	-0.0714	-0.07	-0.141	0.0602	-0.0682	0.0509	0.0482	-0.0228
Hispanic	0.1359	0.1228	0.0393	0.0259	0.0917	0.1542	0.0131	0.1752	0.1618	0.0442	0.0182
Income	0.1731	0.1118	0.1763	0.0113	0.0562	0.1382	-0.0632	0.0048	-0.1592	-0.1151	-0.0347
Married	0.0171	0.0874	0.0684	0.051	0.0099	0.0552	0.0703	0.0855	0.0339	0.0071	0.0381
Education	-0.1448	-0.029	-0.1934	-0.0226	-0.0632	-0.031	0.1183	-0.0477	0.1226	0.0789	0.1104
Children	0.0203	0.0064	0.0412	0.0525	0.0183	0.0008	0.0267	0.0209	0.0323	0.0385	0.0211

	1:10% of 10 vs.				1:1% of 100 vs.			2:1 Match vs.		1:1% of 50 vs.
	1:1% of 100	2:1	1:1% of 50	1:0.5% of 100	2:1	1:1% of 50	1:0.5% of 100	1:1% of 50	1:0.5% of 100	1:0.5% of 100
Female	0.0106	0.1106	0.0047	0.0417	0.1212	0.0153	0.0523	0.1058	0.0688	0.0370
Age	-0.1259	-0.0098	-0.0105	-0.0814	0.1175	0.1127	0.0446	-0.0010	-0.0725	-0.0691
Hispanic	0.1620	0.1487	0.0311	0.0314	0.0133	0.1309	0.1934	0.1176	0.1801	0.0624
Income	0.0672	-0.0989	-0.0542	0.0279	-0.1623	-0.1185	-0.0390	0.0443	0.1250	0.0807
Married	0.1560	0.0364	0.0774	0.0321	0.1195	0.0783	0.1237	0.0411	0.0042	0.0453
Education	-0.1676	0.0061	-0.0358	-0.0033	0.1712	0.1261	0.1576	-0.0411	-0.0090	0.0313
Children	0.0476	0.0589	0.0118	0.0056	0.0113	0.0595	0.0421	0.0708	0.0534	0.0174

4 Results

Summary statistics are reported in Table 4 for the overall sample, and by treatment. We calculate an average donation as the average of charitable allocations over all three decisions for each participant. Overall, an average of 4.79 tokens are allocated to charity. [9]

9. Men donated an average of 4.69 tokens and women donated an average of 4.89 tokens across all treatments; there is no significant difference (MW $p = 0.1533$) in giving by gender. Additional sub-sample analysis by gender is reported in Appendix A.

Table 4: Summary Statistics of *Average Donation* by Treatment

		Overall		
		Mean	SD	N
	No Match	4.46	2.91	209
EV=1	*1:1 Match*	5.16	3.13	199
	1:10% of 10	4.79	3.17	204
	1:1% of 100	5.11	2.84	196
EV=0.5	*2:1 Match*	4.54	2.92	209
	1:1% of 50	4.51	2.91	197
	1:0.5% of 100	4.99	2.93	188
	Total	4.79	2.98	1,402

By treatment, the *1:1 Match* has the largest average donation at 5.16 tokens, with the second most from *1:1% of 100* at 5.11 tokens (MW test comparison to *1:1 Match*, $p = 0.9764$), and the third highest donation is *1:0.5% of 100* at 4.99 tokens (MW test comparison to *1:1 Match*, $p = 0.6221$).

To identify changes in giving behavior based on match treatments, we first compare our *No Match* control to the standard *1:1 Match* and lottery matches of equivalent value. We report Mann-Whitney tests comparing average donations for each treatment relative to *No Match* in Table 5 and relative to *1:1 Match* in Table 6. Consistent with a large portion of previous literature, we find an average donation of 5.16 tokens in the *1:1 Match* is significantly higher (MW $p = 0.0325$, Table 5) than the 4.46 token average donation in *No Match*, with an increase of 15.7% in tokens. Looking at equivalent value lottery matches to *1:1 Match* (EV=1), we find *1:10% of 10 tokens* does not produce statistically different donations (MW $p = 0.3258$, Table 5) compared to the *No Match* condition. However, *1:1% of 100 tokens*, does produce a significant increase of 14.6% in average donations compared to the *No Match* (MW $p = 0.0199$, Table 5), with an average donation of 5.11 tokens.

Looking now at treatments with a lower expected value (EV=0.5), average donations in the *2:1 Match*, are not statistically different (MW $p = 0.8304$, Table 5) from *No Match*. Additionally, when comparing equivalent lottery matches of EV=0.5 to *No Match* we find *1:1% of 50 tokens* is not significantly different from *No Match*, however, *1:0.5% of 100 tokens*

Table 5: *Average Donation* for Treatments to *No Match*

		Mann-Whitney Test P-Values	Difference in Means (Treatment - NM)
		Overall	Overall
EV=1	*1:1 Match*	0.0325**	0.70
	1:10% of 10	0.3258	0.33
	1:1% of 100	0.0199**	0.65
EV=0.5	*2:1 Match*	0.8304	0.08
	1:1% of 50	0.7162	0.05
	1:0.5% of 100	0.0962*	0.53
Note: * p<0.1, ** p<0.05, *** p<0.01			

is marginally significantly different(MW $p = 0.0962$, Table 5), with a substantive difference in magnitude of 0.53 more tokens donated.

Table 6: *Average Donation* for Treatments to *1:1 Match*

		Mann-Whitney Test P-Values	Difference in Means (Treatment - 1M)
		Overall	Overall
EV=1	*1:10% of 10*	0.2582	-0.37
	1:1% of 100	0.9764	-0.05
EV=0.5	*2:1 Match*	0.0522*	-0.62
	1:1% of 50	0.0582*	-0.65
	1:0.5% of 100	0.6221	-0.17
Note: * p<0.1, ** p<0.05, *** p<0.01			

We then compare our lottery treatments with the *1:1 Match* to determine, first, if equivalent EV lotteries increase donations amounts, which could make them more attractive than the deterministic match. Here, neither lottery match with an equivalent value significantly differs in donations (see Table 6) from the *1:1 Match*. There are slight differences in giving magnitude, with *1:10% of 10* donating 0.37 fewer tokens and *1:1% of 100* donating 0.05 fewer tokens compared to a *1:1 Match*. This indicates that lotteries with the same expected value can elicit donations similar to 1:1 matching, but there is no benefit to non-profits to pursue these schemes over the *1:1 Match*.

Second, there may still be a benefit to schemes with a lower expected value because these have the potential to raise more money from smaller donors by extending the match. Thus, we compare our outcomes to the known quantity of a 1:1 Match to determine if the results from these lower expected value matches are statistically lower than the 1:1 match. In comparison to a *1:1 Match*, the *2:1 Match* has marginally statistically lower (MW $p = 0.0522$, Table 6) average donations by 0.62 tokens. In the lottery matching schemes, *1:1% of 50* tokens also produce marginally significantly lower (MW $p = 0.0582$, Table 6) donations by 0.65 tokens. However, there is no significant difference ($p = 0.6221$, Table 6) in average donation between the *1:0.5% of 100* match and the *1:1 Match*. There is a slight difference in the magnitude of average donation as *1:0.5% of 100* has a 0.17 token reduction compared to the average donation in the *1:1 Match*.

Table 7: OLS Regression Models on Average Donation

	(1)		(2)		(3)	
	Base		Base + Risk		Base + Demographics	
Constant	4.458***	(0.201)	4.486***	(0.268)	3.565***	(0.388)
1:1 Match	0.706**	(0.299)	0.707**	(0.300)	0.683**	(0.298)
1:10% of 10	0.331	(0.300)	0.331	(0.300)	0.323	(0.296)
1:1% of 100	0.648**	(0.286)	0.647**	(0.286)	0.572**	(0.284)
2:1 Match	0.080	(0.285)	0.079	(0.285)	0.039	(0.282)
1:1% of 50	0.057	(0.289)	0.057	(0.289)	0.040	(0.283)
1:0.5% of 100	0.528*	(0.293)	0.529*	(0.294)	0.494*	(0.292)
Risk			-0.005	(0.032)	0.008	(0.032)
Female					0.188	(0.161)
Age					0.017***	(0.005)
Hispanic					-0.379*	(0.206)
Income					-0.002	(0.005)
Married					-0.014	(0.182)
Education					0.020	(0.043)
Children in the HH					0.093	(0.187)
N	1402		1402		1402	

Omitted Comparison Group is *No Match*. Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01

We report OLS regression models in Table 7.[10] The OLS results support the unconditional comparisons in the MW tests of *1:1 Match*, *1:1% of 100*, and *1:0.5% of 100* eliciting statistically higher average donations than *No Match* in OLS Models 1 and 2 of Table 7. Due to the truncation of our experiment with a maximum allocation of 10 tokens, we estimate Tobit models to identify any changes in the directionality or significance of our models. We report Tobit regressions in Table A7. Tobit models report slightly increased magnitudes; however, the directionality and significance of variables do not change. Marginal effects for the three Tobit models are reported in the Appendix (see Tables A8, A9, A10)

Returning to our theoretical predictions presented in 3.1, for an expected utility maximizer we predicted individuals will donate more to matches that have more certainty and higher expected values, thus the *1:1 Match* would have the largest donation amounts. Our results confirm this prediction, with the *1:1 Match* having the highest average donations at 5.16 tokens compared to all other treatments (see Table 4) and having significantly higher donations compared to *No Match* (MW $p = 0.0325$, Table 5), which has an *average donation* of 4.46 tokens. Additionally, we considered behaviors under prospect theory, which suggests that for lottery matches an expected utility maximizer will treat matches with small, but different, probabilities with the same large "jackpot" match similarly. A MW test comparing lottery matches to *1:1 Match* in Table 6 indicate average donations raised in *1:1%* and *1:0.5% of 100* lottery matches were not statistically different from average donations raised in *1:1 Match* (MW $p = 0.9764$ and $p = 0.6221$ respectively, Table 6). Thus our results support our theoretical predictions that *1:1%* and *1:0.5%* of 100 token treatments would raise more money than other lottery treatments. In our case, we find that in addition to raising more average donations (5.11 tokens, Table 4) than other lottery matches, they also raised donations not statistically different from the *1:1 Match*.

10. For robustness we also report pooled OLS regressions clustered on participant in Appendix B, Table A5.

4.1 Potential Fundraising Extensions from Lottery Matches

Our results indicate lottery matches with low probabilities of high rewards can elicit donations no different than standard 1:1 matches and all elicit donations significantly higher than when no matching occurs. We next want to identify if lottery matches can increase donations by extending the fundraising campaign matching fund budget, that is, by making the matching donation "go farther". We investigate this possibility by using total *average donations* in three treatments: the *1:1 Match* and two lottery match treatments of *1:1% of 100* and *1:0.5% of 100*.

In our experimental framework, matching costs are (theoretically) limitless. However, in most real-world applications of donation matching, the third-party "matcher" pledges to match individual donations up to a fixed total amount (e.g., up to $10,000). To investigate the potential fundraising extensions of lottery matches to increase donation amounts with a fixed match pledge (sometimes referred to as a "match cap"), we report some simplified back-of-envelope calculations in Table 8 with a fixed match pledge of $1,000.[11] Although our experiment uses experimental tokens with a $0.50 conversion, we present our results in U.S. Dollars (USD) to simplify and enhance applicability.

Table 8: Comparison of potential lottery matches with $1,000 pledged match

	Overall Donations by Treatment for $1000 Pledged Match			Difference from *1:1 Match*		%Δ from 1:1 Match	
	1:1 Match	*1% of 100*	*0.5% of 100*	*1% of 100*	*0.5% of 100*	*1% of 100*	*0.5% of 100*
Individual Donation	$ 1,000.00	$ 1,190.00	$ 3,160.00	$ 190.00	$ 2,160.00	19.00%	216.00%
Match	$ 1,000.00	$ 1,000.00	$ 1,000.00	-	-	-	-
Total	$ 2,000.00	$ 2,190.00	$ 4,160.00	$ 190.00	$ 2,160.00	9.50%	108.00%

For a $1,000 match pledge, we find lottery matches can increase individual donor contributions by 19% for the *1:1%* and 216% for the *1:0.5% of 100* lottery matches compared to a standard 1:1 match. This implies that lottery matches with low probabilities of a high reward (*1:0.5% of 100*) can effectively increase donations by lengthening the duration of the

11. See Table A12 for donation amounts (in USD) used for calculations. Given prospect theory and our statistical results in Table 6, the mechanical prediction would be an increase of 0% for the *1:1% of 100* and 200% for the *1:0.5% of 100*.

fundraising campaign to continue to leverage available matching gift funds. This result is consistent with prospect theory discussed in Section 3.1, which predicts that individuals often overweight small probabilities of winning larger matches (e.g., *1%* and *0.5%*) over more certain matches to increase giving compared to no matches. Donors give more so they will "trigger" the larger match (e.g., 100) as they overweight very small probabilities (i.e., 1% and 0.5%) of a match.

4.2 Donor Participation

Acquiring new donors and increasing average donation size are both important for fundraising. Table 9 reports donor participation across treatments. Overall, 101 participants, or 7% of the sample are non-donors. By treatment, the number of non-donors ranges from 8 to 21, or 4% to 11% of the sample. The *No Match* control has 9% of participants as non-donors with zero contributions. We use a two-sample MW test to determine whether the number of non-donors across treatments differs from the *No Match* condition. We find that *1:1 Match* has a smaller proportion of non-donors by 0.05 (MW $p = 0.0606$) than *No Match*. Additionally, *1:1% of 100* also has fewer (0.05, MW $p = 0.0663$) non-donors proportionally compared to *No Match*. All other donation-matching treatments do not significantly differ from *No Match*, indicating that these frameworks do not increase the number of donors. We find the proportion of donors in *1:0.5% of 100* matches is not significantly (MW $p = 0.7157$) different from *No Match*. Coupled with our earlier results, this indicates that while *1:0.5% of 100* matches potentially increase the donation size compared to *No Match*, it does not increase the number of donors.

These results suggest that the *1:1 Match* and *1:1% of 100* can potentially (MW p-values of 0.061 and 0.066 respectively) elicit donations from a larger proportion of donors in addition to increasing overall donation amounts.

Table 9: Donor participation across treatments with Mann-Whitney comparison tests

	Total N	Non-Donors	Donors	Proportion of Non-Donors	Diff in Mean (Treatment - NM)	*p-value*
No Match	209	19	190	0.091		
1:1 Match	199	8	191	0.040	-0.051	0.0606*
1:10% of 10 Match	204	17	187	0.083	-0.008	0.9222
1:1% of 100 Match	196	8	188	0.041	-0.050	0.0663*
2:1 Match	209	17	192	0.081	-0.010	0.8619
1:1% of 50 Match	197	21	176	0.107	0.016	0.7157
1:0.5% of 100	188	11	177	0.059	-0.032	0.3032
Total	1,402	101	1301	0.072		

Note: * p<0.1, ** p<0.05, *** p<0.01

5 Conclusion

Donation gift matching is a popular fundraising mechanism used by nonprofit organizations to increase charitable donations. Previous literature has mostly found that 1:1 matching, where for every $1 donated a third-party organization donates $1, is effective at increasing donations; however other matching ratios have not been as effective. While effective, 1:1 matching can be expensive, and organizations are interested in cost-effective fundraising. Therefore we are interested in studying the effectiveness of matching gifts using lotteries on charitable donations. This study aims to investigate if lottery matches, where the match to nonprofits was uncertain, could (1) elicit higher charitable donations and (2) extend fundraising campaigns without increased match costs to nonprofit organizations. We implement seven conditions: a *No Match* control and two sets of matching schemes of varying expected value and certainty where EV=1 (*1:1 Match*, *1:10% of 10 tokens*, and *1:1% of 100 tokens*) and EV=0.5 (*2:1 Match*, *1:1% of 50 tokens*, and *1:0.5% of 100 tokens*). In an online experiment, 1,402 participants make decisions regarding donations to three hunger-related charities over three allocation decision tasks. For matches with certainty, we replicate previous findings that a certain*1:1 Match* significantly increases average donations by 0.70 tokens ($0.35), while a certain *2:1 Match* (where for every $2 donated, a third-party organization donates $1) does not significantly increase average donations over no matching.

For lottery matches, we find matches with a low probability (1% and 0.5%) of a high match (100 tokens) elicit donations larger than *No Match* with $p < 0.1$ confidence, and average donations are not significantly different from a *1:1 Match*. Lottery matches with larger probabilities and lower matches with the same expected values (10 tokens and 50 tokens, respectively) did not elicit larger donations than the *No Match* condition. Simple back-of-envelope calculations to investigate potential extension of matching funds to nonprofits by implementing lottery matches with a low probability (*1% and 0.5%*) of a large match (100 tokens) provide insight into the potential extension of fundraising campaigns associated with reducing match costs while having small, but not statistically significant, reductions in individual donations. For a $\$1,000$ match cap, we calculate an increase of donations of 19% using *1:1% of 100* and 219% using *1:0.5% of 100* lottery matches by extending the fundraising campaign duration. These calculations provide insight into the economic implications for nonprofits implementing lottery matches. Specifically findings from the *1:0.5% of 100* treatment demonstrate the ability to raise donation amounts no different from donations raised in *1:1 Match* fundraising campaigns but for a lower matching rate. This would allow fundraising campaigns to leverage matching gift funds by extending fundraising campaigns durations, resulting in increased individual donation amounts up to an estimated 219% from traditional *1:1 Matches*. Efficient fundraising is highly relevant to nonprofit organizations working to raise the maximum amount of funds and allocate limited funds effectively to achieve their goals.

Despite the uncertainty in a lottery match compared to previous matching gift schemes with certain matches, our results are consistent with the theoretical predictions of prospect theory. By overweighting the small probability of a large reward, individuals contribute significantly more than the *No Match* and elicit contributions no different than 1:1 matching despite uncertainty. This result does not hold for lottery matches with smaller match jackpots (e.g., 10 and 50), suggesting a minimum threshold exists.

Our study investigates the impact of matches on charitable giving. Specifically, we investigate the effect of certain and uncertain (lottery) matches. We find lottery matches with a small probability of a large match elicit charitable donations significantly greater than no-matching but not different from commonly-used 1:1 matching schemes. To our knowledge, our study is the first to investigate lottery fundraising mechanisms where the award is given to charitable organizations rather than donors. Lottery matches have the potential to elicit charitable giving at rates no different than 1:1 matching while extending fundraising campaign durations without increasing matching costs, thus allowing nonprofit organizations to increase donations.

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Electronic Supplementary Material of

Jackpot for Good: Can Lottery Matches Increase Charitable Giving?

Amelia Ahles* Joanna N. Lahey† Marco A. Palma‡

A Gender Analysis

We provide a brief sub-sample analysis aimed at identifying any potential gender effects on charitable giving and risk preferences. Table A1 provides an expanded look at the summary statistics provided in Table 4, Section 4 by gender. Overall, we see *Female* participants donate more with a total *average donation* of 4.89 tokens across treatments than *Males* with a total *average donation* of 4.69 tokens, however the difference is not statistically significant (MW $p = 0.1533$). *Male* participants, on average, donate the most (5.56 tokens) in the *1:1 Match*, the second most (4.82 tokens) in *1:0.5% of 100*, and the third most (4.72 tokens) in the *1:1% of 100* treatment. *Female* participants donate the most at 5.50 tokens in the *1:1% of 100*, second most with 5.14 tokens for *1:0.5% of 100*, and third most with 5.08 tokens for *1:10% of 10 tokens*. Interestingly, *Female* participants in the *1:1 Match* have the second lowest *average donation* at 4.68 tokens and only give less in the *No Match* condition.

We report Mann-Whitney tests to compare *average donations* by treatment and gender to *No Match* (Table A2) and *1:1 Match* (Table A3). When comparing *No Match* to our treatments, we see *Male* participants *average donations* are significantly higher ($p < 0.05$) in *1:1 Match*, while *Female* participants *average donations* are marginally higher ($p < 0.10$)

∗. Postdoctoral Research Fellow, Division of Agricultural Sciences & Natural Resources, Oklahoma State University, Stillwater, OK 74078 USA, e-mail: amelia.ahles@okstate.edu

†. Professor, Bush School at Texas A&M University, College Station, TX 77843 USA, e-mail: jlahey@tamu.edu.

‡. Professor and Director Human Behavior Laboratory, Department of Agricultural Economics, Texas A&M University, College Station, TX 77843 USA, tel:+1-9798455284 e-mail: mapalma@tamu.edu.

Table A1: Summary Statistics of *Average Donation* by Treatment and Gender

		Overall			*Male*			*Female*		
		Mean	SD	N	Mean	SD	N	Mean	SD	N
	No Match	4.46	2.91	209	4.57	3.00	110	4.33	2.81	99
EV=1	*1:1 Match*	5.16	3.13	199	5.56	2.99	110	4.68	3.24	89
	1:10% of 10	4.79	3.17	204	4.50	3.17	103	5.08	3.16	101
	1:1% of 100	5.11	2.84	196	4.72	2.57	100	5.50	3.07	96
EV=0.5	*2:1 Match*	4.54	2.92	209	4.27	3.18	94	4.76	2.70	115
	1:1% of 50	4.51	2.91	197	4.28	2.98	99	4.76	2.84	98
	1:0.5% of 100	4.99	2.93	188	4.82	2.95	91	5.14	2.92	97
	Total	4.79	2.98	1,402	4.69	3.00	707	4.89	2.97	695

in *1:10% of 10* and significantly higher ($p < 0.01$) in *1:1% of 100* treatments. When investigating treatments with a lower expected value (EV=0.5), we see *Females* donate marginally ($p < 0.10$) more in *1:0.5% of 100*. In Table A3 we compare *average donations* to the *1:1 Match* using a Mann-Whitney test. We find *Male* participants donate significantly ($p < 0.01$) less in *1:10% of 10* and both *Male* and *Female* participants have marginally ($p < 0.10$) different donations in the *1:1% of 100* with *Males* donating marginally less while *Females* donating marginally more. Looking at treatments with a lower expected value (EV=0.5), we see *Males* donating significantly less ($p < 0.01$) in *2:1 Match* and *1:1% of 50* treatments.

We present OLS Regressions on *average donation* with risk and gender interaction terms in Table A4[4]. Model 4 introduces gender and gender interaction terms to our OLS mode and indicates women donate significantly more ($\hat{\beta} = 0.993, p < 0.10$) in the *1:1% of 100* treatment. Model 5 introduces selected demographics and finds that older participants are donate significantly more ($\hat{\beta} = 0.016, p < 0.01$) and Hispanics donate less ($\hat{\beta} = -0.347, p < 0.10$). Similarly, Tobit regression models on *average donation* with Risk and Gender interactions are reported in Table A11.

4. For robustness we report pooled OLS model in Table A6.

Table A2: *Average Donation* for Treatments to *No Match* by Gender

		Mann-Whitney Test P-Values			Difference in Means (Treatment - NM)		
		Overall	Male	Female	Overall	Male	Female
EV=1	*1:1 Match*	0.0325**	0.0203**	0.5843	0.70	0.99	0.35
	1:10% of 10	0.3258	0.7313	0.0934*	0.33	-0.07	0.75
	1:1% of 100	0.0199**	0.5330	0.0056***	0.65	0.15	1.17
EV=0.5	*2:1 Match*	0.8304	0.4393	0.2999	0.08	-0.30	0.43
	1:1% of 50	0.7162	0.4851	0.2153	0.05	-0.29	0.43
	1:0.5% of 100	0.0962*	0.5276	0.0750*	0.53	0.25	0.81

Note: * p<0.1, ** p<0.05, *** p<0.01

Table A3: *Average Donation* for Treatments to *1:1 Match* by Gender

		Mann-Whitney Test P-Values			Difference in Means (Treatment - 1M)		
		Overall	Male	Female	Overall	Male	Female
EV=1	*1:10% of 10*	0.2582	0.0103***	0.3491	-0.37	-1.06	0.40
	1:1% of 100	0.9764	0.0616*	0.0627*	-0.05	-0.84	0.82
EV=0.5	*2:1 Match*	0.0522*	0.0042***	0.6474	-0.62	-1.29	0.08
	1:1% of 50	0.0582*	0.003***	0.7052	-0.65	-1.28	0.08
	1:0.5% of 100	0.6221	0.1074	0.2906	-0.17	-0.74	0.46

Note: * p<0.1, ** p<0.05, *** p<0.01

Table A4: OLS Regression Models on *Average Donation* with Risk and Gender Interactions

	(1)		(2)		(3)		(4)		(5)	
	Base		1 + Risk		2 + Risk Inter.		3 + Female Inter.		3 + Female Inter.	
Constant	4.458***	(0.201)	4.486***	(0.268)	4.367***	(0.484)	4.471***	(0.517)	3.685***	(0.576)
1:1 Match	0.706**	(0.299)	0.707**	(0.300)	0.380	(0.733)	0.636	(0.770)	0.677	(0.754)
1:10% of 10	0.331	(0.300)	0.331	(0.300)	0.098	(0.726)	-0.450	(0.785)	-0.449	(0.780)
1:1% of 100	0.648**	(0.286)	0.647**	(0.286)	1.050	(0.682)	0.439	(0.748)	0.288	(0.739)
2:1 Match	0.080	(0.285)	0.079	(0.285)	0.147	(0.697)	-0.219	(0.772)	-0.198	(0.767)
1:1% of 50	0.057	(0.289)	0.057	(0.289)	0.304	(0.713)	-0.098	(0.789)	-0.193	(0.768)
1:0.5% of 100	0.528*	(0.293)	0.529*	(0.294)	1.183	(0.731)	0.925	(0.773)	0.928	(0.777)
Risk			-0.005	(0.032)	0.017	(0.079)	0.019	(0.079)	0.023	(0.078)
Risk x 1:1 Match					0.057	(0.120)	0.062	(0.119)	0.054	(0.117)
Risk x 1:10% of 10					0.044	(0.121)	0.064	(0.120)	0.072	(0.120)
Risk x 1:1% of 100					-0.076	(0.110)	-0.052	(0.111)	-0.034	(0.109)
Risk x 2:1 Match					-0.012	(0.113)	-0.017	(0.112)	-0.013	(0.112)
Risk x 1:1% of 50					-0.045	(0.117)	-0.036	(0.117)	-0.016	(0.115)
Risk x 1:0.5% of 100					-0.116	(0.117)	-0.124	(0.118)	-0.111	(0.118)
Female							-0.248	(0.404)	-0.183	(0.394)
Female x 1:1 Match							-0.650	(0.601)	-0.704	(0.599)
Female x 1:10% of 10							0.907	(0.598)	0.796	(0.593)
Female x 1:1% of 100							0.993*	(0.577)	0.959*	(0.570)
Female x 2:1 Match							0.741	(0.578)	0.606	(0.574)
Female x 1:1% of 50							0.716	(0.582)	0.651	(0.571)
Female x 1:0.5% of 100							0.611	(0.589)	0.395	(0.589)
Age									0.016***	(0.005)
Hispanic									-0.347*	(0.208)
Income									-0.003	(0.005)
Married									-0.047	(0.183)
Education									0.022	(0.043)
Children in the HH									0.075	(0.189)
N	1402		1402		1402		1402		1402	

Omitted Comparison Group is *No Match*. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

B Pooled OLS Regressions

Table A5: Pooled OLS Regression Models on 3 Charitable Donations

	(1) Base		(2) Base + Risk		(3) Base + Demographics	
Constant	4.458***	(0.201)	4.486***	(0.267)	3.565***	(0.387)
1:1 Match	0.706**	(0.299)	0.707**	(0.299)	0.683**	(0.297)
1:10% of 10	0.331	(0.299)	0.331	(0.299)	0.323	(0.295)
1:1% of 100	0.648**	(0.286)	0.647**	(0.285)	0.572**	(0.283)
2:1 Match	0.080	(0.285)	0.079	(0.285)	0.039	(0.281)
1:1% of 50	0.057	(0.289)	0.057	(0.289)	0.040	(0.283)
1:0.5% of 100	0.528*	(0.293)	0.529*	(0.293)	0.494*	(0.291)
Risk			-0.005	(0.032)	0.008	(0.032)
Female					0.188	(0.160)
Age					0.017***	(0.005)
Hispanic					-0.379*	(0.205)
Income					-0.002	(0.005)
Married					-0.014	(0.182)
Education					0.020	(0.043)
Children in the HH					0.093	(0.187)
N	4206		4206		4206	

Omitted Comparison Group is *No Match*. Standard errors in parentheses and clustered on participants. * p<0.1, ** p<0.05 *** p<0.01

Table A6: Pooled OLS Regression Models on 3 Charitable Donations with Risk and Gender Interactions

	(1) Base		(2) 1 + Risk		(3) 2 + Risk Inter.		(4) 3 + Female Inter.		(5) 3 + Female Inter.	
Constant	4.458***	(0.201)	4.486***	(0.267)	4.367***	(0.483)	4.471***	(0.514)	3.685***	(0.573)
1:1 Match	0.706**	(0.299)	0.707**	(0.299)	0.380	(0.731)	0.636	(0.766)	0.677	(0.749)
1:10% of 10	0.331	(0.299)	0.331	(0.299)	0.098	(0.724)	-0.450	(0.782)	-0.449	(0.776)
1:1% of 100	0.648**	(0.286)	0.647**	(0.285)	1.050	(0.679)	0.439	(0.745)	0.288	(0.734)
2:1 Match	0.080	(0.285)	0.079	(0.285)	0.147	(0.694)	-0.219	(0.768)	-0.198	(0.762)
1:1% of 50	0.057	(0.289)	0.057	(0.289)	0.304	(0.711)	-0.098	(0.785)	-0.193	(0.764)
1:0.5% of 100	0.528*	(0.293)	0.529*	(0.293)	1.183	(0.728)	0.925	(0.769)	0.928	(0.773)
Risk			-0.005	(0.032)	0.017	(0.079)	0.019	(0.079)	0.023	(0.077)
Risk x 1:1 Match					0.057	(0.120)	0.062	(0.119)	0.054	(0.117)
Risk x 1:10% of 10					0.044	(0.121)	0.064	(0.120)	0.072	(0.119)
Risk x 1:1% of 100					-0.076	(0.110)	-0.052	(0.110)	-0.034	(0.109)
Risk x 2:1 Match					-0.012	(0.112)	-0.017	(0.112)	-0.013	(0.111)
Risk x 1:1% of 50					-0.045	(0.117)	-0.036	(0.117)	-0.016	(0.114)
Risk x 1:0.5% of 100					-0.116	(0.117)	-0.124	(0.117)	-0.111	(0.117)
Female							-0.248	(0.402)	-0.183	(0.392)
Female x 1:1 Match							-0.650	(0.599)	-0.704	(0.595)
Female x 1:10% of 10							0.907	(0.596)	0.796	(0.589)
Female x 1:1% of 100							0.993*	(0.574)	0.959*	(0.567)
Female x 2:1 Match							0.741	(0.575)	0.606	(0.571)
Female x 1:1% of 50							0.716	(0.580)	0.651	(0.567)
Female x 1:0.5% of 100							0.611	(0.586)	0.395	(0.585)
Age									0.016***	(0.005)
Hispanic									-0.347*	(0.206)
Income									-0.003	(0.005)
Married									-0.047	(0.182)
Education									0.022	(0.043)
Children in the HH									0.075	(0.188)
N	4206		4206		4206		4206		4206	

Omitted Comparison Group is *No Match*. Standard errors in parentheses and clustered on participants. * p<0.1, ** p<0.05 *** p<0.01

C oTree Examples

We provide screenshot examples from our online experiment below.

Charity: Action Against Hunger

Action Against Hunger is a global humanitarian organization which is committed to ending world hunger, reaching 28 million people each year. The organization helps malnourished children and provides communities with access to safe water and sustainable solutions to hunger.

Please select the row which corresponds to how much of your 10 token endowment you would like to allocate to You and how much you would like to allocate to Action Against Hunger.

For each token you allocate to Action Against Hunger the charity will receive one bonus ticket.

The value of each bonus ticket is:

- 10 bonus tokens with a chance of 1 in 10
- 0 bonus tokens with a chance of 9 in 10

Each bonus ticket is resolved independently using a lottery wheel that will be shown to you later.

Please read each row carefully. Remember, one round will be selected randomly for payment at the end of the study. So treat each round as if it could be the one that determines your payment.

Allocated to You	Allocated to Charity	Your Choice
10 Tokens	0 Tokens	○
9 Tokens	1 Tokens	○
8 Tokens	2 Tokens	○
7 Tokens	3 Tokens	○
6 Tokens	4 Tokens	○
5 Tokens	5 Tokens	○
4 Tokens	6 Tokens	○
3 Tokens	7 Tokens	○
2 Tokens	8 Tokens	○
1 Tokens	9 Tokens	○
0 Tokens	10 Tokens	○

Click **"NEXT"** when you are ready to continue.

Next

Figure A1: Example of Decision Allocation from oTree Survey

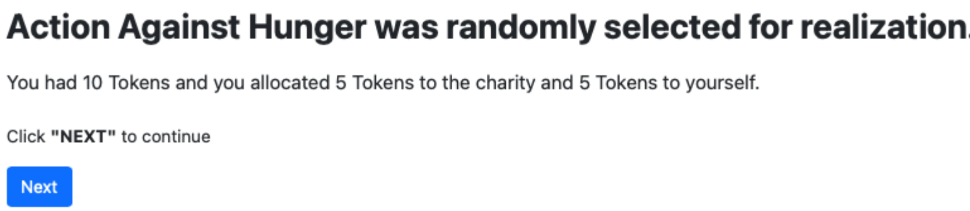

Figure A2: Example of Binding Charity from oTree Survey

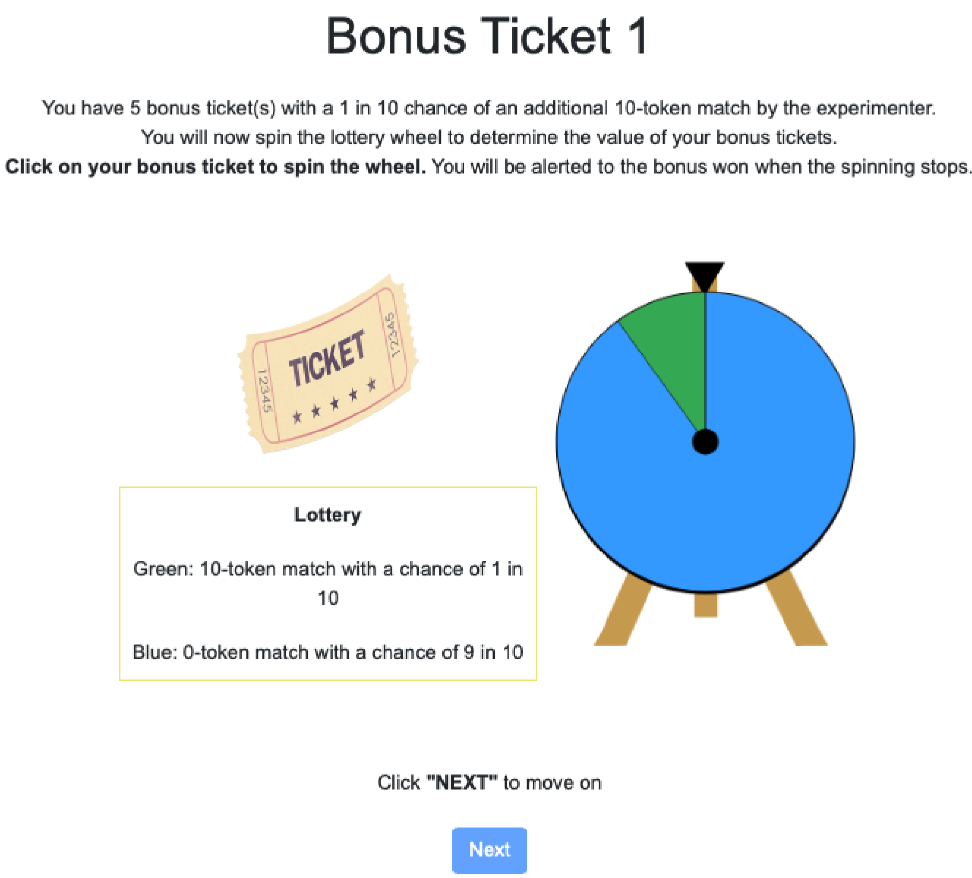

Figure A3: Example of Lottery Match Wheel from oTree Survey

D Tobit Models

Table A7: Tobit Regression on *Average Donation*

	(1) Base		(2) Base + Risk		(3) Base + Demographics	
Constant	4.435***	(0.242)	4.460***	(0.327)	3.443***	(0.465)
1:1 Match	0.879**	(0.356)	0.880**	(0.356)	0.855**	(0.355)
1:10% of 10	0.395	(0.360)	0.395	(0.360)	0.389	(0.355)
1:1% of 100	0.729**	(0.335)	0.728**	(0.335)	0.647*	(0.334)
2:1 Match	0.091	(0.341)	0.090	(0.341)	0.046	(0.337)
1:1% of 50	0.009	(0.348)	0.009	(0.348)	-0.009	(0.342)
1:0.5% of 100	0.610*	(0.349)	0.611*	(0.349)	0.576*	(0.348)
Risk			-0.005	(0.039)	0.009	(0.039)
Female					0.172	(0.191)
Age					0.019***	(0.006)
Hispanic					-0.457*	(0.247)
Income					-0.001	(0.006)
Married					-0.060	(0.213)
Education					0.016	(0.051)
Children in the HH					0.168	(0.220)
σ^2	12.107***	(0.553)	12.107***	(0.553)	11.926***	(0.549)
N	1402		1402		1402	
Uncensored	1170		1170		1170	
Left-Censored	101		101		101	
Right-Censored	131		131		131	

Omitted Comparison Group is *No Match*. Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01

Table A8: Marginal Effects for Model 1

	$\frac{\partial E[Bid^*\|x]}{\partial x}$		$\frac{\partial E[Bid\|x]}{\partial x}$		$\frac{\partial E[Bid\|Bid>0,x]}{\partial x}$		$\frac{\partial Pr[Bid>0\|x]}{\partial x}$	
Constant	4.435***	(0.242)						
1:1 Match	0.879**	(0.356)	0.745**	(0.301)	0.456**	(0.184)	0.004	(0.005)
1:10% of 10	0.395	(0.360)	0.335	(0.305)	0.205	(0.186)	0.005	(0.005)
1:1% of 100	0.729**	(0.335)	0.618**	(0.284)	0.378**	(0.174)	0.005	(0.005)
2:1 Match	0.091	(0.341)	0.077	(0.288)	0.047	(0.176)	0.002	(0.006)
1:1% of 50	0.009	(0.348)	0.007	(0.294)	0.005	(0.180)	0.000	(0.007)
1:0.5% of 100	0.610*	(0.349)	0.517*	(0.296)	0.316*	(0.181)	0.005	(0.005)
Uncensored	1170		1170		1170		1170	
Left-Censored	101		101		101		101	
Right-Censored	131		131		131		131	

Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01

Table A9: Marginal Effects for Model 2

	$\frac{\partial E[Bid^*\|x]}{\partial x}$		$\frac{\partial E[Bid\|x]}{\partial x}$		$\frac{\partial E[Bid\|Bid>0,x]}{\partial x}$		$\frac{\partial Pr[Bid>0\|x]}{\partial x}$	
Constant	4.435***	(0.242)						
1:1 Match	0.879**	(0.356)	0.746**	(0.301)	0.456**	(0.184)	0.004	(0.005)
1:10% of 10	0.395	(0.360)	0.334	(0.305)	0.204	(0.186)	0.005	(0.005)
1:1% of 100	0.729**	(0.335)	0.618**	(0.284)	0.378**	(0.174)	0.005	(0.005)
2:1 Match	0.091	(0.341)	0.076	(0.288)	0.046	(0.176)	0.002	(0.006)
1:1% of 50	0.009	(0.348)	0.008	(0.294)	0.005	(0.180)	0.000	(0.007)
1:0.5% of 100	0.610*	(0.349)	0.518*	(0.296)	0.317*	(0.181)	0.005	(0.005)
Risk			-0.004	(0.033)	-0.002	(0.020)	-0.000	(0.000)
Uncensored	1170		1170		1170		1170	
Left-Censored	101		101		101		101	
Right-Censored	131		131		131		131	

Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01

Table A10: Marginal Effects for Model 3

	$\frac{\partial E[Bid^*\|x]}{\partial x}$		$\frac{\partial E[Bid\|x]}{\partial x}$		$\frac{\partial E[Bid\|Bid>0,x]}{\partial x}$		$\frac{\partial Pr[Bid>0\|x]}{\partial x}$	
Constant	4.435***	(0.242)						
1:1 Match	0.879**	(0.356)	0.725**	(0.300)	0.446**	(0.185)	0.003	(0.005)
10% of 10	0.395	(0.360)	0.330	(0.301)	0.203	(0.185)	0.004	(0.004)
1% of 100	0.729**	(0.335)	0.549*	(0.283)	0.338*	(0.175)	0.005	(0.004)
2:1 Match	0.091	(0.341)	0.039	(0.285)	0.024	(0.175)	0.001	(0.006)
1% of 50	0.009	(0.348)	-0.007	(0.289)	-0.005	(0.178)	-0.000	(0.006)
0.5% of 100	0.610*	(0.349)	0.488*	(0.295)	0.301*	(0.182)	0.005	(0.004)
Risk			0.008	(0.033)	0.005	(0.021)	0.000	(0.000)
Female			0.146	(0.162)	0.090	(0.100)	0.001	(0.001)
Age			0.016***	(0.005)	0.010***	(0.003)	0.000*	(0.000)
Hispanic			-0.387*	(0.208)	-0.238*	(0.128)	-0.005	(0.004)
Income			-0.001	(0.005)	-0.001	(0.003)	-0.000	(0.000)
Married			-0.051	(0.181)	-0.031	(0.111)	-0.000	(0.001)
Education			0.014	(0.043)	0.009	(0.026)	0.000	(0.000)
Children in the HH			0.143	(0.186)	0.088	(0.114)	0.001	(0.001)
Uncensored	1170		1170		1170		1170	
Left-Censored	101		101		101		101	
Right-Censored	131		131		131		131	

Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01

Table A11: Tobit Regressions on *Average Donation* with Risk and Gender Interactions

	(1) Base		(2) 1 + Risk		(3) 2 + Risk Interaction		(4) 3 + Female Interact		(5) 4 + Demographics	
Constant	4.435***	(0.242)	4.460***	(0.327)	4.318***	(0.606)	4.467***	(0.643)	3.597***	(0.708)
1:1 Match	0.879**	(0.356)	0.880**	(0.356)	0.469	(0.911)	0.747	(0.956)	0.801	(0.940)
1:10% of 10	0.395	(0.360)	0.395	(0.360)	0.047	(0.912)	-0.554	(0.980)	-0.550	(0.973)
1:1% of 100	0.729**	(0.335)	0.728**	(0.335)	1.322	(0.830)	0.596	(0.897)	0.422	(0.884)
2:1 Match	0.091	(0.341)	0.090	(0.341)	0.124	(0.853)	-0.377	(0.959)	-0.352	(0.951)
1:1% of 50	0.009	(0.348)	0.009	(0.348)	0.319	(0.875)	-0.128	(0.968)	-0.255	(0.946)
1:0.5% of 100	0.610*	(0.349)	0.611*	(0.349)	1.389	(0.900)	1.085	(0.949)	1.080	(0.951)
Risk			-0.005	(0.039)	0.022	(0.098)	0.025	(0.097)	0.028	(0.096)
Risk x 1:1 Match					0.072	(0.148)	0.076	(0.147)	0.066	(0.145)
Risk x 1:10% of 10					0.066	(0.152)	0.085	(0.150)	0.093	(0.150)
Risk x 1:1% of 100					-0.112	(0.133)	-0.085	(0.134)	-0.064	(0.132)
Risk x 2:1 Match					-0.006	(0.136)	-0.011	(0.136)	-0.007	(0.135)
Risk x 1:1% of 50					-0.056	(0.143)	-0.048	(0.144)	-0.022	(0.141)
Risk x 1:0.5% of 100					-0.138	(0.143)	-0.147	(0.143)	-0.130	(0.142)
Female							-0.358	(0.483)	-0.300	(0.473)
Female x 1:1 Match							-0.699	(0.709)	-0.758	(0.706)
Female x 1:10% of 10							1.027	(0.715)	0.910	(0.708)
Female x 1:1% of 100							1.206*	(0.672)	1.169*	(0.664)
Female x 2:1 Match							1.001	(0.692)	0.859	(0.688)
Female x 1:1% of 50							0.821	(0.698)	0.756	(0.684)
Female x 1:0.5% of 100							0.716	(0.698)	0.480	(0.697)
Age									0.019***	(0.006)
Hispanic									-0.420*	(0.248)
Income									-0.002	(0.006)
Married									-0.097	(0.213)
Education									0.020	(0.051)
Children in the HH									0.142	(0.221)
σ^2	12.107***	(0.553)	12.107***	(0.553)	12.073***	(0.551)	11.953***	(0.548)	11.801***	(0.545)
N	1402		1402		1402		1402		1402	
Uncensored	1170		1170		1170		1170		1170	
Left-Censored	101		101		101		101		101	
Right-Censored	131		131		131		131		131	

Omitted Comparison Group is *No Match*. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

E Additional Tables

Table A12: Donations by charity and overall for 1:1 and low probability of high match lottery treatments

	1:1 Match	1% of 100	0.5% of 100
Action Against Hunger			
Donation by Individual	$ 157.00	$ 125.00	$ 152.00
Match	$ 157.00	$ 300.00	$ 100.00
Total to Charity	$ 314.00	$ 425.00	$ 252.00
Feeding America			
Donation by Individual	$ 162.00	$ 184.50	$ 160.50
Match	$ 162.00	$ 100.00	$ 50.00
Total to Charity	$ 324.00	$ 284.50	$ 210.50
Meals on Wheels			
Donation by Individual	$ 185.50	$ 166.50	$ 161.50
Match	$ 185.50	$ -	$ -
Total to Charity	$ 371.00	$ 166.50	$ 161.50
Total			
Donation by Individual	$ 504.50	$ 476.00	$ 474.00
Match	$ 504.50	$ 400.00	$ 150.00
Total to Charity	$ 1,009.00	$ 876.00	$ 624.00
N	199	196	188