

Comparing Charitable Fundraising Schemes: Evidence from a Natural Field Experiment and a Structural Model[†]

By STEFFEN HUCK, IMRAN RASUL, AND ANDREW SHEPHARD*

We present evidence from a natural field experiment and structural model to shed light on the efficacy of alternative fundraising schemes. In conjunction with the Bavarian State Opera, we mailed 25,000 opera attendees a letter describing a charitable fundraising project organized by the opera house. Recipients were randomly assigned to treatments designed to explore responses to fundraising schemes varying in: the presence of a lead donor; and how individual donations would be matched using the lead donation. The structural model estimates extensive and intensive margin responses, and is then utilized to predict giving behavior in counterfactual fundraising schemes. (JEL C93, D64, L31, L82)

This paper presents evidence from a large-scale natural field experiment designed to shed light on the efficacy of alternative fundraising schemes. We present reduced form evidence on the role of lead gifts, and linear and nonlinear matching schemes in inducing individuals to give to a charitable cause. We then develop and estimate a structural model of giving that is identified from the experimental variation across treatments, to inform the optimal design of fundraising schemes. The analysis provides new insights on individual giving behavior and shows how some standard practices among fundraisers can be improved upon.¹

Much of the existing literature has focused on responses to two types of commonly observed fundraising scheme—linear matching (Eckel and Grossman 2006; Karlan and List 2007; Huck and Rasul 2011) and the provision of lead gifts (List

*Huck: Research Unit Economics of Change, WZB, Reichpietschufer 50, 10785 Berlin, Germany and Department of Economics, University College London (e-mail: s.huck@ucl.ac.uk); Rasul: Department of Economics, University College London, Drayton House, 30 Gordon Street, London WC1H 0AX, UK (e-mail: i.rasul@ucl.ac.uk); Shephard: 522 McNeil Building, University of Pennsylvania, 3718 Locust Walk, Philadelphia, PA 19104 (e-mail: asheph@econ.upenn.edu). We thank Sami Berlinski, Stéphane Bonhomme, Guillermo Caruana, Syngjoo Choi, Heike Harggart, Dean Karlan, David Lee, John List, Derek Neal, Adam Rosen, Georg Weizsäcker, and numerous seminar participants for useful comments. We gratefully acknowledge financial support from the ESRC and ELSE. We thank all those at the Munich Opera House, Actori, and Maurice Lausberg for making this project possible. This paper has been screened to ensure no confidential information is revealed. All errors remain our own.

[†]Go to <http://dx.doi.org/10.1257/pol.20120312> to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

¹Andreoni (2006b) presents evidence from the United States that in 1995, 70 percent of households made some charitable donation with an average donation of over \$1,000, or 2.2 percent of household income. List and Price (2012) provide evidence that in 2003, \$241 billion was given in the United States, corresponding to 2 percent of GDP, 75 percent of which stemmed from individuals.

and Lucking-Reiley 2002; Potters, Sefton, and Vesterlund 2007; Rondeau and List 2008; Bracha, Menietti, and Vesterlund 2011). We build on this literature by enlarging the set of fundraising schemes to encompass both commonly observed and novel schemes, and to compare them within the same setting. Our design provides external validity to aspects of giving behavior that have been previously documented, allows us to provide new evidence on other dimensions of giving behavior, and sheds light on the optimal design of fundraising schemes.

Methodologically, we provide both reduced form and structural form evidence from the natural field experiment on the causal impact of each fundraising scheme on: (i) the extensive margin of giving, namely, whether an individual donates some positive amount; and (ii) the intensive margin of giving, namely, the amount donated. We develop a structural model of giving behavior that simultaneously estimates individual responses on the extensive and intensive margins. The structural model exploits the experimental variation to identify the underlying set of preference parameters consistent with behavior across the fundraising schemes. At a final stage, we utilize the model to predict giving behavior under a series of counterfactual fundraising schemes to make progress on understanding the optimal design of fundraising schemes.²

In conjunction with the Bavarian State Opera in Munich, in June 2006, we mailed 25,000 opera attendees a letter describing a charitable fundraising project organized by the opera house. Our experiment allows us to implement various fundraising schemes in a natural and straightforward way, holding everything else constant. Individuals were randomly assigned to one of six treatments designed to explore behavioral responses to—(i) the presence of a substantial lead donor, which might, for example, act as a signal of project quality (Vesterlund 2003; Andreoni 2006b); (ii) linear matching schemes where contributions were matched at either 50 percent or 100 percent, analogous to considerable reductions in the relative price of charitable giving vis-à-vis own consumption; (iii) nonlinear matching schemes, where contributions above a fixed threshold would be matched at a given rate; and (iv) fixed gift matching schemes, in which *any* positive donation would be matched by a fixed amount. The design of the experiment allows us to compare behavior under commonly observed fundraising schemes that involve a lead donor or linear match rates, to less commonly observed schemes involving nonlinear or fixed gift matching.

In earlier work, Huck and Rasul (2011), we have presented reduced form results from this experiment on the efficacy of schemes in which a lead donor is announced relative to a control group in which no such announcement is made, and the efficacy of *linear* matching schemes versus the lead donor scheme. We found individuals to be highly responsive to the announcement of a lead donor: relative to a control group in which no information on lead gifts is provided, donations given nearly double, but with no change in overall response rates. In terms of linear matching schemes, we previously found that as the charitable good becomes cheaper vis-à-vis own consumption, individuals demand more of it in terms of

²With the exception of DellaVigna, List, and Malmendier (2012) who study whether altruism and social pressure explain giving behavior, there are few papers in the economics of charitable giving that combine field experimental with structural estimation of preference parameters.

donations received *including* the match, but spend less on it themselves in terms of donations given prior to the match. In other words, linear matching leads to partial crowding out of the donations actually given. Hence, from the fundraiser's perspective, the fundraiser is better off announcing the lead donation rather than using it to *linearly* match the donations of others. In that earlier work, we used these linear match treatments to focus on estimating price and income elasticities of giving and compare them to other estimates in the literature derived from experimental and non-experimental data.

The key contributions of the present paper over our earlier work and existing literature are threefold. First, our analysis considers a richer set of fundraising schemes that encompasses novel nonlinear and fixed gift matching. By considering a richer set of schemes that involved nonlinear matching, we can probe far further whether a standard neoclassical model of behavior can match all the observed data or whether additional nonstandard features are required to potentially explain the documented evidence. Second, we develop and estimate a structural model of charitable giving that is identified from the variation induced in the natural field experiment. Third, we use our preferred structural model of giving behavior to explore the effectiveness of alternative charitable fundraising schemes to shed light on the *optimal* fundraising scheme.

On the structural model, we assume a parametric random quasi-linear form for preferences defined over consumption and the donation received by the charitable organization: this utility function implies individuals have warm glow preferences (Andreoni 2006a), or *purely egoistic* preferences in the original terminology of Andreoni (1990). In this baseline model, individuals are heterogeneous with respect to their valuation of the lead donation received (so that preference parameters can depend on individual characteristics), and we allow for the possibility that the presence of the lead donor alters the marginal benefit from donating. This parsimonious specification provides an empirically tractable framework in which we can simultaneously estimate behavior on the extensive and intensive margins of giving.

To better exploit specific features of our empirical setting, we then extend the baseline model to allow for features including: (i) individuals restricting their donation choice to some discrete set; (ii) some fraction of individuals exhibiting what we term "pure warm glow" preferences, so that they derive utility from the value of their donation given, *regardless* of how this is matched, as well as their own private consumption; and (iii) focal point influences, so that some subset of donation amounts might be particularly attractive for some individuals.

Our preferred structural model closely matches the empirically observed response rates across all six treatments: the control group, the lead donor treatment, and the four treatments where the lead donation is matched using a linear or nonlinear scheme. Furthermore, in all but the fixed gift matching treatment, we are able to match not only mean donations given, but also do a good job in fitting the entire distribution of donations. In short, a relatively parsimonious model that simultaneously allows for focal point influences and some individuals to exhibit pure warm glow preferences can explain individual behavior on the majority of margins considered.

The structural estimates reveal that: (i) consistent with the reduced form evidence, characteristics indicating affinity to the opera house increase the mean value of donations; (ii) around one-third of individuals are best characterized as having

pure warm glow preferences; and (iii) individuals place particular prominence on donation amounts of €50 and €100.

On the counterfactual exercises, we could in principle consider almost any matching scheme. However we focus attention to parametric forms that are combinations of the linear and nonlinear schemes implemented in the experiment. These are realistic extensions of commonly observed fundraising schemes. Amongst this set, the counterfactual exercises reveal the optimal fundraising scheme is one in which the charitable organization merely announces the existence of a significant and anonymous lead donor, and does *not* use the lead donation to match donations in any way, be it through linear matching, nonlinear matching, threshold matching, or some combination of the three. If, however, lead donors *insist* their gifts must be matched in some way, our counterfactual exercise shows the fundraiser is best off using a nonconvex matching scheme, that would be an innovation for many fundraisers.

Taken together, our analysis provides a rich set of results that shed new light on individual giving behavior and the optimal design of fundraising schemes, and provide avenues for future research on the role of lead donors in charitable giving. Our main natural field experiment was primarily designed to shed light on the efficacy of alternative fundraising schemes, not to pin down why lead gifts might be so effective. As a first step in this direction, we conclude by providing evidence from a follow-up natural field experiment designed to probe further the question of *why* lead donors are so effective in inducing others to give. This examines how responses to lead donors varies according to their monetary value and anonymity of the lead gift.

The paper is organized as follows. Section I describes the natural field experiment, and presents a conceptual framework in which to understand behavior across the treatments. Section II provides reduced form evidence on responses on the extensive and intensive margins of charitable giving in each treatment. Section III develops and estimates a structural model of individual behavior, and conducts a counterfactual exercise to shed light on the optimal fundraising scheme. Section IV concludes with evidence from the follow-up experiment. The Appendix provides additional results and details on the precise format and wording of the mail out.

I. The Natural Field Experiment

A. Design

In June 2006, the Bavarian State Opera organized a mail out letters to 25,000 individuals designed to elicit donations for a social youth project the opera was engaged in, “Stück für Stück.” These individuals were randomly selected from the opera’s database of customers who had purchased at least one ticket to attend the opera house in the year prior to the mail out. The project’s beneficiaries are children from disadvantaged families whose parents are unlikely to be among the recipients of the mail out, thus making the campaign similar to fundraising drives by aid charities.³

³The project finances small workshops and events for schoolchildren with disabilities or from disadvantaged areas. These serve as a playful introduction to the world of music and opera. It is part of the Bavarian State Opera’s mission to preserve the operatic art form for future generations and the project is therefore a key activity. The

Individuals were randomly assigned to one of six treatments. Treatments varied in two dimensions—whether information was conveyed about the existence of an anonymous lead donor, and how individual donations would be matched by the anonymous lead donor. The mail out letters were identical in all treatments with the exception of one paragraph. The precise format and wording of the mail out is provided in the Appendix.⁴

The control treatment, denoted T1, was such that recipients were provided no information about the existence of a lead donor, and offered no commitment to match individual donations. The wording of the key paragraph in the letter read as follows,

T1 (Control): *This is why I would be glad if you were to support the project with your donation.*

This paragraph is manipulated in the other treatments. In the second treatment, denoted T2, recipients were informed that the project had already garnered a lead gift of €60,000. The corresponding paragraph read as follows,

T2 (Lead Donor): *A generous donor who prefers not to be named has already been enlisted. He will support “Stück für Stück” with €60,000. Unfortunately, this is not enough to fund the project completely which is why I would be glad if you were to support the project with your donation.*

The control and lead donor treatments differ only in that in the latter, recipients are informed of the presence of a lead donor. There is no offer to match donations in any way in either treatment—a donation of €1 corresponds to €1 being received for the project. A comparison of individual behaviors over the two treatments sheds light on whether and how individuals respond to the existence of such lead donors. The literature suggests lead donors might alter the marginal utility of giving of others through a variety of channels, such as lead gifts serving as a signal about the quality of the fundraising project (Vesterlund 2003), snob appeal effects (Romano and Yildirim 2001), or in the presence of increasing returns, such lead gifts eliminate an equilibrium in which all donations are zero (Andreoni 1998).⁵ As our experiment is not designed to disentangle these explanations, when we later develop our model of giving we assume the knowledge of a significant lead gift alters the marginal utility of giving, that captures these channels in a general way.

The next two treatments provided recipients with the same information on the presence of a lead donor, but introduced linear matching, as is commonly observed in fundraising drives. The first of these treatments, denoted T3, informed recipients

research design is a natural field experiment because it occurs in an environment where individuals are naturally asked to provide charitable donations, and mail out recipients do not know they are taking part in an experiment (Harrison and List 2004).

⁴All letters were designed and formatted by the Bavarian State Opera’s staff, and addressed to the individual as recorded in the database of attendees. Each recipient was sent a cover letter describing the project, in which one paragraph was randomly varied in each treatment. The second sheet of the mail out further details how the “Stück für Stück” project was provided. Letters were signed by the General Director of the opera house, Sir Peter Jonas, and were mailed on the same day—June 19, 2006.

⁵Andreoni (2006b) highlights the problem that lead donors have incentives to overstate the quality of the project. Since such deception cannot arise in equilibrium, it follows that lead gifts need to be extraordinarily large to be credible signals of quality. In our study the lead gift is hundreds of times larger than the average donation.

that each donation would be matched at a rate of 50 percent, so that giving €1 would correspond to the opera receiving €1.50 for the project. The corresponding paragraph in the mail out letter then read as follows:

T3 (50 percent Matching): *A generous donor who prefers not to be named has already been enlisted. He will support “Stück für Stück” with up to €60,000 by donating, for each Euro that we receive within the next four weeks, another 50 Euro cent. In light of this unique opportunity I would be glad if you were to support the project with your donation.*

The next treatment, denoted T4, was identical to T3 except the match rate was set at 100 percent, so the corresponding paragraph in the mail out letter read as follows:⁶

T4 (100 percent Matching): *A generous donor who prefers not to be named has already been enlisted. He will support “Stück für Stück” with up to €60,000 by donating, for each donation that we receive within the next four weeks, the same amount himself. In light of this unique opportunity I would be glad if you were to support the project with your donation.*

The final two treatments introduced more novel fundraising schemes, neither of which have been previously studied in Huck and Rasul (2011). The fifth treatment presented recipients with a nonlinear, nonconvex matching scheme. The letter offered a match rate of 100 percent conditional on the donation given being above a fixed threshold—€50. Below this threshold the match rate was zero. This was explained in the mail out letter as follows:

T5 (Nonlinear Matching): *A generous donor who prefers not to be named has already been enlisted. He will support “Stück für Stück” with up to €60,000 by donating, for each donation above €50 that we receive within the next four weeks, the same amount himself. In light of this unique opportunity I would be glad if you were to support the project with your donation.*

Beyond allowing a comparison between common and novel fundraising schemes, this treatment allows us to study the role of interior corner solutions as recipients who would otherwise have given a positive amount below €50 in treatment T4 might find it optimal to give precisely €50. Moreover, the nonconvexity might introduce a focal point for donations at €50. If such focal points influence behavior, then recipients who would have otherwise given at least €50 under treatment T4, might be induced to *reduce* their donation given toward €50 under T5. The structural estimates presented later account for such focal point influences on behavior.⁷

⁶We note that the wording of T3 and T4 differ also in how they refer to the monetary contribution of the lead donor: T3 states the lead donor provides “another 50 Euro cent,” while T4 states that the lead donor provides the “same amount himself.” Hence, a comparison between these treatments picks up a change in the relative price of giving plus any subtle changes induced by how such wording might be interpreted by donors.

⁷Briers, Pandelaere, and Warlop (2007) suggest such conditional gifts provide a reference point for expected donation levels. While these nonlinear treatments are novel in the charitable fundraising literature, they are more commonly observed in savings plans (Madrian 2012).

The final treatment offered recipients a fixed positive match of €20 for any positive donation. This corresponds to a parallel shift out of the budget line and we refer to this as the “fixed gift” treatment. It was explained in the mail out letter as follows:

T6 (Fixed Gift Matching): *A generous donor who prefers not to be named has already been enlisted. He will support “Stück für Stück” with up to €60,000 by donating, for each donation that we receive within the next four weeks regardless of the donation amount, another €20. In light of this unique opportunity I would be glad if you were to support the project with your donation.*

As small donations have enormous leverage, this treatment allows us to bound the share of recipients who do not value the project and would be unlikely to contribute in the presence of small transactions costs of doing so.

Four points are worth bearing in mind regarding the experiment. First, a key distinction between our experimental design and that of Karlan and List (2007) is that they do not have a treatment that isolates the pure impact of a lead donor in the absence of any linear matching. This is precisely what our lead donor treatment T2 captures. Rather they compare their matching treatments with the equivalent of our control treatment T1, where there is no lead gift. Our design allows us to decompose the effect of matching into an impact coming from the presence of the lead donor, and the pure price effects of matching donations. However, we also reiterate that this natural field experiment was primarily designed to shed light on the efficacy of alternative fundraising schemes, not to pin down *why* lead gifts might be effective. In the concluding section, we therefore discuss a follow-up natural field experiment that was designed to probe further the question of why lead donors are so effective in inducing others to give. This examines how responses to lead donors varies according to their monetary value and anonymity of the lead gift.

Second, the opera had no explicit fundraising target in mind, nor was any such target discussed in the mail out. This is key to interpreting behavior when comparing the control and lead donor treatments. For example, by announcing a lead donor that had committed to providing €60,000 in treatment T2, recipients may feel their individual donation is less needed. However, the mail out makes clear that the money raised for the project is not used to finance one large event but rather a series of several smaller events. Hence, the project is of a linearly expandable nature such that recipients likely interpret that their marginal contributions will make a difference.^{8,9}

Third, in treatments T3 to T6, recipients were told the matching schemes would be in place for four weeks after receipt of the mail out. The deadline was not binding: over 97 percent of donations were received during this time frame and the median donor gave within a week of the mail out. Moreover, we find no evidence of

⁸The effects of such seed money are in general ambiguous and depend on whether individuals believe the project is far from, or close to, its designated target and whether these beliefs encourage or discourage donations. Lucking-Reiley and List (2002) demonstrate that as seed money brings donors closer to an explicit target, donations rise on both the extensive and intensive margins. A similar finding is also reported in Rondeau and List (2008).

⁹Although we cannot rule out with certainty that donors perceive there to be an implicit target, we note that if recipients have the same belief that others had donated to such an extent that the €60,000 of the lead donor was already exhausted, and so the match scheme would no longer be in place, there should be no difference in behaviors across treatments T2 to T6. This hypothesis is rejected by the data.

differential effects on the time for donations to be received between any treatment and the control treatment, in which no such deadline was announced.¹⁰

Finally, recipients are told the truth—the lead gift was actually provided and each matching scheme was implemented (so that in the matching schemes, the lead donor *only* contributed to match the donations of others). The value of matches was capped at €60,000 which ensured subjects were told the truth even if the campaign was more successful than anticipated and, crucially, this holds the commitment of the lead donor constant across treatments.

B. Conceptual Framework

We present a simple framework in which to think through the individual utility maximization problem under each treatment. This makes precise what can be inferred from a comparison of behavior across treatments in the reduced form estimates presented in Section II. This framework is then taken to the data using structural estimation methods in Section III. Following standard consumer theory, we assume individual preferences are defined over private consumption, c , and the donation received by the project, d_r . The individual utility maximization problem is,

$$(1) \quad \max_{d_r} u(c, d_r) \text{ subject to } c + d_g \leq y, c, d_g \geq 0, \text{ and } d_r = R_T(d_g),$$

where the first constraint ensures consumption can be no greater than income net of any donation given, $y - d_g$; the second constraint requires consumption and donations given to be nonnegative; and the third constraint denotes the matching scheme that translates donations given into those received by the opera house in treatment T . Under linear matching treatments for example, $d_r = \lambda d_g$. This utility function captures the notion that potential donors care about their own consumption and the *marginal* benefit their donation provides. Given the linearly expandable nature of the project, this marginal benefit relates to d_r .¹¹

Figure 1 graphs the budget sets induced by the six treatments in $(y - d_g, d_r)$ -space. In the control treatment (T1), the budget line has vertical intercept y and a slope of minus one, as for each Euro given by an individual, the project receives one Euro ($d_r = d_g$). The budget set is identical under the lead donor treatment (T2), as there is no matching and, so, the relative price of donations received is unchanged. However, if, for example, individuals infer the project is of high quality due to the existence of a lead donor, the marginal benefit of giving may be altered and, so, affect behavior

¹⁰As recipients were drawn from the database of opera attendees, recipients might know each other. Having knowledge of whether another opera attendee had received the mail out, and the form of the letter they received, may in principle change behavior if there are peer effects in charitable giving. We expect such effects to be qualitatively small and, indeed, the opera house received no telephone queries regarding treatment differences.

¹¹Following the terminology of Andreoni (1990), individuals are thus assumed to have *purely egoistic* preferences, where they do not care about the total amount raised for the charitable cause. If the total amount raised enters the utility function (and so individuals are impure altruists in the terminology of Andreoni (1990)), and is concave in this argument, then individuals should give less if they know there is already a large donation relative to the control group absent such a lead donation. This would be inconsistent with our findings.

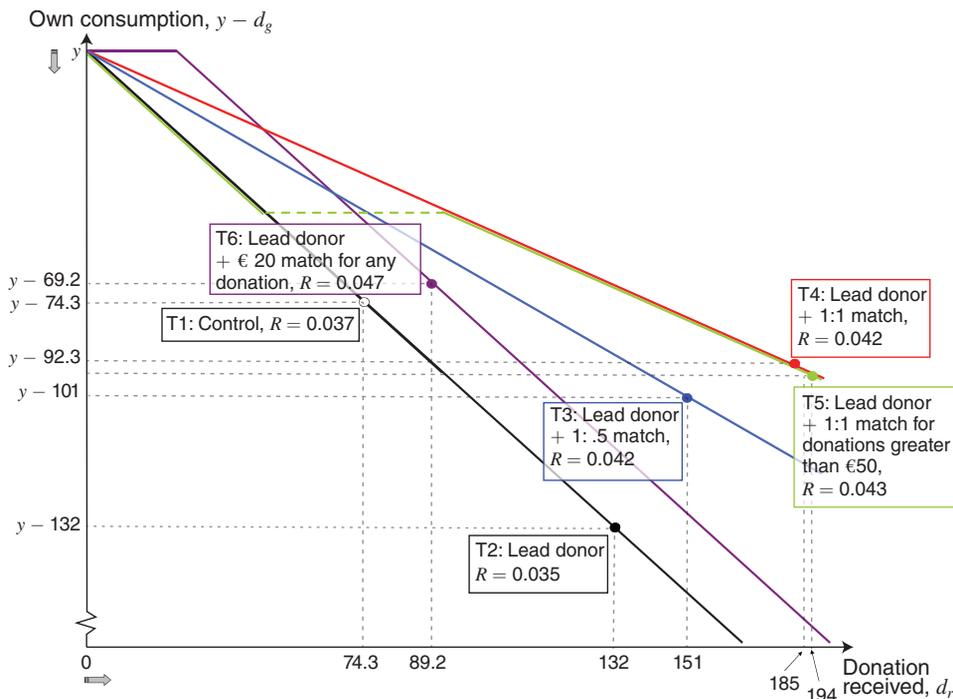


FIGURE 1. THE DESIGN OF THE FIELD EXPERIMENT AND OUTCOMES

on both the extensive and intensive margins. We empirically estimate whether the impact is to increase or decrease donations.

In all remaining treatments individuals are, as in T2, aware of the existence of a lead donor. Hence, in order to isolate the effect of variations in the budget set on behavior, the relevant comparison group throughout is the lead donor treatment T2. The linear matching schemes in treatments T3 and T4 vary the price of donations relative to own consumption so that with the 50 percent match rate in T3, $\lambda = 1.5$, and with the 100 percent match rate in T4, $\lambda = 2$. In both cases the budget set pivots out with the same vertical intercept. As Huck and Rasul (2011) show, comparing treatments T2, T3, and T4 provides estimates of the own price elasticity of charitable donations received as the match rate varies. The structural estimates allow for individuals to have heterogeneous preferences—and, hence, differ in their price elasticities of giving.¹²

An alternative framework would be what we term the “*pure warm glow*” model, a special case of the preferences described in Andreoni (1990, 2006a). This implies donors care only about their own consumption ($y - d_g$) and their donation given (d_g) but not about the value of the match, ($d_r - d_g$). In this special case, the budget sets would be materially identical for donors. However, as documented later, the data

¹²Charitable donations are tax deductible in Germany, which implies the actual price of the donation received will always be marginally lower than assumed here. Any such differences will wash out in the treatment comparisons due to random assignment.

rejects the hypothesis that *on average* donors behave according to this hypothesis. In the structural estimation, we consider a scenario where some fraction of individuals have pure warm glow preferences, and estimate this fraction along with other preference parameters.

The nonlinear matching scheme in treatment T5 causes recipients to face a non-convex budget constraint that partly overlaps with those in T2 and T4. This treatment introduces kinks into the budget line, and, so, can lead to an interior corner solution in the individual optimization problem. This raises the possibility of donations given being crowded in by such schemes. Moreover, the nonconvexity might introduce a focal point for donations at €50. The structural estimation accounts for such focal point influences on behavior.

For each budget set considered, individuals may optimally locate at an exterior corner. Note however that every individual with preferences satisfying $\frac{\partial u}{\partial d_r} \Big|_{d_r=0} > 0$ should make a small positive donation in the fixed gift scheme T6. This treatment should then have the highest response rates, and allows us to bound the share of recipients for whom $\frac{\partial u}{\partial d_r} \Big|_{d_r=0} \leq 0$ and, so, are unlikely to contribute to the project in the presence of small transactions costs of doing so. The structural model simultaneously estimates behavior along the extensive and intensive margins of giving.

II. Descriptive Evidence

A. Sample Characteristics and Treatment Assignment

Individuals that purchase a ticket are automatically placed in the opera house's database. The original mail out was sent to 25,000 individuals in the database. We remove non-German residents, corporate donors, formally titled donors, and recipients to whom we cannot assign a gender—typically couples. The working sample is then based on 22,512 individuals.

Individuals were randomly assigned to one of six treatments. Table 1 tests whether individuals differ across treatments in the individual characteristics obtained from the opera's database. Table 1 reports the p -values on the null hypothesis that the mean characteristics of individuals in the treatment group are the same as in the control group T1. There are almost no significant differences along any dimension between recipients in each treatment.

We see there is an almost equal split of recipients across treatments, and that close to 47 percent of all recipients are female. Columns 2–6 provide information on individuals' opera-related expenditures. This is measured by the number of tickets the individual has ordered in the 12 months prior to the mail out, the number of separate ticket orders that were placed over the same period, the average price paid per ticket, and the total amount spent. Individuals in the sample typically purchase around six tickets in the year prior to the mail out in two separate orders. The average price per ticket is around €86 with the annual total spent on attendance averaging over €400. We use information on the zip code of residence of individuals to identify that

TABLE 1—CHARACTERISTICS OF RECIPIENTS BY TREATMENT

Treatment number and description [number of ind.]	Female [Yes = 1] (1)	Number of tickets bought in last 12 months (2)	Number of ticket orders in last 12 months (3)	Average price of tickets bought in last 12 months (4)	Total value of all tickets bought in last 12 months (5)	Munich resident [Yes = 1] (6)	Year of last ticket purchase [2006 = 1] (7)	<i>F</i> -test of joint significance (8)
T1: Control [<i>N</i> = 3,787]	0.466 (0.008)	6.30 (0.178)	2.23 (0.047)	86.6 (0.666)	416 (7.88)	0.416 (0.008)	0.565 (0.008)	
T2: Lead donor [<i>N</i> = 3,770]	0.478 (0.008) [0.269]	6.27 (0.153) [0.906]	2.22 (0.046) [0.838]	86.3 (0.650) [0.687]	423 (7.73) [0.541]	0.416 (0.008) [0.980]	0.574 (0.008) [0.115]	[0.280]
T3: Lead donor + 1:0.5 match [<i>N</i> = 3,745]	0.481 (0.008) [0.182]	6.39 (0.184) [0.729]	2.20 (0.049) [0.700]	86.8 (0.660) [0.877]	432 (9.63) [0.197]	0.416 (0.008) [0.991]	0.576 (0.008) [0.323]	[0.656]
T4: Lead donor + 1:1 match [<i>N</i> = 3,718]	0.477 (0.008) [0.314]	6.46 (0.148) [0.489]	2.28 (0.050) [0.439]	85.8 (0.667) [0.394]	435 (9.78) [0.124]	0.419 (0.008) [0.819]	0.576 (0.008) [0.772]	[0.394]
T5: Lead donor + 1:1 match for donations greater than €50 [<i>N</i> = 3,746]	0.476 (0.008) [0.377]	6.31 (0.145) [0.969]	2.21 (0.046) [0.788]	85.2 (0.657) [0.132]	419 (7.39) [0.781]	0.426 (0.008) [0.385]	0.567 (0.008) [0.663]	[0.304]
T6: Lead donor + €20 match for any donation [<i>N</i> = 3,746]	0.486 (0.008) [0.082]	6.09 (0.132) [0.359]	2.20 (0.047) [0.616]	86.5 (0.657) [0.843]	416 (8.05) [0.962]	0.428 (0.008) [0.270]	0.556 (0.008) [0.970]	[0.575]

Notes: Mean, standard errors in parentheses. *p*-value on *t*-test of equality of means with control group in brackets. All figures refer to the mail out recipients in each treatment excluding non-German residents, corporate donors, formally titled donors, and recipients to whom no gender can be assigned. The *t*-tests of equality are based on an OLS regression allowing for robust standard errors. All monetary amounts are measured in euros. In columns 2 to 5 the “last twelve months” refers to the year prior to the mail out from June 2005 to June 2006. In column 8, we report the *p*-value on an *F*-test of the joint significance of these characteristics of a regression on the treatment dummy, where the omitted treatment category is the control group.

around 41 percent of recipients reside within Munich (column 6), where the opera house is located. We note that the majority of individuals have attended the opera in the six months prior to the mail out (column 7).¹³

The number of tickets bought, the number of orders placed, and whether or not a person lives in Munich can proxy an individual’s affinity to the opera. This may in turn relate to how they trade-off utility from consumption for utility from donations received by the opera for the “Stück für Stück” project. We later exploit this information in the structural model by allowing underlying preference parameters to vary with these observables.

Finally, we recognize that recipients are not representative of the population—they attend the opera more frequently than the average citizen and are likely to have higher disposable incomes. Our analysis sheds light on how such selected individuals donate toward a project that is being directly promoted by the opera house. To the extent that other organizations *also target* charitable projects toward

¹³In column 8 we report the *p*-value on an *F*-test of the joint significance of these characteristics of a regression on the treatment dummy, where the omitted treatment category is the control group. For each comparison to the control group, we do not reject the null.

those with high affinity to the organization as well as those who are likely to have high income, the results have external validity in other settings.¹⁴ Moreover, while the nonrepresentativeness of the sample may imply the observed *levels* of response or donations likely overstate the response among the general population, we focus attention on *differences* in behavior across treatments that purge the analysis of the common characteristics of sample individuals.¹⁵

B. Reduced Form Evidence

Table 2 provides descriptive evidence on the extensive and intensive margins of giving, by treatment. For each statistic we report its mean, its standard error in parentheses, and whether it is significantly different from that in the control and lead donor treatments, T1 and T2, respectively. Figure 1 provides a graphical representation of the outcomes of each treatment. Column 1 of Table 2 shows that among the full sample of 25,000 original recipients, more than €120,000 was donated, and triggering matches that fully exhausting the €60,000 of the lead donor. In our working sample of 22,512 individual recipients, from a total of 922 donors, €85,900 was donated overall, which, as column 2 shows, corresponds to €127,039 actually raised for the project (including the value of matches), with a mean donation given of €93.2.¹⁶

The Extensive Margin.—Column 3 shows that response rates vary from 3.5 percent to 4.7 percent across treatments, which are almost double those in comparable large-scale natural field experiments on charitable giving (Eckel and Grossman 2006; Karlan and List 2007).¹⁷ However, despite there being large variations in the budget sets individuals face in treatments T1 to T5, there are no statistically significant differences in response rates. Neither the presence of a lead donor nor changes in price significantly affect behavior along the extensive margin.

However, as with many studies of charitable giving, given low responses rates (despite the original mail out being sent to over 22,000 individuals with high affinity to the charitable organization), we are only powered to detect relatively large differences in these response rates across treatments. In consequence, some of the estimated response rates had wide confidence intervals so that, in proportionate terms, large impacts on this margin cannot be ruled out. For example, although as column 3 shows, response rates to the two matching treatments T3 and T4 are not statistically

¹⁴de Oliveira, Croson, and Eckel (2011) use an artefactual field experiment to identify “giving types”: such individuals respond to a given fundraising drive and are found to be more likely to also give to other charitable organizations.

¹⁵Of course, individuals that have affinity to the opera might be very different on observables to those that have affinity to other causes. Our later results show that some observables predict giving both in the reduced form estimates, and that the structural parameter estimates are functions of other observables (as shown in Table A1). As a result, levels of giving will differ across populations affiliated with different charitable causes. Conditional on observables, we find the price responsiveness of targeted donors in this setting is in line with previous elasticity estimates from many different settings (Huck and Rasul 2011).

¹⁶This exceeded the expectations of the Bavarian State Opera which were that €22,000 would be donated overall on the basis of a 1 percent response rate and mean donation of €100.

¹⁷One explanation for the high response rates we obtain may be that the Bavarian State Opera has not previously engaged in fundraising activities through mail outs, nor is the practice as common in Germany as it is in the US.

TABLE 2—FUNDRAISING OUTCOMES BY TREATMENT

Treatment number and description	Comparison group	Aggregates		All recipients		Donors only	
		Total amount donated (1)	Total amount raised (2)	Response rate (3)	Average donation given (4)	Average donation received (5)	Average donation given (6)
T1: Control		10,550	10,550	0.037 (0.003)	2.79 (0.326)	74.3 (6.19)	74.3 (6.19)
T2: Lead donor		17,416	17,416	0.035 (0.003)	4.62 (0.635)	132 (14.3)	132 (14.3)
	T1 Control			[0.564]	[0.010]	[0.000]	[0.000]
T3: Lead donor + 1: .5 matching		15,705	23,558	0.042 (0.003)	4.19 (0.618)	151 (18.9)	101 (12.6)
	T1 Control			[0.355]	[0.044]	[0.000]	[0.061]
	T2 Lead donor			[0.134]	[0.631]	[0.421]	[0.102]
T4: Lead donor + 1:1 matching		14,310	28,620	0.042 (0.003)	3.84 (0.526)	185 (20.7)	92.3 (10.4)
	T1 Control			[0.352]	[0.086]	[0.000]	[0.136]
	T2 Lead donor			[0.133]	[0.350]	[0.037]	[0.025]
T5: Lead donor + 1:1 matching for donations greater than €50		15,671	31,107	0.043 (0.003)	4.18 (0.521)	194 (19.3)	97.9 (9.59)
	T1 Control			[0.249]	[0.023]	[0.000]	[0.039]
	T2 Lead donor			[0.084]	[0.596]	[0.010]	[0.049]
T6: Lead donor + €20 match for any donation		12,248	15,788	0.047 (0.003)	3.27 (0.353)	89.2 (5.51)	69.2 (5.51)
	T1 Control			[0.036]	[0.314]	[0.073]	[0.539]
	T2 Lead donor			[0.008]	[0.063]	[0.006]	[0.000]

Notes: Mean, standard errors in parentheses. *p*-values on tests of equalities on means with comparison group in brackets. All figures are based on the total sample of recipients of the mail outs excluding non-German residents, corporate donors, formally titled donors, and recipients to whom no gender can be assigned. Columns 1–4 refer to all recipients of the mail out (donors and nondonors). Columns 5–8 refer only to donors. The test of equality of means in columns 4, 5, and 7 are based on an OLS regression allowing for robust standard errors. The test of equality of medians in columns 6 and 8 are based on a quantile regression. The response rate is the proportion of recipients that donate some positive amount, as reported in the donation amount column. The actual donation then received by the opera house in each treatment is reported in the donation received column. All monetary amounts are measured in euros.

different from that in T2, the percentage increases are substantial, being 20 percent higher (and the percentage increases on the extensive margin are even higher for T5 and T6 relative to T2). Moreover, if we pool the linear matching treatments together to increase power, then we can detect a statistically significant difference in response rates relates to the lead donor treatment T2 at the 10 percent significance level.

Treatment T6—that introduces a fixed gift and causes a parallel shift out of the budget set for any positive donation—is the treatment that should induce the largest change in the number of donors relative to the control group. The data supports this—the response rate is significantly higher in T6 relative to the other treatments. However, the fact that the response rate in T6 is 4.7 percent highlights that even among this targeted population, 95 percent of individuals cannot be induced to donate. These individuals either do not value the project at all or must face transaction

costs that are sufficiently high to offset the marginal utility they would obtain from giving to this particular cause, and so optimally locate at the corner solution given by the vertical intercept in Figure 1.¹⁸

The Intensive Margin.—The remainder of Table 2 focuses on the intensive margin of giving: column 4 shows the average amount given in each charitable fundraising scheme, including zeroes among nondonors, while the remaining columns focus on statistics among donors. We now briefly describe these reduced form findings for the most relevant comparisons of charitable fundraising schemes.

To begin with, we compare responses to the lead donor treatment relative to the control treatment. Column 5 shows that in the control treatment T1, the average donation given is €74.3. In the lead donor treatment T2, this rises significantly to €132. The near doubling of donations given can only be a response to the presence of a lead donor—the relative price of donations received by the opera house vis-à-vis own consumption is unchanged. The result is not driven by outliers—the median donation is also significantly higher in T2 than in T1 (not shown). In short, the lead donor impacts only the intensive margin of giving.¹⁹

A priori, it could certainly have been the case that the lead donor increased the number of donors, as suggested by theories of why lead donors might matter (Andreoni 1998, Romano and Yildirim 2001, Vesterlund 2003). One explanation for this not occurring is that marginal donors are less affected by the lead donor than are individuals who would be in the right tail of the distribution of donations even in the absence of the lead donor. As a consequence, the lead donor treatment may have quantitatively larger effects on the intensive rather than extensive margins of giving. To provide direct evidence on this, we use quantile regressions to characterize changes in the shape and spread of the conditional distribution of donations received, not just the change in the unconditional mean as shown in Table 2. We estimate the following quantile regression specification at each quantile $\tau \in (0, 1)$,

$$(2) \quad \text{Quant}_\tau(\log(d_{it}) | \cdot) = \delta_\tau T_{2i} + \eta_\tau X_i \text{ for } d_{it} > 0,$$

where T_{2i} is a dummy equal to one if individual i is assigned to the lead donor treatment T2. The parameter of interest, δ_τ , measures the difference at the τ th conditional

¹⁸Huck and Rasul (2010) present evidence from a field experiment in this setting designed to explore whether transactions costs exist, what form they take, and present a method to infer the proportion of recipients affected by them. They show that absent any transactions costs, 6-7 percent of individuals would likely donate to this fundraising drive, almost double the actual observed response rates in T1–T5.

¹⁹Potters, Sefton, and Vesterlund (2007) examine the role of lead contributions in a laboratory setting. They find support for the signaling hypothesis as modeled by Andreoni (2006b). Karlan and List (2007) also provide field evidence of such signaling effects—they find the announcement of the availability of a match from a lead donor, but no specific information on the total value available for matching, increases responses on both extensive and intensive margins of charitable giving. Providing recipients with additional information on the value available for matching—ranging from \$25,000 to \$100,000—however had little additional effect. List and Lucking-Reiley (2002) study the role of seed money on charitable giving but in their research design, seed money serves both as a signal of quality, and also reduces the amount that needs to be collected as the project is of a discrete nature and has a fixed fundraising target. Their design estimates the combined effects of quality signals and the effects of reducing the additional required donations to reach the target. We return to the issue of what drives the effectiveness of lead donors in the concluding section.

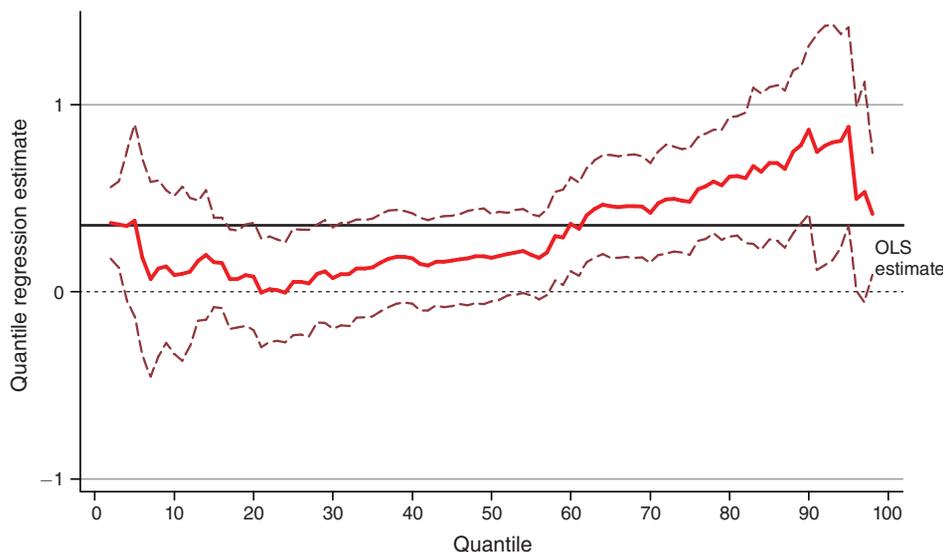


FIGURE 2. QUANTILE REGRESSION ESTIMATES OF LEAD DONOR TREATMENT T2

Notes: Figure 2 shows the estimated quantile regression effect at each quantile of the conditional distribution of the log of donations received, and the associated 95 percent confidence interval. The figure also shows the coefficient on the treatment dummy variable from an OLS regression. The individual characteristics controlled for are whether the recipient is female, the number of ticket orders placed in the 12 months prior to mail out, the average price of these tickets, whether the recipient is a Munich resident, and a dummy variable for whether the year of the last ticket purchase was 2006 or not.

quantile of log donations received between the lead donor treatment and the control group.²⁰

Figure 2 graphs estimates of δ_τ from (2) and the associated 95 percent confidence interval at each quantile when the comparison treatment is T1. This shows that donations in the lowest quantiles of the conditional distribution of donations given are not much affected by the signal, suggesting the MRS for marginal donors is not affected by the lead donor. In contrast, more generous donors are more affected by lead donors, in *absolute* terms, causing the overall distribution of donations given to become more dispersed as it is stretched rightward at higher donation amounts. The later structural analysis estimates how the presence of a lead donor affects the distribution of subjective valuations of the project.²¹

The reduced form evidence on linear matching schemes has been analyzed in our earlier work, Huck and Rasul (2011). To briefly summarize those findings, we see from column 5 in Table 2 that as the relative price of donations received falls

²⁰The individual characteristics controlled for in X_i are whether recipient i is female, the number of ticket orders placed in the 12 months prior to mail out, the average price of these tickets, whether i resides in Munich, and a zero-one dummy for whether the year of the last ticket purchase was 2006.

²¹Current models of lead gifts do not emphasize how the impact of a lead donor varies by how much the individual would give in the absence of such a lead donor. We note, however, that if all agents have the same prior regarding quality (say) and differences in donations are driven by income, then standard utility functions would predict larger absolute increases in donations for the rich, that is, for those who would give more absent the lead donor. This increase in absolute amounts is consistent with our results in Figure 2. The figure does not imply that the proportionate increase in donations in response to lead donors is necessarily increasing across quantiles.

moving from treatment T2 to the linear matching treatments T3 and T4, the average donation received, d_r , continues to rise. The average donation received increases to €151 in T3 with a 50 percent match rate, and to €185 in T4 with a 100 percent match rate. Importantly, as shown in Figure 1 and column 6 of Table 2, as the match rate increases, the donations given, d_g , fall. The average donation given falls from €132 in the lead donor treatment T2 to €101 in T3 with a 50 percent match rate, and to €92.3 in T4 with a 100 percent match rate. These differences are not driven by outliers—the median donation given is significantly lower in treatments T3 and T4 than the lead donor treatment T2 (not shown).²²

Therefore, linear matching does not crowd in donations—rather there is partial crowding out of donations given to an extent that, although donations received increase, they do so less than proportionately to the fall in the relative price of the charitable good.²³ An immediate consequence is that straight linear matching schemes as in treatments T3 and T4 do not pay for the fundraiser. As established in Huck and Rasul (2011), the charitable organization is better off simply announcing the presence of an anonymous and significant lead gift, rather than additionally using the lead gift to match others' donations. In the structural estimation below, we use the estimates from our preferred specification to predict what giving behavior would have been observed at counterfactual match rates, in particular, at match rates coincident with Eckel and Grossman (2006) and Karlan and List (2007). This helps shed light on whether there exists *some* match rates the fundraiser would indeed be better off using rather than just announcing the presence of a lead donor.²⁴

The final two treatments involve novel nonlinear matching schemes. Treatment T5 induces recipients to face a nonconvex budget set. For donations below €50, the budget line is coincident with that of the lead donor treatment T2; for donations at or above €50, it coincides with that of the 100 percent matching treatment T4. On the extensive margin, column 3 of Table 2 shows that recipients are significantly more likely to respond to the nonlinear matching scheme than to the lead donor treatment

²² As discussed in more detail in Huck and Rasul (2011), own price elasticities of charitable giving have been the focus of much of the earlier literature on charitable giving. In comparison to earlier large-scale natural field experiments, we note that Eckel and Grossman (2006) estimate a higher price elasticity of -1.07 as match rates vary from 125 to 133 percent. Non-experimental studies using cross sectional survey data on giving or tax returns, typically find a price elasticity between -1.1 and -1.3 (Andreoni 2006a). Panel data studies using US data on tax returns have varied findings: Randolph (1995) finds short run elasticities to be higher than cross sectional estimates at -1.55 , although Auten, Sieg, and Clotfelter (2002) find the reverse, with elasticities ranging from -0.40 to -0.61 . Fack and Landais (2010) use data from France and a difference-in-difference research design and find similar price elasticities.

²³ An alternative interpretation might be that recipient behavior is driven by the inferences they make about the lead donor over these treatments rather than any changes in relative prices. For example, in T2 the lead donor effectively commits to provide €60,000 irrespective of the behavior of others. In T3 the lead donor commits to providing €60,000 only if other donors provide €120,000. Similarly, in T4 the lead donor commits to providing €60,000 only if other donors provide €60,000. In other words, the level of commitment of the lead donor that recipients may infer is greatest in T2, second highest in T4, and lowest in T3. Three pieces of evidence contradict such an interpretation—(i) donations received monotonically decrease in their relative price—moving from T2 to T3 to T4; (ii) donations given fall as the strength of the commitment rises moving from T3 to T4; (iii) in actuality, the lead donation of €60,000 was exhausted by the donations from the original 25,000 mail out recipients.

²⁴ If the lead donor were to offer their gift *conditional* on such a matching scheme being implemented, then the relevant comparison is with treatment T1, as in Karlan and List (2007). The fundraiser is then better off taking the lead donation and implementing a linear matching scheme rather than not accepting the lead gift. We later use the structural model of giving to make more progress on the design of the optimal fundraising scheme (including nonlinear schemes).

T2. This is in line with standard consumer theory, because as the budget set expands in T5 relative to T2, recipients who found it optimal not to donate in T2 might now optimally choose the interior corner solution. There is no evidence of response rates being higher in T5 than T4.

On the intensive margin, Figure 1 shows that the average outcome in terms of donations given and received in T5 replicate almost exactly those in the 100 percent matching treatment T4—the average donation received in T5 is €194, as opposed to €185 in T4, and the average donation given is €97.9, as opposed to €92.3 in T4. To see why this is so, note that in the lead donor treatment T2 the average donation received is €132. This suggests that the portion of the budget line in T5 that lies to the left of €100 on the x -axis of donations received is irrelevant for many recipients. In essence, treatments T4 and T5 present the average recipient with an almost identical choice. Hence, response rates and donations should not differ markedly between the two.

These results have important implications for fundraisers. On the one hand, non-linear schemes that demand a minimum donation before the match kicks in, have beneficial effects from the fundraiser's point of view in that they—(i) sway those who would have given less than the threshold amount to increase their donation to the threshold level or incrementally above it; (ii) there are no adverse effects on response rates. On the other hand, for those that would have donated more than the threshold amount of €50, these donors effectively face a reduced relative price of charitable giving, which should lead to a partial crowding out of donations as found in the straight linear matching schemes.

The optimal fundraising scheme would balance these effects. As Table 2 shows, T5 raised less money overall than T2 suggesting the threshold amount was not chosen optimally. This is because most donors would have given above this threshold in any case—in T2 the mean donation given was €132. We therefore conjecture that a higher threshold, set somewhere above this amount would have further increased the total donations given. Hence, the fundraiser might be better off by considering sending out tailor-made letters to potential donors, where the matching thresholds are individually adjusted on the basis of observable characteristics correlated with giving behavior. To shed light on the optimal design of fundraising schemes we use our structural estimates to conduct counterfactual analyses on giving behavior in response to variations of the nonconvex scheme where we alter: (i) the threshold level at which the nonconvexity occurs; (ii) match rates above and below the threshold.

Finally, we compare the fixed gift treatment T6 in which recipients are informed of the existence of a lead donor and that *any* positive donation will be matched with €20, to the lead donor treatment T2. As previously shown, response rates are significantly higher in T6 than in T2, in line with standard consumer theory. Theory also suggests these additional donors should be willing to contribute relatively low amounts to the project. This is somewhat supported in the data, as shown in Figure 3. On the one hand, there is a decrease in both the donations given and received in treatment T6 relative to the lead donor treatment T2. However, we do not observe a mass of individuals giving 1 under T6 as might have been predicted under a neoclassical model. Rather, there is a bunching of individuals giving exactly €20 under T6, that is harder to reconcile with a standard model.

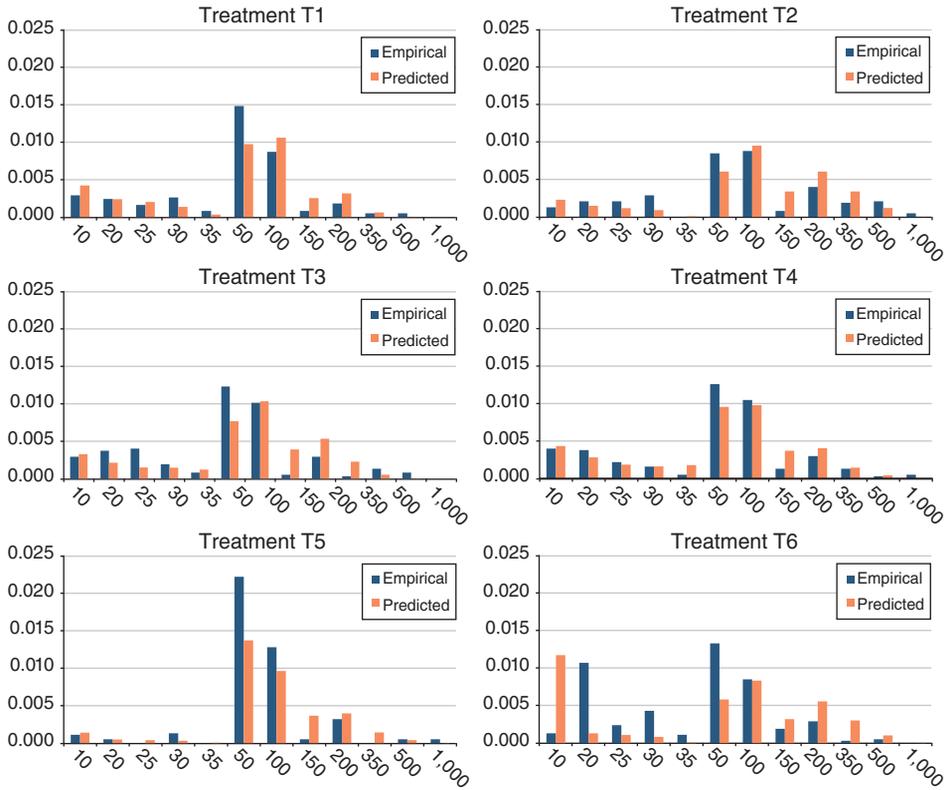


FIGURE 3. EMPIRICAL AND PREDICTED DISTRIBUTIONS OF DONATIONS

Notes: The figure shows the predicted and empirical distribution of positive donation amounts. The horizontal axis measures the amount of donation given. The figures are based on the preferred structural model that assumes a discrete choice set with warm glow preferences and focal points. The choice of donation amounts under the discrete choice set specification is restricted to belong to the set $\mathcal{D}_g = \{0, 10, 20, 25, 30, 35, 50, 100, 150, 200, 350, 500, 1,000\}$. All estimation is performed using data from treatments T1 to T4 only.

We have earlier noted the optimal nonlinear fundraising scheme might offer matching that kicks in above the response an individual would have chosen in the lead donor treatment T2. In some sense, this is precisely what the fixed gift in T6 does for those recipients whose T2 response would have been to donate zero. From that perspective, the crowding in of small donations in T6 vis-à-vis T2 mirrors perfectly the choice of the interior corner solution of small donors in treatment T5 vis-à-vis T2. This again suggests that an optimal fundraising scheme would entail tailor-made nonlinear matching based on what the individual would have offered in T2. To make progress on this front, we later use our preferred structural estimates to conduct counterfactual analyses on giving behavior to variations of the fixed gift fundraising schemes that alter: (i) the threshold level at which the fixed gift is enacted; (ii) the size of the fixed gift.

On the intensive margin of giving under the lead gift treatment, column 5 of Table 2 shows the average donation received in T6 is €89.2—relative to T2, donations given fall by significantly more than €20. This result is not driven by

outliers: median donations received is also significantly lower (by €30) in T6 than T2. This effect remains even in column 6 when differences in the mean (or median) amount *given* is considered. This decrease in donations is partly driven by a mass point of individuals that give precisely €20 under T6. The structural estimates developed below allow for such focal point influences on giving behavior.

Combining the two margins of giving, we see that in aggregate, in T6 €12,248 is donated (by 177 individuals). This is considerably less than the total amount donated in the lead donor treatment T2 (€17,416 by 132 individuals). Hence, although T6 induces more individuals to give, they give relatively small amounts. In addition, it is likely that among those assigned to T6 that would have given under the counterfactual T2 treatment, there is *more than* a €20 reduction or crowding out of their donations. This perverse impact of the fixed gift will also be hard to reconcile with a standard model of preferences.²⁵

III. Structural Form Evidence

A. Baseline Model

We now develop and estimate a structural model of charitable giving to: (i) assess the extent to which we are able to explain giving behavior across the six treatments with a parsimonious model; (ii) predict behavioral responses on the extensive and intensive margins of giving to a richer set of designs of charitable matching schemes than those in the natural field experiment. This latter exercise informs the design of the optimal design of fundraising schemes among the set of schemes that are combinations of the linear and nonlinear schemes implemented.

As in the conceptual framework developed earlier, we assume individuals have pure warm glow preferences defined over their private consumption, c , and the donation received by the project, d_r . Individuals are heterogeneous with respect to their valuation of the lead donation and this is indexed by the one dimensional parameter θ , which has the cumulative distribution function $F_\theta(\cdot; L)$. $L = 1$ denotes the presence of a lead donor (as in treatments T2–T6), with $L = 0$ otherwise. This formulation therefore allows for the possibility that the presence of the lead donor alters the marginal benefit from donating, as suggested by the earlier reduced form evidence.²⁶ We begin by assuming a random quasi-linear form for preferences,

$$(3) \quad u(c, d_r; \theta) = c + \theta d_r - \frac{\alpha}{2} d_r^2,$$

where $\alpha > 0$, and with individuals subject to a budget constraint, $c + d_g \leq y$, and nonnegativity constraint, $d_g \geq 0$. The donation received d_r is related to the

²⁵If charitable giving were an inferior good, this might be consistent with this reduced form evidence from the lead gift treatment. However, Andreoni (2006a) presents evidence from the United States that the proportion of income that is given to charitable causes is U-shaped across the income distribution. It is increasing for households with income greater than \$40K. Such evidence is consistent with charitable giving being a normal good for sufficiently well off households, as are likely to be in our sample of mail out recipients.

²⁶To reiterate, our treatments are not designed to tease apart various explanations of why lead donors might matter (Andreoni 1998; Romano and Yildirim 2001; Vesterlund 2003). As such we model the impact of the lead donor in a general way, and only investigate whether it impacts the marginal utility of donating in some way.

donation given d_g through the function $d_r = R_T(d_g)$, which varies with the fundraising scheme in place in treatment T . This utility specification provides an empirically tractable framework and also permits both intensive and extensive responses when the donation matching rate varies.²⁷ Throughout this section we abstract (for notational simplicity) from any dependence of the structural parameters upon observable demographic characteristics. However, such dependence does not complicate the analysis and will be incorporated in all our empirical specifications.²⁸

Linear Matching.—Under the linear matching treatments T1 to T4, $d_r = \lambda_T d_g$, where λ_T is the matching rate in treatment T . The donation given is strictly positive if $\theta\lambda_T > 1$, that is, the marginal utility of giving at $d_g = 0$ exceeds the marginal utility of consumption. When positive, the donation given satisfies the first-order condition,

$$(4) \quad d_g = \frac{\theta\lambda_T - 1}{\alpha\lambda_T^2},$$

so that d_g is increasing in the individual's valuation, θ . With slight abuse of our earlier notation, we write the associated indirect utility function as

$$(5) \quad u(y; \theta, \alpha, T) = \begin{cases} y + \frac{(\theta\lambda_T - 1)^2}{2\alpha\lambda_T^2} & \text{if } \theta\lambda_T > 1; \\ y & \text{if } \theta\lambda_T \leq 1, \end{cases}$$

which will be useful when examining optimal individual giving behavior in the next treatment.

Nonlinear Matching.—In the nonlinear matching treatment T5, donations are matched one-for-one, but only if the donation given is greater than €50. Thus, in order to determine the optimal choice of d_g we need to consider the utility attained from either not donating, donating exactly €50, or donating some positive amount that is either more than or less than €50. To do so, we consider the parameter restrictions that are consistent with the various piecewise linear sections of the budget set having (or not) an interior solution and comparing maximized utility levels. An exhaustive description of the optimal d_g for all possible parameter values $\{\alpha, \theta\}$ is provided in the Appendix. These giving patterns are also summarized in Figure A1: the lightest shaded area corresponds to the set of parameters where an individual is on the matched section of the budget constraint with $d_g > 50$; the middle gray area is the parameter set where $d_g = 50$; the darkest area is the parameter set where $0 < d_g < 50$.

An important implication of the model under treatment T5 is that for a given α the support of d_g may not be connected, even if the support of θ is. This is because

²⁷The Constant Elasticity of Substitution specification has been used in previous work on charitable giving, such as Andreoni and Miller (2002). Setting $u(c, d_r; \theta)^{-\rho} = c^{-\rho} + \theta d_r^{-\rho}$ would not yield any change in the donation rate as the matching rate is varied. From Table 2 we see that this pattern is clearly rejected in our data.

²⁸The model thus allows us to take seriously the possibility of heterogeneous responses to fundraising schemes. In contrast, the bulk of the earlier literature has considered mean effects. A notable exception is Fack and Landais (2010) who use three-step censored quantile regression methods to address censoring issues related to donors being self-selected and then explore heterogeneous responses to tax reforms in France related to charitable giving.

the matching structure may induce individuals who would have donated slightly below €50 in the lead donor treatment T2, to donate exactly €50. Moreover, for $\alpha < 1/100$ donations below €50 are never optimal. These observations suggest that further heterogeneity and/or model features may need to be incorporated to explain actual giving behavior in this treatment. We return to this issue in Section IIID when we further allow for pure warm glow preferences and focal point influences.

Fixed Gifts.—Under treatment T6 there is a €20 match for *any* strictly positive donation amount so that $d_r = d_g + 20$. We need to consider the possibility of an individual donating: (i) identically zero; (ii) a strictly positive (but negligible) amount; (iii) a strictly positive and nonnegligible amount, $d_g > 0$. At an interior solution where the individual donates $d_g > 0$, their utility is,

$$(6) \quad u(y - d_g, d_g + 20; \theta) = y - d_g + \theta[d_g + 20] - \frac{\alpha}{2}[d_g + 20]^2,$$

which for $d_g > 0$, is maximized when,

$$(7) \quad d_g = \frac{\theta - 1}{\alpha} - 20.$$

Thus there is 100 percent crowding out of donations for individuals who would donate in both T2 and T6. This stark prediction arises because of the absence of any income effects in our simple preference specification, an issue we return to below. The model also predicts the number of individuals who are donating strictly positive (and non-negligible) amounts falls relative to the lead donor treatment T2. These correspond to individuals who would have donated less than €20 in T2. It is straightforward to verify that individuals will donate strictly positive non-negligible amounts in the fixed gift treatment T6 if $\theta > 1 + 20\alpha$.

The baseline model also predicts a mass of individuals donating a negligible amount to the charitable cause. Individuals will prefer to donate this amount relative to either not donating or donating a nonnegligible amount if $10\alpha \leq \theta \leq 1 + 20\alpha$. Individuals do not donate if $\theta < 10\alpha$. The proportion of individuals donating some negligible or non-negligible amount will therefore rise relative to the lead donor treatment T2 provided α is not too high.

B. Discrete Version

Formulating the model with a continuous choice over donation amounts d_g is natural and also useful for exploring the theoretical implications of the model. However, despite the fact that over 900 individuals donate a strictly positive amount across the 6 treatments, the actual data only has 30 positive points of support for donations across all treatments.²⁹ While we are not able to explain why individual

²⁹ Across the full set of treatments T1–T6, three donation values account for almost 60 percent of all donations given; twelve donation values account for over 90 percent of all donations.

donations are concentrated at certain amounts, a discrete choice formulation of the model at least allows us to recognize the existence of this behavior.

We therefore also consider a discrete variant of our baseline model, where we maintain the same underlying choice model as described above, but restrict d_g to belong to some finite and predetermined set \mathcal{D}_g . The theoretical implications of our baseline model with a discrete choice set remain essentially the same as in the continuous choice version discussed above. Throughout we assume that all $K + 1$ elements of \mathcal{D}_g are ordered $0 = d_g^0 < d_g^1 < \dots < d_g^K < \infty$, so that there is a range of θ consistent with the optimal choice $d_g = d_g^k$ for $0 < k < K$. In the linear matching treatments this is easily shown to satisfy,

$$(8) \quad \frac{1}{\lambda_T} + \frac{\alpha\lambda_T}{2} \times [d_g^k + d_g^{k-1}] \leq \theta < \frac{1}{\lambda_T} + \frac{\alpha\lambda_T}{2} \times [d_g^k + d_g^{k+1}].$$

A very similar set of inequalities can be derived under the fixed gift treatment T6, while under the nonlinear matching treatment T5 it is again necessary to compare maximized utilities on the different sections of the budget constraint.³⁰

C. Estimation of the Baseline Model Using T1–T4

We first structurally estimate the baseline model under the alternative assumptions of continuous and discrete choice sets, using maximum likelihood estimation in both cases. The estimation is performed only using data from the linear matching treatments T1–T4, that replicate commonly observed fundraising schemes, with the experimental variation in match rates permitting separate identification of the structural parameters. These parameter estimates then allow the model to be used for an out-of-sample prediction exercise in the remaining treatments T5 and T6, relating to more novel fundraising schemes.³¹

³⁰In particular, in T6, the range of θ consistent with the choice $d_g = d_g^k$ for $1 < k < K$ is,

$$1 + \frac{\alpha}{2} \times [d_g^k + d_g^{k-1} + 40] \leq \theta < 1 + \frac{\alpha}{2} \times [d_g^k + d_g^{k+1} + 40],$$

and with $d_g = d_g^1$ optimal when,

$$\frac{d_g^1}{d_g^1 + 20} + \frac{\alpha}{2} \times [d_g^1 + 20] \leq \theta < 1 + \frac{\alpha}{2} \times [d_g^1 + d_g^2 + 40].$$

For T5, the range of θ such that $d_g > 50$ is optimal is defined by the same set of inequalities as in equation (8) with $\lambda_T = 2$. For any $d_g < 50$, the range of θ must simultaneously satisfy equation (8) with $\lambda_T = 1$, as well as,

$$\theta < \frac{50 - d_g^k}{100 - d_g^k} + \frac{\alpha}{2} \times [100 + d_g],$$

which is the requirement that the utility from $d_g < 50$ strictly exceeds that from $d_g = 50$. Note that the range of θ consistent with a given $0 < d_g < 50$ being optimal may be an empty set.

³¹Given the simple structure of the model under treatments T1–T4 and the fact that these fundraising schemes are most commonly observed, it is convenient and natural to estimate the model on this subset of treatments to assess the out-of-sample predictive ability. We can of course also consider estimations based on an alternative subset of treatments. To identify the parameters of $F_\theta(\cdot; 0)$ it is always necessary to use data from T1. The parameters of $F_\theta(\cdot; 1)$ and α can be separately identified using data only from treatment T5. Parametric identification is possible without experimental variation because we are assuming that the same shape parameters (a mean and variance from a normal distribution) are responsible for giving behavior on both the unmatched and matched sections of the budget constraint. Nonparametric identification, however, requires experimental variation.

In the empirical implementation we specify a parametric distribution of the unobserved heterogeneity θ . This distribution may vary both with individual characteristics X_i , as well as exposure to the lead donor treatment groups ($L = 1$). Throughout we assume this distribution is normal, with unknown mean and variance. The mean of the distributions is allowed to vary with demographic characteristics through a linear index restriction, $\mu_\theta^L = X'\beta_\theta^L$. We do not place any restrictions on these relationships across $L = 0$ and $L = 1$.³² The full parameter vector of our model is then given by $\{\alpha, \beta_\theta^0, \beta_\theta^1, \sigma_\theta^0, \sigma_\theta^1\}$.

Under the linear matching treatments we may rewrite equation (4) as $d_r = \max\{0, d_r^*\}$, where the latent variable d_r^* is defined by

$$(9) \quad d_r^* = \frac{\theta}{\alpha} - \frac{1}{\alpha\lambda_T} = \frac{X'\beta_\theta^L}{\alpha} - \frac{1}{\alpha\lambda_T} + \frac{\epsilon}{\alpha}.$$

The maximum likelihood estimates from the continuous choice baseline model specification can then be obtained from two independent Tobit regressions: the first uses data from treatment T1 and regresses $d_r = d_g$ on the set of individual controls X_i (including a constant); the second uses data from T2–T4 and regresses $d_r = \lambda_T d_g$ on the same set of controls X_i (including a constant) as well as the inverse matching rate λ_T^{-1} . Of course, this equivalence will not hold if heterogeneity is allowed to enter the model more generally, or if restrictions are imposed on the influence of demographics across $L = 1$ and $L = 0$.

When estimating the discrete version of the model we define the choice set,

$$(10) \quad \mathcal{D}_g = \{0, 10, 20, 25, 30, 35, 50, 100, 150, 200, 350, 500, 1,000\}.$$

Individuals observed donating some amount not contained within \mathcal{D}_g are assigned to the nearest donation amount in this set. The likelihood function here is simply comprised of the product of the donation choice probabilities, which themselves are given by the probability that θ belongs to the interval as defined by equation (8).³³

Table A1 presents the preference parameter estimates of $\{\alpha, \beta_\theta^0, \beta_\theta^1, \sigma_\theta^0, \sigma_\theta^1\}$ from the baseline model using data from T1–T4. Panel A shows the estimates from the continuous choice model, and Panel B shows the estimates under the discrete version of the model. Bootstrapped standard errors using 500 repetitions are shown in parentheses. Three points are of note. First, the parameter estimates are very similar, regardless of the assumed continuous or discrete choice set. Second, observables that indicate affinity to the opera house (number of ticket orders placed in the 12 months prior to mail out, whether the year of the last ticket purchase was 2006) increase the mean valuation of donations, θ . Third, there is considerable imprecision in the parameter estimates. Comparing the estimation results with and without the lead donor, our results suggest that exposure to the lead donor treatments changes

³²The individual characteristics controlled for in X_i are whether recipient i is female, the number of ticket orders placed in the 12 months prior to mail out, the average price of these tickets, whether i resides in Munich, and a zero-one dummy for whether the year of the last ticket purchase was 2006.

³³Defining the supremum of the set defined in equation (8) as $\bar{\theta}_T^k(\alpha)$ and the infimum as $\underline{\theta}_T^k(\alpha)$ the probability of donating amount d_g^k is given by $\Phi\left(\frac{\bar{\theta}_T^k(\alpha) - \mu_\theta^L}{\sigma_\theta^L}\right) - \Phi\left(\frac{\underline{\theta}_T^k(\alpha) - \mu_\theta^L}{\sigma_\theta^L}\right)$, where Φ is the cumulative distribution function of the standard normal distribution.

TABLE 3—MODEL FIT FROM BASELINE MODEL

	Response rate			Average donation given		
	Empirical (1)	Continuous (2)	Discrete (3)	Empirical (4)	Continuous (5)	Discrete (6)
T1: Control	0.037 (0.003)	0.037 (0.003)	0.037 (0.003)	74.3 (6.19)	75.9 (7.1)	76.6 (7.1)
T2: Lead donor	0.035 (0.003)	0.034 (0.002)	0.034 (0.002)	132 (14.3)	174*** (15.6)	162** (11.8)
T3: Lead donor + 1: .5 match	0.042 (0.003)	0.040 (0.002)	0.040 (0.002)	101 (12.6)	119 (10.8)	113 (8.2)
T4: Lead donor + 1:1 match	0.042 (0.003)	0.043 (0.003)	0.043 (0.003)	92.3 (10.4)	90.4 (8.3)	87 (6.4)
T5: Lead donor + 1:1 match for donations greater than €50	0.043 (0.003)	0.033*** (0.002)	0.034*** (0.002)	97.9 (9.6)	114* (9.5)	107 (7.8)
T6: Lead donor + €20 match for any donation	0.047 (0.003)	0.050 (0.007)	0.044 (0.004)	69.2 (5.51)	103*** (21.3)	112*** (16.0)

Notes: Standard errors in parentheses. Empirical and predicted donation rates in columns 1 to 3; empirical and predicted conditional average donation given (in euros) in columns 4 to 6. The table shows the fit of our baseline model with a continuous choice set (columns 2 and 5) and a discrete choice set (columns 4 and 6), using the maximum likelihood parameter estimates from Table A1 and the sample distribution of covariates. Columns 1 to 3 report the empirical and predicted response rate (in percentage points); columns 4 to 6 report empirical and predicted conditional average donation given (in euros). Standard errors are in parentheses and are calculated by sampling 500 times from the distribution of parameter estimates.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

the distribution of valuations θ such that: (i) fewer individuals would donate, i.e. $F_\theta(1; 1) > F_\theta(1; 0)$; (ii) the proportion of individuals with high realizations of θ (and therefore higher donations) increases.

Table 3 then shows the fit of both formulations of the model on the two key statistics related to the extensive and intensive margins of giving behavior: the response rate, and the mean donation given conditional on response. Columns 1 and 4 show the empirical values for each statistic. The remaining columns show the model prediction. For each of the 12 moments (the response rate and average donation given for the six treatments), we report whether the empirical moment is significantly different from the model prediction.

Within sample using treatments T1–T4 that relate to commonly observed fundraising schemes, the structural model does well in explaining both the donation rate and mean conditional donations in T1. While the observed response rates in T2–T4 are not statistically different from that predicted by the model, the fit on the intensive margin is much less satisfactory. As columns 4–6 show, the estimated structural model, in either continuous or discrete choice formulations, substantially overpredicts the mean donation given in the lead donor treatment T2 with observed mean donations significantly different from their predicted value, and suggests a very steep price gradient as the matching rate increases.

The out-of-sample fit of both formulations of the model to T5 and T6 are unsatisfactory, as shown in the lower half of Table 3. In the nonlinear matching treatment T5, the response rate is lower (3.3 percent or 3.4 percent) than is empirically observed (4.3 percent), with this difference being statistically significant. While

observed mean donations for this treatment are slightly below that predicted, the estimated baseline model implies a zero probability of donating an amount greater than zero and less than €50, which is at odds with the data.

In the fixed gift treatment T6, the baseline structural model does predict the response rate to be higher than in other treatments and matches quite closely the empirical response rate of 4.7 percent. However, on the intensive margin of giving behavior, the baseline model performs poorly in both continuous and discrete choice formulations. In both cases, donations given are predicted to be considerably higher relative to what is observed with the differences highly statistically significant. This suggests the baseline model under predicts the extent to which under this fundraising scheme, relative to the lead donor scheme, existing donors might reduce their donations as they are crowded out by the fixed gift.³⁴

D. Extensions

The unsatisfactory empirical performance of the baseline model suggests behavior can potentially be better explained through extensions to the model. We consider these extensions in the context of the discrete version of the model, though most apply equally when d_g is continuous. Finally, while we describe introducing each of these extensions in isolation, they can and will be incorporated simultaneously.

Pure Warm Glow Preferences.—We assume there is a fraction π_w of individuals who exhibit what we again refer to as “pure warm glow” preferences. Such individuals derive utility from their own private consumption as well as the value of their donation given d_g , regardless of how this is matched. They do not value any potential matching donation given by the lead donor, $d_r - d_g$. It follows that individuals with pure warm glow preferences behave as described in the baseline model when subject to treatment T1 or T2; when subject to any of the matched treatments their behavior is the same as under T2.³⁵

Allowing for pure warm glow preferences provides a mechanism through which any change in the donation matching rate will, all else equal, generate *smaller* movements in donations given and hence received. Relative to the baseline model above, we then expect responses to the linear matching treatments to be closer to those under the lead donor treatment T2. This may overcome the steep price gradient documented in Table 3 from the baseline structural estimates. Furthermore, provided θ has full support, the presence of such behavior implies that *any* positive donation amount in *any* treatment may be rationalized. This feature is important given that

³⁴The reason the baseline model is unable to fit the response rate in T5 can be seen from Figure A1. The only way the baseline model can increase the donation rate relative to T2 is if $\alpha < 1/100$ (but note that in this case the model would not permit any donations below €50). Thus, given the estimated parameter values, the nonlinear matching structure induces some individuals already donating to increase their donation, but it does not induce non-donors to give.

³⁵An alternative interpretation of this extension is that there exists a fraction π_w of individuals who believe that their donation will be unmatched due to the committed €60,000 of matched funds being exhausted. This formulation is also similar (though not equivalent) to an expected utility maximizer, where the uncertainty concerns the subjective probability that their donation will be matched.

our estimated baseline model implied that in T5 there was a 0 probability of individuals donating a positive amount less than €50.

Focal Points.—We previously noted that actual donations are concentrated at a small number of donation values. Even in the linear matching treatments T1–T4, the three most frequent donation amounts (€20, €50, and €100) account for 60 percent of all positive donations, resulting in a multi-modal distribution of donation amounts. While we are not able to explain why specific donation amounts display such prominence, we incorporate them in our model by allowing individuals to be attached to these focal donation amounts. We proceed as follows.

For each donation amount given d_g^k we introduce an associated captivity parameter ξ_k that enters the utility function additively and therefore makes particular donation choices more or less likely,

$$(11) \quad u(c, d_r; \theta) = \xi_k + c + \theta d_r - \frac{\alpha}{2} d_r^2.$$

Since for certain parameter values, the range of valuations θ consistent with a particular donation amount may have zero measure, we construct the following smoothed probabilities for a given donation amount d_g^k , which are then used when forming the likelihood function,

$$(12) \quad \Pr[d_g = d_g^k] = \int_{\theta} \frac{\exp(u(y - d_g^k, d_r^k; \theta)/\nu)}{\sum_{l=0}^K \exp(u(y - d_g^l, d_r^l; \theta)/\nu)} dF_{\theta}(\theta; L),$$

so that as the smoothing parameter $\nu \rightarrow 0$ the probabilities in equation (12) converge to the original unsmoothed choice probabilities.³⁶

In our empirical applications we restrict ξ_k to be zero for all donation amounts except $d_g \in \{20, 50, 100\}$. When estimating the model using data only from T1–T4 we do not allow the captivity parameters $\{\xi_k\}$ to vary across treatments. Since the nonlinear matching treatment T5 may be expected to strengthen focal behavior especially at $d_g = 50$, and similarly the fixed gift treatment T6 may strengthen it at $d_g = 20$, we also explore the possibility of appropriate parameter shifts when estimating the model using data from alternative treatments. This flexibility might be especially important in allowing the model to better fit the empirical data from the novel fundraising schemes embodied in T5 and T6.

Flexible Curvature.—Our third extension allows for greater flexibility in functional form by specifying preferences as

$$(13) \quad u(c, d_r; \theta) = c + \theta d_r - \frac{\alpha}{\gamma} d_r^{\gamma},$$

³⁶ An alternative behavioral interpretation of the probabilities in equation (12) is that for each donation amount d_g there exists an additive Type-I extreme value error attached to the utility function in equation (11), with a standard deviation that is proportional to ν . In our empirical application we set $\nu = 1/10$.

TABLE 4—MODEL FIT FROM EXTENDED MODELS

	Empirical	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Panel A. Response rate</i>								
T1 Control	0.037	0.037	0.038	0.037	0.037	0.037	0.037	0.037
T2 Lead donor	0.035	0.036	0.035	0.035	0.036	0.038	0.037	0.038
T3 Lead donor + 1:1.5 match	0.042	0.040	0.040	0.041	0.040	0.041	0.041	0.041
T4 Lead donor + 1:1 match	0.042	0.042	0.043	0.044	0.041	0.043	0.043	0.043
T5 Lead donor + 1:1 match for donations greater than €50	0.043	0.036**	0.034**	0.035**	0.036**	0.037	0.037*	0.037
T6 Lead donor + €20 match for any donation	0.047	0.042	0.044	0.045	0.043	0.043	0.044	0.043
Pure warm glow		X			X	X	X	X
Flexible curvature			X					
Focal points				X	X	X	X	X
Focal points T5							X	X
Focal points T6								X
Sample	T1–T6	T1–T4	T1–T4	T1–T4	T1–T4	T1–T6	T1–T5	T1–T6
<i>Panel B. Average donation given</i>								
T1 Control	74.3	76.6	75.4	80.7	80.5	78.6	80.4	78.4
T2 Lead donor	132	136	148	138	138	137	139	137
T3 Lead donor + 1:1.5 match	101	105	105	97	109	112	107	112
T4 Lead donor + 1:1 match	92.3	87.9	82.5	73.9*	92.2	98.5	88.6	98.3
T5 Lead donor + 1:1 match for donations greater than €50	97.9	99.8	101	90.2	106	110	103	110
T6 Lead donor + €20 match for any donation	69.2	106***	104***	95.7***	107***	111***	105***	111***
Pure warm glow		X			X	X	X	X
Flexible curvature			X					
Focal points				X	X	X	X	X
Focal points T5							X	X
Focal points T6								X
Sample	T1–T6	T1–T4	T1–T4	T1–T4	T1–T4	T1–T5	T1–T6	T1–T6

Notes: The table shows the fit of the extended versions of our baseline model to the response rate (in percentage points) and the average donation given (in euros), conditional on some strictly positive donation being made. The results in all columns are calculated using a discrete choice set with donation amounts restricted to belong to the set $\mathcal{D}_g = \{0, 10, 20, 25, 30, 35, 50, 100, 150, 200, 350, 500, 1,000\}$ with the underlying choice model estimated using maximum likelihood and using data from treatments as indicated in the “Sample” row. Pure warm glow indicates the presence of individuals whose utility depends upon the value of the donation given. Flexible curvature allows the curvature of the donation given/received to vary. Focal points indicate the incorporation of focal points in the choice decision. Focal points T5 indicates that the focal parameter at $d_g = 50$ is allowed to change for individuals in the T5 treatment. Focal points T6 indicates that the focal parameter at $d_g = 20$ is allowed to change for individuals in the T6 treatment.

- ***Significant at the 1 percent level.
- **Significant at the 5 percent level.
- *Significant at the 10 percent level.

with $\gamma > 1$, and utility maximized subject to the same set of constraints as before. While this generalization does not change the condition for donations to be positive under linear matching, it does offer more flexibility in responses following any change in the matching rate. If d_g is discrete, then we obtain a modified set of

inequalities determining optimal d_g^k . In particular the range of θ consistent with the optimal choice $d_g^k = d_g^k$ for $0 < k < K$ in treatments T1–T4 is now given by

$$(14) \quad \frac{1}{\lambda_T} + \frac{\alpha \lambda_T^{\gamma-1}}{\gamma} \times \left[\frac{(d_g^k)^\gamma - (d_g^{k-1})^\gamma}{d_g^k - d_g^{k-1}} \right] \leq \theta < \frac{1}{\lambda_T} + \frac{\alpha \lambda_T^{\gamma-1}}{\gamma} \times \left[\frac{(d_g^{k+1})^\gamma - (d_g^k)^\gamma}{d_g^{k+1} - d_g^k} \right].$$

Bounds on θ consistent with choice behavior in the other treatments can similarly be derived.

Estimation of the Extended Models.—The model fit under the alternative extended model specifications is presented in Table 4. Panel A shows the model fit on response rates, and panel B shows the model fit in terms of mean donation given, conditional on some strictly positive donation. For each of prediction, we again report whether it is statistically different from the corresponding empirical moment.

Columns 1–3 in both panels show that introducing each of the extensions in isolation, results in noticeable improvements in the within sample fit in treatments T1–T4 as measured by the response rate (where there are no significant differences between predicted and empirical values) and similarly in mean conditional donation given (where statistical differences only exist in the focal point specification in column 3 for the linear matching treatment T4). Incorporating either pure warm glow preferences, that are estimated for $\hat{\pi}_w = 27$ percent of individuals, a flexible curvature parameter, or focal points, all provide a mechanism through which changes in the matching rate may have a smaller impact on average donations than in the baseline model. When considering each feature in isolation, pure warm glow preferences provide the best fit to mean conditional donations, though the specifications which incorporate focal points do much better in matching other features of the donation distribution.

In terms of out-of-sample fit to treatments T5 and T6 shown in the lower half of each panel in Table 4, we continue to under predict the response rate in the nonlinear matching scheme T5 (around 3.6 percent predicted versus 4.3 percent observed), and these differences are significantly different at conventional levels. In most extensions considered we still obtain preference parameter estimates that leave donations unchanged relative to the lead donor treatment T2. None of the specifications considered are capable of describing giving behavior in the fixed gift treatment T6. This is unsurprising since the extensions considered all improved the within sample fit by making donations *less* responsive to changes in the fundraising scheme in place, $R_T(\cdot)$.

Column 4 presents results from our preferred specification that combines focal points with pure warm glow preferences. Panel C of Table A1 shows the estimated preference parameters from this specification, $\{\alpha, \beta_\theta^0, \beta_\theta^1, \sigma_\theta^0, \sigma_\theta^1, \pi_w, \xi_{20}, \xi_{50}, \xi_{100}\}$. When combining pure warm glow and focal point extensions, the estimated fraction of recipients with pure warm glow preferences rises to $\hat{\pi}_w = 33$ percent. We also see that there is considerable focal attachment at $d_g = 50$ and $d_g = 100$, while ξ_{20} is not statistically different from 0. Figure 3 shows the predicted and empirical distribution of strictly positive donation given amounts from this extended model with both focal

points and pure warm glow preferences. This shows the model generally does well in explaining the entire distribution of positive donations, not just the mean values shown in Table 4.

Figure 3 shows that in the presence of focal points, we are able to explain the shifting distribution of donations given as we vary the linear matching rate. We are also able to well explain, entirely out-of-sample, the general shape of the donations distribution in treatment T5 (including the low probability mass below €50). The model does underpredict the proportion donating at $d_g = 50$, which also accounts for the statistically significant discrepancy in the response rate, where the model predicts a response rate of 3.6 percent versus the empirically observed 4.3 percent. While increasing ξ_{50} would increase donations at this point, it would result in a deterioration in fit at the neighboring donation amounts.

The fit to treatment T6 is the least satisfactory, both in terms of the empirically observed mass at $d_g = 20$ (rather than at the lowest discrete category) as well as the virtual absence of any donations actually observed to be above €200, despite the model predicting such large donations. In summary, the baseline and extended models are unable to explain the presence of more than complete crowding out in the fixed gift treatment T6: it is really this discrepancy between the empirical and predicted amounts at the right hand end of the distribution that leads to the average predicted donation amount in T6 to be so much higher than what is empirically observed.

To understand how well the model performs when using the additional exogenous variation induced by treatments T5 and T6, we also estimate the model (with warm glow and focal point influences), including data from these treatments. The results of this exercise are shown in column 5, with the fit across all treatments shown to be very similar to when we reserved treatments T5 and T6 as a holdout sample.

One interpretation of the model's inability to fully match giving behavior in T6, and to a lesser extent in T5, is that these treatments themselves strengthen individuals' attachment to *specific* donation amounts. Of course such behavior cannot be predicted out-of-sample with our model, and so the preferred way to allow for it is to estimate the structural model using all six treatments and allow the attachment parameters to vary with these treatments. The results of doing so are shown in columns 6 and 7 in Table 4. Estimating the model on treatments T1–T5, column 6 in each panel shows we obtain little improvement in model fit by allowing ξ_k to vary. Indeed, the estimated captivity parameters at $d_g = 50$ is only slightly higher in T5 than it is for T1–T4. By increasing the attachment to a particular donation amount we raise the number of individuals at that amount, but only by drawing individuals from the neighboring donation amounts.

Column 7 shows that when we allow the attachment parameter ξ_{20} to vary with exposure to the fixed gift treatment T6, the substantial overprediction of average donations still remains.

To summarize then, our preferred structural model allows for focal point influences and a certain fraction of individuals having pure warm glow preferences. With these extensions, the model closely matches the empirically observed response rates and mean donation amounts: when using data from all 6 treatments, for 11 out of 12 moments (the extensive and intensive margins of giving across 6 treatments),

the empirical values are not statistically different those predicted by the structural model. Moreover, the model also does a good job in fitting the distribution of donations given in five out of six treatments.

The extended model still performs worse matching the data to the fixed gift treatment T6. One theoretical extension of the baseline model that might help to fit T6 would be to allow income effects. Three points are of note with regard to such an extension. First, income effects might not be very important for our sample of potential donors: they are likely high wealth individuals for whom donation amounts probably correspond to a small share of their income. Second, while such effects are theoretically straightforward to incorporate into our analysis, our data does not include any measures of income, and any attempts to proxy income with other measures produces results that are very sensitive to the way in which income effects are parameterized.³⁷ Third, for income effects to explain giving behavior in T6, donations given would have to be a hugely inferior good for many in the population, and that simply does not fit the evidence from most settings (Andreoni 2006a), and would likely lead to the model fitting T1–T5 less well.

In conclusion, we therefore leave for future research modeling extensions that can better explain behavior in nonlinear treatments such as T6. To reiterate, two key discrepancies exist between the predicted and observed donations under T6, as shown in Figure 3. First, we do not observe a mass of individuals giving 1 under T6 (or at the lowest discrete category), rather there is a mass of individuals that give precisely €20 under T6. Second, at the other extreme, the structural model also does not generate sufficient crowding out among the very highest donations, so that it over predicts the number of donations greater than €200 that really drives the significant difference between predicted and empirical donations.

It is hard to think of simple extensions, at least within a neoclassical framework, that could address both issues to help improve the model fit to T6, and at the same time, not worsen the model fit in the other treatments T1–T5. Taken together, this highlights that there are likely some very specific factors that impact giving behavior in fixed gift treatments that do not arise in other forms of nonlinear fundraising schemes, especially when the fixed gift kicks-in for *any* strictly positive donation.

E. Counterfactual Charitable Fundraising Schemes

We now use our preferred structural model of giving behavior to explore the effectiveness of alternative charitable fundraising schemes. We conduct such counterfactual experiments using the estimated parameters from the structural model

³⁷We first explored the possibility of matching our data to external data sources on income by zipcode. Unfortunately, available data sets such as the German Socio-Economic Panel (for which zipcode information is collected) have insufficient sample size. We were able to collect average house price information for our sample period for the Munich zipcodes. Using these data we then attempted to relate an unknown parametric distribution of income to this house price data and then integrating over this distribution in the likelihood function. Restricting ourselves to the subsample of Munich households considerably reduced sample size. Overall, such attempts to incorporate income effects performed very poorly, with our results highly sensitive to alternative parameterizations on how we allow for the possibility of income effects in the utility function.

with a discrete choice set, pure warm glow preferences, and focal points.³⁸ While in principle we could consider almost any matching scheme, we focus attention to simpler parametric forms, that are more realistic extensions of commonly observed fundraising schemes. The reduced form and structural form evidence presented thus far suggests that from the fundraiser's point of view, among the schemes considered in the experiment, it is optimal for the charitable organization to merely announce the existence of a significant and anonymous lead donor, and not to use the lead donation to match donations in any way. The aim of the counterfactual exercises performed is to explore whether there are other fundraising schemes beyond those in our experiments that out-perform the lead donor treatment. The counterfactual exercises also shed light on how different schemes perform should lead donors *insist* their gifts must be matched in some way.

Table 5 presents the findings from the various counterfactual schemes considered. As a point of comparison, column 1 shows the predicted outcomes from the preferred model for the lead donor treatment T2. At the foot of each column we show the predicted response, and mean donation given conditional on a strictly positive donation being made. Finally, because in some of the counterfactual exercises the response rate and mean conditional donation given might move in opposite directions, we also report the average donation given (including zeroes) to assess the overall performance in terms of revenue raised of each fundraising scheme.

Linear Matching Schemes: Higher Match Rates.—We first use our structural model to predict how revenue raised varies with linear matching rates, $R(d_g) = \lambda^0 d_g$, over a range outside of that considered in our experimental study. We consider matching rates between $\lambda^0 = 2$ through to $\lambda^0 = 4$, which are the match rates as considered in Karlan and List (2007). Columns 2A–2C show that increases in the match rate have little impact on the extensive margin where the initial decision to donate is made: response rates remain at around 4 percent as the match rate moves from $\lambda^0 = 2$ to $\lambda^0 = 4$. However, increasing match rates has a pronounced *negative* effect on average conditional donations given: donations given fall to €91.8 when donations are matched twice over ($\lambda^0 = 2$), they fall to €75.4 when $\lambda^0 = 3$, and they are €66.3 when the match rate is $\lambda^0 = 4$. As the final row on average donations given shows, taking into account both the extensive and intensive margins of giving, increasing match rates to these out-of-sample values leads to further declines in funds raised. Hence, this counterfactual analysis suggests it continues to be the case that as the charitable good becomes cheaper vis-à-vis own consumption, individuals demand more of it in terms of donations received including the match, but spend less on it themselves in terms of donations given prior to the match. From the charitable organization's perspective, more generous linear matching schemes are not an effective fundraising instrument relative to merely announcing the existence of a significant and anonymous lead donor.

³⁸All moments are calculated using the empirical distribution of demographic characteristics across all six experimental treatments. The estimated preference parameters are shown in panel C of Table A1.

TABLE 5—COUNTERFACTUAL CHARITABLE FUNDRAISING SCHEMES

	T2: Lead donor (1)	Linear matching: Higher match rates			Nonlinear matching: Variable thresholds and post-threshold match rates		
		(2A)	(2B)	(2C)	(3A)	(3B)	(3C)
Pre-threshold match rate: λ^0	1	2	3	4	1	1	1
Post-threshold match rate: λ^1	—	—	—	—	1.5	2	2
Threshold: d_χ	—	—	—	—	50	50	100
Value of fixed lead gift: d_f	—	—	—	—	—	—	—
Response rate	0.036	0.041	0.042	0.043	0.036	0.036	0.036
Mean donations given, conditional on a strictly positive donation	138	91.8	75.4	66.3	120	106	108
Average donation given	4.93	3.77	3.19	2.84	4.29	3.77	3.85

(Continued)

Notes: This shows outcomes for counterfactual estimates based on alternative fundraising schemes. In each column we show the predicted response rate (in percentage points), the predicted mean donation given (in euros) conditional on a strictly positive donation being made, and the average donation given (including zeroes) (in euros). All results are calculated using our preferred specification with a discrete choice set, pure warm glow preferences, and focal points. All donation rates and mean conditional donations are calculated using the empirical distribution of covariates observed across treatments T1 to T6. In column 1, predicted behavior in the lead donor treatment T2 is shown. In columns 2A to 2C, we consider linear matching schemes. In columns 3A to 3C, we consider nonlinear matching schemes that vary in the threshold at which the nonlinearity occurs, and the post-threshold matching rate.

TABLE 5—COUNTERFACTUAL CHARITABLE FUNDRAISING SCHEMES (Continued)

	Fixed gifts: Variable thresholds that trigger the fixed gift			Kinked match functions		
	(4A)	(4B)	(4C)	(5A)	(5B)	(5C)
Pre-threshold match rate: λ^0	1	1	1	1	1	1
Post-threshold match rate: λ^1	1	1	1	1.5	2	2
Threshold: d_χ	0	20	50	50	50	100
Value of fixed lead gift: d_f	20	20	20	—	—	—
Response rate	0.042	0.039	0.036	0.036	0.036	0.036
Mean donations given, conditional on a strictly positive donation	107	117	131	126	117	124
Average donation given	4.55	4.59	4.65	4.48	4.17	4.43

(Continued)

Notes: This shows outcomes for counterfactual estimates based on alternative fundraising schemes. In each column we show the predicted response rate (in percentage points), the predicted mean donation given (in euros) conditional on a strictly positive donation being made, and the average donation given (including zeroes) (in euros). All results are calculated using our preferred specification with a discrete choice set, pure warm glow preferences, and focal points. All donation rates and mean conditional donations are calculated using the empirical distribution of covariates observed across treatments T1 to T6. In columns 4A to 4C, we consider variations of the fixed gift donation T6 where we vary the threshold at which the lead gift is provided, and the value of the lead gift. In columns 5A to 5C, we consider kinked matching functions in which two match rates are offered either side of some threshold.

Nonlinear Matching: Variable Thresholds.—The next scheme considered is a generalization of the nonlinear matching scheme T5. We now allow alternative pre- and post-threshold matching rates, denoted λ^0 and λ^1 , respectively, as well as allowing the threshold point itself, $d_\chi \in \mathcal{D}_g$, to vary,

$$(15) \quad R(d_g) = \begin{cases} \lambda^0 d_g & \text{if } d_g < d_\chi; \\ \lambda^1 d_g & \text{if } d_g \geq d_\chi. \end{cases}$$

TABLE 5—COUNTERFACTUAL CHARITABLE FUNDRAISING SCHEMES (*Continued*)

	Generalized threshold matching		
	(6A)	(6B)	(6C)
Pre-threshold match rate: λ^0	1	1	1
Post-threshold match rate: λ^1	2	2	2
Threshold: d_χ	50	50	50
Value of fixed lead gift: d_f	25	75	100
Response rate	0.036	0.036	0.036
Mean donations given, conditional on a strictly positive donation	113	100	95.4
Average donation given	4.02	3.57	3.40

Notes: This shows outcomes for counterfactual estimates based on alternative fundraising schemes. In each column we show the predicted response rate (in percentage points), the predicted mean donation given (in euros) conditional on a strictly positive donation being made, and the average donation given (including zeroes) (in euros). All results are calculated using our preferred specification with a discrete choice set, pure warm glow preferences, and focal points. All donation rates and mean conditional donations are calculated using the empirical distribution of covariates observed across treatments T1 to T6. In columns 6A to 6C we consider a generalized matching scheme that encompasses the other schemes as special cases.

In columns 3A–3C of Table 5 we see that relative to treatment T5 in which the mean donation given was predicted to be €106, donations given are predicted to increase by: (i) decreasing the post-threshold matching rate slightly to $\lambda^1 = 1.5$ (column 3A); and (ii) increasing the threshold that induces the higher match rate to $d_\chi = 100$. With both variations, the response rate remains relatively unchanged at 3.6 percent, but relative to treatment T5 (column 3B) they increase both conditional mean and overall donations. This direction of change is unsurprising since both changes make the matching schemes considered here somewhat closer in structure to the unmatched lead donor treatment T2.

Fixed Gifts: Alternative Thresholds.—The next set of counterfactual fundraising schemes are variants of the fixed gift treatment T6, where rather than a fixed gift being contributed for *any* positive donation, we consider a fixed contributed $d_f \geq 0$ for any donation that exceeds some threshold value $d_\chi \in \mathcal{D}_g$,

$$(16) \quad R(d_g) = \begin{cases} d_g & \text{if } d_g < d_\chi; \\ d_g + d_f & \text{if } d_g \geq d_\chi. \end{cases}$$

As discussed, in Section II in the context of the nonconvex treatment T5, the benefit of this type of design is that it induces some individuals who were not donating to perhaps start donating positive amounts, and for those that were donating a strictly positive amount less than d_χ , to perhaps move to an interior corner solution where they donate more. However, the cost of this design is that individuals who are originally donating more than d_χ may now reduce their donations.

In columns 4A–4C of Table 5 we show the impact of alternative threshold values for the fixed gift to be given, while maintaining the value of the lead gift at $d_f = 20$ as in treatment T6. Starting from a fixed gift threshold that kicks-in at any strictly

positive donation in column 4A ($d_\chi = 0$), the results show that mean donations given are increasing in d_χ , while the response rate declines from 4.2 percent with a threshold $d_\chi = 0$, to 3.6 percent when the threshold is at $d_\chi = 50$. Hence, as the threshold increases, response rates converge to those observed under the lead donor treatment T2. Taking both extensive and intensive margins of giving into account, the final row of Table 5 shows how the average donation given varies (including zeroes). We see that while overall giving increases with the threshold for the fixed gift to be triggered (d_χ), it does so at a relatively slow rate. Overall, we see that variants of the fixed gift treatment generate higher fundraising revenues than alterations in linear match rates or variants of the nonlinear treatment T5 considered above. However, in order to match average donations in the lead donor treatment, unrealistically high threshold levels would need to be set.

Kinked Match Functions.—The remaining counterfactuals use the preferred structural model to explore giving behavior in response to two additional fundraising schemes that, to the best of our knowledge, have not previously been studied in the charitable fundraising literature. The first of these is a kinked matching scheme, where we allow donations to be first matched at rate λ^0 , and for the value of any donation exceeding some threshold value d_χ , to then be matched at a potentially different rate λ^1 . This formulation introduces a kink in the budget set rather than a discontinuity, so that,

$$(17) \quad R(d_g) = \begin{cases} \lambda^0 d_g & \text{if } d_g < d_\chi; \\ \lambda^0 d_\chi + \lambda^1 (d_g - d_\chi) & \text{if } d_g \geq d_\chi. \end{cases}$$

Relative to designs such as in the experimental nonlinear treatment T5, this form of kinked-matching will not induce as much bunching at the threshold value d_χ and will not induce as strong behavioral responses (holding both matching rates constant). We explore the impact of this matching scheme in columns 5A–5C of Table 5, considering an example where $\lambda^0 = 1$. In columns 5A–5B in which we initially consider the case where $d_\chi = 50$, we see that changes in the post-threshold match rate λ^1 have minimal impacts on the response rate, and result in a positive impact on the intensive margin of giving, raising overall donations. In the third counterfactual in column 5C, we find that overall revenue is increased as we increase d_χ to 100, and while this scheme raises more revenue than the linear and nonlinear matching treatments considered earlier, it still remains below what is obtained under the lead donor treatment T2.

Generalized Threshold Matching.—Finally, we consider a generalized matching scheme that nests all the previous design schemes as special cases. Specifically, under this scheme we allow there to be a discontinuity in the budget set as in the variable threshold matching design, but now allow the size of the discontinuity to

be varied independently of the prethreshold and postthreshold matching rates. More precisely, we allow the value of the donation matching to be increased by a fixed gift amount d_f for $d_g \geq d_\chi$,

$$(18) \quad R(d_g) = \begin{cases} \lambda^0 d_g & \text{if } d_g < d_\chi; \\ \lambda^0 d_\chi + \lambda^1 (d_g - d_\chi) + d_f & \text{if } d_g \geq d_\chi. \end{cases}$$

Varying the size of the discontinuity through the fixed gift d_f allows us to influence the incentives for individuals to locate on the alternative linear sections of the budget constraint.³⁹ The results are in columns 6A–6C of Table 5. Starting with a design similar to that in treatment T5, increases in the value of the fixed gift d_f : (i) have little impact on the extensive margin with the response rate stable at 3.6 percent; (ii) *reduce* total donations. Unsurprisingly, as the fixed gift tends to zero, we replicate the results for the kinked matching scheme described above.

In summary, none of the counterfactual fundraising schemes considered in Table 5 generate greater total revenues than does treatment T2, where the lead donor was simply announced. While some counterfactual schemes generate higher response rates (such as the linear matching schemes, and variants of the fixed gift treatment T6), none generate higher fundraising revenues overall. Of course, the counterfactual results are subject to the caveat that the precise design and wording of different matching schemes may induce important focal responses that we are not able to incorporate in these out-of-sample prediction exercises.⁴⁰

Moreover, if lead donors insist their gifts be used in *some* matching scheme, this counterfactual analysis shows that the fundraiser is best off using a nonconvex matching scheme that involves fixed gifts being provided at some strictly positive donation threshold. While these may be viewed as a generalization of the fixed gift matching treatment T6, where the model performs least well, an important distinction is that it no longer links the match to the extensive response, as is true in the original T6 treatment. Restricting attention to counterfactuals based on the treatments T1 to T5 reveals that if lead donors insist their gifts must be matched, then the fundraiser is best off implementing a nonconvex kinked match function as described in the previous subsection. These insights on optimal fundraising are novel in the economics literature on charitable giving, and show how some standard practices among fundraisers can be improved upon. In this sense, there appears to be scope for gains to fundraisers from taking on board insights from the literature studying how to

³⁹We obtain the linear matching rule when $\lambda^0 = \lambda^1$ and $d_f = 0$, conditional lump sum matching when $\lambda^0 = \lambda^1 = 1$, kinked donation matching when $d_f = 0$, and variable threshold matching when $d_f = (\lambda^1 - \lambda^0)d_\chi$.

⁴⁰Under the class of functions that we have considered here we did not obtain a fundraising scheme that outperformed T2 in terms of the total amount donated. By construction, these were all extensions of commonly used incentive schemes. In terms of design more generally, we may consider starting from a scheme with no matching, and perturbing it slightly. Introducing a match that applies to a single point on the schedule results in some individuals reducing their donation given, and some individuals increasing their amount given (possibly from zero) to where this match applies. Depending on the relative size of these groups, it is possible that such a perturbation would either increase or decrease total amounts given. While we did find situations where a deviation of this type raises donations, it typically involved both very small matches, and only actually raised marginally more than T2.

encourage individuals to contribute to their 401(k) savings plans (Madrian 2012), in which linear and nonlinear matching incentives are more commonly observed.

IV. Discussion

We have presented reduced form and structural form evidence from a large-scale natural field experiment designed to shed light on the efficacy of alternative charitable fundraising schemes. The key insight obtained from the structural model is that individual behavior is best explained in a model in which individuals are heterogeneous with respect to their valuation of the lead donation received, some proportion of individuals have pure warm glow preferences, and individuals are subject to focal point influences in giving behavior.

The second key insight of our analysis is based on utilizing this model to understand the optimal design of fundraising schemes within the set of schemes that are combinations of the linear and nonlinear schemes implemented in the natural field experiment. The counterfactual exercises performed using the preferred structural model reveal that, amongst this set, the optimal fundraising scheme is one in which the charitable organization merely announces the existence of a significant and anonymous lead donor, and does *not* use the lead donation to match donations in any way, be it through linear matching, nonlinear matching, threshold matching, or some combination of the three schemes. If, however, lead donors insist their gifts must be matched in some way, the fundraiser is best off using a nonconvex matching scheme that involves fixed gifts being provided at some strictly positive donation threshold.

This is a novel insight for fundraisers, that shows current practices can likely be improved upon in this setting. More broadly, this opens up the possibility of fundraising schemes that are tailored to the characteristics of recipients being more effective than the types of nondiscriminatory fundraising schemes explored here. Indeed, we plan to explore such possibilities in future research.

We conclude by discussing two remaining issues. First, given our finding on the effectiveness of the mere announcement of lead donors over the commitment to use the lead gift to match donations in some way, this naturally begs the question of why fundraisers are typically observed employing the latter type of fundraising scheme. One explanation is that for projects with a specific target to be raised, the announcement of significant lead donors might discourage additional contributions (List and Lucking-Reiley 2002). An alternative explanation might stem from the fact that the same organization is typically not observed experimenting with different fundraising schemes and thus receives little feedback on alternatives. In line with evidence on for-profit firms (Levitt 2006), absent informative feedback on alternative schemes, systematic deviations from optimal fundraising methods might then be more likely.

Another explanation is that lead donors might insist their gifts be used in some matching scheme, say because they want to aggregate others' information. Finally, competition for lead donors between charitable organizations might cause the organizations to have to offer that such gifts will be matched: all else equal, the lead donor might well prefer to provide a gift that is used to match the donations of others. Our counterfactual analysis shows that in this case, the fundraiser is best off

TABLE 6—FOLLOW-UP FIELD EXPERIMENT ON LEAD DONORS

Treatment description	Number of recipients (1)	Response rate (2)	Mean donation, conditional on strictly positive donation (3)
<i>Main 2006 field experiment</i>			
Stück für Stück Project (anonymous lead donor, €60,000)	3,770	0.035 (0.003)	132 (14.3)
<i>Follow-up 2007 field experiment</i>			
Stück für Stück Project (anonymous lead donor, €12,000)	1,034	0.015 (0.004)	102 (31.0)
Stück für Stück Project (named lead donor, €12,000)	992	0.013 (0.004)	113 (38.6)

Notes: Mean and standard errors in parentheses. All monetary amounts are in euros. In the follow-up field experiment in 2007, all figures refers to new recipients that were not part of the 2006 field experiment.

using a nonconvex matching scheme that involves fixed gifts being provided at some strictly positive donation threshold.

Second, our analysis raises the question of *why* potential donors might be so responsive to the presence of lead donors. The literature suggests lead donors might alter the marginal utility of giving of others through a variety of channels, such as lead gifts serving as a signal about the quality of the fundraising project (Vesterlund 2003), snob appeal effects (Romano and Yildirim 2001), or in the presence of increasing returns, such lead gifts eliminate an equilibrium in which all donations are zero (Andreoni 1998). While disentangling such explanations lies beyond the scope of the current paper, we briefly present evidence from a follow-up field experiment we conducted, again in conjunction with the Bavarian State Opera in Munich, a year after the original mail-out.

In this follow-up field experiment we mailed opera attendees a letter describing the same charitable fundraising project, “Stück für Stück,” organized by the opera house. We focus on recipients that had not been part of the original mail-out in 2006. These new recipients were randomly assigned to treatments that varied in whether information was provided on the identity of the lead donor: in the control group the lead donor was anonymous, and in the treatment group the lead donor was revealed to be a member of the “Premium Circle,” the highest level of philanthropic support for the Opera House. In both treatment and control groups the lead donor committed to a significant donation of €12,000 (corresponding to over 100 times the average donation), rather than the €60,000 lead gift in treatment T2 from the earlier field experiment.

Table 6 shows the main results from this follow-up natural field experiment in terms of the extensive and intensive margins of giving. As a point of comparison, the first row highlights outcomes from the original lead donor treatment T2 in the main 2006 experiment. Two results emerge. First, in comparison to the original lead donor treatment in 2006, response rates in both the control and treatment groups in the follow-up experiment are significantly lower. This suggests that as the value of the lead gift falls, so does the likelihood that individuals respond to the fundraising drive. Second, comparing across the 2007 treatments, we see that individuals are

equally responsive on the extensive and intensive margins of giving as we move from an anonymous to a named lead donor, holding constant the value of the lead gift. This suggests the anonymity of the lead donor is less important for predicting others' giving behavior.

Overall, this provides some tentative evidence that lead donors—and in particular the value of the lead donation rather than the identity of the lead donor—might serve as signals about the quality of the fundraising project (Vesterlund 2003). This provides a basis for future research on understanding the role of lead donations for the economics of charitable giving specifically, and on understanding behavior in markets with quality signaling more generally.⁴¹

APPENDIX

In the nonlinear matching treatment T5, donations are matched one-for-one, but only if the donation given is greater than €50. Here we derive the parameter restrictions that determine the optimal choice of d_g by considering the utility attained from either not donating, donating exactly €50, or donating some positive amount that is either more than or less than €50. First, consider the situation where no interior solution is a candidate for a utility maximum. Straightforward calculations show that this requires,

$$\begin{aligned} 0 < \alpha \leq \frac{1}{200} \quad & \text{and} \quad \theta < \frac{1}{2}(1 + 200\alpha) \\ \frac{1}{200} < \alpha \leq \frac{1}{100} \quad & \text{and} \quad \theta < 1; \\ \alpha > \frac{1}{100} \quad & \text{and} \quad \theta < 1 \quad \quad \text{or} \quad 1 + 50\alpha < \theta < \frac{1}{2}(1 + 200\alpha). \end{aligned}$$

The solution with $d_g = 50$ will then be optimal provided that the participation constraint, which requires that the utility from giving exactly €50 exceeds the utility from not giving is satisfied. That is, if $-50 + \theta 100 - \frac{\alpha}{2} 100^2 > 0$. Suppose instead that the only candidate interior solution is on the budget constraint where $d_g \geq 50$. This is true if

$$0 < \alpha \leq \frac{1}{200} \quad \text{and} \quad \frac{1}{2}(1 + 200\alpha) \leq \theta < 1 \quad \text{or} \quad \theta \geq 1 + 50\alpha;$$

⁴¹There obviously remains much to understand about the nature of lead gifts given the nascent literature on such schemes. The few papers that study variants of lead gift schemes in the field, do not point to a clear consensus emerging on the key features of lead gifts. For example, Karlan and List (2007) find the announcement of the availability of a match from a lead donor, but no specific information on the total value available for matching, increases responses on both extensive and intensive margins of charitable giving (relative to a control group in which no lead gift is announced). Providing recipients with additional information on the value available for matching—ranging from \$25,000 to \$100,000—however had little additional impact on giving behavior. Karlan and List (2013) show how revealing the identity of a highly reputable lead donor can further enhance donations of others provided they are aware of the lead donor's reputation. They argue that this heterogeneous treatment effect is strongly suggestive of signaling. Finally, Rondeau and List (2008) also find that lead gifts (challenge gifts) are more effective than matching gifts in the field. their design allows them to attribute this to signaling effects.

TABLE A1—STRUCTURAL PARAMETER ESTIMATES

	Constant	Gender [Female = 1]	Munich resident [Yes = 1]	Average price of tickets bought in last 12 months	Number of ticket orders in last 12 months	Year of last ticket purchase [2006 = 1]
<i>Panel A. Continuous donations given, d_g</i>						
μ_θ^0	-3.065 (2.270)	-0.25 (0.246)	-0.157 (0.223)	0.268 (0.324)	0.051 (0.037)	0.484 (0.346)
μ_θ^1	-9.603 (5.154)	-0.079 (0.245)	-0.217 (0.304)	1.242 (0.762)	0.13 (0.073)	1.262 (0.679)
σ_θ^0	2.008 (1.086)					
σ_θ^1	4.656 (2.321)					
α	0.011 (0.006)					
<i>Panel B. Discrete donations given, d_g</i>						
μ_θ^0	-2.865 (2.029)	-0.238 (0.228)	-0.149 (0.208)	0.263 (0.304)	0.049 (0.033)	0.464 (0.311)
μ_θ^1	-8.719 (4.605)	-0.064 (0.223)	-0.205 (0.278)	1.117 (0.700)	0.12 (0.066)	1.16 (0.612)
σ_θ^0	1.932 -0.976					
σ_θ^1	4.313 (2.074)					
α	0.011 (0.005)					
<i>Extended Model</i>						
<i>Panel C. Discrete donations given, warm glow and focal points</i>						
μ_θ^0	-3.943 (0.326)	-0.301 (0.195)	-0.186 (0.195)	0.333 (0.257)	0.062 (0.024)	0.587 (0.207)
μ_θ^1	-8.789 (0.408)	-0.057 (0.188)	-0.219 (0.207)	1.065 (0.316)	0.122 (0.022)	1.175 (0.210)
σ_θ^0	2.464 (0.036)					
σ_θ^1	4.427 (0.083)					
α	0.013 (0.000)					
π_w	0.328 (0.080)					
ξ_{20}	-0.046 (0.065)					
ξ_{50}	2.271 (0.137)					
ξ_{100}	7.656 (0.254)					

Notes: Baseline model using linear matching treatments T1–T4. Bootstrapped standard errors in parentheses. Panels A and B show the maximum likelihood parameter estimates of our baseline model with a continuous choice set (panel A) and a discrete choice set (panel B). The choice of donation amounts under the discrete choice set specification is restricted to belong to the set $\mathcal{D}_g = \{0, 10, 20, 25, 30, 35, 50, 100, 150, 200, 350, 500, 1,000\}$. Panel C shows maximum likelihood parameter estimates of our preferred specification with warm glow preferences and focal points. All estimation is performed using data from treatments T1 to T4 only, and standard errors are in parentheses. All monetary amounts are measured in 100's of euros. The “last twelve months” refers to the year prior to the mail out from June 2005 to June 2006. Standard errors are in parentheses and are calculated using 500 bootstrap repetitions.

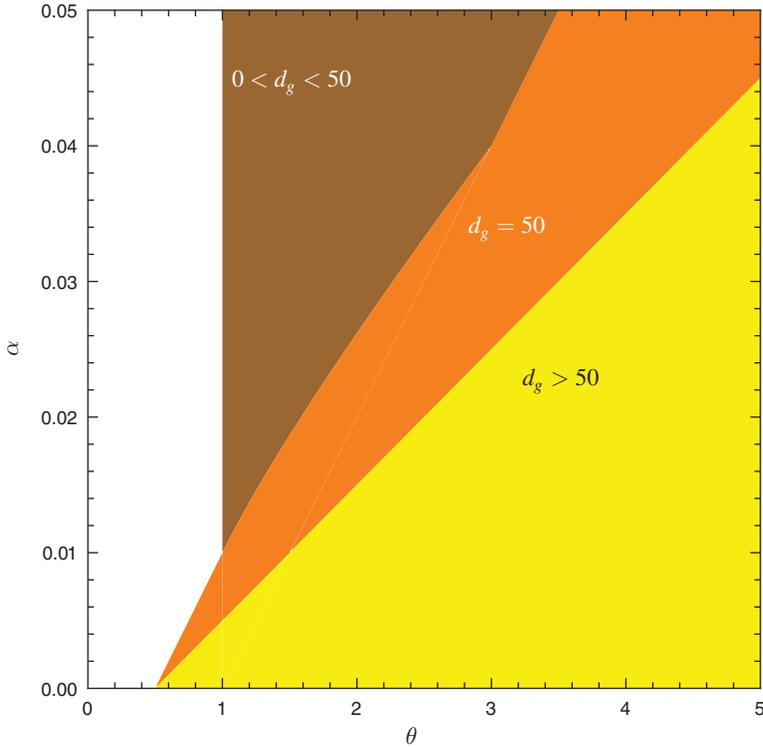


FIGURE A1. GIVING BEHAVIOR IN THE NONLINEAR MATCHING TREATMENT T5

Notes: The labeled shaded areas denote the regions in the parameters space where different giving behavior ($0 < d_g < 50$, $d_g = 50$, and $d_g > 50$) are optimal under the nonlinear matching treatment T5. The unshaded area corresponds to the region in the parameter space where donations are zero.

$$\frac{1}{200} < \alpha \leq \frac{1}{100} \quad \text{and} \quad \theta \geq 1 + 50\alpha;$$

$$\alpha > \frac{1}{100} \quad \text{and} \quad \theta \geq \frac{1}{2}(1 + 200\alpha).$$

Since individuals may optimally choose exactly $d_g = 50$ on this section of the budget constraint, the only additional constraint that we need to consider is the participation constraint, $\theta > \frac{1}{2}$, which is automatically satisfied in each of the cases above. Now, let us suppose that both $d_g \geq 50$ and $0 < d_g < 50$ are candidates. Again, it is straightforward to show that this is true if the following conditions hold:

$$0 < \alpha \leq \frac{1}{200} \quad \text{and} \quad 1 < \theta < 1 + 50\alpha;$$

$$\frac{1}{200} < \alpha < \frac{1}{100} \quad \text{and} \quad \frac{1}{2}(1 + 200\alpha) \leq \theta < 1 + 50\alpha.$$

However, by comparing equation (5) evaluated at $\lambda_T = 2$ to it being evaluated at $\lambda_T = 1$, utility from $d_g \geq 50$ will exceed that from $0 < d_g < 50$ if $\theta > \frac{3}{4}$, which is satisfied in the above. Thus, whenever both sections have candidates for interior solutions, only $d_g \geq 50$ can be optimal. The participation constraint $\theta > \frac{1}{2}$ will again be automatically satisfied.

The most interesting case to consider is when the only feasible interior solution is on the first linear section, where $0 < d_g < 50$. This is true if

$$\begin{aligned} \frac{1}{200} < \alpha \leq \frac{1}{100} \quad \text{and} \quad 1 < \theta < \frac{1}{2}(1 + 200\alpha); \\ \alpha > \frac{1}{100} \quad \text{and} \quad 1 < \theta < 1 + 50\alpha. \end{aligned}$$

Ignoring the participation constraint, we need to determine whether choosing the amount $d_g = 50$ is preferable. To do this we define θ^* such that the utility level of donating this amount strictly exceeds the maximized utility level on the interior section. Using equation (5), this requires

$$-50 + \theta^*100 - \frac{\alpha}{2}100^2 = \frac{(\theta^* - 1)^2}{2\alpha}.$$

This quadratic equation has two solutions, but only the solution $\theta^* = 1 - 10\sqrt{\alpha} + 100\alpha$ is consistent with $d_g < 50$ on the interior section. Thus, under the additional condition that $\theta < \theta^*$, we will have an interior solution with $0 < d_g < 50$. Conversely, if we have $\theta \geq \theta^*$, then $d_g = 50$ is optimal. In both cases the participation constraint will necessarily be satisfied.

These giving patterns are summarized in Figure A1: the lightest shaded area corresponds to the set of parameters where an individual is on the matched section of the budget constraint with $d_g > 50$; the middle gray area is the parameter set where $d_g = 50$; the darkest area is the parameter set where $0 < d_g < 50$.

A. *The Mail Out Letter (Translated)*

Bayerische Staatsoper
Staatsintendant
Max-Joseph-Platz 2, D-80539 München
www.staatsoper.de
[ADDRESS OF RECIPIENT]
Dear [RECIPIENT],

The Bavarian State Opera House has been investing in the musical education of children and youths for several years now as the operatic art form is in increasing danger of disappearing from the cultural memory of future generations.

Enthusiasm for music and opera is awakened in many different ways in our children and youth programme, “Erlebnis Oper” [*Experience Opera*]. In the forthcoming

season 2006/7 we will enlarge the scope of this programme through a new project “Stück für Stück” that specifically invites children from schools in socially disadvantaged areas to a playful introduction into the world of opera. Since we have extremely limited own funds for this project, the school children will only be able to experience the value of opera with the help of private donations.

[This paragraph describes each matching scheme and is experimentally varied as described in the main text of the paper].

As a thank you we will give away a pair of opera tickets for Engelbert Humperdinck’s “Königskinder” on Wednesday, 12 July 2006 in the music director’s box as well as fifty CDs signed by Maestro Zubin Mehta among all donors.

You can find all further information in the enclosed material. In case of any questions please give our Development team a ring on [phone number]. I would be very pleased if we could enable the project “Stück für Stück” through this appeal and, thus, make sure that the operatic experience is preserved for younger generations.

With many thanks for your support and best wishes,

Sir Peter Jonas, Staatsintendant

“Stück für Stück”

The project “Stück für Stück” has been developed specifically for school children from socially disadvantaged areas. Musical education serves many different functions in particular for children and youths with difficult backgrounds – it strengthens social competence and own personality, improves children’s willingness to perform, and reduces social inequality. Since music education plays a lesser and lesser role in home and school education, the Bavarian State Opera has taken it on to contribute to it ourselves. The world of opera as a place of fascination is made attainable and accessible for young people.

In drama and music workshops, “Stück für Stück” will give insights into the world of opera for groups of around 30 children. They will be intensively and creatively prepared for a subsequent visit of an opera performance. These workshops encourage sensual perception – through ear and eye but also through scenic and physical play and intellectual comprehension – all of these are important elements for the workshops. How does Orpheus in “Orphee and Eurydice” manage to persuade the gods to let him save his wife from the realm of dead? Why does he fail? Why poses the opera “Cosi fan tutte” that girls can never be faithful? It is questions like these that are investigated on the workshops.

The workshops are also made special through the large number and variety of people who are involved in them: musicians, singers, directors, and people from many other departments, ranging from costumes and makeup to marketing. The participants in each workshop work through an opera’s storyline, and are introduced to the

production and will meet singers in their costumes as well as musicians. This makes the workshops authentic. After the workshops the participants are invited to see the actual opera production.

Through your donation the project “Stück für Stück” will be made financially viable so that we can charge only a small symbolic fee to the participants. This makes it possible to offer our children and youth programme also to children from socially disadvantaged backgrounds that can, thus, learn about the fascination of opera.

Note: In German, Stück für Stück is a wordplay --- “Stück” meaning “play” as in drama and “Stück für Stück” being an expression for doing something bit by bit.

REFERENCES

- Andreoni, James.** 1990. “Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving.” *Economic Journal* 100 (401): 464–77.
- Andreoni, James.** 1998. “Toward a Theory of Charitable Fund-Raising.” *Journal of Political Economy* 106 (6): 1186–1213.
- Andreoni, James.** 2006a. “Philanthropy.” In *Handbook of the Economics of Giving, Altruism and Reciprocity*, Vol. 2, edited by Serge-Christophe Kolm and Jean Mercier Ythier, 1201–69. Amsterdam: North Holland.
- Andreoni, James.** 2006b. “Leadership Giving in Charitable Fund-Raising.” *Journal of Public Economic Theory* 8 (1): 1–22.
- Andreoni, James, and John Miller.** 2002. “Giving According to GARP: An Experimental Test of the Consistency of Preferences for Altruism.” *Econometrica* 70 (2): 737–53.
- Auten, Gerald E., Holger Sieg, and Charles T. Cloffelter.** 2002. “Charitable Giving, Income, and Taxes: An Analysis of Panel Data.” *American Economic Review* 92 (1): 371–82.
- Bracha, Anat, Michael Menietti, and Lise Vesterlund.** 2011. “Seeds to Succeed? Sequential Giving to Public Projects.” *Journal of Public Economics* 95 (5–6): 416–27.
- Briers, Barbara, Mario Pandelaere, and Luk Warlop.** 2007. “Adding Exchange to Charity: A Reference Price Explanation.” *Journal of Economic Psychology* 28 (1): 15–30.
- de Oliveira, Angela C. M., Rachel T. A. Croson, and Catherine Eckel.** 2011. “The Giving Type: Identifying Donors.” *Journal of Public Economics* 95 (5–6): 428–35.
- DellaVigna, Stefano, John A. List, and Ulrike Malmendier.** 2012. “Testing for Altruism and Social Pressure in Charitable Giving.” *Quarterly Journal of Economics* 127 (1): 1–56.
- Eckel, Catherine C., and Philip J. Grossman.** 2006. “Subsidizing Charitable Giving: A Field Test Comparing Matching and Rebate Subsidies.” Unpublished.
- Fack, Gabrielle, and Camille Landais.** 2010. “Are Tax Incentives For Charitable Giving Efficient? Evidence from France.” *American Economic Journal: Economic Policy* 2 (2): 117–41.
- Harrison, Glenn W., and John A. List.** 2004. “Field Experiments.” *Journal of Economic Literature* 42 (4): 1009–55.
- Huck, Steffen, and Imran Rasul.** 2010. “Transaction Costs in Charitable Giving: Evidence From Two Field Experiments.” *B.E. Journal of Economic Analysis and Policy* 10 (1): 1–35.
- Huck, Steffen, and Imran Rasul.** 2011. “Matched Fundraising: Evidence From a Natural Field Experiment.” *Journal of Public Economics* 95 (5–6): 351–62.
- Huck, Steffen, Imran Rasul, and Andrew Shephard.** 2015. “Comparing Charitable Fundraising Schemes: Evidence from a Natural Field Experiment and a Structural Model: Dataset.” *American Economic Journal: Economic Policy*. <http://dx.doi.org/10.1257/pol.20120312>.
- Karlan, Dean, and John A. List.** 2007. “Does Price Matter in Charitable Giving? Evidence from a Large-Scale Natural Field Experiment.” *American Economic Review* 97 (5): 1774–93.
- Karlan, Dean, and John A. List.** 2013. “How Can Bill and Melinda Gates Increase Other People’s Donations to Fund Public Goods?” <http://karlan.yale.edu/p/Technoserve.pdf>.
- Levitt, Steven D.** 2006. “An Economist Sells Bagels: A Case Study in Profit Maximization.” National Bureau of Economic Research (NBER) Working Paper 12152.

- List, John A., and David Lucking-Reiley.** 2002. "The Effects of Seed Money and Refunds on Charitable Giving: Experimental Evidence from a University Capital Campaign." *Journal of Political Economy* 110 (1): 215–33.
- List, John A., and Michael K. Price.** 2012. "Charitable Giving Around the World: Thoughts on How to Expand the Pie." *CESifo Economic Studies* 58 (1): 1–30.
- Madrian, Brigitte C.** 2012. "Matching Contributions and Savings Outcomes: A Behavioral Economics Perspective." National Bureau of Economic Research (NBER) Working Paper 18220.
- Potters, Jan, Martin Sefton, and Lise Vesterlund.** 2007. "Leading-by-Example and Signaling in Voluntary Contribution Games: An Experimental Study." *Economic Theory* 33 (1): 169–82.
- Randolph, William C.** 1995. "Dynamic Income, Progressive Taxes, and the Timing of Charitable Contributions." *Journal of Political Economy* 103 (4): 709–38.
- Romano, Richard, and Huseyin Yildirim.** 2001. "Why Charities Announce Donations: A Positive Perspective." *Journal of Public Economics* 81 (3): 423–47.
- Rondeau, Daniel, and John A. List.** 2008. "Matching and Challenge Gifts to Charity: Evidence from Laboratory and Natural Field Experiments." *Experimental Economics* 11 (3): 253–67.
- Vesterlund, Lise.** 2003. "The Informational Value of Sequential Fundraising." *Journal of Public Economics* 87 (3–4): 627–57.