Demand for Giving to Multiple Charities: An Experimental Study*

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Abstract

We study how competition among charities affects individuals’ giving behavior. We characterize situations where charities of substitute or complementary causes incentivize donations by offering rebate subsidies. Our theory predicts that an increase in the rebate rate offered by a given charity relative to a substitute charity will shift donations away from the substitute charity, but this “stealing” effect is not expected between complementary charities. Our model further characterizes when total donations increase with rebate subsidies. We test the model in an experimental setting, and demonstrate that the experimental results support our theoretical predictions. We derive the demand for giving at different rebate conditions for substitute and complementary causes. The social net benefit of rebate subsidies is calculated by comparing campaign costs and new donations generated.

Keywords: Charitable giving, rebate subsidies, competition, substitute and complementary charities, price elasticity of giving.

JEL Codes: C90, D62, H41

1 Introduction

In the gigantic industry of philanthropy, multiple organizations operate at the same time and compete constantly. Given that the size of the charitable market is generally stable at around 2% of GDP, there have been worries both in the media and in academic research that competition

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between charities might simply be shifting donations between the organizations (as opposed to increasing total donations), and it might even be socially wasteful. In this paper, we focus on the demand side of this industry and question whether competition among charities triggers new donations or shifts donations from one charity to another without increasing the charitable pie. We further analyze net benefits of campaigns while controlling for their costs.

The first part of our paper provides a theoretical model that studies individuals’ giving behavior when they donate to multiple charities. We assume charities offer rebate subsidies for charitable donations and the rebates are paid by third parties in the form of cash/gifts, or by the government through tax subsidies. The theory predicts that competition using rebate subsidies leads to a simple shift of donations across charities (i.e., one charity “steals” donations from the other charity) when charities have substitute causes, but such stealing effects are not expected among charities with complementary causes. We further characterize when the charitable pie can be increased and how that increase compares with the campaign cost (which has important implications for social welfare).

The second part of our paper tests the model’s predictions by using four laboratory experiments with donations to real charities. In our first (second) experiment, each subject contributes towards two individualized public goods with substitute (complementary) causes and determines the levels of charitable giving singlehandedly. Without strategic incentives, our design provides a clean environment to provide a strong test of theory. By systematically changing the rebates provided for donations to one public good relative to the other, we elicit the demand for giving to multiple charities. Next, we acknowledge that most causes reach out to many people to collect donations. This creates strategic concerns and free-riding incentives, so we also conduct a third experiment to check for robustness by randomly pairing two subjects who simultaneously contribute to the same two charities with substitute causes. Finally, our fourth experiment serves as a control experiment to our second experiment, wherein complementarities between charities were weakened.

We have five main contributions to the literature. First, we provide a simple theory that analyzes how donors respond to competing charities that use different rebate strategies. Second, we provide the first systematic analysis of individual demand to give in an environment with multiple charities by using a controlled laboratory experiment with actual charitable donations and provide support to the theoretical predictions. Unlike previous papers, our paper focuses on identifying the demand for giving to multiple charities at different price conditions. Third, we question to what extent new donations are generated by different rebate campaigns and how the additional donation amounts compare with their campaign costs. Forth, our paper provides evidence on both individualized public goods and standard public goods. This helps us to build a

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1 For an overview of charitable giving, see surveys by List (2011) and Andreoni and Payne (2013). In addition, the concern that a sudden success of campaigns for one cause may adversely affect giving to other charities has been raised in media in the emergence of donations after the September 11, 2001 attacks, Hurricane Katrina in 2005, and the Ice Bucket Challenge for ALS research in 2014. For example, see http://qz.com/249649/the-cold-hard-truth-about-the-ice-bucket-challenge/.
2 In many countries, including the United States, most charitable contributions are tax deductible. Therefore, giving to these charities is cheaper compared to the charities that do not offer tax deductions.
3 Among others, see also Eckel and Grossman (1996) for a dictator game experiment where the recipient is a real charity.
4 For example, Reinstein (2012) focuses on whether expenditure substitution occurs and how it depends on the charities compared by systematically changing the charity being “shocked”. Our paper instead keeps the charity being shocked constant and focuses on studying the demand to multiple charities by identifying the demand at differing price conditions.
bridge between the charitable giving literature and industrial organization literature that extensively studies "business stealing" and "demand expansion," in which firms compete through prices. While the industrial organization literature focuses on private goods and does not deal with free-riding incentives, the charitable giving literature studies the provision of public goods where free-riding is an important concern. Finally, we estimate price elasticities of giving for each of our experiments and contrast these with the findings of the previous literature.

Our paper shows that charities have individual incentives to use rebate/match strategies in a competitive fundraising environment even when the costs of these subsidies are taken into account. However, the effect of rebates on giving is not constant and, therefore, it is important for practitioners and policymakers to understand the demand functions of individuals before they implement their fundraising strategies and adapt policies. We also show that competition among charities may come at a cost to society in terms of lost welfare.

The research on the demand side of the market with competing charities is relatively limited. To our knowledge, there are only three related papers that study fundraising strategies that give price incentives in a multiple charity environment. Krieg and Samek (2014) conduct a laboratory experiment where subjects play two public goods games simultaneously with two different groups. They find evidence of complementarities: giving for both public goods increases with a bonus condition for giving to one of these public goods. Reinstein (2012) conducts a laboratory experiment with real donations and finds that when a price shock leads subjects to increase their giving to the targeted charity, they are far more likely to decrease their giving to the other unshocked charities. In contrast with Krieg and Samek (2014), positive cross-price elasticities between charities that serve similar goals have been identified. In a related paper based on field data, Meer (2017) finds that matching campaigns at DonorsChoose.org increases the likelihood of a project being funded as well as increasing the donations for that project. He does not find a significant effect of a matching campaign for one project on donations to other projects.

Competition among charities that does not create price incentives has also been studied. There are a few empirical papers that study "expenditure substitution" in charitable giving and the results are mixed (Reinstein, 2011; Deryugina and Marx, 2015; Scharf et al., 2015). Harwell et al. (2015) finds, in a lab experiment, that a video-based advertising campaign for one of the charities fully crowds out giving to the other charities without changing the total donations. Corazzini et al. (2015) use a threshold public goods set-up and show that total donations to charities might decrease as the number of charities increases. They also find that when the number of charities is fixed, and charities compete by becoming more efficient, coordination problems arise and total donations to the charitable sector decline. Lange and Stocking (2012) provide a field experiment and show that donor list exchanges between rival charities may increase charitable donations for complementary

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5 In a related paper, Lacetera et al. (2012) studies substitution between neighboring blood drives and finds donations increase with economic incentives but there are large displacement effects. Donors shift their donations to drives with higher economic incentives.

6 Null (2011) also has subjects donating to real charities under different price conditions. However, the aim of that paper is not related to understanding competition across charities. In Null (2011), subjects have a constrained action space and cannot change the amount of total donations under different prices.

7 Previous literature has also studied whether time and money donations are substitutes or complements and found that these are mainly substitutes (Andreoni, Gale and Scholz, 1996; Lilley and Slonim, 2014; Brown, Meer and Williams, 2015). In addition, while not in the context of multiple charities, another related paper is by Cairns and Slonim (2011). They look at the substitution effects of the presence of 2nd collections on 1st collections at Catholic Masses and find a negative effect on 1st donations and a positive effect on total donations.
charities. Clearly, the effect of competition on giving is highly context/environment dependent and is not yet clearly understood.

The theoretical literature on charitable giving and competitive fundraising has focused mostly on the supply side; in particular, this literature mainly addresses inefficiencies in the market size, charity selection, and quality of charities (see, for example, Rose-Ackerman, 1982; Bilodeau and Slivinski, 1997; Aldashev and Verdier, 2010; Aldashev et al., 2014; Krasteva and Yildirim, 2015).

We present our model in Section 2. Section 3 explains the experimental design, procedures and findings. A discussion and conclusions follow in Section 4.

2 Model

One approach to model preferences in charitable giving using economic theory is to define charities as privately provided public goods where donors gain utility from the provision of public goods and/or the act of giving (Bergstrom, Blume, and Varian, 1986; Andreoni, 1989, 1990). It is well-known that modeling such a public goods game among donors introduces free-riding incentives. Since the free-riding problem is not central to our research question, we first assume away the externalities among the donors and model a single-agent charitable giving problem. This scenario not only provides us with a simple benchmark to work on but it also has its own merits. It provides important insights into understanding charities that provide individualized public goods, such as charities matching each donor with a child in need, or a single microfinance project, etc. In addition, in the single-agent case, both pure altruism and warm-glow models (Andreoni and Miller, 2002) make the same predictions, since the total public good is equivalent to the amount given by the single agent. The results derived below provide a theoretical benchmark for our experiments with substitute and complementary charities (Experiments Subs, Comp, and Comp-W).

There is an agent endowed with \( w > 0 \) and she is deciding how much to donate to two charities: A and B. Her utility is a function of her consumption of a private good \( x \geq 0 \), her donations to charity A, \( g_A \geq 0 \), and her donations to charity B, \( g_B \geq 0 \). It is assumed that she is the only agent donating to these charitable causes.

We consider a quasilinear utility function: \( u(x, g_A, g_B) = x + h(g_A, g_B) \), where the function \( h \) is defined on \( \mathbb{R}^2_+ \), continuously differentiable, increasing, and concave in both arguments.

Each charity employs a rebate strategy in its fundraising campaign and we denote the rebate rates of charity A and charity B by \( r_A = (1 - \alpha) \) and \( r_B = (1 - \beta) \), respectively. This means that an agent who donates \((g_A, g_B)\) will consume

\[
w - g_A - g_B + r_A g_A + r_B g_B = w - \alpha g_A - \beta g_B.
\]

We assume that the rebate amounts are paid by third parties (as opposed to the charities themselves) and, therefore, do not affect how much money the cause receives. One may think of this assumption as an external donor or the government financing the rebates. In our experiments, the experimenter pays the rebate amounts. In order to have meaningful rebate campaigns we assume that \( \alpha, \beta \in [0,1) \). It is important to highlight that, under an interior solution assumption, our theory

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8 An extension of the model for multi-donor case follows our analysis of the single-donor case.
9 Examples of rebates in the field include Minnesota Public Radio (Eckel and Grossman, 2008) and Lutheran Social Service (Eckel and Grossman, 2017).
also applies to matching strategies since rebate and matching strategies become mathematically equivalent, i.e., a matching rate of \( m = r/(1 - r) \) is equivalent to a rebate rate of \( r \).\(^{10}\)

The optimization problem of the agent is

\[
\max_{g_A, g_B} w - \alpha g_A - \beta g_B + h(g_A, g_B)
\]

\[
s.t. \quad g_A + g_B \leq w, \quad g_A \geq 0, \quad g_B \geq 0
\]

Note that the agent can donate at most her initial endowment.\(^{11}\) The first-order conditions for the interior solution to this optimization problem are:

\[
\alpha = h_1(g_A, g_B) \quad \text{and} \quad \beta = h_2(g_A, g_B),
\]

where \( h_1 \) and \( h_2 \) are the partial derivatives with respect to the first and second variables, respectively. Define functions \( \tau(g_B) \) and \( \varphi(g_A) \) as implicit solutions to the first-order conditions so that \( \alpha = h_1(\tau(g_B), g_B) \) and \( \beta = h_2(g_A, \varphi(g_A)) \).

By differentiating the equations above, we get

\[
\tau'(g_B) = -\frac{h_{12}}{h_{11}} \quad \text{and} \quad \varphi'(g_A) = -\frac{h_{12}}{h_{22}}
\]

Note that the sign of these derivatives are the same as the sign of the cross-derivative of \( h \).

In particular, \( \tau(g_B) \) and \( \varphi(g_A) \) are decreasing (increasing) if and only if \( h_{12} < 0 \) (\( h_{12} > 0 \)).\(^{12}\) Therefore, for \( h_{12} < 0 \) (\( h_{12} > 0 \)) we will call charities A and B substitutes (complements). Assuming that \( h \) is strictly concave, there is a unique solution to the agent’s optimization problem and this occurs at the intersection of \( \tau(g_B) \) and \( \varphi(g_A) \). This is illustrated in Figures 1a and 1b for the cases of substitute and complementary charities. Note that \( \tau \) is steeper than \( \varphi \). This property guarantees that contributions to each charity would increase if it becomes cheaper to contribute to that charity. A sufficient condition for this property (together with the previous assumptions we have made) is to have \( |h_{XY}| < |h_{XX}| \) for \( X, Y \in \{1, 2\} \), because that implies that \( 0 > \varphi' > -1 \) for the substitutes and \( 1 > \varphi' > 0 \) for the complimentary cases.

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\(^{10}\) A large proportion of our data are consistent with an interior solution assumption, which will be discussed in detail in Section 3.

\(^{11}\) We assume that the donors cannot give more than their endowment even though the rebate amount will cover the deficit. Note that without this cap on total giving, a donor with a $10 endowment can give $6 to each charity and still have a positive amount remaining for private consumption if the rebate rates are high enough.

\(^{12}\) They will be constant if the cross-derivative of \( h \) is zero.
Suppose that the initial rebate rates of charities A and B are $1 - \alpha$ and $1 - \beta$, respectively. Then, charity A increases its rebate rate to $1 - \tilde{\alpha}$, where $\alpha > \tilde{\alpha}$. Define $\tilde{\tau}(g_a)$ as the implicit solution to the new first-order condition, i.e.,

$$\tilde{\alpha} = h_1(\tilde{\tau}(g_B), g_B)$$

Note that for any $g_B$, $h_1(\tau(g_B), g_B) = \alpha > \tilde{\alpha} = h_1(\tilde{\tau}(g_B), g_B)$, and, since $h_{11}$ is assumed to be negative, $\tau(g_B) < \tilde{\tau}(g_B)$. Therefore, increasing the rebate rate will cause a shift of the function $\tau$. Figures 2a and 2b illustrate this effect.

As can be seen from Figures 2a and 2b, increasing the rebate rate of Charity A will lead to a higher level of contribution to Charity A and a lower (higher) level of contribution to Charity B for the substitutes case (for the complements case). The effect on the total contribution is clearly

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13 Note that if the cross-derivative of $h$ was zero, $h_{12} = 0$, and hence if $\phi' = \tau' = 0$, we would have no change in donations to charity B if Charity A increased its rebate rate. The magnitude of the cross-derivative, therefore, might shed light on the mixed findings of the previous literature regarding substitution effects.
positive for the complements case but ambiguous for the substitutes case. The slope of function $\varphi$ at the optimal donation level at the initial rebate rates determines the change in total contributions for the substitutes case. If $0 > \varphi' > -1$ in Figure 2a, the total contributions to charities will increase, i.e., a new fundraising campaign generates additional donations.

Our results show that the charities used in experiments Subs and Subs-M are in line with the substitutes assumption; and the charities used in experiments Comp and Comp-W are in line with the complements assumption. Moreover, as we will see later, our data are consistent with the effects summarized in Figures 2a and 2b.

We acknowledge that most causes reach out to many people to collect donations, so the multi-donor case is quite relevant in application. One may easily extend the model above to a multi-donor case with altruistic preferences. This extension provides a benchmark for our experiment with two-agents (Experiment Subs-M). The comparisons between our findings in the experiments with single and multiple agents for the substitutes case (Subs and Subs-M) will allow us to generalize our results from environments without free-riding issues to environments where donors may free-ride on each others’ donations.

We now assume that there are $N$ agents donating to Charities A and B. In the altruism model below, agents gain utility from total donations to charities. As such, the utilities of agents are modified as:

$$u_i(x, G_A, G_B) = x + h(G_A, G_B)$$

where $G_X = \sum_{i=1}^{N} g_{iX}$ is the total donations to charity $X$ and $g_{iX}$ is the donation of agent $i$ to charity $X \in \{A, B\}$.

The equilibrium total contributions to each charity, $G_A$ and $G_B$, must satisfy the following first-order conditions for the agents who contribute positive amounts:

$$\alpha = h_1(G_A, G_B) \quad \text{and} \quad \beta = h_2(G_A, G_B)$$

We can define functions $\tau(G_B)$ and $\varphi(G_A)$ as implicit solutions to the first-order conditions. Note that these are the same functions as we previously defined for the single-agent case, but this time they are defined on total donations to the charities. One may repeat the same exercise that we performed for a single-agent case by only changing the variables from $g_X$ to $G_X$. All the arguments of the previous subsection will apply here. Note that the contributing agents will donate the same total amounts to the charities as the total amounts donated for the single-agent case. This implies that we expect to see lower average donations per donor when we have multiple agents rather than a single agent. This result is intuitive, since free-riding incentives are now introduced in the model.

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14 In our experiments, $N=2$.
15 If the utility function of an agent depends only on her private consumption and how much she gives away (as in the warm-glow theory), then the optimization problem of the agent is the same as in the previous analysis for a single agent. Hence, we would find the exact same individual contributions as before because the warm-glow assumption alone would eliminate the strategic aspect of the game between multiple agents.
16 The same level of public goods provision prediction relies heavily on the assumption that we use the same $h$ function for two versions of the model.
3 Experiments

We designed four experiments to test the implications of the model outlined above for substitute and complementary causes.

3.1 Design and Procedures

Experiments with substitutable charities took place at the RCGD Robert B. Zajonc Laboratory at the University of Michigan in April and May of 2015; experiments with complementary causes took place at the Experimental Economics Laboratory at the University of Maryland in February 2017. In each experiment, we followed a within-subject design with our treatment variable being the rebate rate.

In total, we had 178 participants recruited from the registered subject pools of the two universities. Instructions were read aloud to the subjects to create common knowledge. The experiments were programmed and conducted with the software z-Tree (Fischbacher, 2007).

We conducted two main experiments: (Subs) wherein substitutable causes were used as the competing charities, and (Comp) wherein complementary causes were competing for donations. In addition, we conducted two control experiments: (Subs-M) wherein substitute charities competed for donations from multiple donors, and (Comp-W) wherein the complementarities between the two causes are weakened. Each subject participated in only one of the experiments. See Table 1 for a summary of the experiments.

<table>
<thead>
<tr>
<th>Experiment</th>
<th># of subjects</th>
<th># of donors assigned to each recipient</th>
<th>Relations between causes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subs</td>
<td>42</td>
<td>1</td>
<td>Substitutes</td>
</tr>
<tr>
<td>Comp</td>
<td>48</td>
<td>1</td>
<td>Complements</td>
</tr>
<tr>
<td>Comp-W</td>
<td>48</td>
<td>1</td>
<td>Weak Complements</td>
</tr>
<tr>
<td>Subs-M</td>
<td>40</td>
<td>2</td>
<td>Substitutes</td>
</tr>
</tbody>
</table>

In our single-agent experiments, subjects contributed to individualized public goods and determined the levels of charitable giving singlehandedly. These experiments eliminated free-riding incentives among multiple agents and converted the game into an individual decision-making problem. One advantage of this simple environment was that it provided the best conditions for the theory to work. If the theory was not consistent with the data here, then we would not expect the theory to work for richer environments.

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17 Our research aims to test the implications of substitute and complementary causes independently (by studying how contributions change as our treatment variable—rebate rate—changes) rather than comparing those cases with each other. Nevertheless, we stress that the two universities are very similar which would likely lead to similar subject pools: both universities are public schools with similar net annual average cost to attend ($16K), median debt for students ($20K-UMD and $22K-UMich), gender composition (46% female-UMD and 49% female-UMich), and similar undergraduate enrollments (about 28K). (The information is from [https://www.goschoolwise.com/tools/compare-colleges](https://www.goschoolwise.com/tools/compare-colleges) and the Universities websites).

18 The ORSEE recruitment system (Greiner, 2004) was used at the University of Michigan.

19 We thank the associate editor and an anonymous referee for encouraging us to test the theoretical predictions of the complementary case.

20 In order to study determinants of giving in a single charity environment, Ottoni-Wilhelm, Vesterlund, and Xie (2014) also employ an individualized public good experiment. In their study, each subject was paired with a child who has lost his/her home in a fire.
In all experiments subjects were asked to make donation decisions to two causes under 5 different situations. At the end of the experiment, one of the situations was chosen at random to determine donors’ payoffs and the donations. In all of the situations, the rebate rate of one cause was fixed at \( r_{\text{fix}} = 0.5 \), and the rebate rate for the other cause took values of \( r_{\text{vary}} \in \{0.1, 0.3, 0.5, 0.7, 0.9\} \). Varying the rebate rate of the second cause in this fashion allows for the systematic study of the effect of changes in rebate strategies on the donations to each charity, as well as its effect on the total donations. It was made clear to the subjects that the experimenter pays the rebates and not the charities.

All five rebate situations were presented on the same screen. Given that we are primarily interested in the changes in donations as a response to the changing rebate rates rather than the absolute donation amounts, we made the changes in the rebate rates as obvious as possible to the subjects. The subjects were free to make decisions in any order and revise their decisions before submitting them.

In each of the 5 situations, subjects started with an endowment of 100 tokens and they decided how many tokens to donate to two causes. The exchange rate was $1 for every 10 tokens. Subjects were also told that they would receive rebates from the experimenters for the donations that they made. The rebates were added to the amount the subjects kept for themselves (if any).

Subjects were provided with a “calculator” as part of their decision screens. Once subjects entered their possible donation amounts for the two causes, the calculator would then provide them with a table with information on the number of tokens left for themselves after donating, the rebate amounts from donations, and the total number of tokens after rebates. Subjects could use the calculator as many times as they liked.

Before the experiment started, each subject took a short quiz to test their understanding. All subjects had to answer the quiz accurately before the experiment could start.

A short questionnaire was implemented at the end of the experiment, and it can be found in Appendix B. We now explain the differences between each experiment in detail.

Experiment “Subs”: Each subject was randomly assigned to one rescued animal in an animal rescue organization and one homeless person who is a resident of a homeless shelter. Subjects were allowed to donate any number of tokens to the two causes from their 100 tokens. The rebate rate for the donations to homeless people was fixed at 0.5 and the rebate rate for the donations to animals was varied. No two subjects gave to the same homeless person or animal. They were told that their donations would be delivered to their assigned homeless person and/or animal in the form of equal-value food or other supplies (such as hygiene products, clothing, etc.)

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\(^{21}\) We kept the number of questions small on purpose in order to allow for subjects to make decisions as carefully as possible.

\(^{22}\) This paper adopted rebates in lieu of matches for the following advantages they provided over matches: First, using rebates, the public goods contributions of individuals and the actual public good provided are identical. This not only simplifies the presentation but also controls for whether individuals have preferences on their own contributions versus total contributions. Second, related to our first point, when matches are used, the strategy space changes from one price condition to another. This may create unintended behavioral consequences that have nothing to do with a subjects’ response to price changes.

\(^{23}\) In all four experiments, subjects were told that the charities are local, however, the name of the charities were not revealed to the subjects.
Experiment “Comp”: Each subject decided how much to donate to purchase tubes of toothpaste and/or toothbrushes for their assigned homeless people. Each tube of toothpaste and each toothbrush cost 5 tokens. Hence, the subjects were able to donate tokens in increments of five towards each cause using their endowment of 100 tokens. The experimenter generated as many toothpaste/toothbrush pairs as possible based on donations of each subject. Each pair was donated to a different homeless person registered to a homeless shelter. Any donations remaining after generating all the toothpaste/toothbrush pairs were not donated or returned to the donating subject. For example, if a subject donated 35 tokens towards tubes of toothpaste and 30 tokens towards toothbrushes, 6 toothpaste/toothbrush pairs were donated to six different homeless people. The experimenter kept the donations towards unpaired items (in this case, one tube of toothpaste). The rebate rate for the donations to toothbrushes was fixed at 0.5 and the rebate rate for donations towards tubes of toothpaste was varied.

Experiment “Subs-M”: This experiment was based on experiment Subs with only one difference. In Subs-M, each subject was anonymously matched with another subject to form a pair. Each pair was randomly assigned to one rescued animal and one homeless person. Each member of the pair simultaneously and anonymously decided how many tokens to donate to his/her group’s assigned animal and homeless person, and how many tokens to keep for him/herself. Subjects did not know how much their partner donated until the end of the experiment (i.e., after their individual donation decisions were made).

Experiment “Comp-W”: This experiment was based on experiment Comp with the only difference being the level of complementarity between toothpaste and toothbrushes. In this experiment, we again generated as many toothpaste/toothbrush pairs as possible based on a subject’s donations and gave each pair to a different homeless person. This time any unpaired donations towards toothpaste or toothbrushes were not kept by the experimenter. Instead, unpaired items were given to a different homeless person as a single tube of toothpaste or a single toothbrush. Since a toothbrush which was not paired with a tube of toothpaste may still have an individual use (and vice-versa), a subject may want to donate unequal number of toothbrushes and tubes of toothpaste without worrying about wasting her donations. Hence, the level of complementarity between the two items was weaker in this experiment than that in experiment Comp.

Note that experiments Comp and Comp-W have a similar structure to the experiments Subs and Subs-M. Donating towards toothbrushes and toothpaste is similar to having two charities, where one charity only provides toothpaste and the other charity only provides toothbrushes. While it is not difficult to find two charities that provide substitutable goods, it is a challenge to find two different charities that provide perfectly complementary goods. One obvious reason is that each charity has an incentive to provide a good that is useful by itself, without need for another charity to perfectly complement its service/product. However, one can imagine many situations where charities provide some level of complementarity and some level of substitution to each other. Our experiment Comp provides a novel way to test the theory in an extreme case, and our experiment Comp-W provides a control experiment where some level of substitution and complementarity exist at the same time and provides a more realistic environment.

3.2 Results

3.2.1. Experiments Subs and Comp

Figures 3a and 3b show the average demand for giving in experiments Subs and Comp as the rebate rate varied. The vertical axis represents the average donations to the cause with the fixed
rebate and the horizontal axis represents the average donations to the cause with the varying rebate rate.

The rebate rate increases from 0.1 to 0.9 (from left to right) in the figures.

As shown in Figure 3a, as expected, donations to the assigned animal increases with the rebate rate. Mann-Whitney tests confirm that the donations increase significantly as the rebate rate increases from 0.3 to 0.5, from 0.5 to 0.7 and from 0.7 to 0.9 (all p-values are less than 0.05). The increase in donations to the assigned animal is not significant as the rebate rate changes from 0.1 to 0.3 (p-value = 0.22). More importantly, it can easily be seen from Figure 3a that the rebate strategy of the animal rescue organization “steals” donations from the homeless shelter. However, the change in donations to the assigned homeless person is not statistically significant for one-step changes from 0.1 to 0.3, or from 0.3 to 0.5, etc. All of the p-values are larger than 0.14 for small rebate changes. Stealing becomes statistically significant for larger changes in rebate rates. For example, donations to the homeless person decrease significantly as the rebate rate changes from 0.1 to 0.7 (p-value = 0.02).

As shown in Figure 3b, donations towards tubes of toothpaste also increase with the rebate rate. The increase in donations is significant as the rebate changes from 0.3 to 0.5 (p-value = 0.01) or from 0.5 to 0.7 (p-value = 0.10). In addition, larger changes in the rebate rate have even more statistical significance, such as the rebate rate change from 0.1 to 0.7 (p-value = 0.00). There is a big difference between experiments Subs and Comp. In the experiment Comp, we do not see stealing. In fact, none of the rebate rate changes have a statistically significant effect on donations towards toothbrushes.

We can also investigate whether increasing the rebate rate increases the charitable pie, or whether it only shifts contributions from one charity to another. Figures 4a and 4b show the average donations to each cause as well as total giving. Tables A.1 and A.2 in Appendix A present the numbers corresponding to Figures 4a and 4b in greater detail. As can be seen from Figures 4a and 4b, total giving increases with the rebate rate in both experiments. The difference is statistically significant mostly for large changes in rebate rate such as from 0.1 to 0.9 (p-values are less than 0.00).

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24 Throughout the paper we report two-tailed results.
0.01 for both experiments). We also see that total giving increases more as the rebate rate becomes larger in Experiment Subs, suggesting a convex total giving function (which we will further investigate using regression analysis).

![Graph of average donations at different rebate rates for Experiment Subs](image1.png)

![Graph of average donations at different rebate rates for Experiment Comp](image2.png)

Figure 4a. Average Donations at Different Rebate Rates: Experiment Subs

Figure 4b. Average Donations at Different Rebate Rates: Experiment Comp

Table 2a reports an OLS regression analysis to test the effect of the rebates on giving to the treated charity (with varying rebates), giving to the untreated charity (with fixed rebate rate) as well as on the total giving. Our main independent variable is rebate, which takes values between 0 and 1. We also test for nonlinear effects of rebates on donations (as suggested by Figure 4a). We use rebate², the square of the rebate rate, to test for nonlinearities in experiment Subs. Note that Table 2a reports linear regressions for experiment Comp as well as for donations to the untreated charity in experiment Subs. This is because we did not find any nonlinearities in those cases. In addition, by using data from our questionnaire, we control for age, gender, family income, political view, religion, previous donations to charities, knowledge of animal and homeless shelters (for experiments Subs and Subs-M) and guesses regarding the chances of a homeless person to own a toothpaste and toothbrush (for experiments Comp and Comp-W). Table 2a reports only the coefficient of variables related with rebate and constant in order to simplify the presentation. Table A.5 in Appendix A provides the full list of coefficients for these regressions.

In both experiments Subs and Comp the donations to the treated charity and total donations increase with the rebate rate of the treated charity. This is in line with our theoretical predictions and earlier observations from Figures 4a and 4b. In the experiment Subs, we find that the marginal increase in giving (and total giving) is higher as the rebate rate becomes larger for the treated charity. Consistent with previous nonparametric tests, there is a negative and statistically significant relationship between rebate from the animal shelter and giving to the homeless person. In other words, the treated charity “steals” donations away from the untreated charity when the causes are substitutes. On the other hand, while not statistically significant, the coefficient of rebate is positive

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25 None of our qualitative results change if we instead run Tobit regression analyses. The results are available upon request from the authors.

26 We have also tried a third order polynomial but that was not statistically significant.

27 See Appendix B for the questionnaire conducted at the end of our experiment.
for the untreated cause in experiment Comp and, therefore, there is no evidence of “stealing” when causes are complements.28

It is important to highlight that in experiment Subs, we see an example of a situation where the effect of the rebate rate is not constant, i.e., the coefficient of rebate² is significant. Hence, for the low rebate rates, the stealing may be a dominating explanation for the increase in donations towards the treated charity, but for the higher rebate rates, larger new donations towards the treated charity are generated and therefore total giving is positively affected by the increase in rebate rates. Our findings not only improve our understanding of demand for giving in a multiple-charity framework with substitute and complimentary causes, but also help us evaluate the literature, as no other study has systematically measured the effect of changing rebate rates.

Table 2a. OLS Regression Analysis for Experiments Subs and Comp

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>Experiment Subs</th>
<th></th>
<th></th>
<th>Experiment Comp</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treated</td>
<td>Untreated</td>
<td>Total</td>
<td>Treated</td>
<td>Untreated</td>
</tr>
<tr>
<td>rebate</td>
<td>-12.49</td>
<td>-18.69***</td>
<td>-27.18*</td>
<td>13.65***</td>
<td>2.29</td>
</tr>
<tr>
<td></td>
<td>(14.89)</td>
<td>(5.11)</td>
<td>(13.92)</td>
<td>(3.65)</td>
<td>(4.02)</td>
</tr>
<tr>
<td>rebate²</td>
<td>62.59***</td>
<td>58.59***</td>
<td>18.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(17.48)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>69.42***</td>
<td>63.77**</td>
<td>132.50***</td>
<td>35.15</td>
<td>42.43</td>
</tr>
<tr>
<td></td>
<td>(22.25)</td>
<td>(30.25)</td>
<td>(45.80)</td>
<td>(35.98)</td>
<td>(35.50)</td>
</tr>
<tr>
<td>Obs.</td>
<td>210</td>
<td>210</td>
<td>210</td>
<td>240</td>
<td>240</td>
</tr>
</tbody>
</table>

Note: * indicates statistical significance at the 10% level, ** significance at 5%, and *** at 1%. Robust standard errors are in parentheses.

Recall that our theoretical predictions rely on the interior solution assumption, i.e., the endowment is not binding. If there were subjects that were constrained by the endowment provided in the experiment, then our results would be confounded.29 For example, in the experiment Comp, if a subject donates all of his/her endowment when rebate rate is low, then there is no room for this subject’s donations to increase as rebate rate increases. This would undermine our results. Alternatively, a subject in the experiment Subs may substitute their donations between charities only because he/she did not have more endowment. This has the potential to impose more stealing. In order to check whether our results are affected by subjects who donate all their endowment, we provide a robustness check by eliminating these subjects from our analysis. Table 2b shows the results.

28 Note that in the experiment Comp, we did not impose perfect complementarity (in the sense of Leontief production technology for toothpaste/toothbrush pairs). Subjects were free to make donations in any way they liked as long as they did not exceed their endowments. In our data, we see that 9 out of 48 subjects made unpaired donations (for example they donated more to toothpaste than toothbrushes), which is not in line with the complementarity assumption. If we drop these 9 subjects from the analysis, then consistent with our model, we see a statistically significant increase at the 1 percent level in toothbrush donations as the rebate rate for toothpaste increases. Naturally, total giving also statistically significantly increases in that case as well.

29 We thank an anonymous referee for pointing out this issue.
First, we see that there are not many subjects that are constrained by the endowment. Second, while our qualitative result for experiment Subs does not change, our results for experiment Comp get stronger when we drop the constrained subjects. For example, we now see that donations to both treated and untreated charities significantly increase in experiment Comp.

<table>
<thead>
<tr>
<th>Table 2b. Robustness Check (dropping corner solutions)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dep. Var.</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>rebate</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>rebate²</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>constant</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Obs.</td>
</tr>
</tbody>
</table>

Note: * indicates statistical significance at the 10% level, ** significance at 5%, and *** at 1%. Robust standard errors are in parentheses.

3.2.2. Experiment Comp-W:

Our robustness experiment Comp-W weakens the complementarity between toothpaste and toothbrushes. Recall that the subjects’ unpaired donations towards toothbrushes or toothpaste are donated to homeless persons as single items in Comp-W. Hence, in this experiment each product has individual value apart from its value when paired with the other product. The relation between a tube of toothpaste and a toothbrush in Comp-W may be thought of as somewhat in between substitutes and complements (as they complement each other when paired but each has some use for a homeless person separately). Our findings for Comp-W support this view.

Figure 5 shows the average donations towards toothbrushes and toothpaste (see Table A.3 for a summary statistics). Note that the slope seems negative but not as steep as the one in Figure 3a for experiment Subs. The trend is somewhat similar to the one in Figure 3b for Experiment Comp as it is again largely flat. Figures 5 and 6 report that even though the subjects respond to the increase in the rebate rate on toothpaste by giving more to this cause, they do not shift donations much from toothbrushes to toothpaste (likely because subjects are aware that these two dental hygiene products have better use together than alone). In fact, Mann-Whitney tests do not show any evidence of stealing (all pairwise comparisons have p-values larger than 0.24). We find a positive relationship between rebate rates and toothpaste donations (i.e., p-value = 0.02 when rebate rate changes from 0.1 to 0.9). We find a positive relationship between rebate rates and total giving (i.e., p-value = 0.08 when the rebate rate changes from 0.1 to 0.9).

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30 We have also performed a similar analysis for the following experiments Comp-W and Subs-M. If anything, our results got stronger. Therefore, we choose to report the results from all data in what follows. The results without the constrained subjects can be requested from the authors.
The rebate rate increases from 0.1 to 0.9 from left to right in the figure.

Table 3 reports OLS regressions in order to test the effect of the rebates on giving to the treated cause (toothpaste), giving to the untreated cause (toothbrushes) as well as total donations. Our main independent variable is again rebate, which takes values between 0 and 1. Here we excluded the variable rebate$^2$ as Figure 6 did not suggest strong nonlinearity and this variable was not significant when included. In addition, by using data from our questionnaire, we control for age, gender, family income, political view, religion, previous donations to charities, and guesses regarding the chances of a homeless person owning a toothbrush/toothpaste. Table 3 reports only the coefficient of the variable rebate and the constant to simplify the presentation. Table A.6 in Appendix A provides the full list of coefficients for these regressions.

As in the case of experiment Comp, here both donations to toothpaste and total donations increase with rebate. In Comp-W we see some mild but (weakly) significant stealing effect as the rebate coefficient is negative and significant at 10% level. Such stealing was not observed in Comp and it was much stronger in Subs (see Table 2 or Table A.5).

Table 3. OLS Regression Analysis for Experiment Comp-W

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>Treated</th>
<th>Untreated</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>rebate</td>
<td>33.07***</td>
<td>-6.82*</td>
<td>26.25***</td>
</tr>
<tr>
<td></td>
<td>(5.47)</td>
<td>(3.90)</td>
<td>(4.78)</td>
</tr>
<tr>
<td>constant</td>
<td>-33.79</td>
<td>5.43</td>
<td>-28.35</td>
</tr>
<tr>
<td></td>
<td>(35.41)</td>
<td>(41.08)</td>
<td>(73.51)</td>
</tr>
<tr>
<td>Obs.</td>
<td>240</td>
<td>240</td>
<td>240</td>
</tr>
</tbody>
</table>

Note: * indicates statistical significance at the 10% level, ** significant at 5%, and *** at 1%. Robust standard errors are in parentheses.
3.2.3. Experiment Subs-M:

Subs-M is the two-agent version of experiment Subs where the charities are considered to be substitutes for each other. In this two-agent version of giving, we see similar results as in the single-agent case. Figure 7 shows average donations to the assigned animal (treated charity) and homeless person (untreated charity). Donations to the assigned animal significantly increase as the rebate rate increases from 0.3 to 0.5, 0.5 to 0.7 and 0.7 to 0.9 (all p-values are less than 0.05), while donations to the assigned homeless person decrease with the rebate rate. Similar to the single-agent case, stealing is not statistically significant at the 5% significance level for small rebate changes (i.e., none of the 20 percentage point changes are significant, such as from 0.1 to 0.3 and 0.7 to 0.9.), but it is significant for larger rebate changes such as from 0.1 to 0.7 (p-value = 0.01).

![Figure 7. Average donations in Subs-M. The rebate rate increases from 0.1 to 0.9 from left to right in the figure.](image)

Figure 7. Average donations in Subs-M. The rebate rate increases from 0.1 to 0.9 from left to right in the figure.

Figure 8 (as well as Table A.4 in Appendix A) show that the total donations increase with the rebate rate (except from 0.1 to 0.3 where stealing cancels out the increased donations to the animal). Small rebate changes initially do not change total giving significantly, but change in total giving is statistically significant as the rebate rate changes from 0.7 to 0.9 (p-value = 0.03), as well as for larger rebate changes. The total giving function is again convex with respect to the rebate rate.

![Figure 8. Average Donations at Different Rebate Rates: Experiment Subs-M.](image)

Figure 8. Average Donations at Different Rebate Rates: Experiment Subs-M.

We repeat the OLS analysis for Experiment Subs-M in Table 4. Results are extremely similar to what we reported for experiment Subs in Table 2. Again, to capture the convex looking increase in total giving as a response to increasing rebate rate, we included variable rebate^2 in the regressions for donation to the treated charity as well as total donations. Giving to the assigned animal increases with the rebate rate and the rate of increase is larger at large rebate levels. Giving to the assigned homeless person decreases as the rebate rate for animal increases, and the relationship is once again linear. The total giving function is convex in the rebate rate and steeply increasing with higher rebate rates. As before, we do not report the coefficients of the demographic variations as well as other variables subjects self-reported in the questionnaire in Table 4 to simplify the presentation. The full list of variables can be found in Table A.7 in Appendix A.
Table 4. OLS Regression Analysis for Experiment Subs-M

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>Treated</th>
<th>Untreated</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>rebate</td>
<td>-8.54</td>
<td>-27.63***</td>
<td>-41.44**</td>
</tr>
<tr>
<td></td>
<td>(12.77)</td>
<td>(7.12)</td>
<td>(16.63)</td>
</tr>
<tr>
<td>rebate²</td>
<td>60.89***</td>
<td></td>
<td>66.16***</td>
</tr>
<tr>
<td></td>
<td>(16.07)</td>
<td></td>
<td>(18.84)</td>
</tr>
<tr>
<td>constant</td>
<td>1.27</td>
<td>53.70***</td>
<td>55.87***</td>
</tr>
<tr>
<td></td>
<td>-8.54</td>
<td>(13.22)</td>
<td>(18.54)</td>
</tr>
<tr>
<td>Obs.</td>
<td>200</td>
<td>200</td>
<td>200</td>
</tr>
</tbody>
</table>

Note: * indicates statistical significance at the 10% level, ** significant at 5%, and *** at 1%. Robust standard errors are in parentheses.

While experiment Subs-M was mainly conducted in order to check the robustness of our results, we can provide important insights for comparing altruism and warm-glow motives. One interesting aspect of our design is that we can actually compare two treatments to see which motive, warm-glow or altruism, is more prevalent for the charities used in the experiment.

The altruism model would predict that individuals, on average, give less when they are in groups of two versus when they are the sole giver. Therefore, individual giving in experiment Subs-M should be lower than in experiment Subs. However, the warm-glow model in isolation suggests that it does not matter if someone else is also contributing to the same cause, so we would expect similar giving across the two experiments.

Comparing Tables A.1 and A.4, individual giving levels seem slightly higher in experiment Subs-M at any given rebate rate. However, according to Mann-Whitney tests, the differences between single- and multiple-agent cases are not statistically significant (p-values range between 0.27 and 0.73). In addition, the result is the same if we perform an OLS regression analysis and add a dummy variable for Experiment Subs (p-values range between 0.68 and 0.87). Therefore, our data suggest that for the charities used in our experiment, the warm-glow model better explains our data.

Experiments Subs and Subs-M provide evidence on both individualized public goods and standard public goods. This helps us to build a bridge between the charitable giving literature and the industrial organization literature (the latter of which extensively studies “business stealing” and “demand expansion” in which firms compete through prices). The dynamics of competition in industrial organization literature is similar to our setting in experiment Subs. We show that similar business stealing concerns apply to the Subs-M case in terms of shifting donations from one charity to another due to rebate competition. Moreover, the increase in total giving due to rebates has the same underlying mechanism as demand expansion in industrial organization.

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31 We can also study the effect of increasing group size on the public goods provision in a multiple-charity environment. Isaac and Walker (1988), Isaac et al. (1994) and Nosenzo et al. (2015) study the effect of group size on the public goods provision in a single public good environment.

32 This type of comparison is justified since both experiments use the same subject pool.
3.2.4. Is rebate wasteful?

We investigate whether rebates are effective fundraising strategies by comparing (opportunity) costs and benefits of rebate-driven campaigns. In this section, we acknowledge that the third party could have used those funds towards the cause instead of fundraising purposes. Therefore, we now treat refunds as a cost, and we are interested in the amount of donations net of paid refunds.  

First, we discuss the experiment Subs. Figure 9 shows the average net benefit (donations – cost of rebates) for both charities as well as total donations at each rebate rate. We find that the animal shelter would have an incentive to use rebates as a response to the homeless shelter’s rebate rate of 50%. Figure 9 suggests that the animal shelter should have a rebate rate of about 0.5, and it should not be overly-aggressive since the net benefit would be lower. On the other hand, donations to the assigned homeless person net of rebates are decreasing with the rebate rate for the assigned animal, which is expected. The surprising result is that total donations (net of total rebates) are decreasing with the rebate rate for the assigned animal. The OLS regressions confirm that net donations decrease with rebate rate for both homeless and total giving at the 1 percent significance level. Therefore, if the rebates are provided by the same source and the aim is to maximize the total net giving rather than the net giving to a certain cause, minimal rebate rates seem to work better. Our results are very similar for the experiment Subs-M, which can be seen in Figure A2 in Appendix A.

Among others, Davis et al. (2005), Davis (2006) and Huck and Rasul (2011) question the usefulness of rebate and match strategies. A rebate/match campaign that diminishes net total giving may look unreasonable in lab experiments with single charity or field experiments where one charity is more salient than the others. However, when we extend the environment to multi-charity case we can see why an individual charity may want to employ such fundraising campaigns. Our findings show that a selfish charity may benefit from moderate level of rebates if it ignores the externality it creates on other competing charities and the overall sector. We further argue that the level of the rebate rate is important to judge if a campaign is good or bad. We point out that the detrimental effects of rebate/match campaigns that are found, especially in field experiments, can only be understood through studying the competitions between charities (see Huck and Rasul, 2011, for a similar point).

Next, we analyze the effectiveness of refunds for the experiment Comp in Figure 10. Interestingly, when complementary causes are used, net donations to the treated cause do not increase with rebate. In contrary, net donations decrease significantly at 1 percent significance level for toothpaste. Surprisingly, net donations to the untreated charity (toothbrush), on the other hand, increases as rebate rate increases (p-value = 0.56 for Comp). Net total donations, however, statistically significantly decrease as rebate rate increases (p-values are less than 0.01). Therefore, competition also has a negative effect on total donations when fundraising costs are incorporated into analysis. Our conclusion is even stronger for experiment Comp-W (see Figure A.1 in Appendix A).

None of the qualitative results presented in this section change if we eliminate the subjects that are constrained by the endowment from the analysis.

In our experiments, the experimenter was financing rebates for both charities. In applications, it might be the government or the same foundation (e.g. the Gates foundation) campaigning for multiple charities.

Note that in contrast to the substitute charities, when complementary charities are involved, increasing rebate rate for one charity benefits the other charity. This is intuitive since individuals increase donations to both charities but only the treated charity pays the cost.
A). In Comp-W, we see a negative effect of rebate rate on net donations to the untreated charity in addition to the treated charity and total giving.

![Figure 9. Effectiveness of Refunds for Experiment Subs](image1)

![Figure 10. Effectiveness of Refunds for Experiment Comp](image2)

It is important to highlight that our conclusion relies on the assumption that crowding out either would not happen or would be limited when the third party donates the funds to the charities instead of offering them as rebates. This assumption would be valid only if individuals have warm-glow preferences. As we show in the previous section, our data are consistent with warm-glow preferences. However, one needs to be careful generalizing this result to other contexts where individuals might mainly be driven by altruistic preferences, implying crowding-out. In such environments, one may expect rebate campaigns to improve net total donations. On the other hand, it is also possible that when a third party becomes a lead donor, this by itself could generate higher donations as shown by Huck and Rasul (2011) and, therefore, our findings in this subsection might even be a lower-bound for the lost welfare.

### 3.2.5. Price Elasticities

We report price and cross-price elasticities in Table 5.\(^{36}\) The price elasticity estimates are consistent with theoretical predictions and our previous analysis.\(^{37}\) We find that donations to the treated charity increase as the price of donations decreases in all our experiments. We see stealing of donations in all experiments with the exception of the experiment Comp. Total donations, nevertheless, increase when the price of donation decreases in all experiments. Even though this result suggests that rebates are beneficial for total donations, when we look at net total donations, we see a decrease in net total donations when the price of donations decrease and the relationship is statistically significant at 1 percent level for Subs-M and Comp-W. According to the elasticity

\(^{36}\) Elasticities are calculated by regressing \(\ln(\text{donations in dollars})\) on \(\ln(\text{price of giving in dollars to the treated charity})\) as well as control variables. We have added 10 cents to the donation levels to avoid a zero donation in logarithm.

\(^{37}\) We report the results from all data. Our results are stronger (especially for the experiment Comp) if we eliminate the subjects that are constrained by their endowment.
estimates, even the treated charity, on average, does not benefit from rebates when the cost of the subsidy is taken into account.

Table 5: Estimated elasticity coefficients

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Don. to treated</th>
<th>Don. to untreated</th>
<th>Total don.</th>
<th>Net don. to treated</th>
<th>Net don. to untreated</th>
<th>Net total don.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subs</td>
<td>-0.87***</td>
<td>0.41***</td>
<td>-0.38***</td>
<td>-0.07</td>
<td>0.35***</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.11)</td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Comp</td>
<td>-0.30***</td>
<td>-0.15*</td>
<td>-0.25***</td>
<td>0.42***</td>
<td>-0.12*</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Subs-M</td>
<td>-0.90***</td>
<td>0.50***</td>
<td>-0.31***</td>
<td>-0.06</td>
<td>0.43***</td>
<td>0.19***</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.11)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Comp-W</td>
<td>-0.51***</td>
<td>0.16**</td>
<td>-0.23***</td>
<td>0.31***</td>
<td>0.13**</td>
<td>0.18***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.08)</td>
<td>(0.06)</td>
<td>(0.04)</td>
</tr>
</tbody>
</table>

Standard errors are in parentheses.

It is reassuring to see that our own-price elasticity estimates of donations (especially for the substitute charities) are within the range of the ones from previous laboratory and field experiments as well as empirical studies.\(^{38}\) As Table 5 (column 1) shows, we have a range of estimates from -0.30 to -0.90. Eckel and Grossman (2003, 2006b) use laboratory experiments in a single charity set-up with rebates. Eckel and Grossman (2003) compute a price elasticity of -0.34, and Eckel and Grossman (2006b) compute a price elasticity of -1.49.

In addition, there are papers that use field experiments to study the effect of rebates on giving. The estimates are in the range of -0.19 and -5.12 (Eckel and Grossman; 2008, 2017). We can also compare our estimates with the estimated price elasticities from the empirical charitable giving literature. As tax rate increases, the price of giving to registered charities decreases since donations to those are tax-deductible and will generate tax rebates. Earlier empirical studies using cross-sectional data typically find the price elasticity to be greater than one in absolute value (\(i.e.,\) Clotfelter; 1985, 1990) Using panel data, Randolph (1995) estimates a price elasticity of -0.5 with respect to persistent price changes and a price elasticity of -1.5 with respect to transitory price changes. More recently, Auten et al. (2002) and Bakija and Heim (2011) find the price elasticity greater than 1 in absolute value, while Huhnerman and Ottoni-Wilhelm (2016) report a price elasticity of -0.2.

Finally, we can also compare our estimates with the papers that compute price elasticities in response to matching campaigns. For example, Eckel and Grossman (2003, 2006b, 2008 and 2017) not only report rebate elasticities but they also report matching elasticities. They find that match price elasticities (of total contributions including matches) are systematically larger than their rebate counterparts and are in the range of -1.10 and -5.43. Karlan and List (2007) conduct a field experiment and report match price elasticities (of gross amount given by the donor—\textit{not} including matches) between 0 and -0.67. Huck and Rasul (2011) report own-price elasticities (of total contributions including matches) between -0.53 and -1.12. It is also important to highlight that

\(^{38}\) The only paper, that we are aware of, that estimates cross-price elasticities in a multiple-charity framework is Reinstein (2012). The cross-price elasticity estimates reported in that paper vary from -0.12 to 2.71.
the results of Huck and Rasul (2011) imply that straight linear matching schemes raise the total donations received including the match value, but partially crowd out the actual donations given excluding the match. They argue that matching might harm fundraising as they reduce donations given, consistent with our results presented in this paper with substitute charities. Our results show that when a charity uses a suboptimal rebate/match strategy, net donations to that charity might decrease.

3.2.6. Individual Analysis

Figures A.3-A.6 (in Appendix A) show donations to the treated and untreated charities for each individual for all experiments, as well as the fitted linear regression lines. One thing is clear: there is quite a bit of heterogeneity in individual preferences in terms of how they react to rebate rate changes. While some individuals are sensitive to the rebate rates, some do not change their contributions with changes in the rebate at all. Table 6 provides a classification of subjects into different categories.

Table 6: Analysis of individual donations

<table>
<thead>
<tr>
<th>% of subjects who</th>
<th>Subs</th>
<th>Comp</th>
<th>Comp-M</th>
<th>Subs-M</th>
</tr>
</thead>
<tbody>
<tr>
<td>never donate to treated</td>
<td>11.9</td>
<td>14.6</td>
<td>8.3</td>
<td>10.0</td>
</tr>
<tr>
<td>increase donations to treated with rebate</td>
<td>64.3</td>
<td>37.5</td>
<td>62.5</td>
<td>70.0</td>
</tr>
<tr>
<td>decrease donations to treated with rebate</td>
<td>0.0</td>
<td>0.0</td>
<td>2.1</td>
<td>0.0</td>
</tr>
<tr>
<td>don’t change don. to treated with rebate</td>
<td>23.8</td>
<td>47.9</td>
<td>27.1</td>
<td>20.0</td>
</tr>
<tr>
<td>never donate to untreated</td>
<td>16.7</td>
<td>14.6</td>
<td>10.4</td>
<td>12.5</td>
</tr>
<tr>
<td>increase donations to untreated with rebate</td>
<td>0.0</td>
<td>29.2</td>
<td>16.7</td>
<td>2.5</td>
</tr>
<tr>
<td>decrease don. to untreated with rebate</td>
<td>35.7</td>
<td>4.2</td>
<td>18.8</td>
<td>37.5</td>
</tr>
<tr>
<td>don’t change don. to untreated with rebate</td>
<td>47.6</td>
<td>52.1</td>
<td>54.2</td>
<td>47.5</td>
</tr>
<tr>
<td>never donate</td>
<td>7.1</td>
<td>14.6</td>
<td>8.3</td>
<td>7.5</td>
</tr>
<tr>
<td>increase total giving with rebate</td>
<td>38.1</td>
<td>33.3</td>
<td>45.8</td>
<td>40.0</td>
</tr>
<tr>
<td>decrease total giving with rebate</td>
<td>0.0</td>
<td>0.0</td>
<td>2.1</td>
<td>0.0</td>
</tr>
<tr>
<td>don’t change total giving with rebate</td>
<td>54.8</td>
<td>52.1</td>
<td>43.8</td>
<td>52.5</td>
</tr>
</tbody>
</table>

Note that the categories listed here do not overlap. Categories may not exactly add up to 100 due to rounding.

Table 6 shows a very similar classification of behavior in experiments Subs and Subs-M. It is also reassuring to see that in experiment Comp, there is a very little percentage of individuals who decrease donations to the untreated charity (4.2% compared with 29.2% who increase donations). One can compare that with experiment Comp-W where 18.8% of individuals decreased their donations to the untreated charity while only 16.7 percent of individuals increased their donations.

39 We have explained some of the heterogeneity based on subjects’ answers to our questionnaire in our previous regression analysis.
40 The classifications are supported by OLS regressions run separately for each individual.
donations to the untreated charity. In terms of how total giving is affected by rebate, we see that while our previous analysis shows that in all treatments there is an increase in total giving when rebate rate increases, a little over half of the individuals do not statistically significantly change their total donations (with the exception of Comp-W experiment).

4 Conclusion

According to the National Center for Charitable Statistics, there are over one and a half million charities in the United States alone that compete for donations. It is extremely important to understand how this competition affects donations to charities and the overall charitable pie.

We have several important contributions to the literature. The biggest fear after a successful campaign for one cause is possible lower funding for other charities, which we also establish in our study when we look at charities with substitute causes. More funding for the animal shelter leads to less funding for the homeless shelter. Next, we look at whether this is a simple shift of donations from one charity to another without increasing the total charitable pie. We find that the animal shelter generates some new donations by increasing rebates, i.e., total giving increases when the rebate rate increases. In addition, we consider charities with complimentary causes. We find that donations to both charities increase when one charity increases its rebate rate. Finally, we make an important discovery. When opportunity costs of rebate campaigns are taken into account, total donations net of the rebate costs decrease as the rebate rate for one of the charities increases. This creates doubts as to whether fundraising campaigns that provide monetary incentives increase social welfare.

Our paper has important policy implications for practitioners who use refunds/matches as fundraising strategies as well as for policy makers who propose tax incentives for giving to certain charities, which would imply a price change for giving to some charities while keeping the price the same for others. We show that the change in giving for a unit change in rebate rate is not constant as rebate rate increases. Understanding the demand at different prices is, therefore, crucial for setting the subsidy levels optimally. Our results confirm that charities have individual incentives to use rebate/match subsidies. However, the charitable sector should keep in mind that the size of the charitable pie for the whole industry declines with competition (when the cost of rebates is accounted for).

We are also able to answer an important question. Among others, Davis et al. (2005), Davis (2006), Meier (2007) and Huck and Rasul (2011) find that rebate/match subsidies are not beneficial for the charities themselves (when the cost of subsidies is taken into account) and they ask the question why rebate/match strategies are so popular in the charitable sector. Since charities are under intense competition, it would be misleading to study fundraising campaigns of charities in isolation and ignoring the dynamics between multiple charities. By offering rebate/match subsidies, charities are able to “steal” donations away from other competing charities—they have individual incentives to use these strategies.

We studied a well-established and tractable theoretical model to provide a benchmark for our experiments that involve charities with both substitute and complimentary causes. Our theoretical results are not limited to rebates but can also be applied to matching strategies since these are mathematically equivalent. While matches are more common in charitable fundraising (i.e., Karlan and List, 2007; Meier 2007; Huck and Rasul, 2011), tax rebates creates important price

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41 Rebates and matches are theoretically equivalent as long as agents are not constrained in their donations (i.e., total donations are less than 100 tokens). This is true for the majority of our data, as can be seen in Section 3.
differences for giving to charities when we compare registered versus non-registered charities. In one case, donations are tax-deductible and in the other case donations are not tax-deductible. Moreover, some charities send gifts to donors with varying valuations, which has a similar spirit to rebates. Having said that, behaviorally, we expect matching strategies to generate more total giving compared to rebate strategies (among others, see Eckel and Grossman, 2003; 2006a; 2006b; 2008; 2017; Davis et al., 2005). Nevertheless, we conjecture that our qualitative results would continue to hold under matching.

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42 Not all studies find a difference between rebate and matching subsidies. Davis (2006) finds no differences between rebates and matches under a novel decision environment that controls for isolation effects.
References


