Can Varying Match Probabilities Increase Donations? Testing a New Fundraising Mechanism
(Working Draft)

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Abstract

This paper explores whether donors are responsive to exogenous changes in the probability of receiving a match. We develop a theoretical model of giving that incorporates uncertainty around matches, and we demonstrate the model is capable of explaining the discrepancies in match-price elasticities of giving observed across previous field experiments and observational studies. We then derive testable hypotheses from the model, and design and run an economic experiment to test these hypotheses. The results of our experiment provide clear evidence that donors are responsive to changes in the probability of receiving a match. As a result, the same donor may respond differently to match subsidies depending on the setting. By varying the probability of receiving a match, fundraisers can use subsidy funds more efficiently. While the optimal match probability varies depending on the match rate offered, in general uncertain matches ($p < 1$) outperform certain matches ($p = 1$).

1 Introduction

Match schemes are commonly used by charitable organizations to boost donations. Putting aside the question of whether a match is the most effective *form* of subsidy the charity can use to increase donations (see the previous chapter), if they want the subsidy to be effective it is important they carefully select the subsidy *rate*. In the case of a match, this means deciding what match rate to offer. While charities aim to maximize donations by choosing the optimal match rate, existing studies show mixed results on the effectiveness of different match rates. Depending on the study, match subsidies either have no effect on donors, partial positive effects but only for some donors, or significantly positive effects for all donors (see, e.g., Rondeau and List (2008), Karlan and List (2007), and Huck and Rasul (2011), respectively).

In this chapter, I aim to develop a better understanding of how match rates influence donor behavior, enabling charities to design more effective fundraisers and advancing our understanding of why people give. To do this, I take a novel approach in modeling matches, framing them in the context of uncertainty. The underlying mechanism is simple and intuitive: because match subsidies typically always place a cap on the total amount of donations that can be matched, donors perceive matches as uncertain. When deciding how much to give, the donor forms beliefs about the likely total giving of all other donors. If they believe the total donations received by the charity are likely to exceed the match limit, they will consider it unlikely that they will receive a match, making the match less effective.

This framework provides an appealing explanation for the apparently conflicting results reported in existing studies: depending on the characteristics of the fundraiser—e.g., its size and scope, the average wealth of the donor pool, etc.—donors will hold different beliefs about the expected total giving of others, and as a result they will also hold different beliefs about the probability of receiving a match. For example, if a lead donor were to offer to match donations to a donor's local church up to a maximum amount of $25k, depending on the size of the church the donor may believe they have a high probability of receiving a match. However, if the same match offer were provided for a large organization like the Red Cross, donors would likely perceive the probability of receiving a match to be negligible. If donors care about the impact of their donation, they will respond to matches differently depending on the characteristics of the fundraiser and their expectations about the total giving of others.[1]

[1] There are two objections that I suspect some readers will be raising at this point. The first is that donors cannot reasonably be assumed to know the characteristics of the fundraiser. While I agree with this and believe that any realistic representation of donor behavior would incorporate this fact, for the current analysis it is inconsequential. Although donors may not know the true characteristics of the fundraiser, they should in most cases still be able to form *beliefs* about the characteristics. For example, in the example provided with the local church and the Red Cross, while it would be unrealistic to expect donors to know the exact number of potential donors for the Red Cross (or even their local church), it is not at all unreasonable to expect that they should *believe* that there are many more potential donors for the Red Cross. The end result of this belief is the same—they will expect the Red Cross to receive more donations and therefore perceive a lower probability of receiving a match.

The second objection I anticipate some readers making is that donors have no way of differentiating between receiving a match and not receiving a match. For example, if a donor provides a gift early in a match campaign before the match limit has been met, and then at some later time the match limit is exceeded, does their donation

I formalize this mechanism by developing a theoretical model in which donors are assumed to be impure-impact givers (Hungerman and Ottoni-Wilhelm, 2021). I assume donors take the total giving of others to be a random variable, forming a probability distribution representing their beliefs about its likely value. These beliefs are assumed to be functions of the characteristics of the fundraiser, including the number of potential donors, their wealth levels, etc., as well as the match rate and match limit.

Analysis of the model highlights a key feature of match subsidies that has received little discussion in the literature: one cannot increase the match rate without either decreasing the match limit or increasing the size of the lead gift. Previous studies have highlighted the importance of the lead-gift effect and argued that one must control for it when estimating the match-price elasticity. However, as the match rate (μ) is increased, if the lead gift (ϕ) is held constant, the *match limit* ($\frac{\phi}{\mu}$) mechanically decreases. For example, if the match rate is doubled—so that every dollar donated receives twice as many matching dollars—it takes half the amount of donations to fully exhaust the lead gift. Thus, holding the lead gift constant, an increase in the match rate creates two counteracting effects: on the one hand, it increases the *potential* impact of the donor's gift *if* a match is received, but at the same time, it also decreases the probability of receiving a match. The magnitude of the effect on the donor's perceived probability of receiving a match will depend on their beliefs about the likely giving of others. Because these beliefs are a function of the characteristics of the fundraiser, the donor's response to a change in the match rate can vary substantially across settings. As I show in Section 3, the same donor can sometimes respond positively to an increase in the match rate (i.e., increase their out-of-pocket donation in response) and other times respond negatively, even when the lead gift amount and the match rate (and the change in the match rate) are the same in both cases. That is, if one fails to account for the difference in the donor's perceived probabilities of receiving a match in each setting, it would appear that the subject is acting inconsistently.

To test the performance of the model, I derive theoretical predictions from it and design a real-incentive (online) laboratory experiment to test the predictions. While the overall aim is to eventually demonstrate that fundraiser characteristics can affect how donors respond to match subsidies by shifting their beliefs about the probability of receiving a match, in this chapter I focus on first establishing that donors are in fact responsive to changes in the probability of receiving a match. To do this, I exogenously vary the probability with which matches are received by simply stating that the individual's donation will be matched with a given probability (e.g., .25, .5, etc.).

The results of the experiment provide strong evidence that donors are responsive to changes in the probability of receiving a match, and the observed behavior of subjects in the experiment is largely consistent with the predictions of the theoretical model. While larger match rates induce larger average donations, this effect diminishes as the match probability decreases. This finding

retroactively become unmatched? I agree that this is an interesting philosophical question—one that truly tickles the mind—but if the donor is concerned with the *impact* of their gift, then the answer is yes. To calculate the impact of their gift, the donor must consider how much the charity would forgo in its absence. From this perspective, it is clear then that their donation did not receive a match.

provides support for the theoretical model, and it also documents the mechanism by which match rate increases can potentially result in a decrease in donations: if the match rate increase induces a large enough reduction in donors' perceived probabilities of receiving a match, the effectiveness of the match will be significantly reduced. These findings document the existence of a new mechanism important to donors' decision-making process and advance our understanding of why people give. The insights developed help to reconcile previous results, and they provide charitable organizations with meaningful guidance for designing more effective fundraisers.

The remainder of this paper is organized as follows. Section 2 discusses related literature. Section 3 develops the theoretical model, presents the assumptions needed, and derives theoretical results. Section 4 presents the experimental design and outlines the experimental procedures. Section 5 presents results, and Section 6 concludes. Proofs of theoretical results are provided in Appendix A. Appendices B, C, and D present additional tables, figures, and materials from the experiment, respectively.

2 Literature Review

There is a large body of literature studying the use of match subsidies in charitable giving. As I will discuss in detail, evidence on the effectiveness of match subsidies is mixed, but there is strong evidence suggesting that, in general, donors prefer matches to the absence of any subsidy (Fang et al., 2021), and that overall matching grants increase donations for the fundraisers using them without crowding out donations to other fundraisers (Meer, 2017). A significant portion of the research on matches involves laboratory and field studies that seek to compare rebates and matches, to identify whether they produce disparate effects on giving (e.g., Eckel and Grossman (2003, 2008); Higgs and Uler (2023)). Importantly, laboratory experiments using match subsidies provide matches that are always certain. Because of this, their results are not particularly germane to a discussion of uncertain matches.

Outside of the laboratory, there have also been several field studies looking singularly at match subsidies. As mentioned in the introduction, this literature has reported inconsistent match-price effects. Rondeau and List (2008) find that individuals are unresponsive to matching gifts but are responsive to challenge gifts,[2] implying that the best match rate is a rate of 0:1 (i.e., no matching). In a natural field experiment, Karlan and List (2007) find that matching offers lead to both higher response rates (i.e., a greater likelihood of giving) and larger donations, but that increasing the match ratio above 1:1 has no additional effect. Similarly, in another natural field experiment, Karlan et al. (2011) find no difference between offering match rates of 1:1 and 1:3, and find only weak evidence that matches have any effect on donations. In fact, they find that the matching only increases giving *after* the match deadline has expired. From the perspective of uncertain matches, if individuals consider the probability of their donations being matched when deciding what to give, these findings would suggest that matching may decrease giving, since the perceived probability of

[2] A challenge gift is where a lead gift is simply announced, but is not used to match the donations of others.

their donations being matched should drop to zero after the deadline has passed.

However, while the studies mentioned provide evidence that larger match rates are not always beneficial, it is not clear that their findings apply more generally. In each of the studies, the experiments were designed for charities that routinely solicit donations, ranging from 3-4 times a year (Rondeau and List, 2008) to monthly (Karlan and List, 2007). Because of this, individuals may form a habit of donating a set amount at each time interval, making them less responsive to one-time changes in the price of giving. Moreover, other studies have found strong evidence of increased giving resulting from larger match rates (Meier, 2007; Huck and Rasul, 2011).

Huck and Rasul (2011) are careful to keep the size of the lead gift constant while varying the match rate, in order to prevent differences in the lead gift from confounding their results. Even after controlling for the effect of the lead gift, they continue to find that larger match rates result in greater charitable receipts. In spite of this, though, they also find that simply announcing the presence of the lead gift generates higher donations. Similar results are also reported in Huck et al. (2015). While counterintuitive, these results are actually consistent with an uncertain-matches framework: if donors respond negatively to a match, they can end up increasing their donations as the match rate is increased, as long as the increase in the match rate sufficiently decreases their perceived probability of receiving a match.

Though it remains an open question whether simply announcing a lead gift is superior to offering a match, there is significant evidence suggesting the lead gift has an important impact on donations, separate from any price effects created by the match (Andreoni, 1998; Chen et al., 2005). The mere presence of a matching grant can serve as a signal of the charity's quality, increasing donations (Vesterlund, 2003). In a recent example of this, Karlan and List (2020) find that matching grants provided by the Bill and Melinda Gates Foundation are more effective when they are given publicly versus when they are given anonymously, suggesting donors interpret the matching grant as a sort of endorsement. Building on the model in Landry et al. (2006), Landry et al. (2010) develop a model that incorporates the quality signal associated with matching grants. Similar to the model I develop, their model incorporates uncertainty in the donor's decision-making process. However, in their model it is the quality of the charity that is uncertain, and the presence of a matching grant acts to increase the probability that the charity is perceived as high-quality.

Beyond any quality signals, however, there is also a great deal of evidence that donors particularly care about their *impact*. Meer (2014) finds that higher overhead costs reduce the amount donated to charities. Similarly, Gneezy et al. (2014) find that donors give more when they're informed that another party is covering the charity's overhead costs. This is true regardless of the amount of overhead costs, implying that it's not that donors are concerned with the efficiency of the charity, but rather that they simply want to attribute their own donation to a larger impact. However, in Green et al. (2015), the authors find that reminding donors of the multiplicative effects of matching grants has no impact on their donations, potentially suggesting they are unmoved by considerations of their impact (or that they had already accounted for the effect of the match on their impact, making the reminder moot). In the model I develop, it is essential that donors consider their impact—if not, changes in the match probability will not enter their utility functions.

That said, irrespective of impact considerations, changes in donors' beliefs about the giving of others may still affect their behavior (Croson, 2007; Shang and Croson, 2009; Croson and Shang, 2013; Smith et al., 2015). Even if donors are completely unconcerned with their impact, they may respond to changes in the donations of others due to reciprocity concerns (Croson, 2007; Fischbacher and Gächter, 2010). In this case, a change in the match rate may cause donors to adjust their donation amounts by shifting their beliefs about the likely total giving of others. Examples of this type of behavior have previously been observed in charitable giving research, and other-regarding preferences have also been documented in other settings (Fehr and Schmidt, 1999; Fehr and Leibbrandt, 2011; Fischbacher et al., 2001).

While the charitable giving literature has identified a long list of possible motivations that may influence donor behavior in the context of matches, little work has been done to study the effect of donors' perceptions about the probability of receiving a match. Yet, this notion is consistent with many aspects of previous findings. Previous results suggest that donors not only care what others give, but they also form beliefs about the behavior of others. Previous results also suggest that donors are concerned with the impact of their donations, seeking to maximize their impact, all else equal. These insights are incorporated in a model with uncertain matches: donors are concerned with their impact (i.e., whether or not they will receive a match), and they form beliefs about the behavior of others (i.e., to derive their perceived probability of receiving a match).

Furthermore, the uncertain-matches framework is also able to provide an intuitive explanation for previous, seemingly inconsistent estimates of the response to match subsidies. Moreover, as I will now discuss, there are several other results for which the uncertain-matches framework provides appealing potential explanations.

One such result is that of Charness and Holder (2019). Using a laboratory experiment, they study how giving decisions are affected by *competition* for matches, both between individuals and between groups. In contrast with Duffy and Kornienko (2010), they find that donations are lower when individuals must compete with one another for their donations to be matched, compared to when their donations are matched with certainty. However, they find that donations increase when individuals are part of a group that competes with another group for their donations to be matched. Charness and Holder are unable to provide a definitive explanation for their findings, but they suggest that individuals may be responding to team effects (i.e., individuals feel as though they are part of a team, and they don't want to be the reason the team loses).

Interestingly, a model where individuals consider the probability of their donations being matched could also explain the findings presented in Charness and Holder (2019). While it is not the focus of their paper, Charness and Holder actually vary the probability of individuals' donations being matched across treatments. When individuals compete with one another for their donations to be matched, their perceived probabilities of being matched should be lower than when their donations are matched with certainty. This suggests that they should give less, which is what Charness and Holder find. When the competition is instead among teams, the perceived probability of being matched should still be less than certainty, which all else equal should decrease donations. However, the potential payoff to an individual of increasing their donation would now be much larger, since their donation could potentially result in the donations of their entire team being matched.[3] For an expected utility maximizer, this large increase in the payoff could more than offset the decreased likelihood of being matched, resulting in larger donations.

A framework in which matches are uncertain can potentially explain observed behavior in other settings as well. In a framed field experiment, Null (2011) finds that donors spread their donations among multiple charities rather than focusing their funds on the charities with the highest match rates, failing to take advantage of the lower prices created by the differential match rates. Null argues this behavior suggests that individuals receive warm glow not only from the amount that they donate, but also from the act of giving itself. That is, there appears to be a fixed benefit to giving, motivating individuals to spread donations across multiple charities. However, an uncertain-matches framework can potentially provide an alternative explanation. If individuals are concerned about the probabilities of their donations being matched, similar behavior might be observed, as spreading donations across multiple charities may hedge their risk and maximize the expected amount of donations receiving a match.

In closing, I now turn to discussing the only other study I am aware of that considers donors' beliefs about the probability of receiving a match, that of Gee and Schreck (2018). Through a combination of theoretical, field, and lab results, Gee and Schreck (2018) find that individuals are more likely to donate when they believe they are more pivotal to securing matching funds.[4] This is an important contribution to the literature because it provides evidence that individuals not only form beliefs about the giving behavior of others but also use these beliefs to form further beliefs about the probability of receiving matching funds. However, there are several ways in which the research I present in this chapter differs from the work done by Gee and Schreck (2018). First, their study considers 'threshold matches,' where subjects are placed in groups and a match is received if the *number of group members* providing a donation reaches some threshold number, similar to the designs used in Offerman et al. (1996) and Anik et al. (2014). While this design allows them to vary subjects' beliefs about the probability of receiving a match, it is a very different design from those used in previous laboratory and field experiments studying the response to match subsidies, and it is not clear what price of giving the subjects face in this setting. Second, in their theoretical model and experimental design there are no match limits, so it is not possible to study the relationship between the match rate and the match limit, and how they may simultaneously influence donors'

[3] This assumes that the individual either receives utility from their impact, or that they receive warm glow from giving and the increase in their team's total donations increases the amount of warm glow they receive. If an individual is purely altruistic (or they receive no warm glow for the team's matched funds), causing their team's donations to be matched will still increase their utility, but the effect will be much smaller, since the total amount received by the charity will only be marginally increased. Note, however, that if an individual believes that their team will win and have its donations matched, they will perceive their price of giving as being lower.

[4] Adena and Huck (2022) combine this insight with the use of customized threshold levels to effectively incentivize donors to contribute more. In their setting, donors aren't grouped, so each donor knows with certainty that they are pivotal to securing the matching funds. Their results provide additional evidence that donors care about their impact.

beliefs about the probability of being matched. Finally, in both their theoretical model and their experimental design subjects are unable to determine the amount they would like to donate. Rather, subjects face a binary decision to either pass an exogenously determined amount to the charity or provide no donation. Because of this, it is not possible to estimate how donation *amounts* respond to changes in the probability of being matched.

A model of giving that incorporates donor uncertainty regarding the receipt of matches is intuitive, consistent with previous results, and provides plausible explanations for a variety of observed behavior. The development of such a model, and its validation in an experimental setting, advances our understanding of why people give and makes an important contribution to the literature.

3 Theory

In this section, I develop a theoretical model of giving in which donors consider matches to be uncertain. Whether or not a donor receives a match depends on the match limit and the total giving of others. Receiving a match is uncertain because donors do not know the total giving of others (at least at the time they are making their donation decision). Instead, each donor views the total giving of others to be a random variable, constructing a probability distribution for its realized value. Each donor's PDF of the total giving of others is a function of the characteristics of the fundraiser, such as the size of the fundraiser (i.e., the number of potential donors) and the average wealth of potential donors. Because fundraiser characteristics vary, the model is able to explain why donors might respond to match subsidies differently depending on the setting.

3.1 Basic Setup

For a given charity, there are a total of N potential donors, where N is exogenously determined. Each potential donor $i = 1, ..., N$ has utility given by the impure impact model of Hungerman and Ottoni-Wilhelm (2021). That is, each potential donor's utility is given by $U_i(w_i - g_i, g_i, R_i + \lambda R_{-i})$. I assume that U_i is strictly increasing and concave in each of its arguments for all i.

Each donor i is endowed with exogenous wealth, $w_i \in \mathbf{R}_+$, from which they choose an amount, $g_i \in [0, w_i]$, to donate to the charity. Let $G = \sum_{i=1}^{N} g_i$ be the total amount passed to the charity by all individuals $i = 1, ..., N$, and let $G_{-i} = \sum_{j \neq i} g_j$ be the total amount of donations passed to the charity by all individuals other than i. Donations to the charity are matched by a third party donor at some match rate, $\mu \in \mathbf{R}_+$, up to the point that the exogenously set lead gift, $\phi \in \mathbf{R}_+$, has been fully depleted. That is, as long as $\mu\,(g_i + G_{-i}) \leq \phi$ (that is, total donations do not exceed the match limit), individual i's donation, g_i, is matched at rate μ, so that the total donation received by the charity (i.e., donor i's *impact*) is $R_i = (1 + \mu)g_i$, consisting of i's donation of g_i and the third party's matching donation of μg_i. If $\mu G_{-i} < \phi < \mu(g_i + G_{-i})$, then i's donation is *partially* matched. In this case, donor i's impact is given by $R_i = g_i + \phi - \mu G_{-i}$. Finally, if $\mu G_{-i} \geq \phi$ (other's total donations exceed the match limit), i's donation, g_i, is not matched, and donor i's impact is given by $R_i = g_i$.

Note that the lead gift amount, ϕ, is different from the match limit, $\frac{\phi}{\mu}$. The lead gift is the total amount of funds available for matching donations, while the match limit is the total amount of donations that can be matched before the lead gift is fully exhausted. Therefore, holding the size of the lead gift, ϕ, constant, increasing the match rate, μ, will mechanically decrease the match limit, $\frac{\phi}{\mu}$. As the match rate is increased, fewer donations are required to fully exhaust the lead gift.[5]

To simplify the analysis, I ignore the possibility of donor i receiving a partial match. Instead, I will assume that donor i considers a partial match to be equivalent to a full match. This is formalized by the following assumption.

Assumption 1 *Donors consider their impact when receiving a partial match to be equivalent to their impact when receiving a full match. For all $i = 1, ..., N$, we have the following:*

$$R_i = \begin{cases} (1+\mu)g_i & \text{for } 0 \leq G_{-i} < \frac{\phi}{\mu} \\ g_i & \text{for } \frac{\phi}{\mu} \leq G_{-i} \leq W_{-i} \end{cases} \tag{1}$$

Under this assumption, donors view the match as binary: they either receive a full match or no match, depending only on whether or not the total giving of others fully exhausts the match limit. This is equivalent to donors simply ignoring the possibility of receiving a partial match. In practice, for large fundraisers with many donors, the probability of receiving a partial match will be negligible and likely would be ignored by the vast majority of donors.[6]

As long as the total giving of others is less than the match limit (i.e., $G_{-i} < \frac{\phi}{\mu}$), donor i will consider their impact to be $R_i = (1+\mu)g_i$. Therefore, donor i's utility is given by:

$$U_i\big(x_i, g_i, R\big) = \begin{cases} U_i\big(w_i - g_i,\ g_i,\ (1+\mu)g_i + \lambda R_{-i}\big) & \text{for } 0 \leq G_{-i} < \frac{\phi}{\mu} \\ U_i\big(w_i - g_i,\ g_i,\ g_i + \lambda R_{-i}\big) & \text{for } \frac{\phi}{\mu} \leq G_{-i} \leq W_{-i} \end{cases} \tag{2}$$

where $W_{-i} = \sum_{j \neq i} w_j$. The parameters μ, ϕ, N, $\mathbf{w}$, λ, and R_{-i} are all exogenous. The total giving of others, G_{-i}, is assumed to be exogenous to g_i, but may be a function of the parameters. Together, the above two expressions give donor i's utility for any choice of $g_i \in [0, w_i]$ and any realization of the total giving of others, G_{-i}.

While (2) gives donor i's utility for any choice of $g_i \in [0, w_i]$ and total giving of others, G_{-i}, they are unable to optimize over (2) because the total giving of others, G_{-i}, is not known with certainty to them. Instead, I assume donors take G_{-i} to be a realization of a random variable $\tilde{G}_{-i}$, and they form beliefs about the distribution of $\tilde{G}_{-i}$ based on observable characteristics of the

[5] For example, consider a lead gift of \$1,000. If a 1:1 match is provided ($\mu = 1$), it will require \$1,000 in donations to fully exhaust the lead gift. However, if the match rate is increased to a 2:1 match ($\mu = 2$), then it will only take \$500 in donations to fully exhaust the lead gift.

[6] In order for a donor to perceive a significant probability of receiving a partial match, they would either need to have a high level of confidence that G_{-i} is very close to (but just below) the match limit, $\frac{\phi}{\mu}$, or they would need to be making a very large donation, g_i, relative to their beliefs about the total giving of others, G_{-i}.

fundraiser. This is formalized by the following definition.

Definition 1 $F_i\big(G_{-i}|N,\mu,\phi,\mathbf{w}\big) = P_i\left(\tilde{G}_{-i} \leq G_{-i}|N,\mu,\phi,\mathbf{w}\right)$ is the CDF of donor i's perceived distribution of G_{-i}, given N, μ, ϕ, and $\mathbf{w}$, where $\mathbf{w}$ is the average wealth level among the fundraiser's population of potential donors, and $\tilde{G}_{-i}$ is a real-valued random variable.

That is, based on the values of N, μ, ϕ, and $\mathbf{w}$, each donor forms a distribution of the likely values of G_{-i}.[7] Assuming donors are expected utility maximizers and $F_i\big(G_{-i}|N,\mu,\phi,\mathbf{w}\big)$ is twice continuously differentiable for all i, donor i will choose $g_i \in [0, w_i]$ to maximize

$$EU_i(g_i|\cdot) = F_i\left(\frac{\phi}{\mu}\middle|N,\mu,\phi,\mathbf{w}\right)U_i\big(w_i - g_i,\ g_i,\ (1+\mu)g_i + \lambda R_{-i}\big) + \left[1 - F_i\left(\frac{\phi}{\mu}\middle|N,\mu,\phi,\mathbf{w}\right)\right]U_i\big(w_i - g_i,\ g_i,\ g_i + \lambda R_{-i}\big), \quad (3)$$

where $F_i(\frac{\phi}{\mu}|\cdot)$ is the donor's perceived probability of being matched, and $[1 - F_i(\frac{\phi}{\mu}|\cdot)]$ is their perceived probability of not being matched. Also note that $U_i\big(w_i - g_i,\ g_i,\ (1+\mu)g_i + \lambda R_{-i}\big)$ is donor i's utility given a certain match (i.e., $F_i(\frac{\phi}{\mu}|\cdot) = 1$ and $\mu > 0$), and $U_i\big(w_i - g_i,\ g_i,\ g_i + \lambda R_{-i}\big)$ is their utility when there is no match (i.e., $F_i(\frac{\phi}{\mu}|\cdot) = 0$ or $\mu = 0$). Thus, EU_i is simply the weighted average of the potential outcomes, match and no match.

The following definitions will be used to simplify the notation in the proceeding analysis:

Definition 2 Donor i's utility when *not* receiving a match is given by

$$U_i^0 \equiv U_i\big(w_i - g_i,\ g_i,\ g_i + \lambda R_{-i}\big). \quad (4)$$

Definition 3 Donor i's utility when receiving a match at rate μ is given by

$$U_i^1 \equiv U_i\big(w_i - g_i,\ g_i,\ (1+\mu)g_i + \lambda R_{-i}\big), \quad (5)$$

Definition 4 Donor i's *perceived probability of receiving a match* is given by

$$p_i \equiv F_i\left(\frac{\phi}{\mu}\middle|N,\mu,\phi,\mathbf{w}\right). \quad (6)$$

Using these definitions, donor i's optimization problem (3) can be rewritten as choosing $g_i \in [0, w_i]$

[7] I assume the parameter values are known by all donors, choosing to instead introduce uncertainty through each donor's construction of their perceived distribution of G_{-i}. However, since each donor forms their own beliefs about the distribution of G_{-i}, the model would be equivalent if donors were to instead each hold unique beliefs about the values of the parameters.

to maximize

$$EU_i(g_i|\cdot) = p_i U_i^1 + (1-p_i)U_i^0 \tag{7}$$

To guarantee that any local maximum is also a global maximum, I also make the following assumption.

Assumption 2 *Let donor i's optimization problem in the absence of a match (i.e., $F(\cdot) = 0$) be given by $\max_{g_i \in [0,w_i]} U_i^0(g_i|\cdot)$, and let their optimization problem in the presence of a certain match (i.e., $F(\cdot) = 1$) be given by $\max_{g_i \in [0,w_i]} U_i^1(g_i|\cdot)$. Then for all $i = 1, ..., N$, we have the following:*

$$(i)\;\; U_{gg}^0 < 0 \; \forall g \in [0, w_i] \tag{8}$$

$$(ii)\;\; U_{gg}^1 < 0 \; \forall g \in [0, w_i] \tag{9}$$

3.2 Model Predictions

3.2.1 The Effect of a Change in the Match Probability

In this section I demonstrate that changes in the perceived probability of being matched (henceforth referred to as p) affect donors' optimal donation amounts. That is, donors should in general be responsive to changes in p. In what follows, I assume interior solutions and drop the i subscripts for brevity. Taking the derivative of (3) with respect to g, the first order condition is given by

$$F\left(\frac{\phi}{\mu}\bigg|\cdot\right)\cdot\left(-\frac{\partial U^1}{\partial x}+\frac{\partial U^1}{\partial g}+(1+\mu)\frac{\partial U^1}{\partial R}\right) + \left[1-F\left(\frac{\phi}{\mu}\bigg|\cdot\right)\right]\cdot\left(-\frac{\partial U^0}{\partial x}+\frac{\partial U^0}{\partial g}+\frac{\partial U^0}{\partial R}\right)=0 \tag{10}$$

where $U^1 = U\big(w-g,\ g,\ (1+\mu)g+\lambda R_{-i}\big)$ is the donor's utility when there is a match, and $U^0 = U\big(w-g,\ g,\ g+\lambda R_{-i}\big)$ is the donor's utility in the absence of a match. Letting $FOC^1(g)$ denote the donor's first order condition given a certain match (i.e. $p=1$), and letting $FOC^0(g)$ denote the donor's first order condition in the absence of a match, the above first order condition can be rewritten as

$$pFOC^1(g) + (1-p)FOC^0(g) = 0. \tag{11}$$

That is, the donor's first order condition given an uncertain match is simply the weighted average of their FOC's for the two possible outcomes (match and no match). This leads to the following result:

Lemma 1: *For each donor i, let $g^0(\mu) \in (0, w)$ be the optimal choice of g in the absence of a* *match, so that* $g^0(\mu)$ *maximizes* $U^0 = U(w-g,\ g,\ g+\lambda R_{-i})$.[8] *Likewise, let* $g^1(\mu) \in (0,w)$ *be the optimal choice of g given a certain match at rate* μ*, so that* $g^1(\mu)$ *maximizes* $U^1 = U(w-g,\ g,\ (1+\mu)g+\lambda R_{-i})$*. Finally, let* $g^*(\mu)$ *be the optimal choice of g given an uncertain match at rate* μ*, so that* $g^*(\mu)$ *maximizes* $EU = pU^1 + (1-p)U^0$*, where* $p \in (0,1)$*. Then* $g^*(\mu) \in \left(g^0(\mu),\ g^1(\mu)\right)$ *for all* μ *such that* $g^0(\mu) \neq g^1(\mu)$*, and* $g^*(\mu) = g^0(\mu) = g^1(\mu)$ *for all* μ *such that* $g^0(\mu) = g^1(\mu)$*.*

Proof of Lemma 1 is provided in appendix A. Lemma 1 states that, for any match rate μ, each donor's optimal choice of g when the match is uncertain (g^*) must fall between their optimal choice of g when no match is received (g^0) and their optimal choice of g when the match is received with certainty (g^1).

Letting g^* denote the optimal choice of g as defined by (11), we can use the implicit function theorem to determine the donor's optimal response to a change in p:

$$\frac{\partial g^*}{\partial p} = \frac{FOC^0(g^*) - FOC^1(g^*)}{|H(g^*)|}, \tag{12}$$

where $|H(g^*)| < 0$ is the determinant of the Hessian for (3) evaluated at g^*.[9] The sign of $\frac{\partial g^*}{\partial p}$ depends on the sign of the numerator in (12), which can vary across donors. However, based on how a donor responds to receiving a certain match at rate μ relative to receiving no match, the sign of $\frac{\partial g^*}{\partial p}$ can be determined. This is formalized in the following lemma:

Lemma 2: *For each donor i and all* μ*, if* $g^1(\mu) > (=) < g^0(\mu)$*, then* $FOC^0\left(g^*(\mu)\right) - FOC^1\left(g^*(\mu)\right) < (=) > 0$ *for all p.*

Proof of Lemma 2 is provided in appendix A. This result leads to Proposition 1.

Proposition 1: *For any donor whose optimal donation increases (decreases) in response to a certain match, their optimal donation when the match is uncertain will be monotonically increasing (decreasing) in their perceived probability of being matched, p. That is, for each donor i, if* $g^1(\mu) > (=) < g^0(\mu)$*, then* $\frac{\partial g^*(\mu)}{\partial p} > (=) < 0$*, where* $\frac{\partial g^*(\mu)}{\partial p} = \frac{\partial g^*}{\partial p}|_\mu$ *is the partial evaluated at the match rate* μ*.*

Proof. Proposition 1 follows directly from applying Lemma 2 to the expression for $\frac{\partial g^*}{\partial p}$ given in equation (12), noting that $|H(g^*)| < 0$.

This result leads to the following testable hypothesis:

Hypothesis 1: *Holding all else equal, each donor's donations will respond monotonically to ex-*

[8] Note that since μ does not enter U^0, $g^0(\mu)$ is constant in μ. That is, $g^0(\mu) = g^0$ for all $\mu \in \mathbf{R}_+$.

[9] Since the donor's optimization problem (3) is a function of only g and we have assumed an interior solution, the Hessian is just the term EU_{gg}. That is, $|H(g^*)|$ is just the second order condition evaluated at g^*. Since U^0_{gg}, $U^1_{gg} < 0\ \forall g \in [0,w]$ and EU is just a weighted sum of U^0 and U^1, it follows that $EU_{gg} < 0\ \forall g \in [0,w]$.

ogenous changes in the probability of being matched.

Note that Hypothesis 1 uses *exogenous* variation in the perceived probability of being matched. That is, the change in p cannot be the result of a change in any of the characteristics of the fundraiser (e.g., μ, ϕ, N, etc.). Such changes in p are possible in a laboratory setting—where the experimenter can directly vary p while holding all else constant—allowing for Hypothesis 1 to be directly tested. Experimental results consistent with Hypothesis 1 will demonstrate that donors' decisions are influenced by the probability of being matched.

3.3 The Charity's Problem

Now that we understand the donor's optimal response to a match subsidy, we can analyze the charity's optimal policy. We approach this problem by considering a charity that wishes to use its subsidy funds as efficiently as possible—that is, to generate as many additional dollars of donations as possible with each dollar of subsidy.

The charity seeks to choose the match rate μ and the match probability p to maximize out-of-pocket donations. The charity is not concerned with the amount of donations received from subsidized funds (i.e., the charity wants to maximize g, not $g + \mu g$). Because of this, the charity will not be concerned if any match funds are "left on the table".[10] However, as μ and p increase, the amount of matching funds needed to cover the fundraiser increases. Since funds are limited, the charity does not simply seek to maximize g regardless of the cost, but instead seeks to get the biggest bang for its buck.[11]

To capture this interplay, we model the charity's problem as selecting p and μ to maximize

$$\Gamma(p, \mu) = \frac{T(p, \mu)}{C(p, \mu)}, \tag{13}$$

where $T(p, \mu) = [g^*(p, \mu) - g^*(0, 0)]$ is the increase in the donor's out-of-pocket donation resulting from the charity's choice of p and μ relative to the no-match scenario,[12] and $C(p, \mu) = p\mu g^*(p, \mu)$ is the expected cost to the charity of offering the match rate μ with probability p. Under this framework, the charity seeks to maximize the per-dollar impact of matching funds.

The question arises: under what conditions will it be optimal for the charity to offer an uncertain match (i.e., $0 < p < 1$)? The charity's FOC with respect to the match probability p can be written as

$$\frac{T_p}{C_p} \cdot \frac{C}{T} = 0 \implies T_p \cdot \frac{p}{T} = C_p \cdot \frac{p}{C} \tag{14}$$

[10] We believe this is a reasonable assumption, so long as the charity believes it can use the match funds in future fundraising efforts.

[11] If the charity simply sought to maximize g, its optimal strategy may well be to off an infinite match rate with probability 1. However, the charity will most likely be unable to fund this strategy.

[12] We assume $g^*(0, 0) = g^*(p, 0) = g^*(0, \mu)$ for all p and μ.

This states that the charity's optimal choice of p sets the elasticity of T equal to the elasticity of C. In other words, the charity should continue increasing p until the resulting increase in expected costs outweighs the increase in donations. If donors are insensitive to changes in p when $p \approx 1$, then the charity's optimal choice will be some $p < 1$.

We formalize the preceding discussion with a formal proof of the existence of an interior solution for the charity. To achieve this, we make the following assumptions:

Assumptions

(i) *No Free Lunch.* The charity cannot increase donations using a costless match program.

$$p = 0 \text{ or } \mu = 0 \implies g^*(p, \mu) = g^*(0, 0)$$

(ii) *Concavity.* Donations are strictly increasing and concave in (p, μ): $\frac{\partial g^*}{\partial p} > 0$, $\frac{\partial g^*}{\partial \mu} > 0$, and g^* is jointly concave in (p, μ).

(iii) *Donations saturate in match probability.* $\lim_{p \to 1} g^*_p(p, \mu) = 0$.

(iv) *Donations saturate in match rate.* $\lim_{\mu \to \infty} g^*_\mu(p, \mu) = 0$.

Theorem. Given the above assumptions, there exists an interior maximum to $\Gamma(p, \mu)$ with $(p, \mu) \in (0, 1) \times (0, \infty)$.

When $p = 0$ or $\mu = 0$, it's straightforward that $\Gamma = 0$. Therefore, we can rule out those boundary solutions. We can also rule out the upper boundary of μ, since C will grow without bound for any $p > 0$. The only boundary condition left to rule out is $p = 1$.

We know the charity will choose p and μ such that $\frac{\partial \Gamma}{\partial p} = 0$, if such a solution exists. To rule out $p = 1$, it suffices to show that $\frac{\partial \Gamma}{\partial p} < 0$ as $p \to 1$. To this end, note that

$$\frac{\partial R}{\partial p} = \frac{\Big[p\,\mu\,g^*(p, \mu)\Big]\Big[g^*_p(p, \mu)\Big] - \Big[g^*(p, \mu) - g^*(0, 0)\Big]\Big[\mu\,g^*(p, \mu) + p\,\mu\,g^*_p(p, \mu)\Big]}{\Big[p\,\mu\,g^*(p, \mu)\Big]^2}. \tag{15}$$

Using our assumption on the saturation of donations in the match probability, we can write

$$\lim_{p \to 1} \frac{\partial R}{\partial p} = \frac{-\Big[g^*(p, \mu) - g^*(0, 0)\Big]\Big[\mu\,g^*(p, \mu)\Big]}{\Big[p\,\mu\,g^*(p, \mu)\Big]^2} < 0 \text{ for all } \mu > 0. \tag{16}$$

Uniqueness

The preceding analysis demonstrates that, given the assumptions, an interior solution must exist. That is, the charity optimizes its use of match funds by offering an uncertain match ($p < 1$). We can define the optimal solution by the first-order conditions. However, we have not shown uniqueness of the solution. To ensure uniqueness, we will need to make an additional assumption:

Assumption. *Strict Quasi-Concavity of* Γ. For any $\alpha \in (0,1)$ and any two points $(p_1, \mu_1),\ (p_2, \mu_2)$,

$$\Gamma\big(\alpha(p_1,\mu_1) + (1-\alpha)(p_2,\mu_2)\big) > \min\big\{\Gamma(p_1,\mu_1),\ \Gamma(p_2,\mu_2)\big\} \text{ if } \Gamma(p_1,\mu_1) \neq \Gamma(p_2,\mu_2).$$

This ensures that any local maximum is also a global maximum. Regardless of this condition, however, the charity's optimal strategy is to set $p < 1$. In the following experiment, we test whether this finding holds in practice. Based on observed behavior, we then estimate the charity's optimal match rate μ and match probability p.

4 Experiment Design and Procedures

From January to March of 2024, I used the Prolific platform to recruit 150 subjects to participate in an online experiment. After choosing to participate in my study on Prolific, subjects are provided with a link to a Qualtrics survey. After completing the Qualtrics survey and verifying their submission in Prolific, participants are paid a $4 base payment through Prolific. In addition to the base payment, subjects are also paid bonus payments ranging from $0-$9, depending on their decisions during the experiment.

Upon opening the Qualtrics survey, subjects are first taken to a consent page. After consenting to participate in the study, they are taken to the instructions page. After reading through the instructions, subjects are then taken to the main task of the experiment. Following the main task, subjects are then asked to complete follow-up tasks to measure their risk preferences, and then are asked to complete some basic survey questions before submitting their survey.

Section 4.1 discusses the main task of the experiment. Section 4.2 discusses the follow-up tasks. Section 4.3 discusses the survey questions included in the experiment. Section 4.4 outlines the procedures used in the experiment. A copy of the full text of the experiment is provided in Appendix D.

4.1 Main Task

In the main task of the experiment, subjects are presented with a menu of 13 decision problems. In each problem, they are provided with an endowment of 80 Tokens (10 Tokens = $1) and asked how much of their endowment they would like to pass to a real charity.[13] Among the 13 decision problems, four different match rates are offered: $\mu \in \{0, 0.5, 1, 2\}$. For each nonzero match rate, the probability of being matched is exogenously varied using four different match probabilities: $p \in \{.25, .5, .75, 1\}$. Table 1 lists the parameters used for each problem in the experiment.

All 13 decision problems are presented simultaneously within a single table. Each row presents a question, and there are five separate columns. The first column contains the description for each

[13]The charity used is charity:water. Subjects are provided with a description of the charity in the experiment instructions. A copy of the full instructions presented to subjects can be found in the appendix to this chapter.

Table 1: Experiment match rates and match probabilities used.

Question	endowment (Tokens)	match rate (μ)	match probability (p)
1	80	0	0
2	80	$1/2$	.25
3	80	$1/2$	.5
4	80	$1/2$	.75
5	80	$1/2$	1
6	80	1	.25
7	80	1	.5
8	80	1	.75
9	80	1	1
10	80	2	.25
11	80	2	.5
12	80	2	.75
13	80	2	1

problem, which informs the subject of their endowment, the match rate, and the probability of receiving a match. With the exception of the one problem that provides no match, the description for each problem has the following format: "*You are endowed with 80 Tokens. There is a* {25%, 50%, 75%, 100%} *chance that your donation will be matched at a* {0.5:1, 1:1, 2:1} *rate by the experimenter.*" The description for the problem with no match reads "*You are endowed with 80 Tokens. There is a* 0% *chance that your donation will be matched by the experimenter.*

The second column of each problem provides a text-entry box in which subjects are prompted to enter the number of Tokens they would like to pass to the charity. After a subject enters a value in column 2 of a given problem, the remaining columns (3-5) automatically populate to provide the subject with the following information: column 3 reports the number of Tokens the subject will hold for themselves (their endowment minus the amount they pass), column 4 reports the total donation that will be received by the charity if no match is received, and column 5 reports the total donation that will be received by the charity if a match is received.[14] These values are reported to subjects to reduce confusion and prevent calculation errors, and subjects are free to edit their responses as many times as they like before submitting them.

Once a subject has provided acceptable responses to all 13 questions, they are able to submit their decisions. If they fail to answer any of the questions, or if they provide an unacceptable response to any of the questions (e.g., they attempt to pass a negative amount or an amount greater than their endowment), they receive an error message informing them of the specific issue and are unable to continue until providing an acceptable response. To maintain incentive compatibility,

[14]For questions that provide a 100% chance of receiving a match, column 4 displays "N/A" regardless of the amount the subject chooses to pass, helping to make it clear to the subject that the match is certain. Likewise, for the question that provides a 0% chance of receiving a match, column 5 displays "N/A" regardless of the amount the subject chooses to pass, helping to make it clear that there is no chance of receiving a match.

Table 2: Parameter values used for each question order.

	Order 1		Order 2		Order 3		Order 4	
Question	μ	p	μ	p	μ	p	μ	p
1	0	0	0	0	1/2	1	2	1
2	1/2	.25	2	.25	1/2	.75	2	.75
3	1/2	.5	2	.5	1/2	.5	2	.5
4	1/2	.75	2	.75	1/2	.25	2	.25
5	1/2	1	2	1	1	1	1	1
6	1	.25	1	.25	1	.75	1	.75
7	1	.5	1	.5	1	.5	1	.5
8	1	.75	1	.75	1	.25	1	.25
9	1	1	1	1	2	1	1/2	1
10	2	.25	1/2	.25	2	.75	1/2	.75
11	2	.5	1/2	.5	2	.5	1/2	.5
12	2	.75	1/2	.75	2	.25	1/2	.25
13	2	1	1/2	1	0	0	0	0

only one problem is randomly selected for payment (Azrieli et al., 2018).

To account for any order effects induced by the order in which the 13 questions are presented, subjects are randomly assigned one of four different orders. The orders used are shown in table 2. The first order exactly matches what is presented in table 1, with questions ordered first by ascending match rates and then by ascending match probabilities. The remaining orders vary by presenting match rates in ascending order and/or match probabilities in descending order, as well as placing the no-match question at either the beginning or end of the list.

4.2 Follow-up Tasks

After completing the main task, subjects are then asked to complete two follow-up tasks to measure their risk preferences: a *Payment Follow-up Task* and a *Donation Follow-up Task*. The order in which the tasks are presented to subjects is randomized across subjects.

Both tasks present subjects with a list of 11 choices, where they must choose either Option A or Option B. In the *Payment Follow-up Task*, Option A always provides the subject with "*A 50% chance of receiving $1, and $0 otherwise*". Option B provides a guaranteed fixed payment, increasing in $.10 increments, from $0 in the first question to $1 in the final question. The *Donation Follow-up Task* is identical, except that the options provide donations to the charity rather than payments to the subject. The presentation of the tasks is modeled after the presentation used by Exley (2016) for similar tasks.[15]

The first and last questions of each follow-up task provide an attention/understanding check. In the first question, subjects are choosing between a lottery that provides a $1 payment (or

[15] See figures A.3 and A.4 in Appendix A of Exley (2016). The lotteries and guaranteed payments used are different, but I have borrowed Exley's instructions.

donation) with 50% probability and a guaranteed payment (or donation) of \$0, so it is expected that all subjects should choose Option A (the lottery) in the first question. In the last question, Option B provides a guaranteed payment (or donation) of \$1, so it is expected that all subjects should prefer Option B in the final question.[16]

The *Payment Follow-up Task* and *Donation Follow-up Task* allow me to estimate subjects' risk preferences for payments and donations, respectively, based on when they choose to switch from Option A to Option B (assuming they switch exactly once). Subjects who are more risk averse will switch from Option A to Option B earlier, while those who are more risk loving will switch later.

4.3 Survey Questions

After completing the follow-up tasks, subjects answer some basic demographic questions, including age, gender, estimated family income, political views (e.g., conservative, liberal, etc.), importance of religion in their life, and estimated charitable contributions within the last year. Subjects are also asked to rate—on a scale of 0 to 10—how familiar they are with charity:water, how well they understood the procedure used to determine their payment, how well they understood the procedure used to determine their total donation, and how confident they were during the experiment that their donation (and any matching donation provided by the experimenter, if applicable) would actually be donated to the charity on their behalf. Summary statistics for subjects' responses to the survey questions are provided in Table B.1.

4.4 Procedures

Once subjects finish answering the survey questions, their payment and total donation are reported to them, including whether their donation received a match. To determine each subject's payment, one question from the main task is randomly selected. Subjects receive the number of Tokens they chose to hold for themselves in the randomly selected problem. These Tokens are converted to US dollars at the rate 10 Tokens = \$1. One problem is then also randomly selected from the *Payment Follow-up Task*. If the subject chose the guaranteed payment (Option B) in the randomly selected problem, then that amount is added to their total payment. If they instead chose the lottery (Option A), the computer 'flips a coin' to determine the outcome of the lottery.[17]

Each subject's total donation is calculated through a similar process to that of their payment. The same randomly selected decision problem that was selected to determine their payment in the main task is also used to determine their total donation. If problem j is the randomly selected problem and it provides a match at rate μ_j with probability p_j, the computer first 'flips a coin' to determine whether the match will be received.[18] If a match is determined to be received, then

[16]If a subject were for some reason to prefer that the charity receive nothing, it would be rational for them to begin by choosing Option B and then switch to choosing Option A.

[17]This is done by drawing a random number x from a uniform distribution over $(0,1)$. If $x < 0.5$, then the subject receives a payment of \$1. Otherwise, the subject receives \$0.

[18]This is done by drawing a random number x from a uniform distribution over $(0,1)$. If $x < p_j$, then the subject receives a match. Otherwise, if $x \geq p_j$, then a match is not received.

the subject receives a match at rate μ_j and their total donation from the main task is given by $(1 + \mu_j)g_j$, where g_j is the amount they chose to pass in question j. If a match is not received, the subject's total donation from the main task is given by g_j. A random question is then also drawn from the *Donation Follow-up Task*, and the resulting additional donation (if any) is added to the subject's total donation.

Subjects' earnings are paid to them through Prolific using bonus payments within two business days after they complete the experiment.[19] This is in addition to the $4 base payment they receive, which is automatically paid to them after they verify their submission in Prolific. The average total payment received by participants (including both the base payment and the bonus payment) is $10.16. The median completion time among participants is 11 minutes and 32 seconds, and the average reward-per-hour received is $20.81.

Subjects' total donations, including any matched funds received, were donated to the charity after the completion of the experiment, in a single lump-sum donation. On average, each subject donated $4.93 to the charity. The total donation received by the charity as a result of the experiment is $738.80.

5 Results

Table B.1 presents summary statistics for subjects. Section 5.1 presents evidence that the probability of receiving a match affects donors' decisions. Section 5.2 presents evidence that donations respond monotonically to changes in the match probability, consistent with the theoretical model and Hypothesis 1. Section 5.3 compares the behavior of three different types of donors: those who increase their out-of-pocket donation in response to a match (*match lovers*), those who decrease their out-of-pocket donation in response to a match (*match haters*), and those who are unresponsive to match subsidies (*match ignorers*). This analysis provides further support for the theoretical model, finding that the data are largely consistent with Hypothesis 1 across donor types. Section 5.4 tests whether subjects' behavior is affected by the order in which the questions are presented to them.

5.1 Evidence that match probabilities matter

Figure 1 shows the average amount passed (i.e., the out-of-pocket donation) by subjects at each match rate and match probability.[20] Figure 1 demonstrates two key findings. First, on average out-of-pocket donations are increasing in the match rate. Second, holding the match rate constant, on average donations increase as the match probability increases. These results can also be seen in tables B.3 and B.5.

[19]In practice, subjects received their bonus payments within 1-2 hours of verifying their submission in Prolific. However, in the description posted to Prolific, and in the experiment instructions, subjects were provided with a guarantee that their bonus payment would be received within two business days.

[20]Figure C.1 shows the average total impact at each match rate and match probability (assuming a match is received).

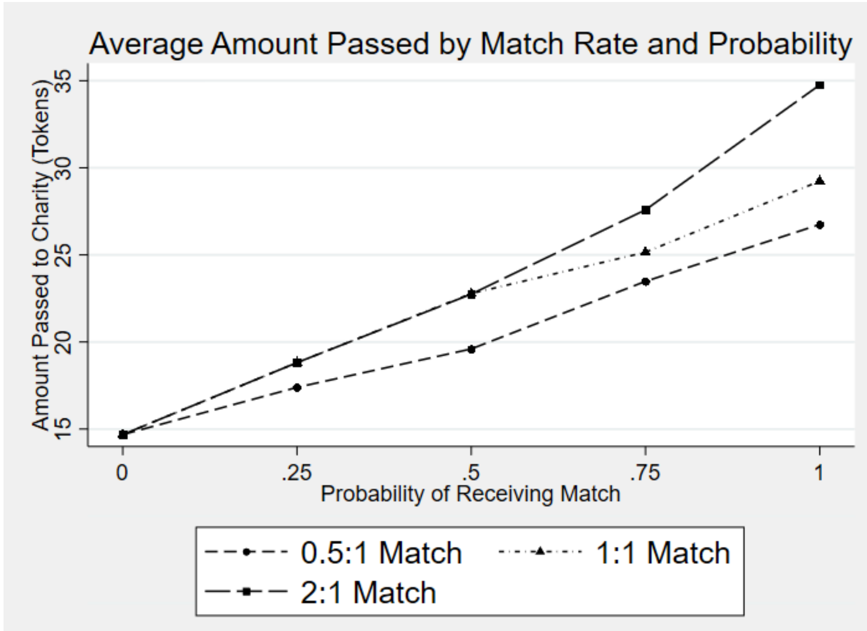

Figure 1: A comparison of the average amount passed (in Tokens) across all subjects.

Table 3 reports regression results for out-of-pocket donations, using a random-effects model and a Tobit model accounting for censoring. When excluding the interaction term between price and match probability, both models estimate statistically significant coefficients on both price and match probability. Subjects increase their out-of-pocket donations as the match rate increases (i.e., as the price decreases), and they also increase their out-of-pocket donations as the probability of receiving a match increases.

When the interaction term between price and match probability is included, the coefficient on price goes to 0. This is consistent with our theoretical predictions. The fact that the coefficient on price goes to 0 implies that subjects are unresponsive to price changes that occur when the probability of receiving a match is zero (i.e., subjects do not respond to matches that occur with probability zero). Instead, the coefficient on the interaction term is significant and negative, implying that subjects become increasingly more responsive to price decreases (increases in the match rate) as the probability of receiving the match increases.

Conversely, the negative coefficient on the interaction term also implies that subjects become increasingly more responsive to increases in the match probability as the match rate increases. In both models, the coefficient on the interaction term is the same magnitude as the coefficient on the match probability. This implies that, when no match subsidy is provided (i.e., price = 1), changes in the match probability have no effect on how much subjects choose to pass. This is again consistent with our theoretical model.

Table 3: Regressions for Amount Passed

logPass	(1)	(2)	(3)	(4)
logPrice	-0.418***	-0.060	-0.639***	-0.037
	(0.091)	(0.117)	(0.097)	(0.240)
Match probability	0.986***	0.566***	1.599***	0.898***
	(0.118)	(0.161)	(0.101)	(0.274)
Match(=1)	-0.084	0.179	-0.130	0.313
	(0.120)	(0.122)	(0.143)	(0.215)
PRICExPROB		-0.574***		-0.952***
		(0.181)		(0.347)
Constant	1.454***	1.454***	0.476**	0.475**
	(0.139)	(0.139)	(0.239)	(0.238)
Model	RE	RE	Tobit	Tobit
Observations	1950	1950	1950	1950

Standard errors in parentheses
Robust standard errors reported for (1) and (2)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Evidence that donations respond monotonically to match probability

On average, subjects increase their out-of-pocket donations in response to an increase in the match rate. And, on average, subjects monotonically increase their donations as the match probability increases. Thus, on average, Hypothesis 1 holds.

However, Hypothesis 1 also predicts that, for any subjects who *decrease* their out-of-pocket donations in response to an increase in the match rate, their donations must monotonically *decrease* as the match probability increases. To check whether this holds in the data, I segment subjects into one of three groups: (1) *match lovers*, who increase their donation in response to a certain match; (2) *match haters*, who decrease their donation in response to a certain match; and (3) *match ignorers*, whose behavior is unaffected by the certain match.

There are two important points regarding the classification of match lovers and haters. First, the classifications are made based on how much a subject passes when no match is received and how much they pass when a match is received *with certainty*. Second, consistent with the theoretical model, this classification is made at the subject-match rate level. For example, the same subject may be classified as a *match lover* for a 0.5:1 match and as a *match hater* for a 2:1 match. The theory allows for subjects to respond positively to some match rates and negatively to others. All that is required is that donations respond monotonically as the match probability varies.

To test the extent to which subjects' behavior is consistent with Hypothesis 1, I classify all subject-match rate pairs and check for monotonicity. For example, if a subject is a *match lover* for a 2:1 match ($\mu = 2$), then it must be the case that $g_i(\mu = 2, p = 0) \leq g_i(\mu = 2, p = .25) \leq g_i(\mu = 2, p = .5) \leq g_i(\mu = 2, p = .75) \leq g_i(\mu = 2, p = 1)$. For a *match hater*, all of the relations are

Table 4: Number of subjects whose decisions are consistent with the predictions of Hypothesis 1.

		0.5:1 Match		1:1 Match		2:1 Match		All Match Rates	
		Count	Percent	Count	Percent	Count	Percent	Count	Percent
Lovers	Non-mon	15	19.23	10	11.36	9	9.38	34	12.98
	Monotonic	63	80.77	78	88.64	87	90.63	228	87.02
	Total	78		88		96		262	
Ignorers	Non-mon	12	18.46	8	14.81	10	21.74	30	18.18
	Monotonic	53	81.54	46	85.19	36	78.26	135	81.82
	Total	65		54		46		165	
Haters	Non-mon	1	14.29	2	25.00	1	12.50	4	17.39
	Monotonic	6	85.71	6	75.00	7	87.50	19	82.61
	Total	7		8		8		23	
All Types	Non-mon	28	18.67	20	13.33	20	13.33	68	15.11
	Monotonic	122	81.33	130	86.67	130	86.67	382	84.89
	Total	150		150		150		450	

reversed. For *match ignorers*, all of the relations hold with equality (i.e., a *match ignorer* should pass the same amount at all match probabilities).

Table 4 shows the number of subjects whose out-of-pocket donations respond monotonically to changes in the match probability, for each donor type (match *lovers*, *ignorers*, and *haters*) and match rate. Overall, subjects' behavior is consistent with Hypothesis 1 nearly 85% of the time. The majority of subjects (58%) are *match lovers* across all match rates, and the proportion of *match lovers* increases as the match rate increases (52%, 58.7%, and 64% of subjects are *match lovers* at the 0.5:1, 1:1, and 2:1 match rates, respectively). Furthermore, subjects' behavior also becomes increasingly consistent with Hypothesis 1 as the match rate increases: about 81% of *match lovers* display monotonicity at the 0.5:1 match rate, close to 89% at the 1:1 match rate, and nearly 91% at the 2:1 match rate.

The second most common type is *match ignorers*, who account for 37% of all subject-match rate pairs. In contrast with the number of *match lovers*, the number of *match ignorers* decreases as the match rate increases: from 43% for the 0.5:1 match, to 36% for the 1:1 match, and 31% for the 2:1 match. As the match rate increases, subjects appear to shift from being *match ignorers* to *match lovers*, perhaps because the match becomes more salient. Overall, the behavior of *match ignorers* is consistent with Hypothesis 1 about 82% of the time.

Few subjects are categorized as *match haters*. Across all match rates, *match haters* only account for 5% of subjects. That being said, among those observed to be *match haters*, nearly 83% display monotonicity in their decisions. Thus, the behavior of *match haters* is largely consistent with Hypothesis 1.

Overall, behavior is largely consistent with Hypothesis 1, with 85% of decisions displaying monotonicity in the match probability. Furthermore, behavior is consistently monotonic across all

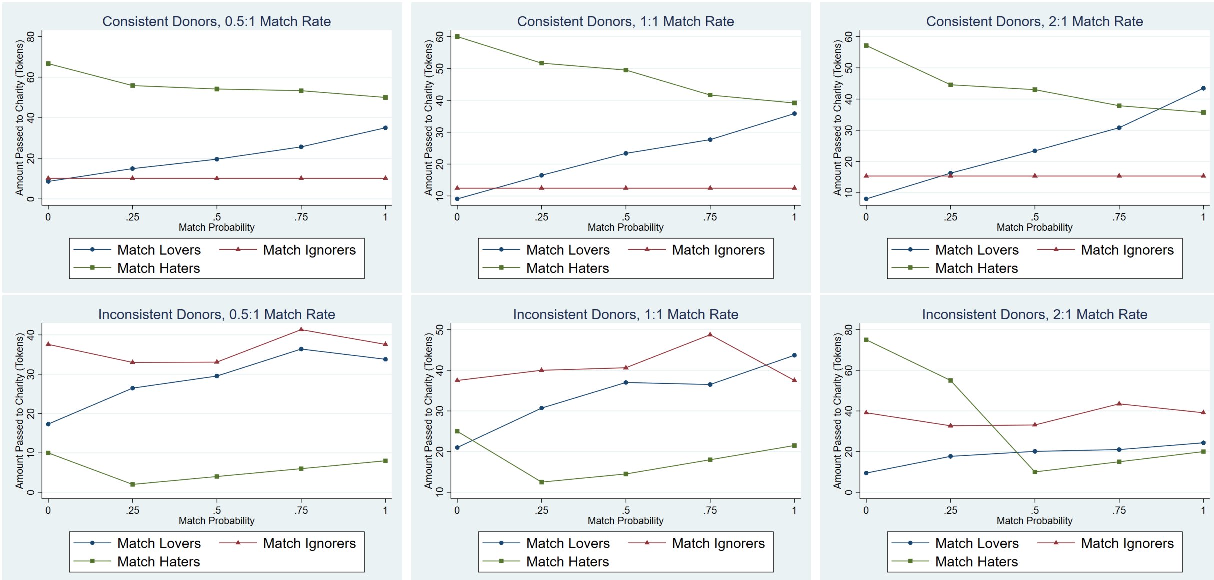

Figure 2: A comparison of the average amount passed (in Tokens) by type and match rate. Top row shows the averages among subjects who behave consistently with Hypothesis 1 (monotonicity); bottom row shows the averages among subjects who violate monotonicity.

three types of subjects, with monotonicity observed more than 80% of the time for all three types: *match lovers*, *match ignorers*, and *match haters*.

5.3 Comparing match lovers, haters, and ignorers

Figure 2 shows the average out-of-pocket donations made by each of the different types of donors. Among subjects who behave consistently with monotonicity (top row), *match haters* are significantly more generous than the other types of donors when no match is provided. As the match probability increases, they provide smaller donations. Given their initial generosity, it appears they are very concerned with how much the charity receives: as the match probability increases, the expected amount received by the charity increases. This behavior suggests that altruistic motives may weigh more heavily in the utility functions of *match haters*.

Table 5 displays the average amount passed by donors of each type, making no distinction between those who behave consistently with Hypothesis 1 and those who behave inconsistently with it. In contrast with *match haters*, *match lovers* give the least amount among all types when no match is provided. However, this group is highly responsive to changes in the match probability, giving about the same amount as *match haters* when the match is received with certainty. (*Match lovers* give less than *match haters* when there is a 0.5:1 certain match, about the same when there is a 1:1 certain match, and more when there is a 2:1 certain match. This reflects the fact that *match lovers* give more as the match rate increases, while *match haters* give less as the match rate increases.)

Match ignorers give more than *match lovers* when no match is provided, but because they are

Table 5: Average amount passed (in Tokens) by each donor type.

		Match Probability				
		$p = 0$	$p = .25$	$p = .5$	$p = .75$	$p = 1$
0.5:1 Match	*Lovers* ($n = 78$)	10.19	17.15	21.49	27.72	34.81
	Ignorers ($n = 65$)	15.22	14.37	14.38	15.91	15.22
	Haters ($n = 7$)	58.57	48.14	47.00	46.57	44.00
1:1 Match	*Lovers* ($n = 88$)	10.44	18.11	24.92	28.68	36.75
	Ignorers ($n = 54$)	16.17	16.54	16.63	17.83	16.17
	Haters ($n = 8$)	51.25	41.88	40.75	35.75	34.75
2:1 Match	*Lovers* ($n = 96$)	8.16	16.41	23.09	29.90	41.67
	Ignorers ($n = 46$)	20.52	19.13	19.22	21.48	20.52
	Haters ($n = 8$)	59.38	45.88	38.88	35.00	33.75

unresponsive to changes in the match rate, they give substantially less than *match lovers* as the match rate increases. On average, *match ignorers* give the least amount of the three types. Their behavior is consistent with pure warm-glow preferences where no warm glow is felt from matched funds (Higgs and Uler, 2023).

5.4 Checking whether question order matters

Figure 3 shows the average out-of-pocket donations of subjects assigned to each of the four different question orders, plotted at each match rate. A gap appears to grow between Orders 1 and 2 and Orders 3 and 4 as the match rate increases. Orders 1 and 2 display the questions in order of increasing match probabilities, whereas Orders 3 and 4 display them in order of decreasing match probabilities (see Table 2). Orders 1 and 2 also display the no-match question first, while it is displayed last in Orders 3 and 4. A preliminary look at Figure 3 suggests these differences may affect subjects' behavior, at least at higher match rates. Figure C.2, which shows average out-of-pocket donations broken down by match rate and match probabilities, shows that the gap between Orders 1 and 2 and Orders 3 and 4 is most prevalent among the 2:1 match-rate questions, growing in size as the match probability increases. This further suggests that subjects' behavior may be influenced by the order in which match probabilities are presented. However, upon closer analysis, there are no statistically significant differences between question orders.

Table B.12 shows the average out-of-pocket donations among subjects assigned to each question order, broken down by each match rate and match probability.[21] The last column reports p-values from one-way ANOVA tests of equality of means. The null hypothesis of equal means across all question orders cannot be rejected for any of the questions, including the 2:1 match questions that

[21] A more detailed analysis of the average out-of-pocket donations in each question for each of the question orders is provided in Tables B.7, B.8, B.9, and B.10.

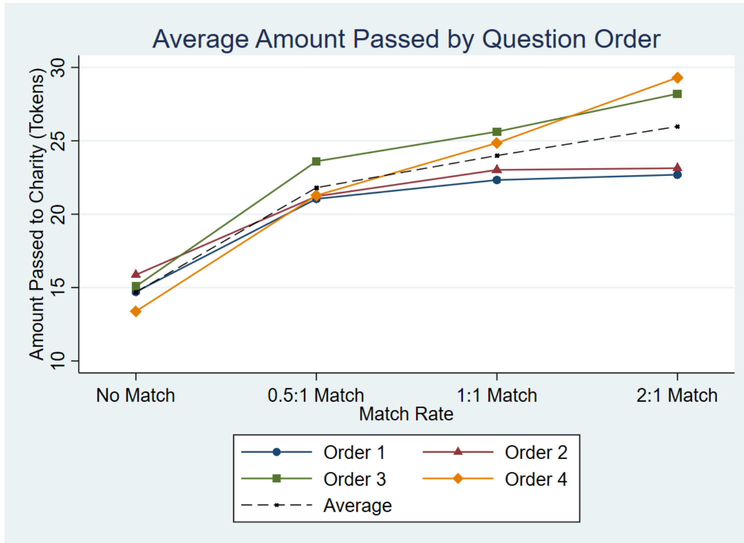

Figure 3: A comparison of the average amount passed (in Tokens) across all subjects for each question order.

appear to diverge in Figure 3.[22]

Table B.11 reports the results of regressions including interaction terms for each of the question orders. With the exception of model 3, Wald tests of the equality of coefficients—for *price*, *match probability*, and the interaction term between *price* and *match probability* (for models 2 and 4)—across question orders fail to reject the null hypothesis of equality. In model 3, the coefficients on *price* are found to be statistically different across question orders (p=.000). This difference is driven by question order 4, for which the estimated coefficient on price is significantly more negative. However, when interaction terms between *price* and *match probability* are included (model 4), the difference between question orders disappears. No statistically significant differences are observed between question orders for the coefficient estimates on *Price*, *Match Probability*, or the interaction term *PRICExPROB*.

Although there is some qualitative evidence that the order in which match probabilities are presented may influence subjects' donation decisions, these differences are not statistically significant. Furthermore, regardless of any potential question-order effects, Figures 3 and C.2 show that the main features of subjects' behavior are consistent across all question orders: first, on average, subjects increase their out-of-pocket donations as the match rate increases; and second, on average, subjects increase their out-of-pocket donations as the probability of receiving a match increases. Across all question orders, subjects are responsive to both the match rate and the match probability.

[22]Because sample sizes are not equal across question orders, it is possible the reported p-values from one-way ANOVA tests are smaller than their true values, increasing the likelihood of rejecting the null hypothesis (Miller Jr, 1997). Given that we still fail to reject the null hypothesis for each question, this strengthens support for our claim that subjects' behavior is not significantly affected by question order.

5.5 The charity's optimal strategy

This section discusses the charity's optimal strategy for selecting μ and p. Can the charity use match funds more efficiently by offering uncertain matches?

The following table presents the average out-of-pocket donation for each value of p and μ.

Table 6: Average out-of-pocket donation for each choice of (p, μ).

	p=0	**p=0.25**	**p=0.5**	**p=0.75**	**p=1**
0:1	14.68	14.68	14.68	14.68	14.68
0.5:1	14.68	17.39	19.6	23.48	26.75
1:1	14.68	18.81	22.78	25.15	29.23
2:1	14.68	18.81	22.75	27.59	34.76

The following table shows the average impact of the match on out-of-pocket donations (i.e., $T(p, \mu) = g^*(p, \mu) - g^*(0, 0)$). With the exception of the 2:1 match at low match probabilities,

Table 7: Average impact of (p, μ) on out-of-pocket donations.

	p=0.25	**p=0.5**	**p=0.75**	**p=1**
0.5:1	2.71	4.92	8.8	12.07
1:1	4.13	8.1	10.47	14.55
2:1	4.13	8.07	12.91	20.08

higher match rates generate greater impacts on out-of-pocket donations. And the same can be said for the match probability. If the charity is interested in maximizing out-of-pocket donations regardless of cost, its optimal strategy appears to be to offer a high match rate with certainty.

However, the charity's optimal strategy is different if it is concerned with the cost of the subsidy. As p and μ increase, so do the expected costs. The following table presents the efficiency ratios $\Gamma(p, \mu) = T(p, \mu)/C(p, \mu)$. When considering the match-fund efficiency ratio, we now see the

Table 8: Match-fund efficiency ratios (T/C).

	p=0.25	**p=0.5**	**p=0.75**	**p=1**
0.5:1	1.247	1.004	0.999	0.902
1:1	0.878	0.711	0.555	0.498
2:1	0.439	0.355	0.312	0.289

opposite relationship: match funds are used more efficiently as p and μ decrease.

6 Conclusion

Match subsidies are a common strategy used by charitable organizations to boost donations. However, despite their popularity, there is no consensus on what the optimal match rate is or, if it differs across settings, how a fundraiser should go about determining it. Existing studies show mixed results on the effectiveness of different match rates, providing contradictory estimates that suggest that match subsidies can have varying impacts on donor behavior.

This research proposes an intuitive model of charitable giving in which donors consider matches to be uncertain, forming beliefs about the expected donations of others and using these beliefs, together with the match limit, to derive their perception of the probability of receiving a match. This model is consistent with previous research, is capable of providing an explanation for the seemingly contradictory match-price elasticity estimates found in previous work, and produces meaningful insights into the interactions between the match rate and the match limit.

The model is based on a simple mechanism: if the total donations of the other donors exceed the match rate, the donor does not consider their donation matched. To formalize this mechanism, a theoretical model was developed, assuming donors are impure-impact givers. Donors form probability distributions about the total giving of others, influenced by fundraiser characteristics, the match rate, and the match limit. The model reveals that increasing the match rate, while holding the lead gift size constant, creates counteracting effects: it increases the potential impact of a gift if a match is received but decreases the probability of receiving a match. Because of this, the effect of changing the match rate is ambiguous, depending on the donor's perceptions about the total giving of others.

Formal theoretical results were derived from the model, and the theoretical predictions were tested through a real-incentive online laboratory experiment. The experiment introduced exogenous variation in the probability of receiving a match in an effort to establish that donors are responsive to changes in the match probability. The results of the experiment confidently showed that donors are indeed responsive to changes in the probability of receiving a match. Larger match rates induce larger average donations, but this effect diminishes as the match probability decreases. Furthermore, donor behavior is observed to be consistent with the predictions of Hypothesis 1 more than 85% of the time. And this consistency holds among all three types of donors: *match lovers*, *match haters*, and *match ignorers*. These findings provide strong support for the theoretical model and demonstrate the importance of considering donors' perceived match probabilities.

Overall, this research advances our understanding of donor behavior and provides charitable organizations with valuable guidance for designing more effective fundraisers. By considering donors' perceived probabilities of receiving a match, charities can optimize their use of lead gifts to maximize donations, thereby enhancing the efficiency and impact of their fundraising efforts.

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A Proofs

Proof of Lemma 1: I will first prove that $g^0 < g^1 \implies g^0 < g^* < g^1$. The proof consists of two parts. First I will show that $g^0 < g^*$, and then I will show that $g^* < g^1$, thus completing the proof that $g^0 < g^1 \implies g^0 < g^* < g^1$.

Recall that g^* is defined by the first order condition $FOC^*(g^*) = pFOC^1(g^*) + (1-p)FOC^0(g^*) \equiv 0$. Likewise, g^0 and g^1 are defined by the first order conditions $FOC^0(g^0) \equiv 0$ and $FOC^1(g^1) \equiv 0$, respectively. By the second order conditions for U^0 and U^1 (Assumption 1), $FOC^0(g)$ and $FOC^1(g)$ are decreasing in g. Furthermore, since EU is a weighted sum of U^0 and U^1, $FOC^*(g)$ must also be decreasing in g. Thus, it follows that $FOC^*(g^0) = pFOC^1(g^0) + (1-p)FOC^0(g^0) > 0$, since $g^0 < g^1$ implies $FOC^1(g^0) > 0$. Finally, since $FOC^*(g^0) > 0$, it follows that $g^* > g^0$.

To see that $g^* < g^1$, note that $FOC^*(g^1) = pFOC^1(g^1) + (1-p)FOC^0(g^1) < 0$, since $g^0 < g^1$ implies $FOC^0(g^1) < 0$. Thus, because $FOC^*(g)$ is decreasing in g, it follows that $g^* < g^1$, thereby demonstrating that $g^0 < g^1 \implies g^0 < g^* < g^1$.

The proof that $g^1 < g^0 \implies g^1 < g^* < g^0$ follows similarly. If $g^1 < g^0$, then $FOC^*(g^0) = pFOC^1(g^0) + (1-p)FOC^0(g^0) < 0$, since $FOC^1(g)$ is decreasing in g. Therefore, $g^1 < g^0$ implies $g^* < g^0$. Furthermore, $g^1 < g^0$ implies $FOC^*(g^1) = pFOC^1(g^1) + (1-p)FOC^0(g^1) > 0$, since

$FOC^0(g)$ is decreasing in g. This implies $g^* > g^1$, thereby demonstrating that $g^1 < g^0 \implies g^1 < g^* < g^0$.

Finally, if $g^0 = g^1$, then both g^0 and g^1 solve $FOC^*(g) = 0$. Thus, $g^* = g^0 = g^1$, completing the proof of Lemma 1.

Proof of Lemma 2: First consider $g^1 > g^0$. From Lemma 1, we have that $g^0 < g^* < g^1$. Therefore, $FOC^0(g^*) < 0$ and $FOC^1(g^*) > 0$, implying $FOC^0(g^*) - FOC^1(g^*) < 0$. That is, $g^1 > g^0 \implies FOC^0(g^*) - FOC^1(g^*) < 0$.

Now consider $g^0 > g^1$. From Lemma 1, we have that $g^1 < g^* < g^0$. Therefore, $FOC^0(g^*) > 0$ and $FOC^1(g^*) < 0$, implying $FOC^0(g^*) - FOC^1(g^*) > 0$. That is, $g^0 > g^1 \implies FOC^0(g^*) - FOC^1(g^*) > 0$.

Finally, consider $g^0 = g^1$. From Lemma 1, we have that $g^* = g^0 = g^1$. Therefore, $FOC^0(g^*) = FOC^1(g^*) = 0$, implying $FOC^0(g^*) - FOC^1(g^*) = 0$. That is, $g^0 = g^1 \implies FOC^0(g^*) - FOC^1(g^*) = 0$, completing the proof of Lemma 2.

B Additional Tables

Table B.1: Summary demographic data for subjects

Summary Statistics	μ	σ	Min	Median	Max
Age	40.05	11.618	20	37	72
Knowledge of charity	1.17	2.342	0	0	9
Understanding of pay	8.23	2.196	0	9	10
Understanding of donation	8.36	1.977	0	9	10
Confidence in donation	7.45	3.095	0	9	10
SEX					
Female	.46	.500			
Male	.51	.501			
Other	.03	.162			
INCOME					
Don't know/Prefer not to answer	.01	.115			
Less than $50,000	.30	.460			
Between $50,000 and $75,000	.32	.468			
Between $75,000 and $100,000	.11	.310			
Between $100,000 and $150,000	.15	.355			
Between $150,000 and $200,000	.05	.212			
More than $200,000	.07	.250			
POLITICS					
Prefer not to say	.00	.000			
Unsure/Undecided	.01	.082			
Liberal	.60	.492			
Moderate	.27	.444			
Conservative	.13	.334			
RELIGION					
Not important	.49	.502			
Somewhat important	.21	.406			
Important	.13	.341			
Very important	.17	.374			
RECENT DONATIONS					
Less than $20	.41	.493			
Between $20 and $50	.24	.429			
Between $50 and $100	.11	.318			
More than $100	.24	.429			
Observations	150				

Table B.2: Regressions including all controls

		(1)	(2)	(3)	(4)
	logPass				
	logPrice	-0.418***	-0.060	-0.640***	-0.037
		(0.091)	(0.117)	(0.097)	(0.240)
	Match probability	0.986***	0.566***	1.599***	0.898***
		(0.118)	(0.162)	(0.100)	(0.274)
	Match(=1)	-0.084	0.179	-0.131	0.313
		(0.121)	(0.122)	(0.143)	(0.215)
	PRICExPROB		-0.574***		-0.952***
			(0.182)		(0.347)
	Age	0.007	0.007	0.016	0.016
		(0.009)	(0.009)	(0.018)	(0.018)
Sex (Female omitted)	Male	-0.307	-0.307	-0.589	-0.589
		(0.242)	(0.243)	(0.409)	(0.409)
	Other	1.355**	1.355**	2.614**	2.616**
		(0.533)	(0.533)	(1.188)	(1.190)
	Income refuse (=1)	2.408	2.408	2.194	2.192
		(2.000)	(2.000)	(3.680)	(3.681)
	logIncome	0.330*	0.330*	0.498	0.498
		(0.178)	(0.178)	(0.304)	(0.304)
Politics (conservative omitted)	liberal	0.804**	0.804**	1.327**	1.328**
		(0.396)	(0.396)	(0.651)	(0.652)
	moderate	0.415	0.415	0.788	0.789
		(0.411)	(0.411)	(0.679)	(0.679)
	unsure/undecided	-0.917*	-0.917*	-1.035	-1.041
		(0.550)	(0.551)	(2.389)	(2.391)
Religion (important omitted)	not important	0.108	0.108	0.299	0.298
		(0.308)	(0.308)	(0.590)	(0.590)
	somewhat important	0.203	0.203	0.424	0.424
		(0.342)	(0.342)	(0.653)	(0.653)
	very important	-0.100	-0.100	-0.195	-0.197
		(0.399)	(0.399)	(0.703)	(0.703)
	logDonation	0.153	0.153	0.232	0.232
		(0.129)	(0.129)	(0.222)	(0.222)
	Knowledge of charity	0.078*	0.078*	0.158**	0.159**
		(0.042)	(0.042)	(0.080)	(0.080)
	Understand payment	0.022	0.022	0.159	0.160
		(0.079)	(0.079)	(0.180)	(0.180)
	Understand donation	-0.187**	-0.187**	-0.479**	-0.480**
		(0.089)	(0.089)	(0.197)	(0.198)
	Donation confidence	0.100**	0.100**	0.206***	0.206***
		(0.039)	(0.039)	(0.068)	(0.068)
	Constant	-2.981	-2.981	-6.401*	-6.403*
		(2.122)	(2.122)	(3.608)	(3.610)
	Model	RE	RE	Tobit	Tobit
	Observations	1950	1950	1950	1950

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Average amount passed by match rate

	Baseline	0.5:1 Match	1:1 Match	2:1 Match
mean	14.68	21.81	24.00	25.98
semean	1.87	.93	.93	.91
min	0	0	0	0
max	80	80	80	80
p50	0	18.13	20	25
count	150	600	600	600

Table B.4: Average amount received by charity (assuming a match is received) by match rate

	Baseline	0.5:1 Match	1:1 Match	2:1 Match
mean	14.68	32.79	47.99	77.93
semean	1.87	1.40	1.85	2.72
min	0	0	0	0
max	80	120	160	240
p50	0	27.25	40	75
count	150	600	600	600

Table B.5: Average amount passed by match rate and match probability

		0.5:1 Match				1:1 Match				2:1 Match			
	Baseline	p25	p50	p75	p100	p25	p50	p75	p100	p25	p50	p75	p100
mean	14.68	17.39	19.6	23.48	26.75	18.81	22.78	25.15	29.23	18.81	22.75	27.59	34.76
semean	1.87	1.85	1.86	2.03	2.13	1.85	1.89	2.00	2.12	1.77	1.87	2.05	2.28
min	0	0	0	0	0	0	0	0	0	0	0	0	0
median	0	10	10	20	20	10	20	20	25	10	20	25	30
max	80	80	80	80	80	80	80	80	80	80	80	80	80
count	150	150	150	150	150	150	150	150	150	150	150	150	150

Table B.6: Average impact (assuming match is received) by match rate and match probability

		0.5:1 Match				1:1 Match				2:1 Match			
	Baseline	p25	p50	p75	p100	p25	p50	p75	p100	p25	p50	p75	p100
mean	14.68	26.17	29.46	35.33	40.19	37.63	45.56	50.31	58.47	56.44	68.24	82.76	104.28
semean	1.87	2.78	2.78	3.04	3.20	3.71	3.77	4.00	4.24	5.31	5.60	6.16	6.84
min	0	0	0	0	0	0	0	0	0	0	0	0	0
median	0	15	15	30	30	20	40	40	50	30	60	75	90
max	80	120	120	120	120	160	160	160	160	240	240	240	240
count	150	150	150	150	150	150	150	150	150	150	150	150	150

B.1 Comparing results across question orders

Table B.7: Question order 1: Average amount passed by match rate and match probability

		0.5:1 Match				1:1 Match				2:1 Match			
	Baseline	p25	p50	p75	p100	p25	p50	p75	p100	p25	p50	p75	p100
mean	14.71	17.29	19.39	23.44	24.05	17.37	22.51	24.29	25.15	18.00	21.12	23.00	28.63
semean	3.58	3.39	3.52	3.86	3.90	3.26	3.59	3.70	3.94	3.39	3.68	3.71	3.95
min	0	0	0	0	0	0	0	0	0	0	0	0	0
median	0	9	10	20	12	12	18	20	15	11	20	20	25
max	80	80	80	80	80	80	80	80	80	80	80	80	80
count	41	41	41	41	41	41	41	41	41	41	41	41	41

Table B.8: Question order 2: Average amount passed by match rate and match probability

		0.5:1 Match				1:1 Match				2:1 Match			
	Baseline	p25	p50	p75	p100	p25	p50	p75	p100	p25	p50	p75	p100
mean	15.87	16.70	19.23	22.73	26.20	18.40	19.90	24.13	29.63	18.63	20.20	23.50	30.20
semean	4.07	4.04	4.39	4.88	4.91	4.19	3.90	4.62	4.81	3.53	3.94	4.28	4.76
min	0	0	0	0	0	0	0	0	0	0	0	0	0
median	7.5	10	10	20	20	10	20	20	22.5	15	15	20	22.5
max	80	80	80	80	80	80	80	80	80	60	80	80	80
count	30	30	30	30	30	30	30	30	30	30	30	30	30

Table B.9: Question order 3: Average amount passed by match rate and match probability

		0.5:1 Match				1:1 Match				2:1 Match			
	Baseline	p25	p50	p75	p100	p25	p50	p75	p100	p25	p50	p75	p100
mean	15.08	18.33	20.03	25.59	30.46	19.95	24.38	27.03	31.13	19.13	24.15	31.36	38.18
semean	3.80	3.70	3.15	3.66	3.97	3.84	3.81	3.84	4.00	3.49	3.50	4.15	4.57
min	0	0	0	0	0	0	0	0	0	0	0	0	0
median	0	10	20	20	30	10	20	25	30	10	20	30	40
max	80	80	80	80	80	80	80	80	80	80	80	80	80
count	39	39	39	39	39	39	39	39	39	39	39	39	39

Table B.10: Question order 4: Average amount passed by match rate and match probability

		0.5:1 Match				1:1 Match				2:1 Match			
	Baseline	p25	p50	p75	p100	p25	p50	p75	p100	p25	p50	p75	p100
mean	13.38	17.10	19.68	22.03	26.30	19.50	23.65	24.98	31.28	19.48	24.95	31.68	41.13
semean	3.64	3.86	4.02	4.13	4.50	3.77	3.87	4.10	4.40	3.78	3.88	4.22	4.77
min	0	0	0	0	0	0	0	0	0	0	0	0	0
median	0	1	3.5	15	17.5	10	22.5	22.5	37.5	10	25	30	40
max	80	80	80	80	80	80	80	80	80	80	80	80	80
count	40	40	40	40	40	40	40	40	40	40	40	40	40

Table B.11: Regressions for Amount Passed by Question Order

	(1)	(2)	(3)	(4)
logPrice	-0.149	0.271	-0.220	0.561
	(0.270)	(0.164)	(0.231)	(0.220)
PRICExOrder2	-0.243	-0.534*	-0.343	-0.922
	(0.333)	(0.081)	(0.222)	(0.183)
PRICExOrder3	-0.138	-0.272	-0.248	-0.440
	(0.406)	(0.331)	(0.341)	(0.495)
PRICExOrder4	-0.693**	-0.576*	-1.100***	-1.124*
	(0.011)	(0.091)	(0.000)	(0.086)
Match probability	0.815***	0.322	1.382***	0.487
	(0.001)	(0.288)	(0.000)	(0.345)
MATCH PROBxOrder2	0.047	0.388	0.039	0.697
	(0.887)	(0.353)	(0.891)	(0.378)
MATCH PROBxOrder3	0.318	0.476	0.354	0.563
	(0.341)	(0.276)	(0.187)	(0.442)
MATCH PROBxOrder4	0.297	0.160	0.432	0.446
	(0.373)	(0.732)	(0.111)	(0.549)
Match(=1)	0.072	0.380*	0.082	0.655
	(0.753)	(0.075)	(0.762)	(0.109)
Match(=1)xOrder2	-0.343	-0.557*	-0.515	-0.940
	(0.290)	(0.066)	(0.208)	(0.129)
Match(=1)xOrder3	0.071	-0.028	0.115	-0.028
	(0.823)	(0.935)	(0.765)	(0.962)
Match(=1)xOrder4	-0.393	-0.308	-0.529	-0.542
	(0.260)	(0.354)	(0.177)	(0.358)
Order 2 (=1)	0.225	0.225	0.295	0.296
	(0.577)	(0.578)	(0.671)	(0.670)
Order 3 (=1)	-0.038	-0.038	-0.070	-0.069
	(0.921)	(0.921)	(0.914)	(0.914)
Order 4 (=1)	-0.250	-0.250	-0.570	-0.572
	(0.507)	(0.508)	(0.378)	(0.376)
PRICExPROB		-0.673**		-1.218*
		(0.048)		(0.063)
PRICExPROBxOrder2		0.466		0.897
		(0.338)		(0.370)
PRICExPROBxOrder3		0.215		0.280
		(0.629)		(0.764)
PRICExPROBxOrder4		-0.187		0.027
		(0.736)		(0.977)
Constant	1.486***	1.486***	0.587	0.586
	(0.000)	(0.000)	(0.196)	(0.197)
Model	RE	RE	Tobit	Tobit
Observations	1950	1950	1950	1950

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: Average amount passed in each question order.

		Order 1	Order 2	Order 3	Order 4	p-value†
No Match	$p = 0$	14.71	15.87	15.08	13.38	.974
		(22.95)	(22.30)	(23.76)	(23.05)	(.988)
0.5:1 Match	$p = .25$	17.29	16.70	18.33	17.10	.992
		(21.69)	(22.15)	(23.10)	(24.40)	(.893)
	$p = .5$	19.39	19.23	20.03	19.68	.999
		(22.53)	(24.02)	(19.66)	(25.44)	(.448)
	$p = .75$	23.44	22.73	25.59	22.02	.932
		(24.70)	(26.72)	(22.87)	(26.09)	(.806)
	$p = 1$	24.05	26.20	30.46	26.30	.745
		(24.99)	(26.87)	(24.80)	(28.46)	(.806)
1:1 Match	$p = .25$	17.37	18.40	19.95	19.50	.959
		(20.84)	(22.93)	(23.99)	(23.81)	(.814)
	$p = .5$	22.51	19.90	24.38	23.65	.872
		(22.98)	(21.37)	(23.78)	(24.48)	(.887)
	$p = .75$	24.29	24.13	27.03	24.98	.955
		(23.71)	(25.28)	(23.97)	(25.94)	(.936)
	$p = 1$	25.15	29.63	31.13	31.27	.692
		(25.24)	(26.36)	(24.98)	(27.80)	(.907)
2:1 Match	$p = .25$	18.00	18.63	19.13	19.48	.991
		(21.71)	(19.31)	(21.77)	(23.91)	(.689)
	$p = .5$	21.12	20.20	24.15	24.95	.781
		(23.58)	(21.60)	(21.88)	(24.52)	(.855)
	$p = .75$	23.00	23.50	31.36	31.68	.254
		(23.73)	(23.42)	(25.93)	(26.70)	(.828)
	$p = 1$	28.63	30.20	38.18	41.13	.142
		(25.31)	(26.07)	(28.53)	(30.18)	(.688)
Count		41	30	39	40	

Note: Out-of-pocket donations are reported. Standard deviations are shown in parentheses. †One-way ANOVA tests of equality of means across all four question orders. Bartlett's equal-variances tests are reported in parentheses.

C Additional Figures

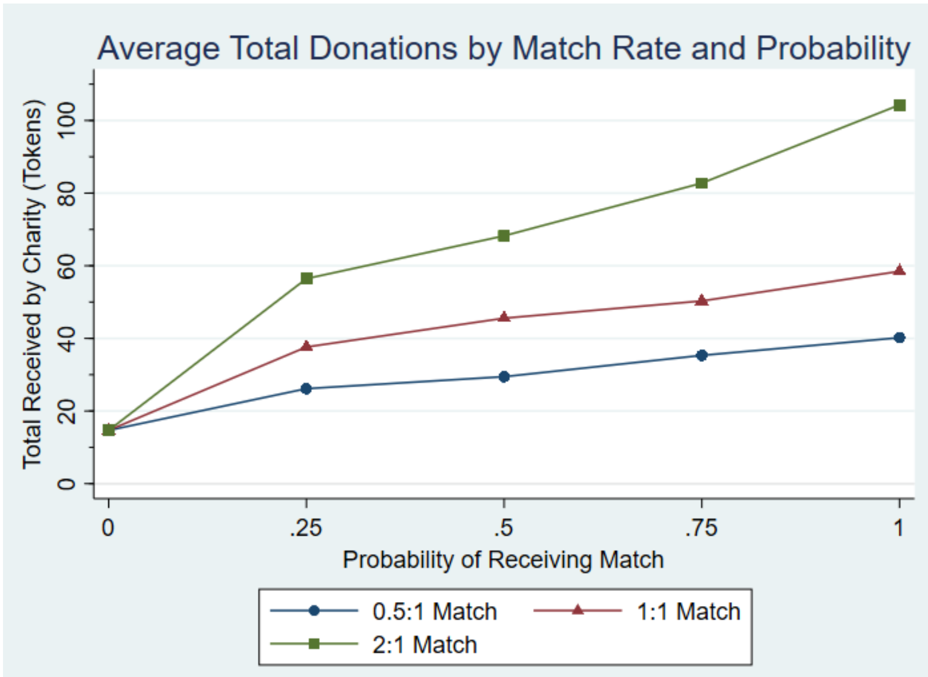

Figure C.1: A comparison of the average total impact (in Tokens, assuming a match is received) across all subjects.

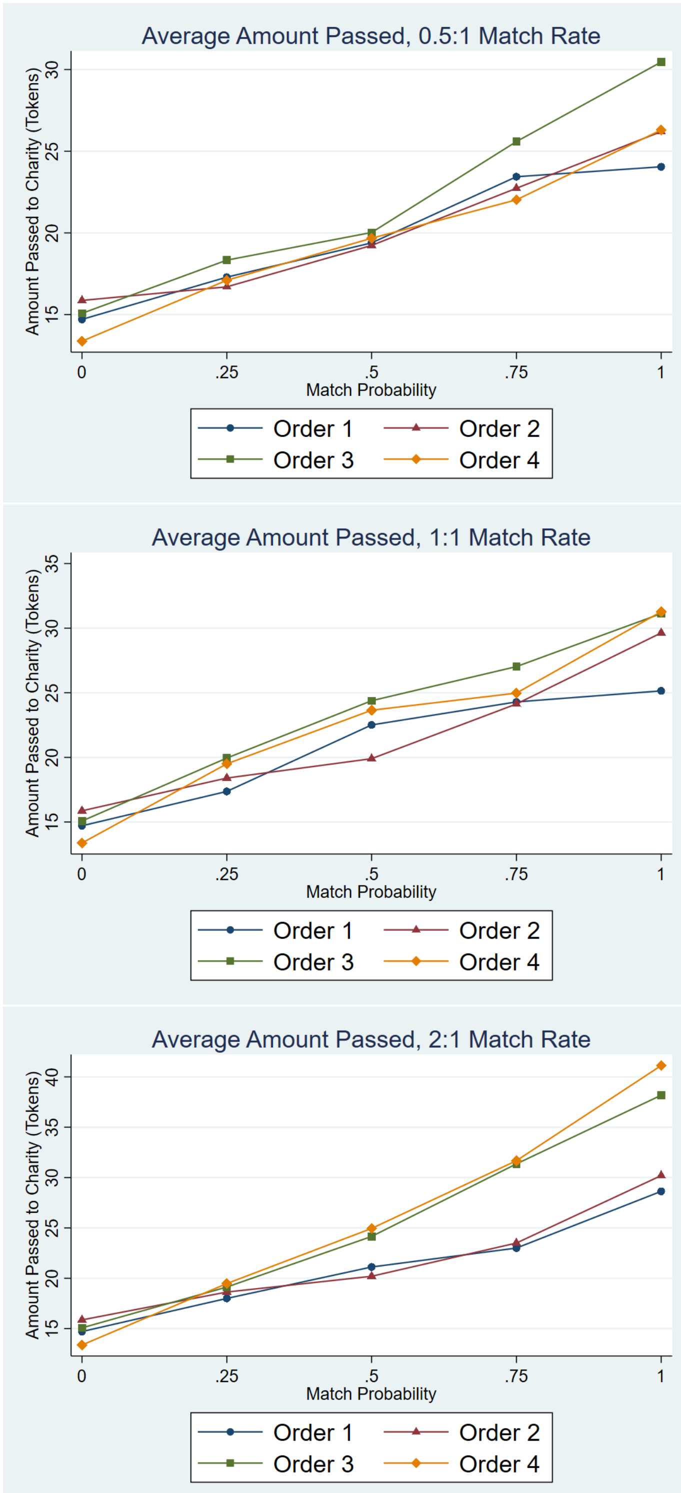

Figure C.2: Comparison of the average amounts passed across question orders for each match rate and match probability.

D Experiment Materials

D.1 Donation follow-up task

Donation Follow-up Task

Please answer the following questions. For each question, select whether you prefer Option A or Option B.

Option A will always be *the Charity receives a $1 donation with probability 50%, and a $0 donation otherwise.*

Option B will be *the Charity receives a donation of some dollar amount*. As you proceed down the rows of the list, the amount of the donation received by the Charity will increase from $0 to $1.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. **Most people begin by preferring Option A and then switch to Option B, so one way to complete this list is to determine at which row you prefer to switch from Option A to Option B.**

At the conclusion of the experiment, one row will be randomly selected, and a donation will be made to the Charity on your behalf based on the decision you have made in the selected row. If you have selected the lottery option (Option A) in the randomly selected row, the computer will flip a coin to determine the outcome of the lottery. All donations will actually be donated to the Charity, and you will be informed of the outcome of this process at the conclusion of the experiment. **(Note that any donations provided to the Charity in this task are provided by the experimenter and do not affect your earnings.)**

	Select your preferred option.		
	Option A	Option B	
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.10 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.20 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.30 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.40 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.50 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.60 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.70 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.80 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$0.90 donation
$1 donation with probability 50%, and $0 donation otherwise	○	○	$1 donation

Figure D.1: Donation follow-up task example screen

D.2 Payment follow-up task

Payment Follow-up Task

Please answer the following questions. For each question, select whether you prefer Option A or Option B.

Option A will always be *you receive a $1 payment with probability 50%, and a $0 payment otherwise.*

Option B will be *you receive a payment of some dollar amount*. As you proceed down the rows of the list, the amount of the payment you receive will increase from $0 to $1.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. **Most people begin by preferring Option A and then switch to Option B, so one way to complete this list is to determine at which row you prefer to switch from Option A to Option B.**

At the conclusion of the experiment, one row will be randomly selected, and you will be paid based on the decision you have made in the selected row. If you have selected the lottery option (Option A) in the randomly selected row, the computer will flip a coin to determine the outcome of the lottery. You will be informed of the outcome of this process at the conclusion of the experiment.

	Select your preferred option.		
	Option A	Option B	
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.10 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.20 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.30 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.40 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.50 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.60 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.70 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.80 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$0.90 payment
$1 payment with probability 50%, and $0 payment otherwise	○	○	$1 payment

Figure D.2: Payment follow-up task example screen

D.3 Main task decision sheet

ALLOCATION DECISION PROBLEMS

Below are 13 allocation problems. Read each allocation problem carefully. For each allocation problem, you must decide how to allocate the endowment listed in column (1) between yourself and *charity: water* ("the Charity").

Remember that only one of the problems will be randomly selected to determine payment. If you would like to review the instructions, click here: Instructions.

	Enter the number of Tokens you would like to pass to the Charity. Pass	The total number of Tokens held for yourself. Your Earnings	Total donation received by the Charity if a match **is not** received. Total Donation (if **no match**)	Total donation received by the Charity if a match **is** received. Total Donation (**with match**)
1.) You are endowed with 80 Tokens. There is a 100% chance that your donation will be matched at a 2:1 rate by the experimenter.	20	60	N/A	60
2.) You are endowed with 80 Tokens. There is a 75% chance that your donation will be matched at a 2:1 rate by the experimenter.	20	60	20	60
3.) You are endowed with 80 Tokens. There is a 50% chance that your donation will be matched at a 2:1 rate by the experimenter.	20	60	20	60
4.) You are endowed with 80 Tokens. There is a 25% chance that your donation will be matched at a 2:1 rate by the experimenter.	20	60	20	60
5.) You are endowed with 80 Tokens. There is a 100% chance that your donation will be matched at a 1:1 rate by the experimenter.	20	60	N/A	40
6.) You are endowed with 80 Tokens. There is a 75% chance that your donation will be matched at a 1:1 rate by the experimenter.	20	60	20	40
7.) You are endowed with 80 Tokens. There is a 50% chance that your donation will be matched at a 1:1 rate by the experimenter.	20	60	20	40
8.) You are endowed with 80 Tokens. There is a 25% chance that your donation will be matched at a 1:1 rate by the experimenter.				
9.) You are endowed with 80 Tokens. There is a 100% chance that your donation will be matched at a 0.5:1 rate by the experimenter.			N/A	
10.) You are endowed with 80 Tokens. There is a 75% chance that your donation will be matched at a 0.5:1 rate by the experimenter.				
11.) You are endowed with 80 Tokens. There is a 50% chance that your donation will be matched at a 0.5:1 rate by the experimenter.				
12.) You are endowed with 80 Tokens. There is a 25% chance that your donation will be matched at a 0.5:1 rate by the experimenter.				
13.) You are endowed with 80 Tokens. There is a 0% chance that your donation will be matched by the experimenter.				N/A

Figure D.3: Main task example screen

D.4 Survey questions

The following questions were included as part of a survey subjects were asked to complete after completing the main task and follow-up tasks of the experiment, but before being informed of their bonus payment amount. A response was required for each question.

1. What is your age in years? [**subjects enter an integer value into a text-entry box**]

2. What is your gender?

   a) Male

   b) Female

   c) Other

3. What is you best estimate of your family's annual Income? In addition to your own personal earnings, include income earned by your parents and/or guardians if they give you financial support in whole or in part.

   a) Less than $50,000

   b) Between $50,000 and $75,000

   c) Between $75,000 and $100,000

   d) Between $100,000 and $150,000

   e) Between $150,000 and $200,000

   f) More than $200,000

   g) Don't know/Prefer not to answer

4. How would you describe your political views?

   a) conservative

   b) moderate

   c) liberal

   d) unsure/undecided

   e) prefer not to say

5. How important is religion in your life?

   a) very important

   b) important

   c) somewhat important

   d) not important

6. During the past 12 months, how much money have you donated to charitable causes?
   a) Less than $20
   b) Between $20 and $50
   c) Between $50 and $100
   d) More than $100
7. How well do you know **charity: water**? Please rate your prior knowledge on a 0 to 10 scale, where 0 indicates no prior information at all and 10 indicates perfect knowledge: [**subjects enter an integer value (between 0 and 10) into a text-entry box**]
8. How well did you understand how your earnings are calculated in this experiment? Please rate your understanding on a 0 to 10 scale, where 0 indicates no understanding at all and 10 indicates a perfect understanding: [**subjects enter an integer value (between 0 and 10) into a text-entry box**]
9. How well did you understand how your total donation is calculated in this experiment? Please rate your understanding on a 0 to 10 scale, where 0 indicates no understanding at all and 10 indicates a perfect understanding: [**subjects enter an integer value (between 0 and 10) into a text-entry box**]
10. While making your donation decisions in this experiment, how confident were you that your donation (and any applicable matching donation) will actually be donated to **charity: water** on your behalf? Please rate your level of confidence on a 0 to 10 scale, where 0 indicates no confidence at all and 10 indicates complete confidence: [**subjects enter an integer value (between 0 and 10) into a text-entry box**]

D.5 Instructions

Introduction. Thank you for participating in this online experiment. This experiment is interested in studying how individuals make decisions. You will be making decisions individually. Your decisions and earnings during the experiment will be confidential and will only be associated with an ID number.

Compensation. You will be compensated for your participation. At the end of the experiment, you will receive a show-up reward of $4. This show-up reward is not contingent on the decisions that you make during the experiment, and it will be yours to keep just for participating. You will automatically receive this payment through Prolific upon completion of the experiment.

In addition to the show-up reward, you will also have an opportunity to earn additional money, which will be paid to you through Prolific in the form of a bonus payment. The amount of your bonus payment will depend on the decisions you make in the experiment and luck, as will be explained in detail below.

During the experiment, your earnings will be calculated in Tokens. At the end of the experiment the total amount of Tokens you have earned will be converted to US Dollars at the following rate:

10 Tokens = 1.00 US Dollar

Your $ earnings (including the $4 show-up reward and any bonus payments you earn) will be paid to you in private through Prolific. The show-up reward will be paid automatically once you have registered your submission in Prolific. Your bonus payment will be paid through Prolific within 1-2 business days after your submission has been received. **Bonus payments are backed by the University of Maryland and are guaranteed to be paid to you within 1-2 business days after you register your survey response in Prolific.** If you do not receive your bonus payment with 2 business days, or if you believe an error has been made regarding your bonus payment, please reach out to the research team using the contact information provided in the Consent Form.

The Charity. During the experiment you will be provided with opportunities to make donations to **charity: water**, a nonprofit organization that works to bring safe and clean drinking water to the more than 700 million people in the world living without access to clean water. The majority of people without access to clean water live in isolated rural areas, and they must spend hours every day walking many miles to collect water for their families. This water often carries diseases that lead to sickness. **charity: water** works with local experts and community members to install sustainable water solutions, including wells, piped water systems, BioSand Filters, and systems for harvesting rainwater. 100% of any donations you provide to **charity: water** will go toward funding water projects.

Allocation Decisions. In this experiment, you will be presented with 13 allocation decision problems. In each problem, you will be endowed with a certain number of Tokens, and you will be asked to allocate these Tokens between yourself and *charity: water* ("the Charity"). You will do this by deciding the number of Tokens that you would like to pass to the Charity. You cannot pass a negative number of Tokens, and you cannot pass more Tokens than what you are endowed with in any given problem. Any Tokens you choose to pass will be donated to the Charity. Any Tokens you do not pass will be paid to you after the completion of the experiment.

Any Tokens you choose to pass to the Charity may also be matched by the experimenter, increasing the total amount received by the Charity as a result of your donation. The total amount received by the Charity will depend on the *match rate* offered by the experimenter.

Match rate: the match rate is the rate at which your donation will be matched. There are three different match rates you will be presented with in this experiment:

0.5:1. A match rate of 0.5:1 means that for each \$1 you donate, an additional \$0.50 will be provided by the experimenter. Thus, for each \$1 you donate, the charity will receive a total of \$1.50 (your \$1 plus a matching \$0.50 provided by the experimenter).

1:1. A match rate of 1:1 means that for each \$1 you donate, an additional \$1 will be provided by the experimenter. Thus, for each \$1 you donate, the charity will receive a total of \$2 (your \$1 plus a matching \$1 provided by the experimenter).

2:1. A match rate of 2:1 means that for each \$1 you donate, an additional \$2 will be provided by the experimenter. Thus, for each \$1 you donate, the charity will receive a total of \$3 (your \$1 plus a matching \$2 provided by the experimenter).

The probability of receiving a match varies across decision problems. After you have submitted decisions for all problems, the computer will randomly determine whether your donation will receive a match, based on the match probability listed in each decision problem. For example, if a problem provides a 25% chance of receiving a match, then the computer will randomly provide a match 25% of the time, and 75% of the time it will not provide a match.

An example of the type of allocation decision problems you will be presented with is given on the next page.

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Example Allocation Decision Problems

An example of the type of allocation decision problems you will be presented with is given below. For each decision problem, you are asked to enter the number of Tokens you would like to pass to the Charity. You do this by typing your desired number of Tokens into the box provided in the Pass column. Once you enter the number of Tokens you would like to pass to the Charity, the computer will automatically calculate and display the corresponding values for the remaining columns.

Example Allocation Decision Problems:

	Enter the number of Tokens you would like to pass to the Charity. Pass	The total number of Tokens held for yourself. Your Earnings	Total donation received by the Charity if a match **is not** received. Total Donation (if **no match**)	Total donation received by the Charity if a match **is** received. Total Donation (**with match**)
1.) You are endowed with 80 Tokens. There is a 0% chance that your donation will be matched by the experimenter.	20	60	20	N/A
2.) You are endowed with 80 Tokens. There is a 50% chance that your donation will be matched at a 0.5:1 rate by the experimenter.	30	50	30	45
3.) You are endowed with 80 Tokens. There is a 100% chance that your donation will be matched at a 2:1 rate by the experimenter.			N/A	

Feel free to enter Pass values in the example problems above, and note how the remaining columns automatically fill after you do so. Each of the remaining columns is summarized below:

> *Your Earnings*: this column reports your earnings (in Tokens) for each allocation decision problem, based on your decision of how many Tokens to pass to the Charity. It is the number of Tokens you hold for yourself, which is equal to your Endowment minus the amount you choose to Pass.
>
> *Total Donation (if* ***no match****)*: this column reports the total donation (in Tokens) that will be received by the Charity if your donation **does not** end up being matched. This column is equal to the number of Tokens you choose to Pass.
>
> *Total Donation (****with match****)*: this column reports the total donation (in Tokens) that will be received by the Charity if your donation **does** end up being matched. This column is always larger than the number of Tokens you choose to Pass, since it also includes the matching donation provided by the experimenter. The exact amount in this column will depend on the *match rate* offered by the experimenter.

Note that in Example Problem 1 the *Total Donation (****with match****)* column displays "N/A" regardless of the number of Tokens you choose to Pass. This is because in this problem there is a 0% chance that your donation will be matched. Therefore, you know with certainty that your donation will not be matched, and the total donation received by the Charity will be equal to the value listed in the *Total Donation (if* ***no match****)* column.

Similarly, in Example Problem 3 the *Total Donation (if* ***no match****)* column displays "N/A" regardless of the number of Tokens you choose to Pass. This is because in this problem there is a 100% chance that your donation will be matched. Therefore, you know with certainty that your donation will be matched, and the total donation received by the Charity will be equal to the value listed in the *Total Donation (****with match****)* column.

For Example Problem 2, there is a 50% chance that your donation will be matched. Therefore, there is a 50% chance that the total donation received by the Charity will be equal to the value listed in the *Total Donation (****with match****)* column, and a corresponding 50% chance that the total donation received by the Charity will be equal to the value listed in the *Total Donation (if* ***no match****)* column.

On the next page, we'll review how your bonus payment and total donation will be determined. After that, you'll be ready to complete the experiment.

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Determining Your Payment and Total Donation. Once you have entered appropriate decisions for each problem, you will be able to submit your decisions. After submitting your decisions, **one problem will be randomly selected to determine your payment and the total donation received by the Charity.** Your decision of how much to pass to the Charity in the randomly selected problem will determine the amount of your bonus earnings in this experiment. Your bonus earnings will be equal to the amount listed in the *Your Earnings* column of the decision problem randomly selected for payment.

You will be obligated to pass to the Charity the amount you have entered in the *Pass* column of the randomly selected problem. This amount, plus any matched funds provided by the experimenter (if applicable), will actually be donated to the Charity.

Informing You of Your Payment and Total Donation. You will be informed of which problem was randomly selected for payment at the end of the experiment. At that time, you will also be informed of your total bonus earnings based on your decision in the randomly selected problem. Your bonus earnings will be paid to you through Prolific within 1-2 business days after you complete the experiment and register your submission through Prolific. The show-up reward, which is in no way affected by your decisions in this experiment, will be automatically paid to you once you register your submission in Prolific.

You will also be informed as to whether or not your donation was randomly determined to receive a match, along with the total donation that will be provided to the Charity on your behalf. The procedure used to determine whether you receive a match is detailed below.

Determining Whether Your Donation Will Receive a Match. The total donation received by the Charity will depend on whether or not your donation ends up receiving a match. The computer will randomly determine whether or not your donation will receive a match, based on the match probability listed in the randomly selected decision problem. For example, if the decision problem randomly selected to determine your payment provides a 25% chance of receiving a match, then the computer will randomly match your donation 25% of the time (and *not* match your donation the remaining 75% of the time).

All donations provided by participants of this study, including any applicable matching contributions (as determined by the procedure detailed above), will be donated to *charity: water* in a single, lump-sum donation at the conclusion of the study. **This donation is backed by the University of Maryland and will actually be provided to the Charity.**

If you have finished reading through these instructions, you are free to continue to the experiment.