

Comparing Charitable Fundraising Schemes:
Evidence from a Field Experiment and a Structural Model

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COMPARING CHARITABLE FUNDRAISING SCHEMES: EVIDENCE FROM A FIELD EXPERIMENT AND A STRUCTURAL MODEL*

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Abstract

We present evidence from a natural field experiment designed to shed light on the efficacy of alternative fundraising schemes. In conjunction with the Bavarian State Opera House, we mailed 25,000 regular opera attendees a letter describing a charitable fundraising project organized by the opera house. Recipients were randomly assigned to six treatments designed to explore behavioral responses to fundraising schemes varying in two dimensions: (i) the presence of a lead donor; (ii) whether and how individual donations would be matched using the lead donation. We provide reduced form evidence from the field experiment on the causal impact of each fundraising scheme on the extensive and intensive margins of giving. We then develop and estimate a structural model of giving behavior that simultaneously estimates individual responses on both margins. We utilize the structural model to predict giving behavior in counterfactual fundraising schemes. The evidence suggests 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, non-linear matching, threshold matching, or some combination of the three. We conclude by discussing evidence from a follow-up field experiment designed to probe further the question why lead donors are effective.

Keywords: charitable giving, field experiment, structural estimation.

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1 Introduction

This paper presents evidence from a large-scale natural field experiment designed to shed light on the efficacy of alternative fundraising schemes. We study the role of lead gifts, linear and non-linear matching schemes by presenting reduced form evidence from the experiment, and estimating a structural model of giving to inform the optimal design of fundraising schemes. We provide new insights and show how some standard practices among fundraisers can be improved upon.¹

Much of the existing literature has focussed on responses to two forms of commonly observed fundraising schemes—linear matching [Eckel and Grossman 2006, Karlan and List 2007, Huck and Rasul 2011] and the provision of lead gifts [List and Lucking-Reilly 2002, Potters *et al.* 2007, Rondeau and List 2008, Bracha *et al.* 2012]. 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 field experiment on the causal impact of each fundraising scheme on: (i) the extensive margin of giving, namely, the percentage of individuals that donate some positive amount; (ii) the intensive margin of giving, namely, the amount donated. We then 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 natural field 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 may act as a signal of project quality [Vesterlund 2003, Andreoni 2006b]; (ii) linear matching schemes where contributions were matched at either 50% or 100%, analogous to considerable reductions in the relative price of charitable giving vis-à-vis own consumption; (iii) non-linear matching schemes, where contributions above a fixed threshold would be matched at a given rate; (iv) fixed gift matching schemes, in which *any* positive donation would be matched by a fixed amount. The design of the field experiment allows us to compare behavior under commonly

¹Andreoni [2006a] presents evidence from the US that in 1995, 70% of households made some charitable donation with an average donation of over \$1000, or 2.2% of household income. List and Price [2012] provide evidence that in 2003, \$241billion was given in the US, corresponding to 2% of GDP, three quarters of which stemmed from individuals.

²With the exception of DellaVigna *et al.* [2011] 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.

observed fundraising schemes that involve a lead donor or linear match rates, to less commonly observed schemes involving non-linear or fixed gift matching.

Our main results from the reduced form analysis are as follows. First, despite their ubiquity in fundraising campaigns, linear matching schemes do not pay for the fundraiser. As shown in Huck and Rasul [2011], 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. In other words, linear matching leads to partial crowding out of the donations actually received, therefore reducing the revenues raised.

Second, potential donors are quantitatively most sensitive to the presence of a lead donor. Relative to a control group in which no information on lead gifts is provided, donations given increase by 44%, with no change in overall response rates. Comparing this effect with the results from our 100% linear matching treatment we find that individuals are quantitatively more sensitive to lead donors than to a halving of the relative price of charitable giving for example. Given the nature of the charitable project, which has no fixed-cost element, one explanation is that the presence of the anonymous lead donor—who commits to provide €60,000 or around 600 times the average donation—serves as a credible signal of the project’s quality as predicted by Vesterlund [2003]. Moreover, the effect of the signal is heterogeneous across individuals—the effect is increasing in the amount individuals would have donated in the absence of the signal, so more generous donors are more affected. Our design, in contrast to Karlan and List [2007] for example, is able to identify the pure impact of such lead donors, absent any offer to use the lead donation to match others’ donations in some way.³

Third, well-designed non-linear matching schemes that require a minimum donation before the match rate kicks-in cause donations given to be *crowded in* with little or no change in the overall proportion of recipients that donate in the first place. This effect is in line with standard consumer theory that predicts when individuals face a non-convex budget set, those that would give relatively little in the presence of no matching might find it optimal to choose an interior corner solution and donate more.

Finally, the fixed gift scheme leads to the highest response rates, as expected. However, we find that even among this targeted group of regular opera attendees, 95% make no contribution to the project. These individuals either do not value the project at all, or, face transactions costs that are sufficiently high to offset any warm glow they feel from giving to this particular cause [Huck and Rasul 2010]. Furthermore, the new donations drawn in with this treatment are relatively

³This is in line with the results of Potters *et al* [2007] who examine the role of lead contributions in a laboratory setting. They find support for the signaling hypothesis as modelled 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.

small in magnitude. Overall, this fundraising scheme leads to full crowding out of donations given—individuals reduce one-for-one donations given in response to the effective income transfer received, to leave unchanged the donation actually received by the project, and to increase own consumption by the amount of the fixed gift. Hence such matching schemes do not pay for the fundraiser.

We then develop and estimate a structural model of charitable giving. We assume a parametric random quasi-linear form for preferences, in which individual preferences are defined over consumption and the donation received by the charitable organization. In this baseline model, individuals are heterogeneous with respect to their valuation of the lead donation received, and we allow for the possibility that the presence of the lead donor alters the marginal benefit from donating. We also allow the preference parameters to depend on individual characteristics. This parsimonious specification provides an empirically tractable framework in which we can simultaneously estimate behavior on the extensive and intensive margins of charitable giving.

To better exploit design features of the field experiment, we then extend the baseline model to allow for: (i) individuals restricting their donation choice to some finite and pre-determined discrete set; (ii) some fraction of individuals exhibiting *pure* warm glow preferences, so that they derive utility from their own private consumption as well as the value of their donation given, regardless of how this is matched; (iii) focal point influences, so that some subset of donation amounts might be particularly prominent among individuals.

Our preferred structural model is able to closely match the empirically observed response rates, mean donation amounts, and distribution of donations given, for the control group for whom no matching scheme is offered, as well as for those matching schemes involving a lead donor, linear matching, and non-linear matching. The structural model does less well in fitting responses to the fixed gift matching scheme. The structural estimates reveal that: (i) consistent with the descriptive evidence, characteristics indicating affinity to the opera house increase the mean value of donations; (ii) around 34% of individuals are best characterized as having pure warm glow preferences; (iii) individuals place particular prominence on donation amounts of €50 and €100.

At a final stage, we use our preferred structural model of giving behavior to explore the effectiveness of alternative charitable fundraising schemes. 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. These counterfactual exercises confirm that 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, non-linear matching, threshold matching, or some combination of the three schemes.

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.

The paper is organized as follows. Section 2 describes the natural field experiment, and presents a conceptual framework in which to understand behavior across the treatments. Section 3 provides

descriptive evidence on responses on the extensive and intensive margins of charitable giving in each treatment. Section 4 presents the reduced form analysis of individual decisions of whether and how much to donate in each treatment. Section 5 develops and estimates a structural model of individual preferences that best explain giving behavior, and conducts a counterfactual prediction exercise to shed light on the optimal fundraising scheme. Section 6 concludes with evidence from a follow-up field experiment designed to probe further the question of *why* lead donors are effective, and shows how responses to lead donors vary according to: (i) the value of the lead donation; (ii) the anonymity of the lead donor. The Appendix provides additional results and details on the precise format and wording of the mail out.

2 The Field Experiment

2.1 Design

In June 2006 the Bavarian State Opera organized a mail out of letters to 25,000 individuals designed to elicit donations for a social youth project the opera was engaged in, “Stück für Stück”. The project’s beneficiaries are children from disadvantaged families whose parents are almost surely not among the recipients of the mail out, reducing the role for gift exchange or reciprocity in driving donations [Falk 2007], and making the campaign similar to fundraising drives by aid charities.⁴

The recipients 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. Recipients 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.⁵

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*

⁴The 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.

⁵All 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. On the second sheet of the mail out further details on the “Stück für Stück” project were provided. Letters were signed by the General Director of the opera house, Sir Peter Jonas, and were mailed on the same day—Monday 19th June 2006.

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 one Euro corresponds to one Euro 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].⁶

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 that each donation would be matched at a rate of 50%, so that giving one Euro 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% 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%, so the corresponding paragraph in the mail out letter read as follows,

T4 (100% 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.*

Comparing behavior in the linear matching treatments T3 and T4 to T2 allows us to estimate the own price elasticity of donations received, as the price of giving relative to the price of own consumption is experimentally varied.⁷

To be able to later present novel evidence on optimal fundraising schemes, the final two treatments introduce less commonly observed fundraising schemes. The fifth treatment presented recipients with a non-linear, non-convex matching scheme. The letter offered a match rate of 100% 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,

⁶Andreoni [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.

⁷We 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.

T5 (Non-linear 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 also 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 non-convexity 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 towards €50 under T5. The structural estimation presented later will account for such focal point influences on behavior.

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.⁸

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 signalling effect 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.

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

⁸Huck and Rasul [2010] present evidence from another 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.

that recipients likely interpret that their marginal contributions will make a difference.^{9,10}

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% 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 differential effects on the time for donations to be received between any treatment and the control treatment, in which no such deadline was announced.¹¹

Finally, recipients are told the truth—the lead gift was actually provided and each matching scheme was implemented. 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.

2.2 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 4. This framework is then taken to the data using structural estimation methods in Section 5. Following standard consumer theory, we assume individuals have complete, transitive, continuous, monotone, and convex preferences over their private consumption, c , and the donation received by the project, d_r . The individual utility maximization problem is,

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

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 non-negative; 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 .

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

⁹The 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 [List and Lucking-Reiley 2002]. Rondeau and List [2008] present experimental evidence on the effects of lead donations in the presence of explicit targets.

¹⁰Although we cannot rule out with certainty that donors perceive their 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.

¹¹As 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.

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 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 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% match rate in T3, $\lambda = 1.5$, and with the 100% 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. As the price of consumption is normalized to one, if the match rate changes from λ to λ' , the relative price of donations received, p , falls from $\frac{1}{\lambda}$ to $\frac{1}{\lambda'}$ so the own price elasticity of donations received is,

$$\epsilon_{d_r,p} = \left(\frac{\Delta d_r}{\Delta p} \right) / \left(\frac{d_r}{p} \right) = \left(\frac{\Delta d_r}{\frac{1}{\lambda} - \frac{1}{\lambda'}} \right) / \left(\frac{d_r}{\frac{1}{\lambda}} \right). \quad (2)$$

where d_r is the average donation received in the baseline treatment with match rate λ , and Δd_r is the change in donations received as the match rate increases from λ to λ' .¹² The reduced form estimates allow us to recover the average own price elasticity among the sample donors, or equivalently, recover this elasticity assuming all sample donors have the same elasticity. The structural estimates allow for individuals to be heterogeneous along this dimension.

Two point predictions on this own price elasticity of donations are of note. First, if recipients are engaged in pure donation targeting—where individuals always choose a particular d_r independent of the price of donations received—then moving from a match rate of λ to λ' implies $\Delta d_r = 0$ and $\Delta d_g = \frac{\lambda - \lambda'}{\lambda'} d_g < 0$. Hence the own price elasticity of donations received is $\epsilon_{d_r,p} = 0$ so the increased match rate leads to full crowding out of donations given. Second, if preferences are characterized by *pure warm glow*—where individuals *only* care about the donation given rather than that actually received. If the match rate then increases from λ to λ' this leads to $\Delta d_g = 0$ and $\Delta d_r = (\lambda' - \lambda) d_g > 0$ so the own price elasticity of donations *received* is $\epsilon_{d_r,p} = -\frac{\lambda'}{\lambda}$.¹³

The reduced form estimates are informative of whether, on average, behavior can be characterized by either special case, or equivalently, allow us to test whether all individuals have the same

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.

¹³The *pure warm glow* model, a special case of the preferences described in Andreoni [1990], implies donors actually care only about their own consumption ($y - d_g$) and their donation given (d_g) but not about the donation received (d_r). In this special case the budget sets would be materially identical for donors. However, as documented later, the data rejects the hypothesis that donors behave according to the pure warm glow hypothesis.

type of special-case preference. The structural estimates allow for heterogenous preferences, and we consider a scenario where some fraction of individuals have pure warm glow preferences, and estimate this fraction along with the preference parameters.

The non-linear 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.

For each budget set considered, individuals may optimally locate at an exterior corner. Note however that every individual with preferences satisfying $\left. \frac{\partial u}{\partial d_r} \right|_{d_r=0} > 0$ 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 $\left. \frac{\partial u}{\partial d_r} \right|_{d_r=0} \not\geq 0$ and so are unlikely to contribute to the project in the presence of small transactions costs of doing so.¹⁴

3 Descriptive Evidence

3.1 Sample Characteristics and Treatment Assignment

Individuals that purchase a ticket are automatically placed on the opera house’s database. The original mail out was sent to 25,000 individuals on 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 treatments, so that individuals are indeed randomly

¹⁴Under the assumption that the source of income transfers does not matter—so that individuals respond in the same way to the fixed gift of €20 in T6 from the anonymous donor as they would to an increase in their own income by €20, the field experiment can also shed light on expenditure and income elasticities of charitable giving, as have been previously estimated in the literature using non-experimental methods. More precisely, the opera database contains information on individual expenditures on opera tickets in the twelve months preceding the mail out, denoted x . Then in a comparison of treatments T6 and T2 and further assuming individuals have a fixed budget for the opera that can be divided between attendance and charitable donations, the expenditure elasticity of donations received is,

$$\epsilon_{d_r,x} = \left(\frac{\Delta d_r}{\Delta x} \right) / \left(\frac{d_r}{x} \right) = \left(\frac{\Delta d_r}{20} \right) / \left(\frac{d_r}{x} \right),$$

where x denotes the annual expenditure on the opera in the baseline treatment T2, d_r is the average donation received in treatment T2, and Δd_r is the change in donations received between T6 and T2. Moreover, treatments T2 and T6 can further be used to estimate the income elasticity of own consumption,

$$\epsilon_{c,y} = \left(\frac{\Delta(y - d_g)}{\Delta y} \right) / \left(\frac{y - d_g}{y} \right) \approx 1 - \frac{\Delta d_g}{20},$$

where Δd_g is the change in donations given between T6 and T2, and as the budget share of donations given is small, $(y - d_g/y)$ is approximately equal to one. If recipients retain all the additional income with no increase in donations given then $\epsilon_{c,y} = 1$. Alternatively, if there is full crowding out of donations given then $\epsilon_{c,y} = 2$.

assigned into treatments.¹⁵

Columns 1 and 2 show that there is an almost equal split of recipients across treatments, and that close to 47% of all recipients are female. Columns 3 to 7 provide information on individuals' attendance at the opera. This is measured by the number of tickets the individual has ordered in the twelve 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 just under €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 40% of recipients reside within Munich, where the opera house is located. Finally, we note that the majority of individuals have attended the opera in the six months prior to the mail out.¹⁶

Two further points are of note. First, 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. In contrast, the average price per ticket bought might better proxy individual income. We later exploit this information to shed light on whether on the extensive margin, donors differ from non-donors predominantly in terms of their affinity to the opera, or in terms of their incomes. The structural model we later estimate also allows underlying preference parameters to vary with these observables.¹⁷

Second, 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 therefore sheds light on how such selected individuals donate towards a project that is being directly promoted by the opera house. To the extent that other organizations target charitable projects towards 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. Moreover, while the non-representativeness 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.

3.2 Donors and Non-Donors

Table 2 shows how donors and non-donors differ on observable characteristics. We report the mean and standard error of each characteristic, as well as the p -value on the null hypothesis that the characteristic is the same among donors and non-donors in the same treatment. Column 1

¹⁵The one exception is that there are slightly more females in T6 relative to T1. However we note that there are no significant gender differences between those in T6 and T2, which forms a more natural group from which to identify the causal effect of the specific matching scheme in T6.

¹⁶In Column 10 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.

¹⁷Of course, we cannot rule out the existence of 'opera buffs' whose expenditures on opera tickets are beyond their means. Insofar as such individuals exist, average ticket price might also reflect an element of affinity.

shows the number of donors overall and by treatment.

We see that individuals that have purchased more tickets in the year prior to the mail out, have placed more separate orders over the same time period, and have last attended the opera more recently are significantly more likely to donate in *each and every* treatment. In contrast, the average price per ticket does not differ significantly between donors and non-donors in five out of the six treatments. Munich residents are not more likely to respond in each treatment. As a further check, we exploit additional information on average house rents in Munich by zip code, measured in Euros per square meter. For the subset of recipients in Munich, Column 9 shows that in each treatment, the house rental price between donors and non donors is not significantly different, again suggesting that income proxies are not much correlated with behavior on the extensive margin of giving.

Taken together these results suggest that affinity to the opera house is strongly correlated to behavior along the extensive margin of whether to donate or not. Characteristics that more closely proxy individual income are less correlated with giving behavior on the extensive margin.

3.3 Recipient Behavior: Extensive and Intensive Margins

Table 3 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.

First, Column 1 shows that response rates vary from 3.5% to 4.7% 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].¹⁸

Second, 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, we note that the percentage changes in response rates are large across treatments, even if not statistically different from each other.

As made clear earlier, 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% highlights that even among this targeted population, 95% of individuals cannot be induced to donate. These individuals either do not value the project at all or must face transactions costs that are sufficiently high to offset any warm glow they feel from giving to this particular cause, and so optimally locate at the corner solution given by the vertical intercept in Figure 1.¹⁹

¹⁸One 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.

¹⁹Huck and Rasul [2010] present evidence from a field experiment in this setting designed to explore whether

Column 2 shows that, despite the response rates being not statistically significantly different from each other in the first four treatments, the total amounts donated vary considerably across treatments. Among the full sample of 25,000 recipients more than €120,000 were donated, 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 3 shows, corresponds to €127,039 actually raised for the project (including the value of matches), with a mean donation given of €93.2.²⁰

Column 4 shows the average amount given including zeroes among non-donors. This shows that donations given are significantly higher in all treatments relative to the control group with the exception of the fixed gift treatment. In comparing donations relative to the lead donor treatment, we find no significant differences in amounts given (including zeroes) among all treatments, again with the exception of the fixed gift treatment.

The remaining columns focus on statistics among donors. 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—Column 6 shows the median donation is also significantly higher in T2 than in T1.

This suggests the marginal rate of substitution between consumption and donations received is altered when individuals are aware of the existence of an anonymous lead donor who has already pledged a substantial monetary amount to the project. While such a lead donor does not induce new donors to enter, recipients who like the project to begin with like it even more when they observe that somebody else is already strongly committed to it. We provide further reduced and structural form evidence on how lead donors matter later in the paper.

In terms of linear matching schemes, we see that as the relative price of donations received falls 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% match rate, and to €185 in T4 with a 100% match rate. Importantly, as shown in Figure 1 and Column 7 of Table 3, 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 to €101 in T3 with a 50% match rate, and to €92.3 in T4 with a 100% match rate. Column 8 reiterates that 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.

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. An immediate consequence is

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% of individuals would likely donate to this fundraising drive, almost double the actual observed response rates in T1-T5.

²⁰This exceeded the expectations of the Bavarian State Opera which were that €22,000 would be donated overall on the basis of a 1% response rate and mean donation of €100.

that straight linear matching schemes as in treatments T3 and T4 do not pay for the fundraiser. We conclude 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. We later use the structural estimates to see whether this conclusion continues to hold when we predict how individuals would have responded to other match rates.²¹

The final two treatments involve non-linear matching schemes. Treatment T5 induces recipients to face a non-convex 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% matching treatment T4. Figure 1 shows that the average outcome in terms of donations given and received in T5 replicate almost exactly those in the 100% 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. We later use the structural estimates to predict what giving behavior would have been had alternative threshold values and match rates been offered.

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, and the lead donor treatment T2 in which recipients are only informed of the existence of the lead donor. As previously discussed, 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 strongly supported in the data, as best illustrated in Figure 1—there is a decrease in both the donations given and received in treatment T6 relative to the lead donor treatment T2. Column 5 of Table 3 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. Column 6 shows the median donations received is also significantly lower (by €30) in T6 than T2. These effects remain even in Columns 7 and 8 when differences in the mean and median amounts *given* are considered. It is worth noting that this decrease in donations is largely 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.

4 Reduced Form Evidence

We now present reduced form evidence on the extensive and intensive margins of giving. This also allows us to establish the robustness of the simple mean comparisons in Table 3, to probe further

²¹If 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.

some aspects of giving behavior, and to provide a transparent comparison to much of the existing literature using field experiments in charitable giving.

On the extensive margin of charitable giving, we estimate a probit model for whether any donation is given or not. Whether individual i donates or not depends on the budget set she faces as embodied in the treatment she is assigned to, T_i . We also control for individual characteristics X_i , that include 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 dummy for whether the year of the last ticket purchase was 2006.²² We report marginal effects and calculate robust standard errors throughout.

On the intensive margin of charitable giving, the central econometric concern is that even with random assignment into treatments, we cannot in general make valid causal inferences conditional on donations being positive because those that choose to donate are likely to differ from those that choose not to donate. Table 2 already highlights the observable dimensions along which donors differ to non donors. To address this issue we first estimate for the entire sample of recipients the following OLS specification for the donation received by the opera house from recipient i , d_{ri} ,

$$d_{ri} = \delta_1 T_i + \eta_1 X_i + \varepsilon_i, \quad (3)$$

so that $d_{ri} = 0$ for non donors, ε_i is a disturbance term and all other controls are as previously defined. Under the assumption of no spillover effects between treatments, the parameter of interest δ_1 then measures the average treatment effect on the donation received of individual i being assigned to treatment T_i relative to whichever is the omitted treatment.²³

Inference can be made on positive donations only under the condition that $E[\varepsilon_i | T_i, X_i, D_i = 1] = 0$ [Angrist 1997], so that unobserved determinants of the amount donated, conditional on giving, treatment assignment and observable characteristics, are orthogonal to unobserved determinants of the decision to donate. Under this assumption, we can estimate the treatment effects conditional on a positive donation being made using a hurdle model that explicitly assumes the initial decision to donate ($D_i = 0$ or 1) may be separated from the decision of how much to donate, namely, the choice over d_r conditional on $D_i = 1$. A simple two-tiered model for charitable giving has, as a first stage, the probit model described above. At the second stage, we assume donations received are log normally distributed conditional on any donation being given so $\log(d_{ri}) | (T_i, X_i, D_i = 1) \sim N(\delta_2 T_i + \eta_2 X_i, \sigma^2)$. The maximum likelihood estimator of the second stage parameters, (δ_2, η_2) , is the OLS estimator from the following regression,

$$\log(d_{ri}) = \delta_2 T_i + \eta_2 X_i + z_i \text{ for } d_{ri} > 0, \quad (4)$$

²²We also experimented with alternative controls in X_i . For example, the number of tickets bought may serve as an alternative proxy for affinity rather than the number of orders placed. However, we prefer the latter measure as the former may be confounded by recipients attending the opera with their friends and family. The main results are robust to slight alterations in the controls.

²³The disturbance term may in part capture determinants of charitable giving such as guilt or shame. We are implicitly assuming that such motives do not interact with the treatments so that comparisons of the change in behavior between treatments is informative.

where we calculate robust standard errors throughout [Wooldridge 2002]. For each treatment, we therefore present both the OLS and hurdle model estimates, with the caveats associated with each set of results. In contrast, the later structural analysis simultaneously models the decision to give and the amount given.

In all specifications, when estimating the response to the presence of a lead donor, we compare the data from treatments T1 and T2 where the former is the reference group; when estimating the response to linear matching schemes we compare the data from treatments T2, T3, and T4, where T2 is the reference group, and we include two dummies for whether recipient i is assigned to treatment T3 or to T4; when estimating the response to the non-linear matching scheme we compare the data from treatments T2 and T5 and from T4 and T5 where, in each case the former is the reference group; and when estimating the response to the fixed gift scheme, we compare the data from treatments T2 and T6 where T2 is the reference group.

4.1 Lead Donor

Comparing behavior between the control treatment T1 and the lead donor treatment T2 provides estimates of the effect of a lead donor on the extensive and intensive margins of charitable giving. Table 4 presents the results. Column 1 shows that, in line with the earlier descriptive evidence, recipients are no more likely to respond in the lead donor treatment T2 than they are to respond in the control group T1. This suggests the marginal donor does not much change in response to being informed about the presence of a substantial lead donor. However, on the intensive margin, Column 2 shows that recipients in the lead donor treatment T2 donate significantly more than those in the control treatment. Conditional on donating, the hurdle model estimate confirms this result in Column 3. The magnitude of this effect implies that donations increase by around $\exp \hat{\delta}_2 - 1 = 44\%$ moving from the control group T1 to the lead donor treatment T2.²⁴

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]. The evidence however suggests that the response rate is not much changed relative to the control group. One explanation is that the extent to which the MRS between consumption and donations given is affected by lead donors is an increasing function of the amount the individual would have donated in the absence of the lead donor. In other words, marginal donors are less affected by the lead donor than are individuals who would have donated more 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.

²⁴Although not the focus of our study, the coefficients on the other controls in Columns 1, 2, and 3 of Table 4 show that recipients who are generally more likely to donate some positive amount, under either treatment, are those that have—(i) placed more ticket orders in the 12 months prior to the mail out; (ii) paid a higher average price per ticket over the same period; (iii) last attended in the opera in the six months prior to the mail out. However, the magnitude of the first two effects is relatively small, while the last effect is considerable—those that attended the opera more recently are 2% more likely to respond than those that have not attended recently, other things equal. This is a quantitatively large effect given the response rate in the treatments is 3.6%. Recipients that have placed more ticket orders in the 12 months prior to the mail out, and have paid a higher average price per ticket over the same period, donate significantly more regardless of whichever treatment they are assigned to.

To provide direct evidence on this, we use quantile regression methods to characterize changes in the shape and spread of the conditional distribution of donations received, not just the change in the mean as estimated in (4). We therefore estimate the following quantile regression specification at each quantile $\tau \in [0, 1]$,

$$\text{Quant}_\tau(\log(d_{ri})|.) = \delta_\tau T_2 + \eta_\tau X_i \text{ for } d_{ri} > 0. \quad (5)$$

The parameter of interest, δ_τ , measures the difference at the τ th conditional quantile of log donations received between the lead donor treatment T_2 and the control group.

Figure 2 graphs estimates of δ_τ from (5) and the associated 95% confidence interval at each quantile when the comparison treatment is T1. This shows that the effect of the lead donor is more pronounced on those individuals that would have given more under the control treatment. 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, all else equal, causing the overall distribution of donations given to become more dispersed as it is stretched rightward at higher donation amounts.²⁵ The later structural analysis estimates how the presence of a lead donor affects the distribution of subjective valuations of the project. Consistent with these reduced form results, we find that the lead donor changes this distribution such that the effect on giving is primarily on the intensive margin.

4.2 Linear Matching

The remaining Columns of Table 4 consider behavioral responses to the other common fundraising scheme considered in the field experiment: linear matching schemes. We compare responses on the extensive and intensive margin of recipients in treatments T3, which introduces a 50% match rate, and T4, which introduces a 100% match rate, relative to treatment T2 that involves no match rate. In all treatments, recipients are aware of the existence of a lead donor, and so comparisons to behavior in T2 isolate the pure price effects of the fundraising schemes.

Column 4 shows that, in line with the descriptive evidence, recipients are no more likely to respond to either price matching treatment than to the baseline treatment, T2. On the intensive margin, the OLS estimates in Column 5 show that relative to recipients in the lead donor treatment T2 which involves no match rate—(i) larger donations are received in treatment T3, although this

²⁵We find little evidence that the effect of the lead donor on individual’s propensity to donate varies by their observable characteristics. In particular, individuals that attend the opera more frequently or purchase more expensive tickets are not differentially sensitive on the extensive margin to the signal. The only robust evidence of such heterogeneous responses to the presence of a lead donor are that men are 1% *less* likely to respond to the presence of a lead donor, and women are .9% *more* likely to respond to such information. However there is no differential effect by gender on the intensive margin. We are unaware of other studies that document whether women are more responsive to quality signals in the marketplace, or whether in the specific context of charitable giving, women are more sensitive on the extensive margin to the presence of lead donors. As a point of comparison, we note that men and women donate similar amounts in T1—the mean donation of men (women) is €76 (€72) and the median donation for both is €50.

is not quite significantly different from zero at conventional levels; (ii) significantly larger donations are received in treatment T4. These results are confirmed using the hurdle model specification in Column 3 based only on positive donations.²⁶

In Column 6 we also report the implied own price elasticity of donations received, $\epsilon_{d_r,p}$. This varies from $-.534$ when we consider the behavioral response in T3 vis-à-vis T2, to -1.12 when considering T4 vis-à-vis T3. In terms of special cases, in five out of six tests these estimated own price elasticities reject the null that average behavior is characterized by individuals having pure warm glow preferences ($\epsilon_{d_r,p} = -\frac{\lambda'}{\lambda}$) or by donation targeting ($\epsilon_{d_r,p} = 0$).

Considering donations given (excluding the match), the evidence suggests that as the match rate increases, there is *partial* crowding out of donations given, even if donations received increase on average. Hence, despite their ubiquity in fundraising campaigns, linear matching schemes harm the fundraiser because they reduce donations given. The fundraiser would be better off simply using a large donation as an announced lead gift, rather than using it to match donations.²⁷

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.

4.3 Non-linear Matching

We next estimate the behavioral response of recipients to the non-linear matching scheme T5 that induces a non-convex budget set. While the natural reference group is the lead donor treatment T2, we also use the data from the 100% linear matching treatment T4 because the budget lines in T4 and T5 coincide for donations given greater than or equal to €50. The results are reported in Table 5. At the foot of the each column we report p-values on the null hypothesis that the coefficients on the T_4 and T_5 dummy variables are equal.

²⁶An alternative interpretation of the results might be that recipient’s 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 given the match rate. 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.

²⁷As 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%. 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 *et al.* [2002] find the reverse, with elasticities ranging from $-.40$ to $-.61$. Fack and Landais [2010] use data from France and a difference-in-difference research design and find similar price elasticities.

On the extensive margin, Column 1 shows that recipients are significantly more likely to respond to the non-linear matching scheme than to the lead donor treatment 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, the OLS estimates in Column 2 of all donations show significantly larger donations are received in T4 and T5 relative to T2 on average. The hurdle model estimates in Column 3 show that conditional on a donation being made, donations received are significantly higher in T5 than treatment T4.

The wording in which treatment T5 is described in the mail out letter might lead to $d_g = \text{€}50$ becoming focal in recipient’s minds. If so, then relative to T4 there ought to be bunching in the distribution of donations given *from above* at $d_g = \text{€}50$ in T5. No such bunching above $d_g = \text{€}50$ is predicted in the standard model of consumer choice—this segment of the budget line is available under both T4 and T5. One extension we consider in the structural estimation in Section 5 accounts for such focal point influences on giving behavior.²⁸

The analysis highlights that by removing a portion of the budget set for donations given less than $\text{€}50$ in T5 relative to T4, most small donors optimally move to the interior corner solution rather than the exterior solution, while large donors are unaffected—the response rates are almost identical in treatments T4 and T5. This is in contrast to some findings in the psychology literature, where consumers are sometimes observed forgoing a decision altogether in the presence of an expanded choice set [Iyengar and Lepper 2000].

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, nor of focal points. On the other hand, for those that would have donated more than the threshold amount of $\text{€}50$, 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 3 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 $\text{€}132$. 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 predicted donations in the absence of any matching. We explore this further by using our structural estimates to conduct counterfactual analyses on giving behavior in response to variations of the non-convex scheme where we alter: (i) the threshold level at which the non-convexity occurs; (ii) match rates above and below the threshold.

²⁸Briers *et al.* [2007] suggest such conditional gifts provide a reference point for expected donation levels.

4.4 Fixed Gift Matching

The remaining columns of Table 5 present evidence on the behavioral response of recipients to our second novel non-linear matching scheme, the fixed gift where recipients are informed that all donations will be matched by an additional €20. The relevant comparison is again with treatment T2. On the extensive margin Column 4 shows that, in line with the descriptive evidence in Table 3, recipients are significantly more likely to respond to the fixed gift scheme. On the intensive margin, Column 5 shows the value of donations received is however no different to that under the lead donor treatment T2 that involves no matching. This result is replicated using the hurdle model estimate in Column 6 based only on positive donations.

Column 7 estimates a specification analogous to (4) for donations given rather than received. The result shows that donations given are significantly *lower* in the fixed gift treatment T6. The magnitude of this effect suggests donations given fall by around 37% moving from the lead donor treatment T2 to the fixed gift treatment T6. While the results suggest the fixed gift increases the proportion of recipients that are willing to donate, for those that do, the offered match leads individuals to reduce their donation given to such an extent that the donations actually received by the project are reduced overall.

One issue with the comparison of these treatments is that there may be a drawing in of new donors in T6 with very flat indifference curves. These individuals give small amounts in the fixed gift treatment T6 and would not have given at all had they been assigned to the counterfactual treatment T2. This issue is explored further in the structural model below.

One final remark is in order. Earlier, we have noted the optimal non-linear 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 non-linear 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 by altering: (i) the threshold level at which the fixed gift is enacted; (ii) the size of the fixed gift.²⁹

²⁹>From Column 6 we can estimate the implied expenditure elasticity of donations received, $\epsilon_{d,r,x}$, using the method described in Section 2. We find this to be .006, which although significantly different from zero, is a quantitatively small effect. From Column 7 we can estimate the implied income elasticity of own consumption $\epsilon_{c,y}$ —this is found to be 1.92, which is significantly different from zero and we cannot reject the null that $\epsilon_{c,y} = 2$ so there is full crowding out of donations given by the fixed €20 match. As the expenditure elasticity of donations received is close to zero, this suggests that donations given are likely to have a weak, but positive, relationship with income. The fact that the income effect is found to be so weak in turn implies, that the observed price effects in treatments T3 and T4 are nearly all attributable to substitution rather than income effects. Studies using cross sectional data have typically reported income elasticities in the range .4 to .8 [Andreoni 2006a]. Panel data estimates include those of Randolph [1995], who finds short run income elasticities to be considerably smaller at .09. Auten *et al.* [2002] use a similar panel of tax payers and find short run elasticities of .29. In the field, Eckel and Grossman [2006] report a far higher income elasticity of 1.07. These estimates are in sharp contrast to our

5 Structural Form Evidence

5.1 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.

As in the conceptual framework developed earlier, in our baseline model we assume individuals have 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 in the earlier analysis, we remain agnostic as to whether this is because the lead donation provides a signal of the project quality or for some other reason. We begin by assuming a random quasi-linear form for preferences,

$$u(c, d_r; \theta) = c + \theta d_r - \frac{\alpha}{2} d_r^2, \quad (6)$$

where $\alpha > 0$, and with individuals subject to a budget constraint, $c + d_g \leq y$, and non-negativity constraint, $d_g \geq 0$. The donation received d_r is related to the 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.³⁰ 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.³¹

5.1.1 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

findings, that unlike earlier studies, are based on experimental variation in income as induced by a parallel shift out of the budget set faced by recipients in treatment T6, although this variation of €20 is of course very small relative to total income.

³⁰The 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 3 we see that this pattern is clearly rejected in our data.

³¹The 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.

satisfies the first order condition,

$$d_g = \frac{\theta\lambda_T - 1}{\alpha\lambda_T^2}, \quad (7)$$

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,

$$u(y; \theta, \alpha, T) = \begin{cases} y + \frac{(\theta\lambda_T - 1)^2}{2\alpha\lambda_T^2} & \text{if } \theta\lambda_T > 1; \\ y & \text{if } \theta\lambda_T \leq 1. \end{cases} \quad (8)$$

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

5.1.2 Non-linear Matching

In the non-linear 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 yellow area corresponds to the set of parameters where an individual is on the matched section of the budget constraint with $d_g > 50$; the orange area is the parameter set where $d_g = 50$; the brown 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 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 5.4 when we further allow for pure warm glow and focal point influences.

5.1.3 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 non-negligible amount, $d_g > 0$. At an interior solution where the individual donates $d_g > 0$, their utility is,

$$u(y - d_g, d_g + 20; \theta) = y - d_g + \theta[d_g + 20] - \frac{\alpha}{2}[d_g + 20]^2, \quad (9)$$

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

$$d_g = \frac{\theta - 1}{\alpha} - 20. \quad (10)$$

Thus there is 100% 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. The model also predicts that 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 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 non-negligible 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.

5.2 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 six treatments as Table 2 shows, the actual data only has 30 positive points of support for donations across all treatments.³² While we are not able to explain why individual 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 pre-determined set \mathbf{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 \mathbf{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,

$$\frac{1}{\lambda_T} + \frac{\alpha\lambda_T}{2} \times [d_g^k + d_g^{k-1}] \leq \theta < \frac{1}{\lambda_T} + \frac{\alpha\lambda_T}{2} \times [d_g^k + d_g^{k+1}]. \quad (11)$$

A very similar set of inequalities can be derived under the fixed gift treatment T6, while under the non-linear matching treatment T5 it is again necessary to compare maximized utilities on the

³²Across the full set of treatments T1–T6, three donation values account for almost 60% of all donations given; twelve donation values account for over 90% of all donations.

different sections of the budget constraint.³³

5.3 Estimation of 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, that relate more to novel fundraising schemes.³⁴

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 $L = 1$.³⁵ 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 re-write equation (7) as $d_r = \max\{0, d_r^*\}$, where

³³In 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 (11) with $\lambda_T = 2$. For any $d_g < 50$, the range of θ must simultaneously satisfy equation (11) 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.

³⁴Given 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. Non-parametric identification however requires experimental variation.

³⁵The 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.

the latent variable d_r^* is defined by,

$$d_r^* = \frac{\theta}{\alpha} - \frac{1}{\alpha\lambda_T} = \frac{X'\beta_\theta^L}{\alpha} - \frac{1}{\alpha\lambda_T} + \frac{\epsilon}{\alpha}. \quad (12)$$

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,

$$\mathbf{D}_g = \{0, 10, 20, 25, 30, 35, 50, 100, 150, 200, 350, 500, 1000\}. \quad (13)$$

Individuals observed donating some amount not contained within \mathbf{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 (11).³⁶

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 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 6 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. 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. However, the fit in T2–T4 is much less satisfactory especially on the intensive margin. As

³⁶Defining the supremum of the set defined in equation (11) 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 $\Phi\left(\frac{[\bar{\theta}_T^k(\alpha) - \mu_\theta^L]/\sigma_\theta^L}{1}\right) - \Phi\left(\frac{[\underline{\theta}_T^k(\alpha) - \mu_\theta^L]/\sigma_\theta^L}{1}\right)$, where Φ is the cumulative distribution function of the standard normal distribution.

Columns 4 to 6 show, the estimated structural model, in either continuous or discrete choice formulations, substantially over-predicts the mean donation given in the lead donor treatment T2, and suggests a very steep price gradient as the matching rate increases.

The out-of-sample fit of both formulations of the model are also unsatisfactory, as shown in the lower half of Table 6. In the non-linear matching treatment T5, the response rate is far lower (3.3% or 3.4%) than is empirically observed (4.3%), and the average donation given are higher than is observed.

In the fixed gift treatment T6, the baseline structural does predict the response rate to be higher than in other treatments and matches quite closely the empirical response rate of 4.7%. 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. 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.³⁷

5.4 Extensions

The unsatisfactory empirical performance of the baseline model motivates us to explore a number of extensions. 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.

5.4.1 Pure Warm Glow Preferences

We assume there exists some fraction π_w of individuals who exhibit 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 therefore follows that individuals with pure warm glow preferences behave as described in the baseline model when subject to treatment T1 or T2, and when subject to any of the matched treatments their behavior is the same as under T2.³⁸

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 baseline model above, we would then expect responses to the linear matching treatments to be closer to those under the lead donor treatment T2. This may

³⁷The reason the baseline model is unable to fit T5 can be seen very clearly from Figure A1. The only way the baseline model can increase the donation rate relative to T2 (aside from possible influences due to demographic differences) 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 non-linear matching structure induces some individuals already donating to increase their donation amount, but it does not induce non-donors to give.

³⁸An 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.

overcome the steep price gradient documented in Table 6 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.

5.4.2 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% 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 d_g^k we introduce an associated parameter ξ_k that enters the utility function additively and therefore makes particular donation choices more or less likely,

$$u(c, d_r; \theta) = \xi_k + c + \theta d_r - \frac{\alpha}{2} d_r^2. \quad (14)$$

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,

$$\Pr[d_g = d_g^k] = \int_{\theta} \frac{\exp(u(y - d_g^k, d_r^k; \theta)/\nu)}{\sum_{l=0}^K \exp(u(y - d_g^l, d_r^l; \theta)/\nu)} dF_{\theta}(\theta; L), \quad (15)$$

so that as the smoothing parameter $\nu \rightarrow 0$ the probabilities in equation (15) converge to the original unsmoothed choice probabilities.³⁹

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 non-linear 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.

³⁹An alternative behavioral interpretation of the probabilities in equation (15) is that for each donation amount d_g there exists an additive Type-I extreme value error attached to the utility function in equation (14), with a standard deviation that is proportional to ν . In our empirical application we set $\nu = 1/10$.

5.4.3 Flexible Curvature

Our third extension allows for greater flexibility in functional form by specifying preferences as,

$$u(c, d_r; \theta) = c + \theta d_r - \frac{\alpha}{\gamma} d_r^\gamma, \quad (16)$$

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

$$\frac{1}{\lambda_T} + \frac{\alpha \lambda_T^{\gamma-1}}{\gamma} \times \left[\frac{(d_g^k)^\gamma - (d_g^{k-1})^\gamma}{d_g^k - d_g^{k-1}} \right] \leq \theta < \frac{1}{\lambda_T} + \frac{\alpha \lambda_T^{\gamma-1}}{\gamma} \times \left[\frac{(d_g^{k+1})^\gamma - (d_g^k)^\gamma}{d_g^{k+1} - d_g^k} \right]. \quad (17)$$

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

5.4.4 Estimation of Extended Models

The model fit under the alternative extended model specifications is presented in Table 7. 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. Columns 1 to 3 in both panels show that introducing each of the extensions in isolation, results in noticeable improvements in the within sample fit as measured by the response rate and mean conditional donation given in treatments T1–T4. Incorporating either pure warm glow preferences (estimated for $\hat{\pi}_w = 27\%$ 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, 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, as discussed further below.

In terms of out-of-sample fit to treatments T5 and T6 shown in the lower half of each panel, we continue to systematically under predict the response rate in the non-linear matching scheme T5 (3.6% versus 4.3% observed). 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 warm glow preferences. Panel C of Table A1 shows the estimated preference parameters from this specification, $\{\alpha, \beta_\theta^0, \beta_\theta^1, \sigma_\theta^0, \sigma_\theta^1, \pi_w, \xi_{20}, \xi_{50}, \xi_{100}\}$. We see that when combining warm glow and focal point extensions, the estimated fraction of recipients with warm glow preferences rises to $\hat{\pi}_w = 34\%$ of individuals. We also see that there is considerable focal attachment at $d_g = 50$

and $d_g = 100$, while $\widehat{\xi}_{20}$ is not statistically different from zero. Figure 3 shows the predicted and empirical distribution of strictly positive donation given amounts from this extended model with both focal points and warm glow preferences. This shows that the model generally does well in explaining the entire distribution of donations, not just the mean shown in Table 7.

However, despite the presence of focal points, the model still under predicts donations at $d_g = 50$ slightly across all fundraising schemes. While increasing ξ_{50} would increase donations at this point, it would result in a deterioration in fit at the neighboring donation amounts. The general shape of the distribution is also correct in the out-of-sample prediction exercise for the non-linear matching treatment T5, although the proportion donating at $d_g = 50$ is under predicted which also accounts for the discrepancy response rate, where the model predicts a response rate of 3.6% versus the empirically observed 4.3%.

The fit to treatment T6 is clearly the least satisfactory, both in terms of the 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.

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 5 and 6 in Table 7. Estimating the model on treatments T1–T5, Column 5 in each Panel shows we obtain little improvement in model fit by allowing ξ_k to vary. Indeed, the estimated captivity parameters at $d_g = 50$ are essentially the same for T5 as 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 6 shows that when we allow the attachment parameter ξ_{20} to vary with exposure to the fixed gift treatment T6, the substantial over-prediction of average donations remains.

A natural extension of the baseline model that might help to fit T6 would be to allow income effects. 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.⁴⁰

⁴⁰We 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, as shown in Table 1. 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.

5.5 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 with a discrete choice set, warm glow preferences, and focal points.⁴¹ 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 field 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 field experiments that out-perform the lead donor treatment.

Table 8 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.

5.5.1 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% 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 €89.1 when donations are matched twice over ($\lambda^0 = 2$), they fall to €74.4 when $\lambda^0 = 3$, and they are €66.9 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.

⁴¹All 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.

5.5.2 Non-Linear Matching: Variable Thresholds

The next scheme considered is a generalization of the non-linear 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, $d_\chi \in \mathbf{D}_g$, to vary,

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

In Columns 3a to 3c of Table 8 we see that relative to treatment T5 in which the mean donation given was predicted to be €96.7, donations given are predicted to increase by: (i) decreasing the post-threshold matching rate slightly to $\lambda^1 = 1.5$ (Column 3a); (ii) increasing the threshold that induces the higher match rate to $d_\chi = 100$. With both variations, the response rate remains relatively unchanged at 3.7%, 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.

5.5.3 Fixed Lead 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 $d_\chi \in \mathbf{D}_g$,

$$R(d_g) = \begin{cases} d_g & \text{if } d_g < d_\chi; \\ d_g + d_f & \text{if } d_g \geq d_\chi. \end{cases} \quad (19)$$

As described in Section 4 in the context of the non-convex 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 8 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 shows that mean donations given are increasing in d_χ , while the response rate declines from 4.1% with a threshold $d_\chi = 0$, to 3.7% 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 8 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

that alterations in linear match rates or variants of the non-linear 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.

5.5.4 Kinked Match Functions

The remaining counterfactuals use the preferred structural model to explore giving behavior in response to two 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,

$$R(d_g) = \begin{cases} \lambda^0 d_g & \text{if } d_g < d_\chi; \\ \lambda^0 d_\chi + \lambda^1 (d_g - d_\chi) & \text{if } d_g \geq d_\chi. \end{cases} \quad (20)$$

Relative to designs such as in the experimental non-linear 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 to 5c of Table 8, considering an example where $\lambda^0 = 1$. In Columns 5a-5b where 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 matching treatments considered, it still remains below what is obtained under the lead donor treatment T2.

5.5.5 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 pre- and post-threshold matching rates. More precisely, we allow the value of the donation matching to be increased by a fixed gift amount d_f for $d_g \geq d_\chi$,

$$R(d_g) = \begin{cases} \lambda^0 d_g & \text{if } d_g < d_\chi; \\ \lambda^0 d_\chi + \lambda^1 (d_g - d_\chi) + d_f & \text{if } d_g \geq d_\chi. \end{cases} \quad (21)$$

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.⁴² The results

⁴²We 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 $d_f = (\lambda^1 - \lambda^0)d_\chi$.

are in Columns 6a-6c of Table 8. 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 3.7%; (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 8 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 which we are not able to incorporate in these out-of-sample prediction exercises. Moreover, if lead donors insist their gifts be used in some matching scheme, this counterfactual analysis shows that in this case, the fundraiser is best off using a non-convex matching scheme that involves fixed gifts being provided at some strictly positive donation threshold.

6 Discussion

We have presented reduced form and structural form evidence from a field experiment designed to shed light on the efficacy of alternative charitable fundraising schemes. The key insight obtained from the evidence is that the presence of large and anonymous lead gifts substantially increase donations given with no reduction in response rates. In contrast, straight linear matching schemes are not profitable for the fundraiser, despite their ubiquitous usage in fundraising drives. Moreover, the counterfactual exercises performed using the preferred structural model confirm that 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, non-linear matching, threshold matching, or some combination of the three schemes.

In terms of the external validity of these findings, two points are of note. First, our analysis throughout is based on a sample of opera attendees. While the non-representativeness of the sample may imply the observed *levels* of response or donations likely overstate the response among the general population, the results we have emphasized throughout are identified from *differences* in behavior across treatments that purge the analysis of the common characteristics of sample individuals. Second, our results have external validity for other organizations that also target charitable fundraising towards those with high affinity to the organization.⁴³

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

⁴³de Oliveira *et al.* [2011] present evidence from 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.

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]. This is not the case in this empirical setting because of the linearly expandable nature of the project being funded. 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 recent evidence on for-profit firms [Levitt 2006], absent informative feedback on alternative schemes, systematic deviations from optimal fundraising methods might then be more likely. A final explanation is that lead donors might insist their gifts be used in some matching scheme, say because they want to aggregate others' information. Our counterfactual analysis shows that in this case, the fundraiser is best off using a non-convex 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 9 shows the main results from this follow-up field experiment in terms of the extensive and intensive margins of giving. As a point of comparison, the first row highlights outcomes in relation to the lead donor treatment T2 in the main 2006 experiment. Two main 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. On the donation given, this falls by around 19% in each 2007 treatment, but neither difference is statistically significant. 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—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.

A Appendix

In the non-linear 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,

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

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,

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

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,

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

However, by comparing equation (8) 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,

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

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 (8), 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 yellow area corresponds to the set of parameters where an individual is on the matched section of the budget constraint with $d_g > 50$; the orange area is the parameter set where $d_g = 50$; the brown area is the parameter set where $0 < d_g < 50$.

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Table 1: Characteristics of Recipients by Treatment

Mean, standard error in parentheses

P-value on t-test of equality of means with control group in brackets

Treatment Number	Treatment Description	Number of Individuals	Female [Yes=1]	Number of Tickets Bought in Last 12 Months	Number of Ticket Orders in Last 12 Months	Average Price of Tickets Bought in Last 12 Months	Total Value of All Tickets Bought in Last 12 Months	Munich Resident [Yes=1]	Year of Last Ticket Purchase [2006=1]	House Rental Price 2006	F-test of Joint Significance
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	Control	3787	.466 (.008)	6.30 (.178)	2.23 (.047)	86.6 (.666)	416 (7.88)	.416 (.008)	.565 (.008)	11.2 (.021)	
2	Lead donor	3770	.478 (.008) [.269]	6.27 (.153) [.886]	2.22 (.046) [.838]	86.3 (.650) [.722]	423 (7.73) [.541]	.416 (.008) [.980]	.574 (.008) [.420]	11.2 (.021) [.979]	[.370]
3	Lead donor + 1:5 match	3745	.481 (.008) [.182]	6.39 (.184) [.737]	2.20 (.049) [.700]	86.8 (.660) [.873]	432 (9.63) [.197]	.416 (.008) [.991]	.576 (.008) [.329]	11.2 (.021) [.905]	[.752]
4	Lead donor + 1:1 match	3718	.477 (.008) [.314]	6.46 (.148) [.496]	2.28 (.050) [.439]	85.8 (.667) [.397]	435 (9.78) [.124]	.419 (.008) [.819]	.576 (.008) [.347]	11.2 (.021) [.785]	[.481]
5	Lead donor + 1:1 match for donations greater than €50	3746	.476 (.008) [.377]	6.31 (.145) [.977]	2.21 (.046) [.788]	85.2 (.657) [.132]	419 (7.39) [.781]	.426 (.008) [.385]	.567 (.008) [.849]	11.2 (.021) [.447]	[.318]
6	Lead donor + €20 match for any donation	3746	.486 (.008) [.082]	6.09 (.132) [.353]	2.20 (.047) [.616]	86.5 (.657) [.861]	416 (8.05) [.962]	.428 (.008) [.270]	.556 (.008) [.416]	11.2 (.021) [.428]	[.579]

Notes: 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 3 to 6 the "last twelve months" refers to the year prior to the mail out from June 2005 to June 2006. In Column 9, the "house rental price" measure is the price of renting a flat measured in Euros per month per square meter. This measure is available only for Munich zipcodes. In Column 10, 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.

Table 2: Characteristics of Donors and Non Donors by Treatment

Mean, standard error in parentheses

P-value on test of equality of means between donors and non-donors in brackets, by treatment

Treatment Number and Description	Number of Responses	Female [Yes=1]	Number of Tickets Bought in Last 12 Months	Number of Ticket Orders in Last 12 Months	Average Price of Tickets Bought in Last 12 Months	Total Value of All Tickets Bought in Last 12 Months	Munich Resident [Yes=1]	Year of Last Ticket Purchase [2006=1]	House Rental Price 2006
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
All Donors	922	.475 (.016)	8.71 (.353)	2.91 (.105)	87.6 (1.45)	642 (24.9)	.421 (.016)	.702 (.015)	11.2 (.021)
All Non Donors		.477 (.003) [.896]	6.20 (.065) [.000]	2.19 (.020) [.000]	86.2 (.274) [.341]	414 (3.42) [.000]	.420 (.003) [.965]	.563 (.003) [.000]	11.2 (.021) [.657]
1 Control	142	.394 (.041) [.080]	8.55 (.970) [.019]	2.87 (.245) [.009]	87.1 (3.65) [.901]	585 (47.0) [.000]	.380 (.041) [.376]	.697 (.039) [.000]	11.2 (.108) [.855]
2 Lead donor	132	.530 (.044) [.226]	9.52 (.954) [.000]	3.36 (.374) [.002]	88.1 (4.21) [.669]	666 (66.1) [.000]	.394 (.043) [.600]	.742 (.038) [.000]	11.3 (.114) [.386]
3 Lead donor + 1:5 match	156	.449 (.040) [.412]	9.67 (1.09) [.002]	2.88 (.235) [.004]	87.3 (3.33) [.874]	662 (55.1) [.000]	.365 (.039) [.183]	.654 (.038) [.040]	11.2 (.113) [.673]
4 Lead donor + 1:1 match	155	.426 (.040) [.190]	7.96 (.746) [.041]	2.75 (.274) [.083]	88.9 (4.13) [.452]	619 (58.2) [.001]	.413 (.040) [.886]	.748 (.035) [.000]	11.2 (.108) [.957]
5 Lead donor + 1:1 match for donations greater than €50	160	.563 (.039) [.025]	8.11 (.703) [.010]	2.60 (.177) [.028]	90.7 (3.14) [.079]	698 (69.7) [.000]	.475 (.040) [.206]	.694 (.037) [.000]	11.2 (.097) [.887]
6 Lead donor + €20 match for any donation	177	.486 (.038) [.994]	8.58 (.719) [.000]	3.07 (.243) [.000]	83.8 (2.98) [.367]	623 (63.9) [.001]	.480 (.038) [.160]	.684 (.035) [.003]	11.2 (.086) [.992]

Notes: 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 tests of equality are based on an OLS regression allowing for robust standard errors. All monetary amounts are measured in Euros. In Columns 3 to 6 the "last twelve months" refers to the year prior to the mail out from June 2005 to June 2006. In Column 9, the "house rental price" measure is the price of renting a flat measured in Euros per month per square meter. This measure is available only for Munich zipcodes.

Table 3: Fundraising Outcomes by Treatment

Mean, standard error in parentheses

P-values on tests of equalities on means with comparison group in brackets

Treatment Number	Treatment Description	Comparison Group	All Recipients				Donors Only			
			Response Rate	Total Amount Donated	Total Amount Raised	Average Donation Received, All Recipients	Average Donation Received	Median Donation Received	Average Donation Given	Median Donation Given
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	Control		.037 (.003)	10550	10550	2.79 (.326)	74.3 (6.19)	50 (6.19)	74.3 (6.19)	50
2	Lead donor		.035 (.003)	17416	17416	4.62 (.635)	132 (14.3)	100 (14.3)	132 (14.3)	100
		T1 Control	[.564]			[.010]	[.000]	[.000]	[.000]	[.000]
3	Lead donor + 1:1.5 matching		.042 (.003)	15705	23558	4.19 (.618)	151 (18.9)	75 (12.6)	101 (12.6)	50
		T1 Control	[.355]			[.044]	[.000]	[.005]	[.061]	[.999]
		T2 Lead donor	[.134]			[.631]	[.421]	[.131]	[.102]	[.000]
4	Lead donor + 1:1 matching		.042 (.003)	14310	28620	3.84 (.526)	185 (20.7)	100 (10.4)	92.3 (10.4)	50
		T1 Control	[.352]			[.086]	[.000]	[.000]	[.136]	[.999]
		T2 Lead donor	[.132]			[.350]	[.037]	[.999]	[.025]	[.000]
5	Lead donor + 1:1 matching for donations greater than €50		.043 (.003)	15671	31107	4.18 (.521)	194 (19.3)	120 (9.59)	97.9 (9.59)	60
		T1 Control	[.249]			[.023]	[.000]	[.000]	[.039]	[.138]
		T2 Lead donor	[.084]			[.596]	[.010]	[.102]	[.049]	[.000]
6	Lead donor + €20 match for any donation		.047 (.003)	12248	15788	3.27 (.353)	89.2 (5.51)	70 (5.51)	69.2 (5.51)	50
		T1 Control	[.036]			[.314]	[.073]	[.024]	[.539]	[.999]
		T2 Lead donor	[.008]			[.063]	[.006]	[.065]	[.000]	[.002]

Notes: 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 non-donors). 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.

Table 4: Common Fundraising Schemes

Marginal effects reported in probit regressions

Robust standard errors in parentheses

Dependent variable:	<u>T2: Lead Donor</u>			<u>T3 and T4: Linear Matching Schemes</u>		
	Any Positive Donation [Yes =1]	Donation Received	Log (Donation Received)	Any Positive Donation [Yes =1]	Donation Received	Log (Donation Received)
	(1) Probit	(2) OLS	(3) Hurdle Model	(4) Probit	(5) OLS	(6) Hurdle Model
Lead Donor Treatment T2	-.003 (.004)	1.83*** (.711)	.366*** (.122)			
50% Linear Match Treatment T3				.007 (.005)	1.61 (1.12)	.178 (.128)
100% Linear Match Treatment T4				.007 (.005)	3.07** (1.22)	.457*** (.124)
Implied Own Price Elasticity [T2 - T3]						-.534 (.385)
t-test: pure warm glow						[.013]
t-test: donation targeting						[.167]
Implied Own Price Elasticity [T3 - T4]						-1.12 (.444)
t-test: pure warm glow						[.047]
t-test: donation targeting						[.012]
Implied Own Price Elasticity [T2 - T4]						-.915 (.249)
t-test: pure warm glow						[.093]
t-test: donation targeting						[.000]
Mean of Dependent Variable (€)	.036	3.70	102	.039	4.22	107
Observations	7557	7557	274	11233	11233	443

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Robust standard errors estimated throughout. In Columns 1 and 4 a probit regression is estimated where the dependent variable is equal to one if the recipient responds to the treatment with any positive donation, and zero otherwise. Marginal effects are reported. In Columns 3 and 6 the second stage of a hurdle model is estimated assuming the donation amounts follow a log normal distribution. The dependent variable is the log of the donation received. In Columns 1 to 3 the reference treatment group throughout is the control treatment (T1). The reference treatment group in Columns 4 to 6 is the lead donor treatment (T2). All specifications control for the recipient's gender, 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. The null hypothesis when testing for pure warm glow preferences is that $\epsilon_{dr,p} = -\lambda/\lambda$; the null hypothesis when testing for donation targeting is that $\epsilon_{dr,p} = 0$.

Table 5: Novel Fundraising Schemes

Marginal effects reported in probit regressions

Robust standard errors in parentheses

Dependent variable:	T5: Non-linear Matching			T6: Fixed Lead Gift			
	Any Positive Donation [Yes =1]	Donation Received	Log (Donation Received)	Any Positive Donation [Yes =1]	Donation Received	Log (Donation Received)	Log (Donation Given)
	(1) Probit	(2) OLS	(3) Hurdle Model	(4) Probit	(5) OLS	(6) Hurdle Model	(7) Hurdle Model
100% Linear Match Treatment T4	.007 (.005)	3.08** (1.22)	.377*** (.105)				
Non-linear Matching Treatment T5	.008* (.005)	3.85*** (1.22)	.560*** (.099)				
Fixed Gift Matching Treatment T6				.013*** (.004)	-.372 (.750)	.012 (.112)	-.456*** (.104)
Mean of Dependent Variable (€)	.040	6.87	173	.041	4.42	107	96
Equality of Treatments T4 and T5	[.730]	[.594]	[.035]				
Observations	11234	11234	447	7516	7516	309	309

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Robust standard errors estimated throughout. In Columns 1 and 4 probit regressions are estimated where the dependent variable is equal to one if the recipient responds to the matching treatment with any positive donation, and zero otherwise. Marginal effects are reported. In Columns 3, 6 and 7 the second stage of a hurdle model is estimated assuming the donation amounts follow a log normal distribution. In Columns 3 and 6 the dependent variable is the log of the donation received. In Column 7 the dependent variable is the log of the donation given. The reference treatment group throughout is the lead donor treatment (T2). In Columns 1 to 3 we also report the p-value on the null hypothesis that the coefficients on the dummy variables for treatments T4 and T5 are equal. All specifications control for the recipient's gender, 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.

Table 6: Model Fit from Baseline Model

Empirical and Predicted Donation Rates in Columns 1 to 3; Empirical and Predicted Conditional Average Donation Given (in Euros) in Columns 4 to 6
Standard Errors in Parentheses

		<u>Response Rate</u>			<u>Average Donation Given</u>		
		(1) Empirical	(2) Continuous	(3) Discrete	(4) Empirical	(5) Continuous	(6) Discrete
T1	Control	.037 (.003)	.037 (.003)	.037 (.003)	74.3 (6.19)	75.9 (7.1)	76.6 (7.1)
T2	Lead Donor	.035 (.003)	.034 (.002)	.034 (.002)	132 (14.3)	174 (15.6)	162 (11.8)
T3	Lead donor + 1:.5 match	.042 (.003)	.040 (.002)	.040 (.002)	101 (12.6)	119 (10.8)	113 (8.2)
T4	Lead donor + 1:1 match	.042 (.003)	.043 (.003)	.043 (.003)	92.3 (10.4)	90.4 (8.3)	87 (6.4)
T5	Lead donor + 1:1 match for donations greater than €50	.043 (.003)	.033 (.002)	.034 (.002)	97.9 (9.6)	114 (9.5)	107 (7.8)
T6	Lead donor + €20 match for any donation	.047 (.003)	.050 (.007)	.044 (.004)	69.2 (5.51)	103 (21.3)	112 (16.0)

Notes: 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.

Table 7: Model Fit from Extended Models

	A. Response Rate							B. Average Donation Given							
	Empirical	(1)	(2)	(3)	(4)	(5)	(6)	Empirical	(1)	(2)	(3)	(4)	(5)	(6)	
T1	.037	.037	.038	.037	.038	.037	.038	T1	74.3	76.6	75.4	77.1	71	79.1	72.7
T2	.035	.036	.035	.034	.037	.037	.039	T2	132	136	148	143	131	136	124
T3	.042	.040	.040	.041	.040	.041	.041	T3	101	105	105	103	104	105	105
T4	.042	.042	.043	.044	0.041	.043	.042	T4	92.3	87.9	82.5	80.1	89.4	87.4	94.3
T5	.043	.036	.034	.036	.037	.037	.039	T5	97.9	99.8	101	96.4	96.5	99.9	101
T6	.047	.042	.044	.046	.040	.044	.042	T6	69.2	106	104	93.9	110	104	108
Pure Warm Glow	X				X	X	X	Pure Warm Glow	X				X	X	X
Flexible Curvature			X					Flexible Curvature		X					
Focal Points				X	X	X	X	Focal Points			X	X	X	X	X
Focal Points T5						X	X	Focal Points T5					X	X	
Focal Points T6							X	Focal Points T6							X
Sample	T1-T6	T1-T4	T1-T4	T1-T4	T1-T4	T1-T5	T1-T6	Sample	T1-T6	T1-T4	T1-T4	T1-T4	T1-T4	T1-T5	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 $D_g = \{0, 10, 20, 25, 30, 35, 50, 100, 150, 200, 350, 500, 1000\}$ 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 as described in Section 5.4.1. Flexible curvature allows the curvature of the donation given/received to vary as described in Section 5.4.3. Focal points indicate the incorporation of focal points in the choice decision as described in Section 5.4.2. 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.

Table 8: Counterfactual Charitable Fundraising Schemes

	T2: Lead Donor	Linear Matching: Higher Match Rates			Non Linear Matching: Variable Thresholds and Post-Threshold Match Rates			Fixed Lead Gifts: Variable Thresholds That Trigger the Fixed Gift			Kinked Match Functions			Generalised Threshold Matching		
	(1)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)	(5a)	(5b)	(5c)	(6a)	(6b)	(6c)
Pre-threshold Match Rate: λ^0	1	2	3	4	1	1	1	1	1	1	1	1	1	1	1	1
Post-threshold Match Rate: λ^1	-	-	-	-	1.5	2	2	1	1	1	1.5	2	2	2	2	2
Threshold: d_x	-	-	-	-	50	50	100	0	20	50	50	50	100	50	50	50
Value of Fixed Lead Gift: d_f	-	-	-	-	-	-	-	20	20	20	-	-	-	25	75	100
Response Rate	.037	.040	.041	.040	.037	.037	.037	.041	.039	.037	.037	.037	.037	.037	.037	.037
Mean Donations Given, Conditional on a Strictly Positive Donation	131	89.1	74.4	66.9	109	96.7	100	111	117	123	117	108	117	102	92.0	87.7
Average Donation Given	4.85	3.56	3.05	2.68	4.03	3.58	3.70	4.55	4.56	4.55	4.33	4.00	4.33	3.77	3.40	3.25

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 non-linear matching schemes that vary in the threshold at which the non-linearity occurs, and the post-threshold matching rate. In Columns 4a to 4c we consider variations of the fixed lead 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, and in Columns 6a to 6c we consider a generalized matching scheme that encompasses the other schemes as special cases.

Table 9: Follow-Up Field Experiment on Lead Donors

Mean and standard error in parentheses

Treatment Description	(1) Number of Recipients	(2) Response Rate	(3) Mean Donation, Conditional on Strictly Positive Donation
<u>Main 2006 Field Experiment</u>			
Stück für Stück Project (anonymous lead donor, €60,000)	3770	.035 (.003)	132 (14.3)
<u>Follow-Up 2007 Field Experiment</u>			
Stück für Stück Project (anonymous lead donor, €12,000)	1034	.015 (.004)	102 (31.0)
Stück für Stück Project (named lead donor, €12,000)	992	.013 (.004)	113 (38.6)

Notes: 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.

Table A1: Structural Parameter Estimates
Baseline Model Using Linear Matching Treatments T1-T4
Bootstrapped Standard Errors in Parentheses

Panel A. Continuous Donations Given, dq

	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]
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)					

Panel B. Discrete Donations Given, dq

	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]
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)					

Preferred Model

Panel C. Discrete Donations Given, Warm Glow and Focal Points

	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]
μ_{θ}^0	-6.120 (0.500)	-0.437 (0.285)	-0.267 (0.284)	0.506 (0.373)	0.091 (0.034)	0.851 (0.298)
μ_{θ}^1	-14.288 (0.681)	-0.092 (0.296)	-0.342 (0.327)	1.701 (0.490)	0.193 (0.035)	1.856 (0.331)
σ_{θ}^0	3.546 (0.146)					
σ_{θ}^1	6.962 (0.216)					
α	0.022 (0.001)					
π_w	0.344 (0.076)					
ξ_{20}	0.031 (0.227)					
ξ_{50}	5.505 (0.655)					
ξ_{100}	13.349 (1.131)					

Notes: 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 $D_g=(0,10,20,25,30,35,50,100,150,200,350,500,1000)$. 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 1: The Design of the Field Experiment and Outcomes

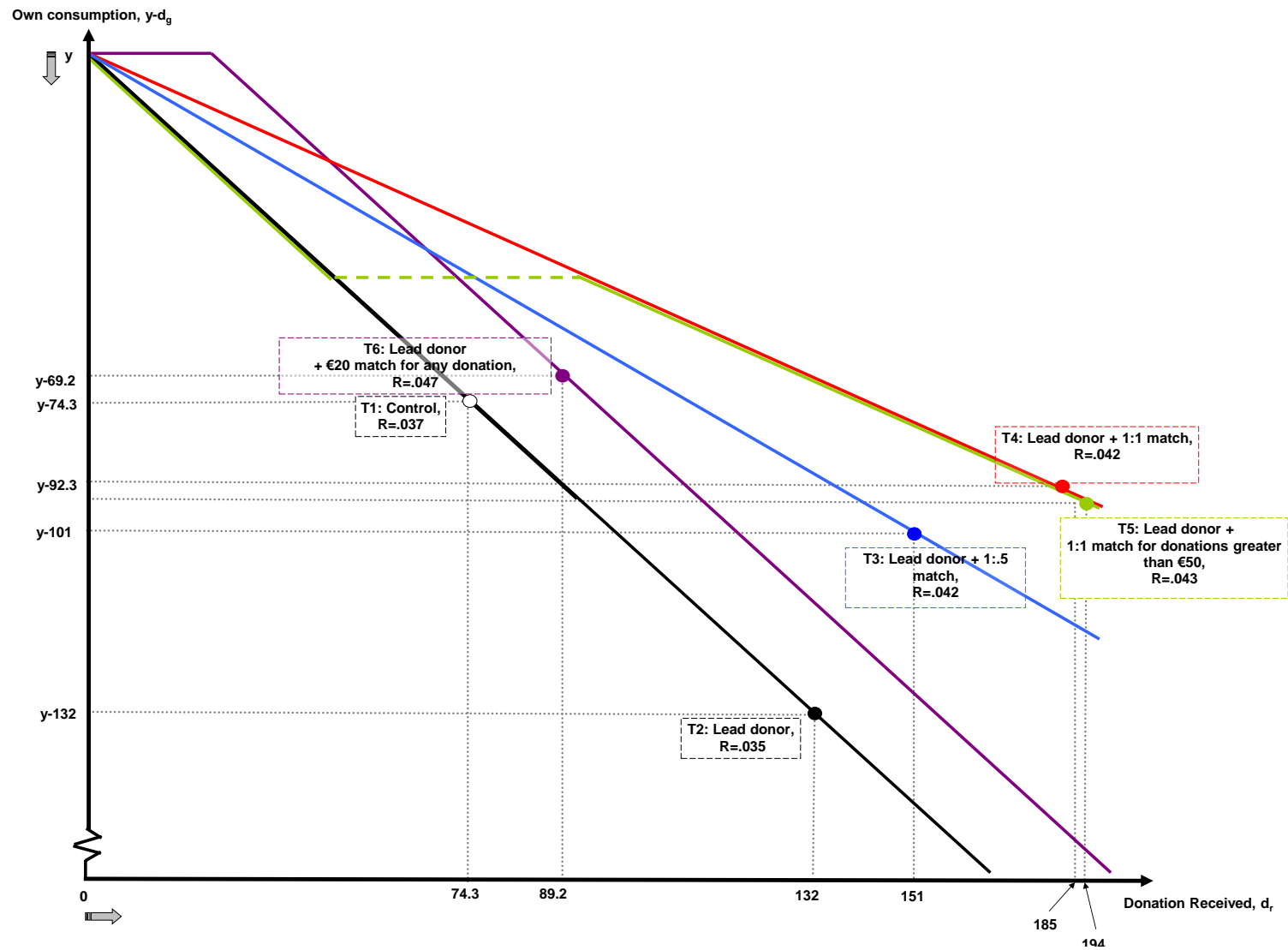
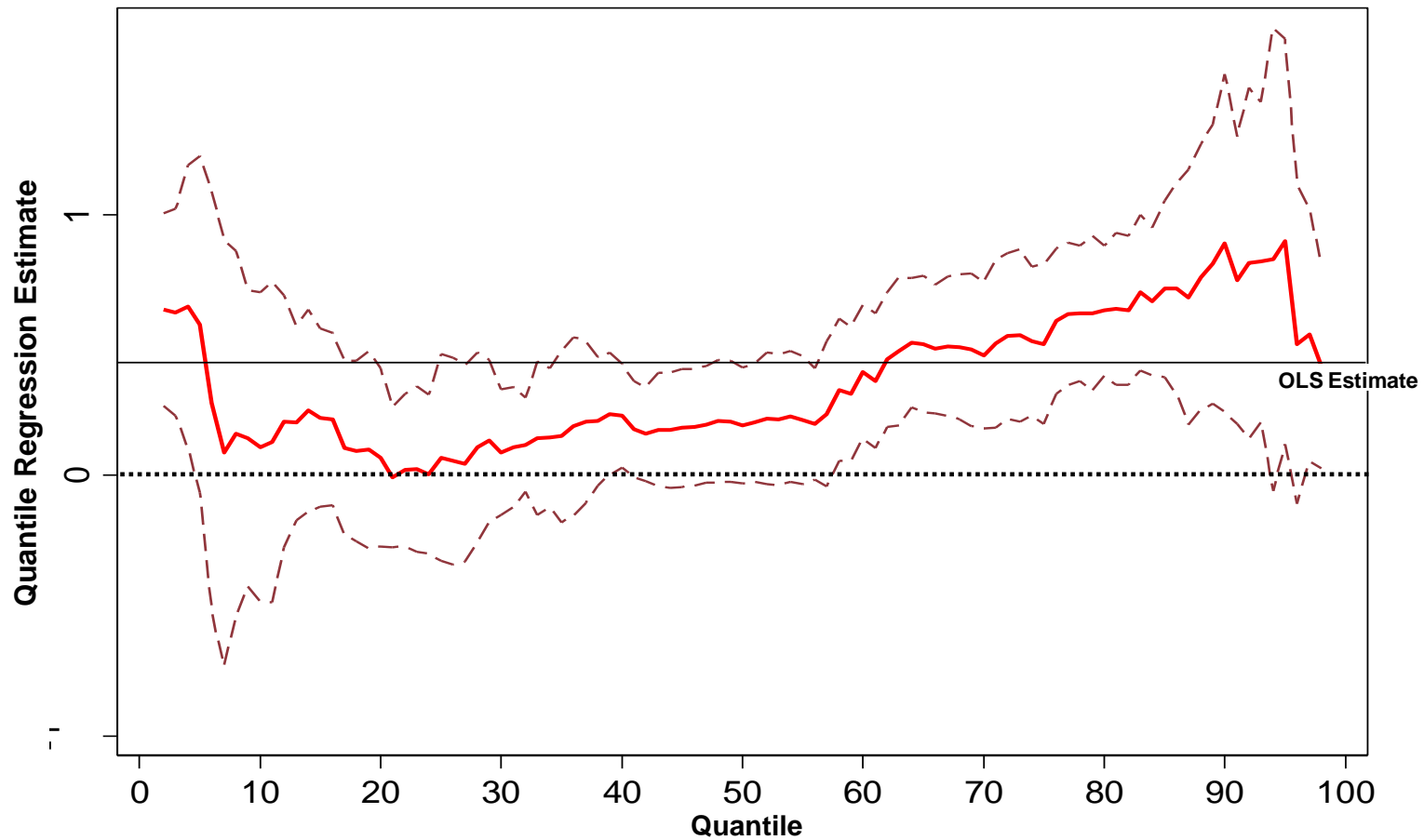
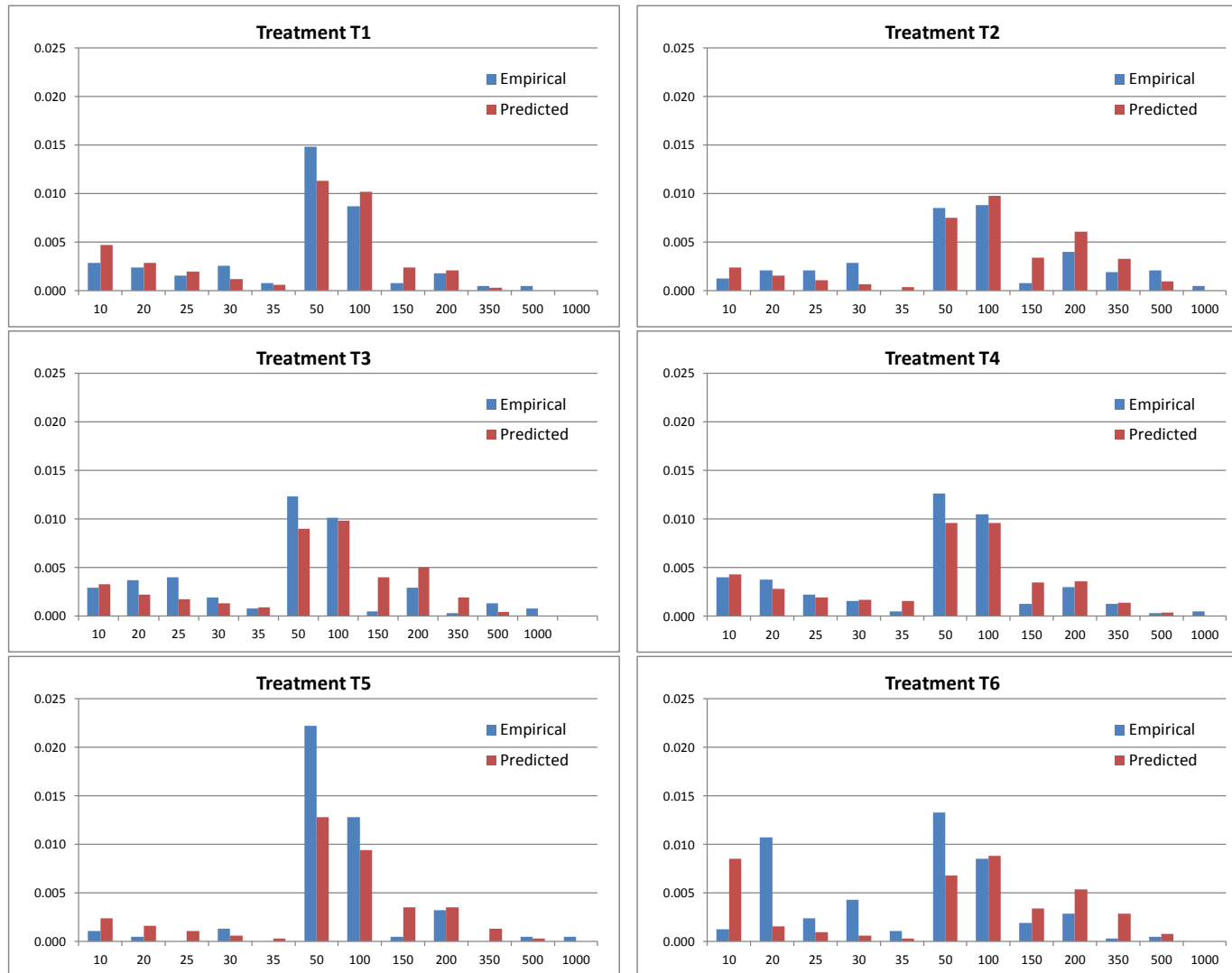


Figure 2: Quantile Regression Estimates of Signaling Treatment T2



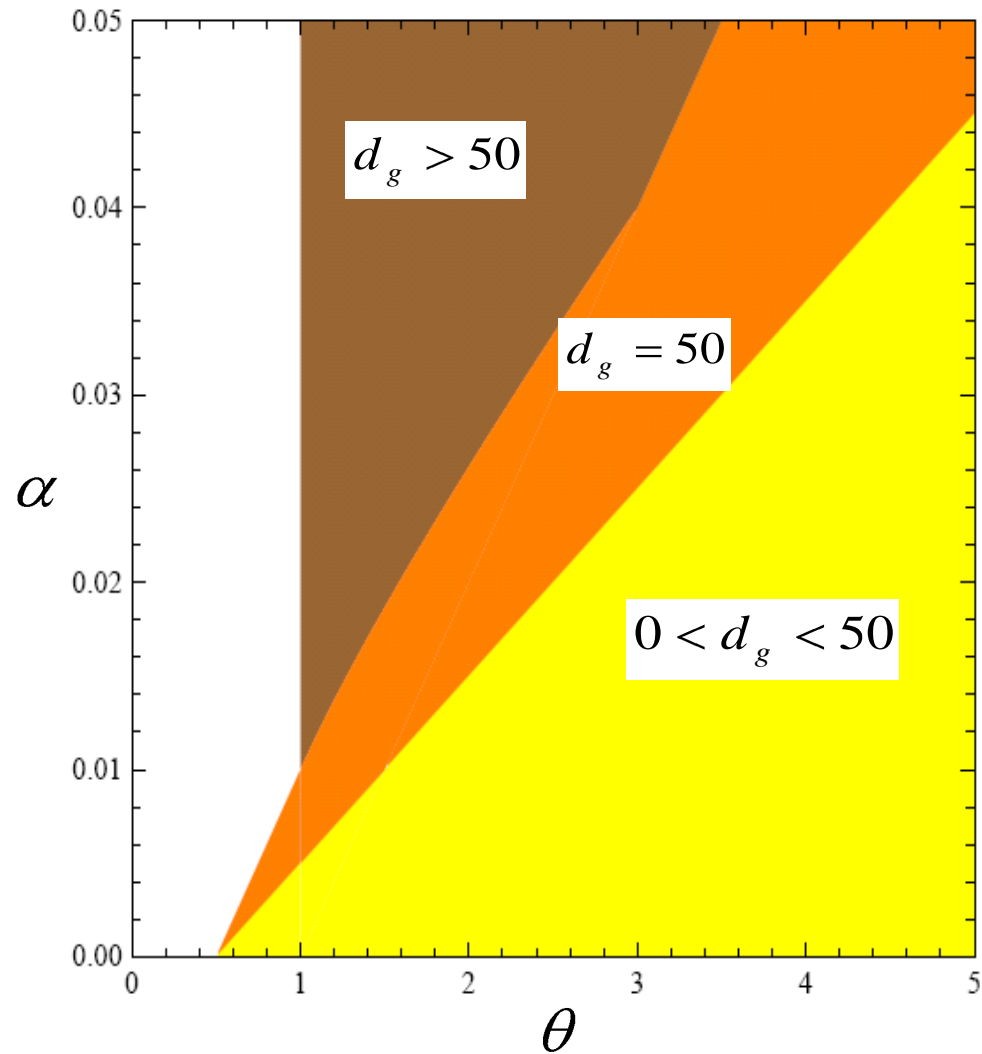
Notes: Figure 2 shows the estimated quantile regression effect at each quantile of the conditional distribution of the log of donations received, and the associated 95% confidence interval. The figure also shows the coefficient on the treatment dummy variable from an OLS regression. The individual characteristics 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.

Figure 3: Empirical and Predicted Distributions of Donations



Notes: The figure shows the predicted and empirical distribution of positive donation amounts. Horizontal axis measure 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 $D_g = \{0, 10, 20, 25, 30, 35, 50, 100, 150, 200, 350, 500, 1000\}$. All estimation is performed using data from treatments T1 to T4 only.

**Figure A1: Giving Behavior in the
Non-Linear Matching Treatment T5**



Notes: The yellow area corresponds to the set of parameters where $d_g > 50$. The orange area is the parameter set where $d_g = 50$. The brown area is the parameter set where $0 < d_g < 50$.

Appendix: 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

Appendix: The Mail Out Letter (Translated)

“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.