(Un)Informed Charitable Giving[*]

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Abstract

Evidence suggests that donors have little demand for information before giving to charity. To understand this behavior and its policy implications, we present a model in which each individual can acquire costly information about her true value of charity. We observe that an individual who considers giving less is less likely to become informed; and indeed, an uninformed donor is, on average, *less* generous than an informed one. This implies that since the free-rider problem in giving worsens in a larger population, the percentage of informed givers becomes vanishingly small, leaving the total expected donations strictly below its highest level to be reached by a fully informed population. We show that while a direct government grant to the charity causes severe crowding-out by discouraging information acquisition, a matching grant increases donations by encouraging it. We further show that a "warm-glow" motive for giving does not necessarily weaken incentives to be informed, and that a (first-order) stochastic increase in true values for charity may actually *decrease* donations.

JEL Classifications: H00, H41, D82, D83

Keywords: charitable giving, search cost, value of information, crowding-out, warm-glow

"It is more difficult to give money away intelligently than to earn it in the first place."— Andrew Carnegie (The Gospel of Wealth, 1889)

1 Introduction

According to a recent survey conducted by Hope Consulting,[1] 65% of people did *no* research before donating to a charity.[2] One explanation for this "disinterest" in information

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[*] We thank Tom Nechyba and participants of the Duke theory lunch for comments, and Osman Kocas for research assistance. All remaining errors are ours.

[1] The 2010 survey includes 4,000 people with incomes over $80K in the U.S, and its results are available at <www.hopeconsulting.us/money-for-good>.

[2] This evidence is consistent with online fundraising statistics. According to 2011 eNonprofit Benchmarks Study across five sectors, the average open rate for email fundraising is 13%; click-through rate is 2%; and the response rate is 0.08% (www.e-benchmarksstudy.com). That is, out of every 10,000 deliverable email solici-

could be that people give to the same organization. But, the same survey also found that despite significant loyalty in giving, 85% of donors would value more information about the charitable projects. An alternative explanation could be that people are motivated purely by a "warm-glow" obtained from the act of giving, rather than by altruism. Yet, the surveyed people were most worried about their money being wasted by the charity.[3] In this paper, we offer a rational explanation by explicitly identifying donors' incentives to seek information. In doing so, we contribute to the theoretical, policy-making, and fund-raising aspects of charitable giving.

On the theory side, we endogenize the information structure in a relatively standard public good game by introducing a search cost. On the policy side, we show that a government grant to the charity can influence donors' search behavior and thus the extent of the crowding out. And, on the fund-raising side, we show that it may be in the fund-raiser's best interest to inform donors or at least reduce their search cost.

We cast our model as private provision of a "discrete" public project that yields little to no benefit when unfinished, such as a new bridge, local library, public radio program, or attracting a concert to town. Unlike the extant literature, we assume that each donor is initially uninformed of her true value for the project; however, she can find it out by researching, perhaps through navigating the charity's website, calling its employees, or opening its solicitation letter. The decisions to research and to donate are privately made.

A donor's decision to search for information trades off its (net) benefit and cost. It is intuitive that being informed should be more beneficial to a donor who considers giving more. Due to the classical free-riding incentive, however, a donor will consider giving less as the population grows; and indeed, we show that in a large economy, the equilibrium probability of being informed converges to zero! Such uninformed giving adversely affects the provision of the public good (even in the limit) because we also show that an uninformed individual is, on average, *less* generous than an informed one. In particular,

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tations, 1,300 are opened by their subject lines; 200 are clicked through the links for more information about the cause, but only 8 end up generating donations. See also Chen, Li, and McKee-Mason (2006) for a field experiment of online fundraising. In direct mail fundraising, it is difficult to track who actually opens and reads solicitation mails, but a 1% response rate is often considered a success (Bray 2010, Sharpe 2007).

The survey evidence is also consistent with the experimental finding of Fong and Oberholzer-Gee (2011): although donors become more generous if they know their assistance benefits a group they like, only a *third* of subjects purchase such information prior to giving.

[3] In addition, there is ample evidence that people often possess both the altruistic and warm-glow motives for giving; see, e.g., Andreoni (1993), Eckel et al. (2005), Palfrey and Prisbrey (1997), Ribar and Wilhelm (2002). Andreoni (2006a) and Vesterlund (2006) provide excellent surveys of charitable giving literature.

with a positive search cost, the total expected donation never reaches its highest level that would obtain if all donors were exogenously informed. For the fund-raiser, this means that informing donors or at least reducing their search costs would increase the likelihood of a successful project.

Our analysis has important policy implications. As is common in models of pure public goods,[4] a *direct* government grant to charity would crowd out private giving if information were costless. With costly information, however, a direct grant further crowds out private giving by discouraging information acquisition. While this observation raises questions about the efficacy of a direct grant, we show that a *matching* government grant will have the opposite effect: it will encourage donors to be informed and give more as a result. We believe that this novel (informational) rationale for the use of matching grants in fund-raising complements others in the literature that are based on lowering the price of giving (e.g., Auten et al. 2002, Karlan and List 2007).

Our investigation sheds light on two additional fund-raising issues. First, contrary to common wisdom,[5] it reveals that a warm-glow motive for giving does not necessarily diminish one's incentives to be informed about the charity; in contrast, since a warm-glow donor would have a greater incentive to give, we demonstrate that she might also have a greater incentive to search than to stay uninformed and give less. Second, unlike the case with exogenously informed donors, we find that a (first-order) stochastic increase in donors' values for the charity may actually *decrease* their total expected donations, and thus the probability of the project's success, when information is costly to acquire. The reason is that while stochastic dominance may imply higher values and thus higher expected contributions from informed donors, it may also imply lower variance and thus a lower benefit from being informed, decreasing expected contributions. This means that the project design can be a nontrivial task for the fund-raiser even if it costs little to add value-enhancing features to the project.

Related Literature. As mentioned above, our theoretical model is cast as private provision of discrete public goods. Admati and Perry (1991), Bagnoli and Lipman (1989), and Palfrey and Rosenthal (1984) offer early analyses under complete information and a commonly known cost. To these, Nitzan and Romano (1990) and McBride (2006) introduce cost uncertainty while Laussel and Palfrey (2003), Martimort and Moreira (2010), and Menezes

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[4] See, e.g., Bergstrom et al. (1986).

[5] Indeed, the Hope Consulting report views warm-glow motive to be a primary obstacle to informed giving.

et al. (2001), among others, introduce private information to valuations for the public good. The closest paper to our setting in this literature is by Barbieri and Malueg (2010), who consider both private information and cost uncertainty. Our benchmark case with an *exogenous* search behavior can be viewed as an extension of Barbieri and Malueg's.

In highlighting potential informational problems with charitable giving, our paper relates to Andreoni and Payne (2003, 2011), Andreoni (2006b), Eckel and Grossman (1996), Fong and Oberholzer-Gee (2011), and Vesterlund (2003). Andreoni and Payne assume that fund-raisers can eliminate donors' search costs by contacting them.[6] They empirically demonstrate that a significant portion of the crowding out can be attributed to reduced fund-raising effort. Our paper complements theirs by focusing on donors' equilibrium incentives to search. Eckel and Grossman (1996) experimentally show that individuals give more generously when they are paired with recipients who belong to their preferred group. Fong and Oberholzer-Gee (2011) experimentally investigate individuals' willingness to pay for such information (as in our model), and find that only one third of subjects do so. Both papers, however, consider a dictator game between the donor and the recipient; therefore, unlike in our model, a free-rider problem in giving does not affect the donor's demand for information.

Finally, Andreoni (2006b) and Vesterlund (2003) examine "common value" settings where charity's quality is unknown to donors. They show that a large leadership gift can signal quality and generate subsequent donations. Instead, we consider a "private value" setting in which people have heterogenous preferences for the charity.

The rest of the paper is organized as follows. The basic model is presented in the next section, followed by a benchmark analysis with an exogenous search behavior in Section 3. Section 4 characterizes the symmetric equilibrium with endogenous search. The policy implications for government grants are considered in Section 5. Section 6 examines the consequences of the warm-glow motive as well as a first-order stochastic increase in valuations. Section 7 concludes. Proofs of all formal results are relegated to an appendix.

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[6] Correa and Yildirim (2011) theoretically characterize the optimal fundraiser set depending on donors' preferences, incomes, and solicitation costs.

2 Basic Model

A fund-raiser collects donations from $n \geq 2$ risk-neutral individuals with purely altruistic motives to provide a discrete public good.[7] At the outset, each individual i is uncertain of her value, v_i, for the public good but believes that it is an independent draw from a continuous distribution whose support is $[0, 1]$.[8] Let F and f denote the c.d.f. and the p.d.f. of this distribution, respectively, with mean μ and variance σ^2. We assume that individual i can learn v_i by incurring a fixed search cost, $s \geq 0$, which could simply be the opportunity cost of reading the charity's website or its solicitation letter. Neither her search decision nor its outcome is observed by others. Based on their private information, individuals simultaneously make contributions toward the public good. Let $x_i \geq 0$ be i's contribution and $X \equiv \sum_i x_i$ be the total.

The (discrete) public good is provided if and only if $X \geq c$, where c is the production cost. At the time of the contributions, c is unknown to both the donors and the fund-raiser. It is, however, commonly believed that c is independent of all v_i's and *uniformly* distributed in $[0, k]$, with $k > 1$. The contributions are of subscription nature (Admati and Perry, 1991): they are refunded if the cost threshold is not met ex post; but the excess funds are kept by the fund-raiser.[9] In the case of no public good, donors receive a reservation utility of 0. As is common in the literature, the objective of the fund-raiser is to maximize the probability of providing the public good, which, given the uniform cost, means maximizing the expected contributions, $\overline{X}$, in equilibrium. Our solution concept is *symmetric* Bayesian-Nash equilibrium.

2.1 Discussion of the Assumptions

We envision that the production cost, c is largely determined by uncertain market conditions. For instance, the exact cost of a construction project may be the result of a procurement auction; the price of a high-tech equipment needed for a radio program may depend on fluctuating supply conditions; and the minimum number of ticket sales needed for a concert may be uncertain due to the rival venues. (See, Nitzan and Romano 1990, McBride 2006, and Spencer et al. 2009 for more examples.)

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[7] We consider a warm-glow motive in Section 6.

[8] The unit interval is a normalization. What is important is that there be potentially very low and very high value donors in the population to avoid the (uninteresting) equilibria with everyone or no one contributing. We could, however, allow for negative values to signify undesirable charitable projects.

[9] Perhaps, they are used for other projects that the donors do not care about.

The assumption of the uniform cost distribution is restrictive, but (1) it greatly facilitates the analysis, and (2) it helps isolate the endogenous nature of information acquisition. The assumption that $k > 1$ simply means that $k > v_i$ – even the highest-value donor would not unilaterally guarantee the project's success.

With respect to the refund policy, it is, in general, well-understood that more money is raised with a refund than without it (see, e.g., Admati and Perry 1991, and Palfrey and Rosenthal 1984 in theory; Marks and Croson 1998, Rondeau et al.1999, and Spencer et al. 2009 in experiments). This is also true in a stark way in our setting: if there were no refunds, then the unique equilibrium would generate *no* contributions. While a refund policy may be difficult to implement in some cases, it is not in others. For instance, in the wake of advanced technology, many donation pledges can now be made online by credit cards; and it is quite feasible that if pledges are insufficient to cover the cost, credit cards are not charged. Similarly, it is a common practice to fully refund concert tickets if the event is cancelled.

To develop a benchmark as well as a first step toward understanding incentives to be informed, we begin our analysis by fixing donors' search behavior.

3 Benchmark: Exogenous Information

Suppose that with a fixed probability ϕ, each donor privately knows her value v_i while with probability $1 - \phi$, she is uninformed. Let $\bar{z}(\phi)$ be the total expected contributions by $n - 1$ donors in a symmetric equilibrium. Then, an informed donor i who gives x_i will enjoy utility $v_i - x_i$ with the probability of the provision, $\frac{x_i + \bar{z}(\phi)}{k}$, and reservation utility 0, otherwise. As a result, i's expected utility from being informed can be expressed as:[10]

$$u^I(x_i, v_i) \equiv (v_i - x_i)\left(\frac{x_i + \bar{z}(\phi)}{k}\right). \tag{1}$$

Maximizing (1) with respect to x_i yields i's optimal informed contribution:

$$x^I(v_i, \bar{z}(\phi)) = \max\{0, \frac{v_i - \bar{z}(\phi)}{2}\}. \tag{2}$$

Not surprisingly, donor i's contribution is increasing in her value and decreasing in others' contributions, $\bar{z}(\phi)$. In particular, $\bar{z}(\phi)$ constitutes the cutoff value for i to start giving.

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[10] To be more precise, the probability of provision is $\min\{\frac{x_i + \bar{z}(\phi)}{k}, 1\}$. This probability is, however, strictly less than 1 in any symmetric equilibrium. To see why, note first that $\bar{z}(\phi) < k$; otherwise, if $\bar{z}(\phi) \geq k$, $x_i = 0$ would be optimal for some donor i independent of v_i. Second, for $\bar{z}(\phi) < k$, it is strictly better for donor i to choose $x_i = 0$ than to choose $x_i = k - \bar{z}(\phi)$ since $v_i < k$.

With probability $1-\phi$, donor i is uninformed of v_i, in which case her expected utility is simply:

$$u^U(x_i) = E[u^I(x_i, v_i)] = u^I(x_i, \mu), \tag{3}$$

whose maximization results in i's optimal uninformed contribution:

$$x^U(\phi) = x^I(\mu, \bar{z}(\phi)). \tag{4}$$

Eq.(4) reveals that in our model, an uninformed donor behaves the same as an informed donor with the mean valuation, μ. Refer to Figure 1.

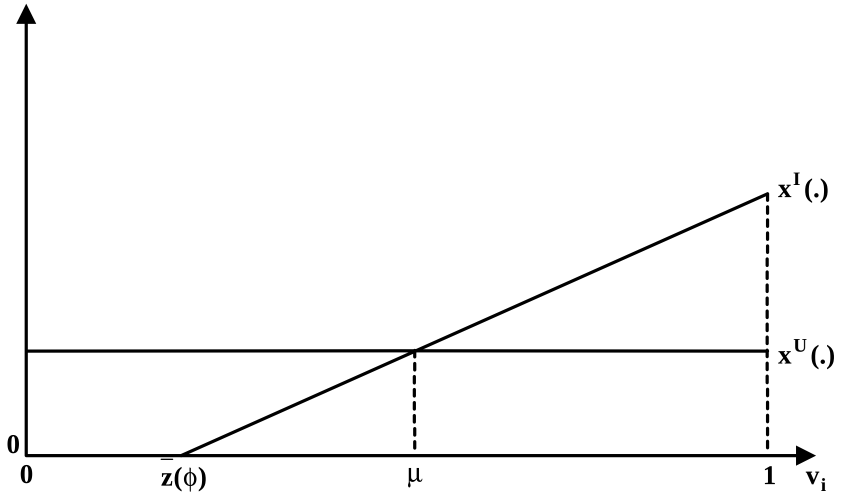

Figure 1. Informed and Uninformed Contributions

By monotonicity, note that the informed contribution exceeds the uninformed whenever the donor's value is above the mean, i.e., $v_i \geq \mu$. Note also that an informed donor may be more or less generous than an uninformed donor, depending on the discovery of her value. For the fund-raiser, it is, however, also important to know how the expected contribution by an informed donor, namely $\bar{x}^I(\phi) \equiv E[x^I(v_i, \bar{z}(\phi))]$, compares with the uninformed contribution, $x^U(\phi)$. The following result establishes this key comparison along with the equilibrium existence.

Proposition 1. *For a fixed $\phi \in [0,1]$, there is a unique symmetric equilibrium, and it satisfies:*

$$\bar{x}^I(\phi) > x^U(\phi),$$

where $\overline{x}^I(\phi)$ *can be expressed as:* $\overline{x}^I(\phi) = \frac{1}{2}\int_{\overline{z}(\phi)}^{1}[1 - F(v)]dv.$

That is, in equilibrium, the expected informed contribution is strictly larger than the uninformed contribution. This relation directly follows from the Jensen's inequality because, as is also evident from Figure 1, $x^I(v_i, \overline{z}(\phi))$ is convex in v_i, and $\overline{z}(\phi) \in (0, 1)$ in equilibrium. Intuitively, an uninformed donor can be considered contributing for *any* value realization and taking the expectation of these contributions, resulting in $x^U(\phi) = \max\{0, E\frac{v_i - \overline{z}(\phi)}{2}\}$ by (4). Note, however, that the lowest of these contributions corresponding to the lowest values close to zero are necessarily *negative*, i.e., $\frac{v_i - \overline{z}(\phi)}{2} < 0$, which can never happen for an informed donor.

Proposition 1 suggests that in equilibrium, the total expected contributions, $\overline{X}(\phi)$, and thus the likelihood of the provision, should increase with the amount of information, ϕ, in the population. This suggestion would obviously be true if the individual contributions did not change with ϕ; but they do as the next result shows.

Proposition 2. *In equilibrium, both* $\overline{x}^I(\phi)$ *and* $x^U(\phi)$ *are strictly decreasing, whereas* $\overline{X}(\phi)$ *is strictly increasing in* ϕ.

Proposition 2 demonstrates that as each donor anticipates others to be informed with a higher probability, she believes their aggregate contributions to be higher, and in turn, reduces her own. Despite this reduction, the total expected contributions increase in equilibrium, confirming her initial belief.

Proposition 2 has two important implications. First, the amount of information in the population and the observed individual contributions are likely to be inversely related. That is, the more informed the population, the worse the free-rider problem is, though not to the extent of depressing the total expected contributions. Second, the fund-raiser would strictly prefer having more informed donors.

Proposition 2 further reveals that the two extreme information regimes, $\phi = 0, 1$, constitute the bounds for the total expected contributions, i.e., $\overline{X}(0) \leq \overline{X}(\phi) \leq \overline{X}(1)$. Since these two extreme regimes will also play a role in identifying equilibrium incentives to be informed in the next section, we briefly characterize them here. For $\phi = 0$, note that $x^U(0) = \frac{\mu - \overline{z}(0)}{2}$ and $\overline{z}(0) = (n-1)x^U(0)$. Thus, in a fully uninformed population,

$$x^U(0) = \frac{\mu}{n+1} \text{ and } \overline{X}(0) = n\frac{\mu}{n+1}. \tag{5}$$

For $\phi = 1$, on the other hand, equilibrium contributions are determined by:[11] $\overline{x}^I(1) = \frac{1}{2}\int_{\overline{z}(1)}^1 [1 - F(v)]dv$ and $\overline{z}(1) = (n-1)\overline{x}^I(1)$. Thus, the following equation uniquely solves $\overline{z}(1)$:

$$\overline{z}(1) = \frac{n-1}{2}\int_{\overline{z}(1)}^1 [1 - F(v)]dv, \tag{6}$$

and thus, in a fully informed population,

$$\overline{x}^I(1) = \frac{\overline{z}(1)}{n-1} \text{and } \overline{X}(1) = \frac{n}{n-1}\overline{z}(1). \tag{7}$$

From (6), it is worth observing that $\overline{z}(1) \to 1$ as $n \to \infty$. Thus, in a large informed population, eq.(2) implies that each contribution, $x^I(v_i, \overline{z}(1))$, approaches 0, while the total expected contributions, $\overline{X}(1)$, approaches 1.

4 Endogenous Information

While enlightening, the benchmark is restrictive in that it does not allow individuals to actively search for information to ascertain how closely the charitable project aligns with their preferences. In fact, it may still be the person's decision to receive and process the information even if the fund-raiser provides it through a website, solicitation letter, or phone call. By taking such actions, the fund-raiser may simply be lowering the search cost, s. When deciding whether to become informed, each person will trade off this cost and the value of being informed, which we characterize next.

4.1 The Value of Information

Ignoring the search cost, let $U^I(\overline{z})$ and $U^U(\overline{z})$ be the indirect utilities for each individual from being informed and uninformed, respectively, where $\overline{z}$ is, as before, the sum of expected donations by others. Formally,

$$U^I(\overline{z}) = E\left[\max_{x_i}(v_i - x_i)(\frac{x_i + \overline{z}}{k})\right] \tag{8}$$

and

$$U^U(\overline{z}) = \max_{x_i}(\mu - x_i)(\frac{x_i + \overline{z}}{k}). \tag{9}$$

Then, the value of information for each individual can be defined as:

$$\Delta(\overline{z}) \equiv U^I(\overline{z}) - U^U(\overline{z}).$$

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[11] This fully informed case is also the one considered by Barbieri and Malueg (2010).

Lemma 1.

- *Both* $U^I(\bar{z})$ *and* $U^U(\bar{z})$ *are strictly increasing in* $\bar{z} \in [0,1]$.
- $\Delta(\bar{z})$ *is strictly positive and strictly decreasing in* $\bar{z} \in [0,1)$, *with* $\Delta(0) = \frac{\sigma^2}{4k}$ *and* $\Delta(1) = 0$. *Moreover,*
$$\Delta''(\bar{z}) = \frac{1}{2k} \times \begin{cases} -F(\bar{z}) & if \quad \bar{z} \leq \mu \\ 1 - F(\bar{z}) & if \quad \bar{z} > \mu. \end{cases}$$
- $\Delta(\bar{z})$ *is strictly decreasing in k.*

Lemma 1 says that an individual always benefits from others' contributions, $\bar{z}$, and that this benefit is greater for an informed individual. To understand why, note that $\bar{z}$ has two effects on one's payoff: a direct effect through the probability of public good provision and an indirect effect through her optimal contribution. While the direct effect is present regardless of one's state of information, the indirect effect is more pronounced for an informed individual since she can tailor her contribution to $\bar{z}$ better than an uninformed individual.

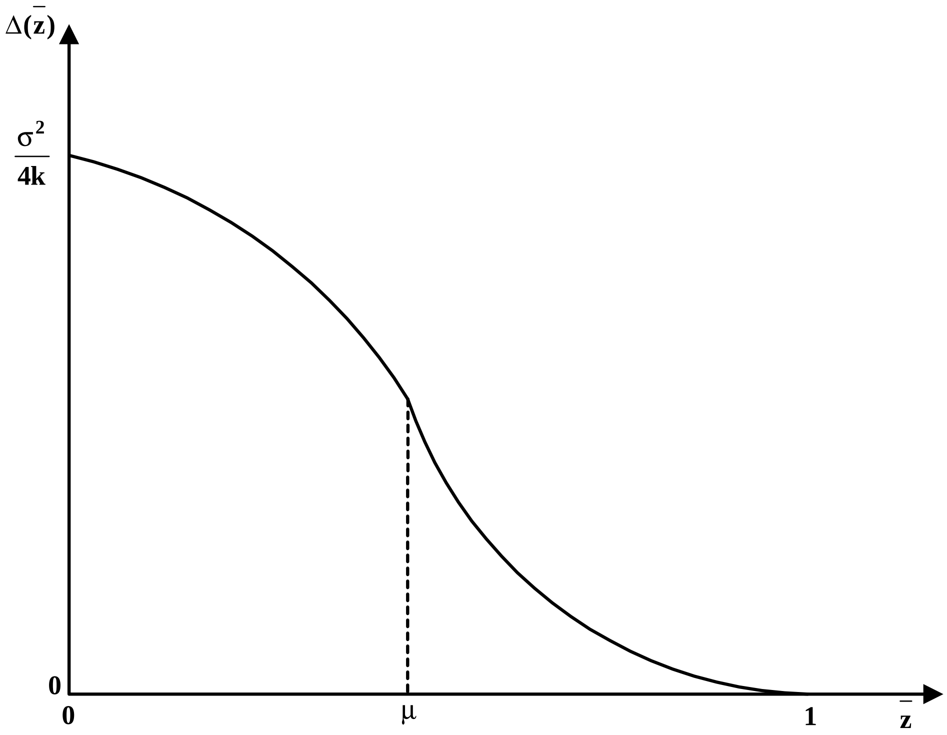

Figure 2. The Value of Information

Lemma 1 also says that the value of information decreases with others' contributions (see Figure 2). This also makes sense: learning about the charitable project should be more valuable for someone who is contemplating giving a larger amount. But, as others contribute more, she will free ride and give less. For instance, if others' contributions already reached the maximum level of the public good, $\overline{X} = 1$, then the individual would optimally give nothing regardless of her value, rendering information worthless, $\Delta(1) = 0$. By the same token, being informed would be most valuable for someone who believes herself to be the sole contributor. Finally, the value of information strictly decreases as the project becomes (stochastically) costlier and thus less likely to succeed.

In what follows, it will be more convenient at times to decompose $\Delta(\overline{z})$ as

$$\Delta(\overline{z}) \equiv \frac{1}{k}\Lambda(\overline{z}), \tag{10}$$

where, by Lemma 1, $\Lambda(\overline{z})$ is strictly decreasing in $\overline{z}$, with $\Lambda(0) = \frac{\sigma^2}{4}$ and $\Lambda(1) = 0$.

4.2 Equilibrium Characterization

Let ϕ^* be the (symmetric) equilibrium probability that a donor learns her value. Then, the equilibrium value of information for a given donor is $\Delta(\overline{z}(\phi^*))$, where, as before, $\overline{z}(\phi^*)$ is the expected contributions by $n-1$ others. Clearly, a fully uninformed equilibrium with $\phi^* = 0$ occurs if $s \geq \Delta(\overline{z}(0))$, and a fully informed equilibrium with $\phi^* = 1$ occurs if $s \leq \Delta(\overline{z}(1))$, where $\overline{z}(1)$ is determined by eq.(6). That is, for a sufficiently high search cost, donors will remain uninformed while for a sufficiently low search cost, they will learn their valuations prior to giving. For an intermediate search cost, i.e., $\Delta(\overline{z}(1)) < s < \Delta(\overline{z}(0))$, donors will strictly mix between searching and not searching. Employing (10), the following result offers a complete characterization of the symmetric equilibrium, which is also depicted in Figure 3 below.

Proposition 3. *Let* $\overline{z}(0) = \frac{n-1}{n+1}\mu$, *and* $\overline{z}(1)$ *be the unique solution to:* $z = \frac{n-1}{2}\int_z^1 [1 - F(v)]dv$. *Then, the unique symmetric equilibrium is described as follows:*

- *for* $sk \geq \Lambda(\overline{z}(0))$,

$$\overline{X}^* = \frac{n}{n-1}\overline{z}(0) \text{ and } \phi^* = 0,$$

- *for* $sk \leq \Lambda(\overline{z}(1))$,

$$\overline{X}^* = \frac{n}{n-1}\overline{z}(1) \text{ and } \phi^* = 1,$$

- *for* $\Lambda(\bar{z}(1)) < sk < \Lambda(\bar{z}(0))$,

$$\overline{X}^* = \frac{n}{n-1}\Lambda^{-1}(sk) \text{ and } \phi^* = \frac{\frac{\Lambda^{-1}(sk)}{n-1} - x^{U*}}{\overline{x}^{I*} - x^{U*}} \in (0,1),$$

where

$$\overline{x}^{I*} = \frac{1}{2}\int_{\Lambda^{-1}(sk)}^{1}[1 - F(v)]dv \text{ and } x^{U*} = \max\{0, \frac{\mu - \Lambda^{-1}(sk)}{2}\}.$$

Aside from the fully informed and fully uninformed equilibria, Proposition 3 describes the mixed strategy equilibrium, in which only part of the population is likely to be informed. In general, it can be easily verified that the probability of being informed, ϕ^* is decreasing in the search cost, s. Since, on average, uninformed donors give less, this implies that the expected total contribution, $\overline{X}^*$ is also decreasing in s. Proposition 3 further indicates that the project cost, k, has the same effect on donor's behavior as the search cost, s: a donor who is less optimistic about the project cost will also attach a lower value to being informed.

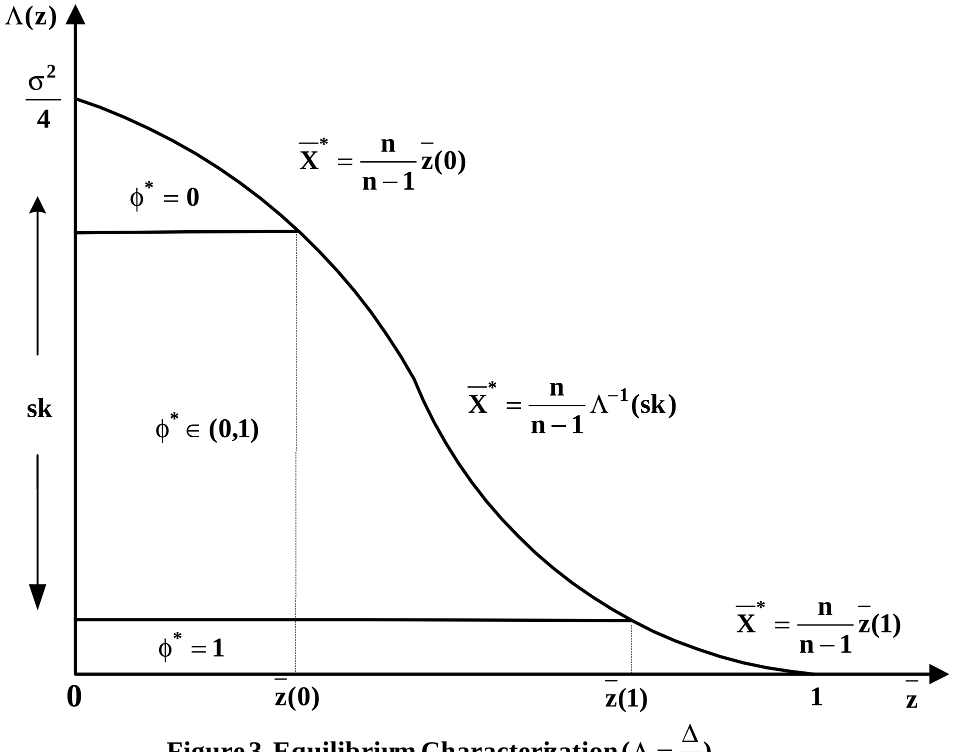

Figure 3. Equilibrium Characterization $(\Lambda = \frac{\Delta}{k})$

Proposition 3 suggests that in order to increase the expected contributions, the fund-raiser should reduce donors' search cost. For instance, the fund-raiser can directly contact donors; make his project website more user-friendly; or design more informative solicitation letters.[12] Proposition 3 also suggests that the fund-raiser should reduce the expected cost of the project.[13] It is worth noting that with a fixed search behavior, a lower project cost would have *no* effect on equilibrium contributions in our model (see eq.2), but with endogenous search, it would encourage donors to be informed and increase their contributions as a result.[14]

Note that in a finite economy, the presence of a positive search cost does not necessarily lower the total expected contributions from its highest level attainable with a fully informed population so long as all individuals become informed in equilibrium. This is because search cost is sunk at the time of the contribution decision. Given that many charities have access to a large donor base, it is, however, important to know whether the fully informed equilibrium continues to exist in a large economy. The following proposition shows that this is not the case.

Proposition 4. *For any $s > 0$, as $n \to \infty$, we have $\phi^* \to 0$ and $\overline{X}^* \to \max\{\mu, \Lambda^{-1}(sk)\}$. Moreover, as $n \to \infty$,*

$$n \times \phi^* \to \begin{cases} 0 & if \quad sk \geq \Lambda(\mu) \\ 2\Lambda^{-1}(sk) / \int_{\Lambda^{-1}(sk)}^{1} [1 - F(v)]dv & if \quad sk < \Lambda(\mu). \end{cases}$$

Proposition 4 says that for any positive search cost, only a negligible fraction of donors will invest in being informed in a large economy. Specifically, with a small search cost, the equilibrium probability of being informed, while positive in a finite economy, converges to zero. The intuition is that as the population grows, so does the sum of others' expected contributions, diminishing one's value of being informed (see Figure 1). Nevertheless, the population does not turn completely uninformed in the limit because the expected number of informed donors, $n \times \phi^*$, is positive and finite. Note that since the fully informed equilibrium is no longer attainable in a large economy, the total expected contribution is

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[12] Indeed, charitable fundraising is a higly professional and innovative industry. Every year, billions of dollars are spent on professional fundraisers (Kelly, 1998).

[13] For instance, the fundraiser may seek additional bidders to lower cost for a construction project.

[14] The uniform cost assumption plays a role here, but it clearly serves our purpose in highlighting the endogenous nature of information.

bounded away from its highest level, 1.[15] That is, the search friction remains effective even in a large economy. These main conclusions continue to hold for a high search cost, too: the population becomes completely uninformed in both finite and limit economies, where the total expected contribution converges to the mean valuation.

Though somewhat extreme, Proposition 4 is consistent with the survey evidence alluded to in the introduction, that only a small percentage of donors do any research before giving. Assuming that the search cost is not too large, our model predicts that in a large economy, only those individuals who seek information about the charity will make a donation. As such, our model predicts a strong correlation between the click-through and response rates in online fund-raising.

5 Government Grants

A fundamental policy issue in public finance is the effectiveness of government grants to charity. Numerous empirical and experimental studies find crowding out of private donations at varying degrees, attributing them to donors' preferences (see Andreoni 2006a and Vesterlund 2006 for a literature review). As in the standard models of giving (e.g., Bergstrom et al. 1986, and Andreoni 1990), these studies ignore informational problems associated with charitable giving. In contrast, Andreoni and Payne (2003, 2011) have recently drawn attention to these problems and uncovered that 70 to 100% of the crowding-out can be explained by the reduced fund-raising efforts aimed at informing donors. As an alternative policy, Andreoni and Payne (2011, p. 342) suggest that "...in general, requirements that charities match a fraction of government grants with increases in private donations could be a feasible response to crowding out." Several recent papers on fund-raising strategies offer strong evidence in favor of matching grants (e.g., Chen et al. 2006, Eckel and Grossman 2008, Karlan and List 2007, and Meier 2007).

By extending our basic model, we provide a new and informational rationale for the use of matching grants. We show that while a direct grant causes additional crowding out by discouraging information acquisition, a matching grant increases private giving by encouraging it.[16]

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[15] It is also worth noting from Proposition 3 that for a low search cost, since the expected informed contribution, $\overline{x}^{I*}$ is independent of n, it is bounded away from 0 even in the limit, which is, clearly, not the case under our benchmark with a fixed search behavior.

[16] Although we cast our analysis in terms of government grants, it equally applies to other exogenous sources of funding for charity.

5.1 Direct Grant

Let R denote the direct grant available to the charity if the public good is produced. Then, similar to (1) and (3), the expected payoffs of an informed and uninformed donor i can be written respectively:

$$u^I(x_i, v_i) = (v_i - x_i)\left(\frac{x_i + \bar{z} + R}{k}\right) \tag{11}$$

$$u^U(x_i, \mu) = (\mu - x_i)\left(\frac{x_i + \bar{z} + R}{k}\right) \tag{12}$$

Note that R raises donor i's marginal cost of giving to $\frac{2x_i+\bar{z}}{k} + \frac{R}{k}$ while leaving her marginal benefit unchanged at $\frac{v_i}{k}$ and $\frac{\mu}{k}$, respectively. Thus, private donations will be crowded out in the "classical" sense regardless of the donor's information. But, since a donor who considers giving less is less likely to search, we also expect an "informational" crowding-out when search is endogenous, further depressing private donations. Proposition 5 formalizes these observations.

Proposition 5. *Let $R < 1$ be the level of the government grant. Then, in equilibrium*

(a) *with a fixed search ϕ, $\overline{X}(\phi, R)$ is strictly decreasing in R while the total revenue, $R + \overline{X}(\phi, R)$ is strictly increasing in R;*

(b) *with an endogenous search, both $\phi^*(R)$ and $\overline{X}^*(R)$ are decreasing in R. Moreover, $R + \overline{X}^*(R)$ is strictly decreasing in R if and only if $\phi^*(R) \in (0, 1)$.*

With a fixed search behavior, only the classical crowding out is operational. Thus, part (a) says that the expected donations will decrease, but they will not be completely crowded out. With an endogenous search, part (b) reveals that the informational crowding out is also operational. Most interestingly, part (b) reveals that the total crowding out can now exceed dollar-for-dollar, rendering the direct grant ineffective. To understand why, note that in a mixed strategy equilibrium, the value of information must be equal to its cost for donors, i.e. $\Delta(\bar{z}(\phi^*) + R) = s$. That is, an increase in R is exactly offset by a lower ϕ^* in equilibrium so that $\bar{z}(\phi^*) + R = \Delta^{-1}(s)$. Since the average donation per person is $\bar{z}(\phi^*)/(n-1)$, the total donations is

$$\overline{X}^*(R) = \frac{n}{n-1}\bar{z}(\phi^*) = \frac{n}{n-1}\Delta^{-1}(s) - \frac{n}{n-1}R,$$

which implies that $\frac{\partial}{\partial R}\overline{X}^*(R) = -\frac{n}{n-1} < 0$. Note that since, by Proposition 4, a mixed strategy equilibrium is the unique one as the population grows, the adverse effect of the grant is likely to remain.[17] Note also that $R + \overline{X}^*(R)$ is increasing in R if the equilibrium is fully informed or fully uninformed so that marginal incentives for information acquisition are not in place.

5.2 Matching Grant

Under a matching grant, the government funding is tied to private donations. Let $R_m = r \times X$, where r is the match ratio. Then, the expected payoffs of the informed and the uninformed donor are modified as follows:

$$u^I(x_i, v_i) = (v_i - x_i)(1+r)\left(\frac{x_i + \overline{z}}{k}\right) \tag{13}$$

$$u^U(x_i, \mu) = (\mu - x_i)(1+r)\left(\frac{x_i + \overline{z}}{k}\right) \tag{14}$$

From (13) and (14), it is evident that, similar to the direct grant, an increase in the matching grant raises the likelihood of the public good provision. However, in contrast to the direct grant, the matching grant leads to a *proportional* increase in both the marginal benefit and the marginal cost of giving, regardless of the donor's information. Hence, the classical crowding out is not present under a matching grant. But, since the value of information also increases by $(1+r)$, the matching grant encourages donors to be informed, which, in turn, positively affect their donations, as the following proposition shows.[18]

Proposition 6. *Let $r < k - 1$ be the matching ratio. Then, in equilibrium,*

- **(a)** *with a fixed search ϕ, $\overline{X}(\phi)$ is neutral to r;*
- **(b)** *with an endogenous search, if $\phi^*(r) \in (0,1)$, then $\phi^*(r)$ and $\overline{X}^*(r)$ are strictly increasing in r.*
- **(c)** *Let R be the direct grant equal to the (expected) matching grant, i.e., $R = r\bar{X}^*(r)$. Then, the matching grant generates higher total expected donations than does the direct grant.*

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[17] Although they use a different model, Andreoni and Payne (2011) find evidence of a 124 % crowding out in a treatment including youth development organizations.

[18] As is also clear in the proof, the matching grant in our model effectively reduces the project cost to $\overline{k} = k/(1+r)$, which requires $r < k - 1$ to satisfy $\overline{k} > 1$.

According to part (a) of Proposition 6, with a fixed search behavior, private giving is unaffected by the matching grant due to the absence of the classical crowding out. With an endogenous search, however, the matching grant encourages informed giving and raises private donations, as indicated in part (b). Part (c) reinforces this finding by noting that a matching grant engenders more private donations than does an equal amount of direct grant.

Comparing Propositions 5 and 6, our analysis has the following testable implication: a matching grant is likely to increase the percentage of informed giving whereas a direct grant is likely to decrease this percentage. More importantly, it points to an informational rationale for the use of matching grants. As such, it complements other explanations in the literature based on lowering the price of giving (e.g., Auten et al. 2002, Karlan and List 2007) as well as those based on motivating the fund-raiser who is the sole source of information for donors (Andreoni and Payne 2003, 2011).[19]

6 Warm-Glow Motive

As noted in the Introduction, one reason for the low percentage of informed giving could be that individuals also experience a "warm-glow" from giving (see n.3), which simply dampens incentives to discover altruistic preferences, v_i, for the public good. An extension of our model, however, reveals that this logic is not necessarily true; on the contrary, because a warm-glow donor may possess a greater incentive to contribute than a pure altruist (without such a motive), she may also possess a greater incentive to be informed.

Suppose that if the public good is provided, an individual who contributes x_i receives not only her altruistic utility v_i but also a warm-glow utility wx_i, where $w \in [0,1]$. If not, she obtains her reservation utility 0 as before. Given others' expected contributions, $\bar{z}$, an informed individual's expected utility becomes

$$\begin{aligned} u^I(x_i; v_i) &= (v_i + wx_i - x_i)\left(\frac{x_i + \bar{z}}{k}\right) \qquad (15) \\ &= (v_i - (1-w)x_i)\left(\frac{x_i + \bar{z}}{k}\right) \end{aligned}$$

Eq.(15) implies that a warm-glow donor would behave as though her marginal cost

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[19] Our findings also offer a first theoretical answer to the experimental observation of Chen et al. (2006) as to "...why one contribution mechanism might consistently draw more curiosity [about a fundraising campaign] than another." (p.20)

of giving were lower. Note that instead of choosing x_i, individual i can be considered choosing $\widehat{x}_i = (1-w)x_i$, in which case eq.(15) reduces to

$$u^I(x; v_i) = (v_i - \widehat{x}_i)\left(\frac{\widehat{x}_i + \widehat{z}}{(1-w)k}\right), \tag{16}$$

where $\widehat{z} = (1-w)\overline{z}$. Comparing (16) with (1), it is evident that a warm-glow donor would also behave the same as a pure altruist who believes the project to be less costly and thus more likely to succeed. By Lemma 1, this belief strengthens her incentive to be informed of v_i. The equilibrium of the game with contributions $\widehat{x}_i$ can be readily characterized by replacing k with $(1-w)k$ in Proposition 3, and noting that $\phi^* = \widehat{\phi}^*$and $\overline{X}^* = \frac{\widehat{X}^*}{1-w}$.

Proposition 7. *Suppose that donors have identical warm-glow preferences such that* $w \leq 1 - \frac{1}{k}$*. Then, both* ϕ^* *and* $\overline{X}^*$ *are increasing in* w*.*

The intuition behind Proposition 7 parallels that of the matching grant discussed above. Warm-glow donors are more optimistic about the project's completion and thus have a greater value of being informed. Since, on average, informed donors give more, the result follows.

7 Stochastic Increase in Values

In the analysis up to now, we have taken the distribution of valuations, F, as given. In order to increase donations, however, the fund-raiser can sometimes influence this distribution through the project design. For instance, the fund-raiser can add sidewalks and bike paths to a bridge project; he can introduce internet access and children's space to a library project; or he can promise to include local as well as the world news in a new public radio program. Conceivably, these additional features to a project will make it more appealing to donors and positively shift their distribution of valuations. To the extent that this occurs at little extra cost, it is natural to conjecture that the expected contributions, and thus the likelihood of the project's success, should increase. We show that while with an exogenous search, this conjecture is correct, with an endogenous search, it is not. In particular, we show that with an endogenous search, the expected contributions may fall despite higher valuations!

To formalize our arguments, we let $F(v; \alpha)$ be a family of distributions on $[0, 1]$ such that $F_\alpha(v; \alpha) \leq 0$. That is, a higher α makes high valuations more likely in the sense of a first-order stochastic dominance (FOSD). A trivial implication of FOSD is that the mean valuation, μ, increases with α.[20] For a fixed search probability, ϕ, FOSD thus reveals from eq.(2) and (4) that on average, both informed and uninformed donors contribute more for any $\bar{z}(\phi)$ when they have stochastically larger values for the public good. This observation leads us to:

Proposition 8. *Fixing $\phi \in [0,1]$, the total expected contributions in equilibrium increases with a FOSD shift in the value distribution, i.e., $\overline{X}(\phi;\alpha)$ increases with α.*

Proposition 8 indicates that with a fixed search behavior, individuals, on average, become more generous as they become more likely to have high values. With endogenous search, FOSD affects contributions by also affecting individuals' incentives to search. Note that since a FOSD shift in distribution can reduce its uncertainty, it can also weaken incentives to become informed, reducing expected donations as a result. The next example demonstrates that this negative effect on the equilibrium search may outweigh the positive effect of FOSD identified in Proposition 8.

Example 1. *Consider the following special case of the beta distribution: $F(v;\alpha) = v^{\alpha}$, with $v \in [0,1]$ and $\alpha \geq 1$. Clearly, $F_{\alpha}(v;\alpha) \leq 0$, and the mean and variance are respectively given by $\mu = \frac{\alpha}{\alpha+1}$ and $\sigma^2 = \frac{\alpha}{(\alpha+1)^2(\alpha+2)}$. Table 1 shows that expected total contributions, $\overline{X}^* = \frac{n}{n-1}\bar{z}^*$, can be decreasing in α. In the calculations, we take $k = 1.01$ and $s = .01$, but do not assign any population size, n given that $\bar{z}^*$ is independent of n in a mixed strategy equilibrium.*[21]

α	μ	σ^2	ϕ^*	$\bar{z}^*$
1.5	.6	.06858	.80346	.54986
1.6	.615	.06575	.73565	.55315
1.7	.630	.06303	.64179	.55478
1.8	.643	.06042	.51193	.55470
1.9	.655	.05793	.33264	.55288
2.0	.667	.05556	.08154	.54914

Table 1. Nonmonotone Contributions with FOSD

Inspecting Table 1, note that for α values between 1.5 and 2, $\bar{z}^*$, and thus $\overline{X}^*$, first rises and then falls with α, indicating a non-monotonicity with FOSD. In particular, for

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[20] Simply note that $\mu = \int_0^1 [1 - F(v;\alpha)]dv$.

[21] For this parametric example, $\bar{z}^* = \left[\mu \times \left(\frac{1}{2} - \frac{2sk}{\sigma^2}\right)\right]^{\frac{1}{\alpha+2}}$ whenever $\frac{1}{2} - \mu^{\alpha+1} < \frac{2sk}{\sigma^2} < \frac{1}{2}$.

α between 1.7 and 2, $\bar{z}^*$ strictly decreases, which is in sharp contrast with Proposition 7. As hinted above, the intuition comes from the fact that FOSD, while increasing the mean valuation, may reduce uncertainty (see σ^2), and in turn, reduce the need for costly information (see ϕ^*). Since, on average, uninformed donors give less than the informed, total donations may suffer even from a favorable shift in the value distribution.

The message from Example 1 is that even without the cost concerns, the project design for the charity is a nontrivial matter when donors need to invest in information. Designing a more appealing project for donors may not necessarily generate larger donations, and guarantee the project's success, if the donors lose interest in finding out about the project and become "average" givers instead.

8 Conclusion

According to one estimate, a public charity registers with the Internal Revenue Service (IRS) every 10 to 15 minutes (NY Times 2009). With countless new projects, a donor is unlikely to know her true value without researching a project, perhaps through navigating the charity's website, calling its employees, or simply opening its solicitation letter. Evidence, however, suggests that people do little research before giving. To rationalize this behavior and explore its policy implications, we have examined a relatively standard model of giving with costly information.

From a theory perspective, our model is the first to endogenize the information structure in this environment. From a policy perspective, our investigation provides a novel and informational rationale for the widespread use of matching grants. And from a fund-raising strategy perspective, our analysis suggests that the fund-raiser should facilitate the donors' search by lowering their costs. It also suggests that introducing value-enhancing features to a charitable project may not necessarily enhance donations.

We believe that our analysis has produced at least four testable predictions.

1. On average, an informed donation exceeds an uninformed one.
2. The more informed the population, the lower the individual donation.
3. The larger the population, the lower the percentage of informed giving.
4. A direct grant discourages informed giving whereas a matching grant encourages it.

We should note that our results are robust to heterogenous search costs across donors. In particular, they may be assumed to draw search costs independently from a continuous distribution, $G(s)$ with $s \in [\underline{s}, \overline{s}]$. In this case, it can be verified that there will be a unique symmetric cutoff s^* such that a donor with $s \leq s^*$ will search, and a donor with $s > s^*$ will not. However, all the comparative statics under a fixed cost can be shown to hold under heterogenous costs, albeit at the expense of additional technical complexity. For instance, as $n \to \infty$, we have $s^* \to \underline{s}$, making the probability of being informed converge to zero, as in the present model.

While generating significant insights, we believe that our paper only scratches the surface. For instance, it would be useful to explore the complementary setting in which people have *common* but uncertain values for the public good. This could be relevant in environments where the quality of the charity –not individual preferences – is the driving factor for giving. Another pressing issue is the competition among charities and its effect on donor search. With so many charities, it is important to know whether donors focus their search and develop loyalty in giving; or they split their search effort and help keep a healthy competition.

A Appendix

Proof of Proposition 1. Fix $\phi \in [0,1]$. Since $x^U(\phi) = x^I(\mu, \overline{z}(\phi))$, we can write $\overline{z}(\phi) = (n-1)[\phi E x^I(v, \overline{z}(\phi)) + (1-\phi)x^I(\mu, \overline{z}(\phi))]$. Define $J(z) \equiv (n-1)[\phi E x^I(v,z) + (1-\phi)x^I(\mu,z)] - z$. Clearly, $J(0) = (n-1)\mu > 0$ and $J(1) = -1 < 0$. Moreover, $J(z)$ is continuous and strictly decreasing in $z \in [0,1]$. Hence, there is a unique $\overline{z}(\phi) \in (0,1)$ that solves $J(z) = 0$. Since $\overline{z}(\phi)$ uniquely determines $x^I(v, \overline{z}(\phi))$, there is a unique symmetric equilibrium for each $\phi \in [0,1]$.

Next, note that $x^I(v, \overline{z}(\phi))$ is convex in v. Thus, by Jensen's inequality, $\overline{x}^I(\phi) = E x^I(v, \overline{z}(\phi)) \geq x^I(\mu, \overline{z}(\phi)) = x^U(\phi)$. For $\overline{z}(\phi) \in (0,1)$, it also follows that $\overline{x}^I(\phi) \neq x^U(\phi)$, revealing that $\overline{x}^I(\phi) > x^U(\phi)$. Finally, by definition, $\overline{x}^I(\phi) = E\max\{0, \frac{v-\overline{z}(\phi)}{2}\} = \int_{\overline{z}(\phi)}^1 \frac{v-\overline{z}(\phi)}{2} dF(v)$. A simple integration by parts shows $\overline{x}^I(\phi) = \frac{1}{2}\int_{\overline{z}(\phi)}^1 [1-F(v)]dv$.■

Proof of Proposition 2. We first prove that $\overline{x}^I(\phi) > \frac{\mu}{n+1}$. Note that since $x^U(\phi) \geq \frac{\mu - \overline{z}(\phi)}{2}$ by definition, we have $2x^U(\phi) + \overline{z}(\phi) \geq \mu$. Moreover, given that $\overline{x}^I(\phi) > x^U(\phi)$ by Proposition 1, we also have $2x^I(\phi) + \overline{z}(\phi) > \mu$ and $\overline{z}(\phi) < (n-1)x^I(\phi)$. Together, $(2 + (n-1))x^I(\phi) > \mu$, which implies that $\overline{x}^I(\phi) > \frac{\mu}{n+1}$, as desired.

Now, we consider two cases for $x^U(\phi)$. If $x^U(\phi) > 0$, then by definition, $x^U(\phi) = \frac{\mu - (n-1)[\phi\overline{x}^I(\phi) + (1-\phi)x^U(\phi)]}{2}$, which reveals $x^U(\phi) = \frac{\mu - (n-1)\phi\overline{x}^I(\phi)}{2 + (n-1)(1-\phi)}$. Inserting this into $\overline{z}(\phi) = (n-1)[\phi\overline{x}^I(\phi) + (1-\phi)x^U(\phi)]$, we obtain

$$\overline{z}(\phi) = (n-1)\frac{\mu(1-\phi) + 2\phi\overline{x}^I(\phi)}{2 + (n-1)(1-\phi)} \equiv Z(\phi, \overline{x}^I(\phi)) \tag{A-1}$$

Since $\overline{x}^I(\phi) = E\max\{0, \frac{v - Z(\phi, \overline{x}^I(\phi))}{2}\}$, Proposition 1 implies

$$2\overline{x}^I(\phi) = \int\limits_{Z(\phi, \overline{x}^I(\phi))}^{1} [1 - F(v)]dv. \tag{A-2}$$

Differentiating both sides of (A-2) with respect to ϕ yields $2\overline{x}^{I\prime}(\phi) = -[1 - F(Z(.))](\frac{\partial}{\partial\phi}Z(.) + \frac{\partial}{\partial\overline{x}^I}Z(.) \times \overline{x}^{I\prime})$, which, by arranging terms, yields that

$$\overline{x}^{I\prime} = -[1 - F(Z(.))]\frac{\frac{\partial}{\partial\phi}Z(.)}{2 + [1 - F(z(.))]\frac{\partial}{\partial\overline{x}^I}z(.)} < 0,$$

because $Z(.) \in (0,1)$; $\frac{\partial}{\partial\overline{x}^I}Z(.) > 0$; and $\frac{\partial}{\partial\phi}Z(.) = \frac{2(n-1)(n+1)}{(2+(n-1)(1-\phi))^2}\left[\overline{x}^I(\phi) - \frac{\mu}{n+1}\right] > 0$ from (A-1).

If, on the other hand, $x^U(\phi) = 0$, then $2\overline{x}^I(\phi) = \int_{(n-1)\phi\overline{x}^I(\phi)}^1 [1 - F(v)]dv$. Differentiation again shows $\overline{x}^{I\prime}(\phi) < 0$. By (2), the fact that $\overline{x}^{I\prime}(\phi) < 0$ implies that $\overline{z}(\phi)$ is strictly increasing in ϕ, which, in turn, implies that $x^U(\phi)$ is strictly decreasing in ϕ whenever $x^U(\phi) > 0$. Moreover, since, in a symmetric equilibrium, $\overline{X}(\phi) = \frac{n}{n-1}\overline{z}(\phi)$, $\overline{X}(\phi)$ is strictly increasing in ϕ. ■

Proof of Lemma 1. Applying the Envelope theorem on (8),

$$U^{I\prime}(\overline{z}) = \frac{1}{k}E[v - x^I(v;\overline{z})] = \frac{1}{k}\left(\mu - \overline{x}^I(\overline{z})\right),$$

where $\overline{x}^I(\overline{z}) = E\max\{0, \frac{v-\overline{z}}{2}\}$, as before. Since $\overline{x}^I(\overline{z}) \leq \frac{\mu}{2}$, we have $U^{I\prime}(\overline{z}) > 0$.

Applying the Envelope theorem on (9), we also have

$$U^{U\prime}(\overline{z}) = \frac{1}{k}(\mu - x^U(\overline{z})).$$

Thus,

$$\begin{aligned} \Delta'(\overline{z}) &= \frac{1}{k}\left(\mu - \overline{x}^I(\overline{z})\right) - \frac{1}{k}(\mu - x^U(\overline{z})) \\ &= \frac{1}{k}[x^U(\overline{z}) - \overline{x}^I(\overline{z})] < 0 \text{ (by Proposition 1).} \qquad \text{(A-3)} \end{aligned}$$

Since $x^U(\mu) = 0$, $\Delta'(\mu)$ exists, which means $\Delta'(\overline{z})$ exists for all $\overline{z} \in [0,1]$. Since $\overline{x}^I(1) = x^U(1) = 0$, we also have $\Delta(1) = \{Ev - \mu\} = 0$. Thus, $\Delta(\overline{z}) > 0$ for $\overline{z} \in [0,1)$. Note also that,

$$\Delta(0) = \frac{1}{k}\left[\int_0^1 \left(\frac{v}{2}\right)^2 dF(v) - \left(\frac{\mu}{2}\right)^2\right] = \frac{1}{k}Var(\frac{v}{2}) = \frac{\sigma^2}{4k}.$$

To derive $\Delta''(\overline{z})$, differentiate (A-3) with respect to $\overline{z}$ and observe that :

$$\Delta''(\overline{z}) = \frac{1}{2k} \times \begin{cases} -F(\overline{z}) & if \quad \overline{z} \leq \mu \\ 1 - F(\overline{z}) & if \quad \overline{z} > \mu, \end{cases}$$

where we use the facts: $\frac{\partial}{\partial\overline{z}}\overline{x}^I(\overline{z}) = -\frac{1}{2}[1 - F(\overline{z})]$ and $\frac{\partial}{\partial\overline{z}}x^U(\overline{z}) = -\frac{1}{2}$ whenever $x^U(\overline{z}) > 0$.

Finally, since $\Delta(\overline{z}) = \frac{1}{k}\Lambda(\overline{z})$ for some function Λ, $\Delta(\overline{z})$ is strictly decreasing in k. ■

Proof of Proposition 3. Let $\overline{z}(0) = \frac{n-1}{n+1}\mu$, and $\overline{z}(1)$ be the unique solution to: $z = \frac{n-1}{2}\int_z^1 [1 - F(v)]dv$. Since $\overline{z}'(\phi) > 0$ by Proposition 2, and $\Delta'(\overline{z}) < 0$ by Lemma 1, it follows that $\Delta(\overline{z}(\phi))$ is strictly decreasing in ϕ. Clearly, $\phi^* = 0$ is a (symmetric) equilibrium if $s \geq \Delta(\overline{z}(0))$, or equivalently if $sk \geq \Lambda(\overline{z}(0))$. In this case, $\overline{X}^* = \frac{n}{n-1}\overline{z}(0)$. On the other hand, if $sk \leq \Lambda(\overline{z}(1))$, $\phi^* = 1$ is an equilibrium, in which case $\overline{X}^* = \frac{n}{n-1}\overline{z}(1)$.

Finally, suppose $\Lambda(\overline{z}(1)) < sk < \Lambda(\overline{z}(0))$. Then, there is a unique $\phi^* \in (0,1)$ that solves $\Lambda(\overline{z}(\phi^*)) = sk$, which is an equilibrium. To characterize this mixed strategy equilibrium, note that $\overline{z}^* = \Lambda^{-1}(sk)$, which implies that $\overline{X}^* = \frac{n}{n-1}\Lambda^{-1}(sk)$ and $x^{I*} = \frac{1}{2}\int_{\Lambda^{-1}(sk)}^{1}[1-F(v)]dv$ by Proposition 1. If $\Lambda^{-1}(sk) < \mu$, then $x^{U*} = \frac{\mu-\Lambda^{-1}(sk)}{2} > 0$. Since $\overline{z}^* = (n-1)[\phi^*\overline{x}^{I*} + (1-\phi^*)x^{U*}]$, it follows that $\phi^* = \frac{\frac{\Lambda^{-1}(sk)}{n-1}-x^{U*}}{x^{I*}-x^{U*}}$. Observe that since $\overline{x}^{I*} > x^{U*}$ by Proposition 1, we have

$$\phi^* > 0 \iff \frac{\Lambda^{-1}(sk)}{n-1} - x^{U*} > 0 \iff \frac{(n-1)\mu}{n+1} < \Lambda^{-1}(sk) \iff \Lambda(\overline{z}(0)) > sk,$$

which is true by hypothesis. Note also that $\phi^* < 1$ because $\Lambda(\overline{z}(1)) < sk$, or equivalently $\overline{z}(1) > \Lambda^{-1}(sk)$. If, on the other hand, $\mu \geq \Lambda^{-1}(sk)$, then $x^{U*} = 0$, in which case $\phi^* = \frac{\Lambda^{-1}(sk)}{(n-1)\overline{x}^{I*}}$. Using a similar argument, we see that $\phi^* \in (0,1)$. ■

Proof of Proposition 4. Since $\overline{z}(1) = \frac{n-1}{2}\int_{\overline{z}(1)}^{1}[1-F(v)]dv$ by (6), it is easy to verify that as $n \to \infty$, we have $\overline{z}(1) \to 1$ and thus $\Lambda(\overline{z}(1)) \to 0$. From Proposition 3, this means that as $n \to \infty$, we have (1) $\overline{X}^* \to \mu$ if $sk > \Lambda(\mu)$, or if $\Lambda^{-1}(sk) < \mu$, and (2) $\overline{X}^* \to \Lambda^{-1}(sk)$ if $sk \leq \Lambda(\mu)$, or if $\Lambda^{-1}(sk) \geq \mu$. But, these are equivalent to stating that $\overline{X}^* \to \max\{\mu, \Lambda^{-1}(sk)\}$. From Proposition 3, it also readily follows that $\phi^* \to 0$ as $n \to \infty$.

To prove the last part, note that if $sk \geq \Lambda(\mu)$, then $\phi^* = 0$ for each n, and thus $n \times \phi^* = 0$. If, on the other hand, $sk < \Lambda(\mu)$, then $\phi^* = \frac{\frac{\Lambda^{-1}(sk)}{n-1}}{\overline{x}^{I*}}$ since $x^{U*} = 0$. This means that $n \times \phi^* \to \frac{\Lambda^{-1}(sk)}{\overline{x}^{I*}}$, where $\overline{x}^{I*} = \frac{1}{2}\int_{\Lambda^{-1}(sk)}^{1}[1-F(v)]dv$, completing the proof. ■

Proof of Proposition 5. Let $\hat{z}(\phi, R) = \overline{z}(\phi) + R$. To prove part (a), note that given that $\overline{z}(\phi) = (n-1)[\phi\overline{x}^I(\phi) + (1-\phi)x^U(\phi)]$ and $x^U(\phi) = \max\{0, \frac{\mu-\hat{z}(\phi,R)}{2}\}$, $x^U(\phi)$ and $\hat{z}(\phi, R)$ can be rewritten, respectively,

$$x^U(\phi, \overline{x}^I) = \max\left\{\frac{\mu-(n-1)\phi\bar{x}^I(\phi)-R}{2+(n-1)(1-\phi)}, 0\right\}$$

$$\hat{Z}(\phi, \overline{x}^I, R) \equiv \hat{z}(\phi, R) = (n-1)\max\left\{\phi\bar{x}^I(\phi), \frac{2\phi\bar{x}^I(\phi)+(1-\phi)\mu-(1-\phi)R}{2+(n-1)(1-\phi)}\right\} + R, \tag{A-4}$$

where $\overline{x}^I(\phi) = \frac{1}{2}\int_{\hat{z}(\phi,R)}^{1}[1-F(v)]dv$ by Proposition 1.

Differentiating $\overline{x}^I(\phi)$ with respect to R yields $\frac{d\bar{x}^I(\phi)}{dR} = -\frac{(1-F(\hat{Z}))\frac{\partial\hat{Z}}{\partial R}}{2+(1-F(\hat{Z}))\frac{\partial\hat{Z}}{\partial\bar{x}^I}} < 0$. Consider two cases for $x^U(.)$.

- $x^U(.) = 0$. Then, $\overline{X}(\overline{x}^I, \phi) = n\phi\overline{x}^I$ and $\frac{\overline{X}(\overline{x}^I,\phi)}{dR} = n\phi\frac{d\bar{x}^I}{dR} < 0$. Moreover, $\frac{\partial\hat{Z}}{\partial\bar{x}^I} = (n-1)\phi$, $\frac{\partial\hat{Z}}{\partial R} = 1$ and

$$\frac{d(\overline{X}(\overline{x}^I,\phi)+R)}{dR} = -n\phi\frac{1-F(\hat{Z})}{2+\phi(1-F(\hat{Z}))(n-1)} + 1 = \frac{2-\phi(1-F(\hat{Z}))}{2+(n-1)(1-F(\hat{Z}))\phi} > 0.$$

- $x^U(.) > 0$. Then, $\overline{X}(\overline{x}^I,\phi) = \frac{n}{n-1}[\hat{Z}(\phi,\overline{x}^I) - R]$ and

$$\frac{d\overline{X}(\overline{x}^I,\phi)}{dR} = \frac{n}{n-1}\left[\frac{d\hat{Z}}{dR} - 1\right] + 1 = n\frac{2\phi\frac{d\overline{x}^I(\phi)}{dR} - (1-\phi)}{2+(n-1)(1-\phi)} < 0.$$

Moreover, after substituting for $\frac{d\overline{x}^I(\phi)}{dR}$, and using the facts that $\frac{\partial\hat{Z}}{\partial\overline{x}^I} = \frac{2\phi(n-1)}{2+(n-1)(1-\phi)}$, and $\frac{\partial\hat{Z}}{\partial R} = \frac{2}{2+(n-1)(1-\phi)}$, we have $\frac{d(\overline{X}(\overline{x}^I,\phi)+R)}{dR} = \frac{1+\phi F(\hat{Z})}{n+1-\phi(n-1)F(\hat{Z})} > 0$.

Next, we prove part (b). Note that by Lemma 1, $\Delta(\hat{z})$ is strictly decreasing in $\hat{z}$. Moreover, $\hat{z}(0,R) = \frac{n-1}{n+1}\max\{(\mu-R),0\} + R$, and $\hat{z}(1,R)$ uniquely solves $z = \frac{n-1}{2}\int_z^1[1-F(v)]dv + R$. Clearly, $\frac{d\hat{z}(0,R)}{dR} > 0$ and $\frac{d\hat{z}(1,R)}{dR} = \frac{2}{2+(n-1)(1-F(\hat{z}(1,R)))} > 0$. We now exhaust the three equilibrium regions in Proposition 3.

- For $sk \geq \Lambda(\hat{z}(0,R))$, the equilibrium involves $\phi^*(R) = 0$ and $\overline{X}^*(\phi,R) = \frac{n}{n-1}(\hat{z}(0,R) - R)$. Thus, $\frac{d\overline{X}^*(\phi,R)}{dR} = \frac{n}{n-1}\left(\frac{d\hat{z}(0,R)}{dR} - 1\right) \leq 0$, and $\frac{d\overline{X}^*(R)+R}{dR} > 0$.

- For $sk \leq \Lambda(\hat{z}(1,R))$, the equilibrium involves $\phi^*(R) = 1$ and $\overline{X}^*(\phi,R) = \frac{n}{n-1}(\hat{z}(1,R) - R)$. Moreover, $\frac{d\phi^*(R)}{dR} = 0$ for all R such that $sk \leq \Lambda(\hat{z}(1,R))$. Therefore, in this region $\frac{d\overline{X}^*(\phi,R)}{dR} = \frac{n}{n-1}\left(\frac{d\hat{z}(1,R)}{dR} - 1\right) \leq 0$ and $\frac{d\overline{X}^*(\phi,R)+R}{dR} > 0$.

- For $\Lambda(\hat{z}(1,R)) < sk < \Lambda(\hat{z}(0,R))$, the mixed strategy equilibrium involves $\phi^*(R) = \frac{\frac{\Lambda^{-1}(sk)-R}{n-1} - x^{U*}}{\hat{x}^{I*} - x^{U*}}$ and $\overline{X}^*(R) = \frac{n}{n-1}\left(\Lambda^{-1}(sk) - R\right)$. Since, in equilibrium, $\Lambda(\hat{z}^*(R)) = sk$, we have $\hat{z}^*(R) = \Lambda^{-1}(sk)$. It is immediate that both $\overline{X}^*(R)$ and $\overline{X}^*(R) + R = \frac{1}{n-1}\left(n\Lambda^{-1}(sk) - R\right)$ are decreasing in R. Moreover, $\frac{\partial\phi^*(R)}{\partial R} = -\frac{\partial\hat{z}^*(\phi,R)/\partial R}{\frac{d\hat{z}^*(\phi,R)}{d\phi}}$. The equilibrium value of $\hat{z}^*(\phi,R)$ is given by

$$\hat{z}^*(R) = \frac{n-1}{2}\phi\int_{\hat{z}^*}^1[1-F(v)]dv + \frac{n-1}{2}(1-\phi)\max\{\mu-\hat{z}^*,0\} + R \tag{A-5}$$

Differentiating (A-5) with respect to R results in

$$\begin{aligned}\frac{\partial\hat{z}^*(R)}{\partial R} &= \begin{cases} 1/(1+\frac{n-1}{2}(1-\phi F(\hat{z}^*))) & if \quad \hat{z}^* \leq \mu \\ 1/(1+\frac{n-1}{2}\phi(1-F(\hat{z}^*))) & if \quad \hat{z}^* > \mu \end{cases} \\ &> 0.\end{aligned}$$

Differentiating (A-5) with respect to ϕ results in

$$\begin{aligned}\frac{d\hat{z}^*(\phi, R)}{d\phi} &= \begin{cases} \int_0^{\hat{z}^*} F(v)dv/(2+(1-\phi F(\hat{z}^*))) & if \quad \hat{z}^* \leq \mu \\ \int_{\hat{z}^*}^1 (1-F(v))dv/(2+\phi(1-F(\hat{z}^*))) & if \quad \hat{z}^* > \mu \end{cases} \\ &> 0.\end{aligned}$$

Hence, $\frac{d\phi^*(R)}{dR} < 0$. ■

Proof of Proposition 6. From equations (13) and (14), it is immediate that $\overline{x}^I(\phi)$ and $\bar{x}^U(\phi)$ are independent of r; and so is $\overline{X}(\phi) = n[\phi\overline{x}^I(\phi) + (1-\phi)\bar{x}^U(\phi)]$, proving part (a). To prove part (b), note that the value of information is $(1+r)\Delta(\bar{z}) = \frac{\Lambda(\bar{z})}{\bar{k}}$, where $\bar{k} = \frac{k}{1+r}$. Thus, it suffices to show that ϕ^* and $\overline{X}^*$ are decreasing in $\bar{k}$.

Take any $\bar{k}' > \bar{k}$. If $s\bar{k} \geq \Lambda(\bar{z}(0))$, then, by Proposition 3, $\phi^*(\bar{k}) = \phi^*(\bar{k}^{'}) = 0$ and $\overline{X}^*(\bar{k}) = \overline{X}^*(\bar{k}^{'}) = \frac{n}{n-1}\bar{z}(0)$. If, on the other hand, $sk \leq \Lambda(\bar{z}(1))$, then either $s\bar{k}' < \Lambda(\bar{z}(1))$, which implies that $\phi^*(\bar{k}) = \phi^*(\bar{k}') = 1$ and $\overline{X}^*(\bar{k}) = \overline{X}^*(\bar{k}') = \frac{n}{n-1}\bar{z}(1)$, or $s\bar{k}' > \Lambda(\bar{z}(1))$, which implies that $\phi^*(\bar{k}') < 1$ and $\overline{X}^*(\bar{k}') < \overline{X}^*(\bar{k}) = \frac{n}{n-1}\bar{z}(1)$.

Finally, if $\Lambda(\bar{z}(1)) < s\bar{k} < \Lambda(\bar{z}(0))$, then since $\Lambda(\bar{z}^*(\bar{k})) = \bar{k}s$, simple differentiation yields: $\dfrac{\partial \bar{z}^*(\bar{k})}{\partial \bar{k}} = \dfrac{s}{\Lambda'(\bar{z}^*(\bar{k}))} = \frac{s}{\bar{x}^{U*} - \bar{x}^{I*}} < 0$. Hence, $\dfrac{\partial \overline{X}^*(\bar{k})}{\partial \bar{k}} < 0$. To show that $\dfrac{\partial \phi^*(\bar{k})}{\partial \bar{k}} < 0$, first suppose that $\bar{z}^*(\bar{k}) > \mu$. Then, $x^{U^*} = 0$ and $\dfrac{\partial \phi^*(\bar{k})}{\partial \bar{k}} = \dfrac{\partial}{\partial \bar{k}}[\frac{\bar{z}^*(\bar{k})}{(n-1)\bar{x}^{I*}(\bar{k})}]$. Since $\dfrac{\partial}{\partial \bar{k}}\bar{x}^{I*}(\bar{k}) = -\dfrac{1-F(\bar{z}^*)}{2} \times \dfrac{\partial}{\partial \bar{k}}\bar{z}^*(\bar{k}) = \dfrac{1-F(\bar{z}^*)}{2} \times \dfrac{s}{\bar{x}^{I*}(\bar{k}) - x^{U*}(\bar{k})} > 0$, it follows that

$$\frac{\partial \phi^*(\bar{k})}{\partial \bar{k}} = \frac{-s(n-1) - (n-1)\bar{z}^*(\bar{k})\dfrac{\partial \bar{x}^{I*}(\bar{k})}{\partial \bar{k}}}{[(n-1)\bar{x}^{I*}(\bar{k})]^2} < 0.$$

Next, suppose that $\bar{z}^*(\bar{k}) \leq \mu$. Then, $x^{U*}(\bar{k}) = \dfrac{\mu - \bar{z}^*(\bar{k})}{2}$, which implies that $\dfrac{\partial}{\partial \bar{k}}x^{U*}(\bar{k}) =$

$-\dfrac{1}{2} \times \frac{\partial}{\partial \bar{k}} \overline{z}^*(\bar{k})$. Hence,

$$\begin{aligned}
\frac{\partial \phi^*(\bar{k})}{\partial \bar{k}} &= \left\{ \begin{array}{c} (\frac{-(n+1)s}{2(\overline{x}^{I*}(\bar{k}) - x^{U*}(\bar{k}))})(n-1)(\overline{x}^{I*}(\bar{k}) - x^{U*}(\bar{k})) + \\ +(\frac{(n-1)s}{2(\overline{x}^{I*}(\bar{k}) - x^{U*}(\bar{k}))})(\frac{(1-F(\overline{z}^*)}{2} - \frac{1}{2})(\overline{z}^*(\bar{k}) - (n-1)x^{U*}(\bar{k})) \end{array} \right\} \times \\
&\quad \frac{1}{[(n-1)(\overline{x}^{I*}(\bar{k}) - x^{U*}(\bar{k}))]^2} \\
&= \left\{ \begin{array}{c} (\frac{-(n+1)s}{2})(n-1) + \\ +(\frac{(n-1)s}{2(\overline{x}^{I*}(\bar{k}) - x^{U*}(\bar{k}))})(\frac{-F(\overline{z}^*)}{2})(\overline{z}^*(\bar{k}) - (n-1)x^{U*}(\bar{k})) \end{array} \right\} \times \\
&\quad \frac{1}{[(n-1)(\overline{x}^{I*}(\bar{k}) - x^{U*}(\bar{k}))]^2} < 0, \text{ as desired.}
\end{aligned}$$

To prove part (c), suppose that for $r < k - 1$, $R(r)$ is the direct grant such that $R(r) = r\bar{X}^*(r)$. Since, by Proposition 6, $\frac{d\bar{X}^*(r)}{dr} \geq 0$, we have $\frac{dR(r)}{dr} = \bar{X}^*(r) + r\frac{d\bar{X}^*(r)}{dr} \geq 0$. Moreover, $\bar{X}^*(0) = \bar{X}^*(R(0))$ as $R(0) = 0$. Then, since, by Proposition 5, $\frac{d\bar{X}^*(R(r))}{dr} = \frac{\partial \bar{X}^*(R(r))}{\partial R} \frac{\partial R(r)}{\partial r} \leq 0$, it follows that $\bar{X}^*(r) \geq \bar{X}^*(R(r))$. ■

Proof of Proposition 7. Since warm-glow effectively reduces the cost bound to $(1 - w)k$, it suffices to show that ϕ^* and $\overline{X}^*$ are decreasing in k. The proof is analogous to that of Proposition 6. ■

Proof of Proposition 8. Let $F(v;\alpha)$ be such that $F_\alpha(.) \leq 0$. Note that for a fixed $z \in [0, 1]$, both $Ex^I(v, z; \alpha)$ and $x^I(\mu(\alpha), z)$ are increasing in α, and so is $J(z;\alpha)$ that is defined in the proof of Proposition 1. Then, the unique solution $\overline{z}(\phi;\alpha) \in (0, 1)$ to $J(z;\alpha) = 0$, and thus $\overline{X}(\phi;\alpha) = \frac{n}{n-1}\overline{z}(\phi;\alpha)$, is increasing in α, too. ■

References

[1] Admati, A., and M. Perry (1991)."Joint projects without commitment." *Review of Economic Studies* 58, 259–76.

[2] Andreoni, J. (1990). "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving," *Economic Journal* 100, 464-77.

[3] Andreoni, J. (1993). "An experimental test of the public-goods crowding-out hypothesis". *American Economic Review* 83, 1317–27.

[4] Andreoni, J. (2006a). *Philanthropy*, in S-C. Kolm and J. Mercier Ythier, eds., Handbook of Giving, Reciprocity and Altruism, Amsterdam: North Holland: 1201-69.

[5] Andreoni, J. (2006b). "Leadership giving in charitable fund-raising". *Journal of Public Economic Theory* 8, 1–22.

[6] Andreoni, J., and A. Payne (2003). "Do government grants to private charities crowd out giving or fundraising?" *American Economic Review* 93, 792–812.

[7] Andreoni, J., and A. Payne (2011). "Is crowding out due entirely to fundraising? Evidence from a panel of charities," *Journal of Public Economics* 95 334–43

[8] Auten, G., H. Seig, and C. Clotfelter. 2002. "Charitable Giving, Income, and Taxes: An Analysis of Panel Data." *American Economic Review*, 92(1): 371–82.

[9] Bagnoli, M., and B. Lipman (1989). "Provision of public goods: fully implementing the core through private contributions." *Review of Economic Studies* 56, 583–601.

[10] Barbieri, S, and D. Malueg (2010). "Threshold uncertainty in the private-information subscription game." *Journal of Public Economics* 94 848–61.

[11] Bray, I., 2010. *Effective Fundraising for Nonprofits: Real-World Strategies That Work.* NOLO: Berkeley, CA

[12] Bergstrom, T. , L. Blume, and H. Varian. (1986). "On the Private Provision of Public Goods," *Journal of Public Economics*, 29, 25-49.

[13] Chen, Y., Xin Li, and J. K. MacKie-Mason (2006). "Online Fund-Raising Mechanisms: A Field Experiment," *Contributions to Economic Analysis & Policy*, 5(2), Article 4.

[14] Correa, A., and H. Yildirim (2011). "A Theory of Charitable Fundraising with Costly Solicitations," working paper.

[15] Eckel, C., and P. Grossman (1996). "Altruism in anonymous dictator games." *Games and Economic Behavior* 16, 181–91.

[16] Eckel, C., and P. Grossman (2008). Subsidizing charitable contributions: a natural field experiment comparing matching and rebate subsidies. *Experimental Econonomics* 11, 234-52.

[17] Eckel, C, P. Grossman, and R. Johnston (2005). "An experimental test of the crowding out hypothesis," *Journal of Public Economics* 89 1543–60.

[18] Fong, C. F., and F. Oberholzer-Gee (2011). "Truth in giving: Experimental evidence on the welfare effects of informed giving to the poor," *Journal of Public Economics* 95, 436–44.

[19] Karlan, D., and J. List. 2007. "Does Price Matter in Charitable Giving? Evidence from a Large-Scale Natural Field Experiment." *American Economic Review*, 97(5): 1174–93.

[20] Kelly, K. *Effective Fund-Raising Management*. Hillsdale, N.J.: Erlbaum, 1998.

[21] Laussel, D., and T. Palfrey (2003). "Efficient equilibria in the voluntary contributions mechanism with private information." *Journal of Public Economic Theory* 5, 449–478.

[22] Marks, M., and R. Croson (1998). "Alternative rebate rules in the provision of a threshold public good: an experimental investigation." *Journal of Public Economics* 67 (2), 195–220.

[23] Martimort, D., and H. Moreira (2010). "Common agency and public good provision under asymmetric information." *Theoretical Economics* 5, 159–213.

[24] McBride, M., (2006). "Discrete public goods under threshold uncertainty." *Journal of Public Economics* 90, 1181–99.

[25] Meier, S. (2007). "Do Subsidies Increase Charitable Giving in the Long Run? Matching Donations in a Field Experiment." *Journal of the European Economic Association*, 5(6): 1203–22.

[26] Menezes, F., P. Monteiro, and A. Temimi (2001). “Private provision of discrete public goods with incomplete information.” *Journal of Mathematical Economics* 35, 493–514.

[27] Nitzan, S., and R. Romano (1990). “Private provision of a discrete public good with uncertain cost.” *Journal of Public Economics* 42, 357– 70.

[28] Palfrey, T., and J. Prisbrey (1997). “Anomalous behavior in public goods experiments: how much and why?” *American Economic Review* 87, 829–46.

[29] Palfrey, T., and H. Rosenthal (1984). “Participation and the provision of discrete public goods: a strategic analysis.” *Journal of Public Economics* 24, 171– 93.

[30] Ribar, D., and M. Wilhelm (2002). “Altruistic and joy-of-giving motivations in charitable behavior.” *Journal of Political Economy* 110, 425–57.

[31] Rondeau, D., W. Schulze, and G. Poe (1999). “Voluntary revelation of the demand for public goods using a provision point mechanism.” *Journal of Public Economics* 72 (3), 455–70.

[32] Sharpe, A., 2007. http://ezinearticles.com/?Response-Rates-to-Expect-in-Direct-Mail-Fundraising-with-Acquisition-and-Renewal-Appeal-Letters&id=465481.

[33] Spencer, M., S. Swallow, J. Shogren, and J. List (2009). “Rebate Rules in Threshold Public Good Provision.” *Journal of Public Economics* 93(5-6): 798-806.

[34] Strom, S. “Charities Rise, Costing U.S. Billions in Tax Breaks,” *New York Times*, 2009

[35] Vesterlund, L. (2003). “The informational value of sequential fundraising,” *Journal of Public Economics* 87, 627–57.

[36] Vesterlund, L. (2006). Why do people give? , in (W. Powell and R.S. Steinberg, eds.), *The Nonprofit Sector: A Research Handbook*, 2nd Edition, pp. 568–87, New Haven, CT: Yale University.