Personalized Fundraising: A Field Experiment on Threshold Matching of Donations

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Personalized fundraising:

A field experiment on threshold matching of donations

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Abstract

We study a form of threshold matching in fundraising where donations above a certain threshold are topped up with a fixed amount. We show theoretically that threshold matching can induce *crowding in* if appropriately personalized. In a field experiment, we explore how thresholds should be chosen depending on past donations. The optimal choice of thresholds is rather bold, approximately 75% above past donations. Additionally, we explore how thresholds should be set for new donors as a function of their personal characteristics and demonstrate the benefits of personalization as opposed to setting a general threshold that applies to all recipients of a fundraising call.

JEL classifications: C93, D64, D12

Keywords: Charitable giving, field experiments, matching donations, personalization

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1. Introduction

The charitable sector is a backbone of our society. Many areas of our life would be left neglected without voluntary contributions and the activities of nonprofits. These areas include food aid, emergency measures, refugee aid, human rights, and many more. In 2018 U.S. charities received an estimated $410.02 billion from individuals, bequests, foundations and corporations (*Giving USA* 2018) and many charitable organizations engage in repeated fundraising activities to raise income, employing a variety of techniques designed to enhance the fundraising effectiveness.

One such widely technique popular is linear donation matching, where each dollar someone donates is topped up with another dollar or at some other fixed rate. While linear matching has been shown to increase the response rate—that is, the fraction of people who do donate (crowding in small donations)—it has also been shown to reduce out-of-pocket donations for those who would have contributed anyway. This happens because the price elasticity of donors tends to be less than (absolute) one: They choose a higher total donation including the match but spend less on it. Such crowding out harms the performance of fundraising campaigns that rely on relatively large gifts (Rondeau and List 2008; Gneezy, Keenan, and Gneezy 2014; Huck and Rasul 2011). Additionally, the method is not exploiting heterogeneity of donors as, for example, expressed in past donation amounts. We study an alternative matching scheme designed to avoid crowding out and to make the most of known differences in the willingness to give—a scheme where donations above a *personalized threshold* are matched with a fixed amount.

Given the persistence of donation amounts documented in the literature, we also offer a tool that can push donors into higher donation categories. While thresholds have been explored before, our paper is the first that studies how more detailed information about potential donors can be used to calculate predicted donations that help to optimize individual thresholds. We show how, in line with a simple model, such schemes can increase individual donation levels.

We believe that personalized matching schemes have great potential in improving the effectiveness of fundraising drives for which some information on individual characteristics of donors or their past donations is available. It offers enhanced budget sets to donors, which may be necessary in a world where charities fiercely compete with each other and it does so while avoiding the pitfalls of a reduced price that triggers crowding out. Moreover, the scheme is easy to administer and easy to explain.

In a brief theory section, we explore the effects of varying thresholds around the donation value that we would expect in the absence of matching. While the details depend on the precise local shape of individuals' indifference curves, we show that an appropriately set threshold can always generate an increase in the donation level.

In a field experiment, we vary threshold levels relative to past donations for recipients who responded to previous calls and relative to predicted donations for recipients who did not donate in the past but for whom we observe some characteristics that correlate with giving behavior among donors. Our findings largely mirror theoretical predictions. For past donors, we document that threshold matching with a threshold set at the level of the past donation or somewhat above increases donations. The maximum increase is achieved at a threshold of around 75% above the past donation. Thresholds below past donations result in lower donation levels. For recipients who have not yet donated, we predict their optimal donation in the absence of a match by extrapolating from past donor behavior and their individual characteristics. On the basis of this prediction, we can set the threshold in the same way as it was done with past donors and obtain similar results. The most effective threshold is around 75% above the predicted donation.

Although average behavior lines up nicely with our theoretical predictions, for some past donors treated with higher thresholds we observe contrarian behavior not predicted by theory: implicitly asked to give more, they give less. Moreover, also not predicted by theory, we observe somewhat declining response rates with higher thresholds. We conclude that thresholds that are too low relative to past or predicted donations or much too high decrease giving and are to be avoided.

If predictions are not feasible because the designer of the campaign lacks information about past behavior and personal characteristics of potential donors that correlate with giving, we find that comparatively low uniform thresholds are best for total revenue. For the sample of recipients who have not donated in the past, the effects on the extensive and intensive margin seem to be very similar to those that we know from the literature on defaults and suggestions (see also the literature section below): increasing the threshold has a negative effect on the response rate and a positive effect on the value of donation chosen. For the sample of past donors, we find no relationship between the level of a non-personalized random threshold and the donation return.

We proceed as follows. In Section 2 we relate our paper to the existing literature. In Section 3 we outline the basic theory. Section 4 presents the design and implementation of the experiment and Sections 5, 6, and 7 our results. Section 8 concludes.

2. Literature

Matching

Donation matching is popular and mostly takes the form of doubling donations with funds committed by a lead donor. This reduces the price of charitable giving and, unsurprisingly, donors react choosing larger total donations that are received by the charity, that is, larger donations *including* the match. However, most studies on matching show that charitable donations have price elasticities between 0 and -1: as the price falls, consumers demand more but spend less on it.[1] In other words, matching causes crowding out reducing out-of-pocket donations (Rondeau and List

[1] In order to measure the pure effect of the price change induced by a matching scheme one has to control for the signalling value of a commitment to match. Comparisons of matching schemes with controls that have neither matching nor a fixed commitment from a lead donor generate composite effects with estimated price elasticities that can be weakly positive (see, for example, Karlan and List 2007).

2008; Gneezy, Keenan, and Gneezy 2014; Huck and Rasul 2011).[2] On the other hand, linear matching attracts additional small donors. Which effect (negative or positive) prevails might depend on the composition of the target group. As shown by Huck, Rasul, and Shephard (2015), charitable organizations seem to be better off using funds offered for matching as *unconditional* lead gifts.[3] In both cases, the funds serve as a strong signal of a charity's quality (Vesterlund 2003; Andreoni 2006; Huck and Rasul 2011). Reasons why matching is still popular in practice might include competition or simply inertia among charities.

The literature has proposed some alternative forms of matching, all without personalization, which include matching funds going to a different project (Adena and Huck 2017), nonconvex matching schemes (Huck, Rasul, and Shephard 2015), matching conditional on a minimum number of donors in a group (Gee and Schreck 2018), matching for donations above the median (Charness and Holder 2019), or matching conditional on giving fixed amounts to two funds (Meier 2007). The closest study to ours is Castillo and Petrie (2019), who study the optimal choice of a threshold for matching in a non-personalized campaign. In a large-scale field experiment with e-mail solicitations for different charities, they provide donors with a menu of three thresholds such that donations at the level of the first threshold ($X) and above, up to the level of the second threshold, are matched with $X, and so forth, inducing a budget set with multiple kinks. By varying the menu of thresholds, they are able to structurally estimate the optimal menu of uniform thresholds. They conclude that optimal uniform thresholds would have to be set very high, which is in stark contrast to our findings on non-personalized thresholds.

[2] See Adena, Hakimov, and Huck (2019) for a review of the degree of crowding out in field experiments on matching. A recent paper by Krasteva and Saboury (2021) suggests that incomplete information aggravates the underperformance of matching incentives. For some other recent studies on matching, see Diederich et al. (2019) and Gallier et al. (2019).
[3] For studies on lead donations or seed money, see List and Lucking-Reiley (2002), Gneezy, Keenan, and Gneezy (2014), and Rondeau and List (2008).

Defaults, suggestions, and donation grids

Thresholds may be perceived as implicit suggestions creating a link to the literature on defaults, suggestions, and donation grids in charitable giving. This literature offers a rather mixed picture. While some studies find positive effects of higher suggestions on revenue (Adena, Huck, and Rasul 2014), others find no effects (Altmann et al. 2019) or even detrimental effects (Adena and Huck 2020; Reiley and Samek 2018). Most of the studies confirm, however, that defaults and suggestions bring more individuals to donate exactly the suggested amount but suggestions that are set too high lead to a reduction in the response rate (for a review of the early literature on suggestions, see Bekkers and Wiepking 2010).[4]

Personalization

A number of studies include some element of personalization of suggested amounts or grids.[5] Edwards and List (2014) conduct a field experiment, in which a university asked its alumni for donations. The authors implemented treatments with no suggestion, a suggestion of $20, a "personalized" suggestion of $20.01-$20.08 that corresponded to the year of graduation, and a random suggestion of $20.01-$20.08. They found that participants gave $20.00-$20.08 more often when suggested, and "personalized" suggestions resulted in more compliance. Since the suggested amounts were relatively low compared to the donation values in the no-suggestion treatment, suggestions resulted in an increase in the response rate and a decrease in the average donation. There were no overall differences in the average revenue between treatments. Reiley and Samek (2018) study grids with five suggested amounts and a write-in option in the context of a fundraising call for a radio station. Grids were either exogenously set or relative to previous donations. Overall, personalization had little effect, which the authors partially attribute to donors' preferences for round numbers. De Bruyn and Prokopec (2013) study personalization of the first amount of a grid

[4] Studies of donation grids (appeals scales, attraction points) in marketing refer to an interplay between internal and external referents (the last being the appeals scales and round numbers) that exert different pulling effects (Desmet and Feinberg 2003; Desmet 1999).

[5] Other forms of personalization documented in the literature include asking the right expert for contributions to Wikipedia (Chen et al. 2018) and matching potential donor's and recipient's names (Munz, Jung, and Alter 2018).

and the steepness of grids. The scale with the highest starting amount (180% of the past donation) and the steepest range resulted in the highest donations and return.[6] Lee and Feinberg (2018) study personalized grids and conclude that, while grids exert substantial attraction effects, donors are more easily persuaded to give less than more. Altmann et al. (2018) make out-of-sample predictions based on a structural model in a context with defaults. They find that an optimal default should be set at double the past donation level. A recent study by Goswami and Urminsky (2020) combines personalization with 1:1 matching rather than defaults or grids. The authors offer 1:1 matching for donation amounts above the past gift and compare it to standard 1:1 matching for all gifts and a no-matching condition. This form of matching does not generate higher out-of-pocket gifts and does not increase overall giving.

3. Theory sketch

Consider a potential donor who has to allocate her income on private consumption and a charitable good.[7] She cares about the donation *received* by the charity and about her own consumption.[8] We assume that her indifference curves are strictly convex. We denote her out-of-pocket donation (or donation given) by x and her optimal out-of-pocket donation in the absence of matching by x^*. Let us now consider the effect of a personalized threshold matching scheme. Let t denote the threshold, that is, donations with $x \geq t$ will be matched with some positive fixed amount m, such that the donation received by the charity will be equal to $x + m$. Now assume that x^*, the optimal donation in the absence of matching, is known and that the fundraiser sets $t = x^*$. This results in a shift of the lower part of the donor's budget constraint to the right (see Figure 1, upper panel)—the donation received by the charity jumps to $x + m$, if the match applies. The new optimal donation given is

[6] This conclusion is based on our calculations using the summary statistics provided in the paper. The pattern is, however, far from uniform and the differences between treatments are not statistically significant.
[7] Essentially, we follow a partial equilibrium approach here, that is, we do not model the donor as anticipating further and possible altered fundraising calls from other charities etc. In essence, our model has no time dimension; it is completely static. This is a simplification but given the mental constraints that decision makers face when looking ahead, perhaps not too unrealistic.
[8] If total giving enters into a donor's utility function (like in standard public good games) our analysis holds as long as total giving is not perceived as a function of the threshold.

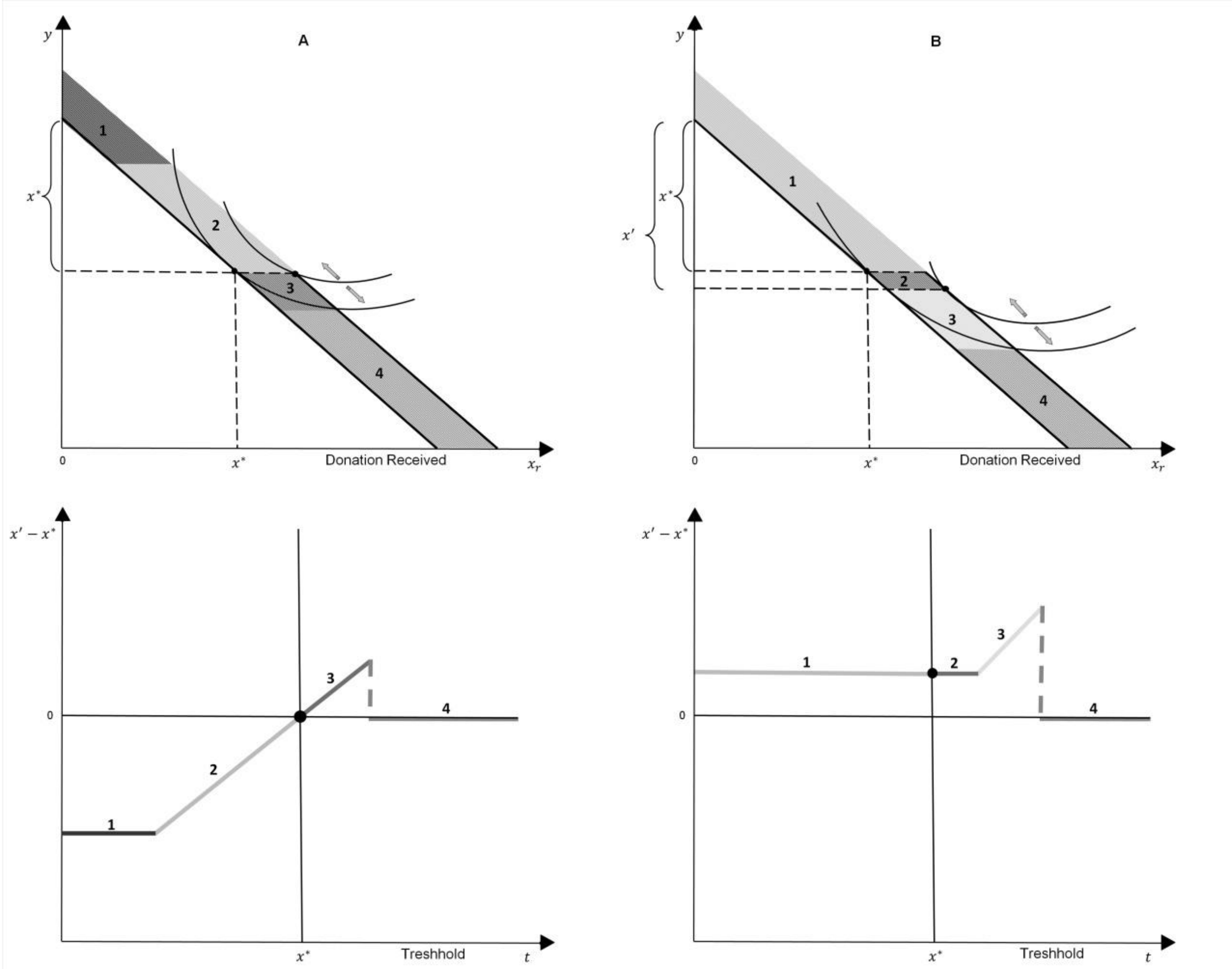
denoted by x' and we must have $x' \geq x^* = t$. There are, however, threshold levels with $t > x^*$, such that the optimal donation strictly increases: just imagine a very small increase in the threshold $t' = t + \epsilon$. Essentially, we can distinguish two cases depending on the precise shape of the donor's indifference curves. In the first case (scenario A on the left of Figure 1), a threshold $t = x^*$ generates a corner solution and the donation given remains unchanged with $x' = x^* = t$. Marginally increasing the threshold then leads to a strict increase in out-of-pocket giving, that is, we have $\frac{\partial x'}{\partial \mathrm{t}}|_{t=x^*} > 0$. In the second case (scenario B on the right of Figure 1), with a threshold $t = x^*$, the donor's new optimal choice is an interior solution which implies an immediate discrete positive jump in out-of-pocket giving, that is, $\mathrm{x}' > x^*$.

Of course, in practice, any increase in t will be discrete. In scenario A, a further increase of t leads first to an increase in out-of-pocket giving and then to a jump back to the originally optimal donation without matching. In scenario B, a further increase of t first results in a constant higher level of the donation given, $\mathrm{x}' \geq x^*$to then increase further. But, ultimately, if t becomes too large, the donor will revert back to the amount optimal in the absence of matching. For schematic effects of changing the threshold relative to x^* on the change of donations given, again relative to x^*, see the bottom panel of Figure 1. Note that, in scenario A, lowering the threshold will decrease the donation given until it stays constant. In scenario B, lowering the threshold will not produce any change in the donation given. From these theoretical considerations we establish two aims for our field experiment:

Aim 1: Show that the introduction of a threshold slightly above the donation that would be optimal without the match leads to strictly higher out-of-pocket donations.

Aim 2: Find the threshold that maximizes out-of-pocket donations. It must be somewhere to the right of the optimal donation without a match.

Figure 1: Theoretical predictions



Notes: The figure presents two possible scenarios, which depend on the shape of the indifference curves (assuming strict convexity in both cases). The upper panel presents the budget set in a y-x_r-space, with x_r denoting the donation received by the charity and y denoting private consumption. Both figures show how the budget set expands if threshold matching is offered for donations given at and above the optimal donation without the match, x^*. In the left upper panel, the new donation given with matching, x', is equal to x^*, and in the right panel it is larger than x^*, as indicated on the vertical axis. The shadowed part of the figure presents all other possible expansions of the budget set depending on at which level the threshold for matching is set (with the lower space belonging to the new budget set). The bottom panel shows how a change in threshold relative to x^* results in a new donation given x' being smaller, equal, or larger than x^*. The segments are numbered such that they match the segments in the upper panel. Note that the length of the segments in the bottom panel depends on the exact shape of the indifference curves, and has thus illustrative character only.

The first aim can be achieved easily. We simply set the threshold slightly above the predicted donation and see what happens. The second aim may be harder to achieve, as we have no *a priori* information about the location of the optimal threshold and, indeed, there is the risk that, if it is very large, we might miss it.

4. Design of the experiment and implementation

Data

We partnered with an opera house that, additionally to its main operations, provides a social youth program for schoolchildren from disadvantaged areas offering access to culture and music. The project is financed through donations and the recipients of the fundraising call are individuals from the database of opera customers. The database includes customers who registered online, bought tickets per telephone, e-mail, or fax, or registered when buying tickets in person. Close to 60% of customers in this database registered online, the remainder used the other means of purchase. The opera staff carefully went through the database (names and addresses), in order to exclude any duplications, opera employees or any other person not intended to receive the mailing, and to avoid households receiving more than one mailing. The opera started engaging in this type of fundraising just two years earlier and had run a total of two fundraising drives prior to this one.[9] The first campaign took place at the end of November 2015, the second at the end of November 2016, and this particular campaign at the end of November 2017. Thus, we have a (small) set of past donors we can draw on, previous non-donors, and a set of new customers. Past donors are individuals who bought tickets in the opera season 2014/2015 and lived in Germany, Austria or Switzerland, received a donation letter in one or both of the previous campaigns, and donated in one or both of the previous campaigns. Previous non-donors are customers who bought tickets in the season 2014/15 and received a fundraising letter in one or both of the previous campaigns but have not donated. New customers entered the customer database in the opera season 2016/17 and were not asked for donations in previous campaigns. For past donors and previous non-donors we know a

[9] See Adena and Huck (2019a) for details of previous campaigns.

number of individual characteristics including the number and value of tickets purchased that serve as proxies for income and affinity with the opera house, as well as (self-indicated) gender, family, academic status, and the place of living. For the set of new customers, the personal information was not available *ex ante* but some information was available *ex post*, see Table A1 in the Appendix for some additional information on the three types of customers.

Implementation

For past donors, we set x^*, the optimal donation in the absence of matching, to be equal to the highest past donation.[10] For previous non-donors,[11] we relied on regression results examining how observable characteristics translated into donation amounts of past donors to make (out-of-sample) predictions for their x^*.[12] We selected customers with high predicted donation values, and employed some rounding techniques for x^* that employ a grid, on which donation amounts are typically chosen.[13]

[10] The literature has documented sizable persistence in donation choices. Charitable giving in one year is the best predictor for giving in the next year (Meier 2007; Landry et al. 2010) and the amounts chosen are usually very close to the previous amounts (Adena and Huck 2019b). The data from previous campaigns of the opera house reveals that a subset of past donors gave twice in the previous years (a retention rate of 36.5% in the second call), and there is indeed a high correlation between the donation amounts of repeat donors (0.778, significant at $p<0.0001$, see Figure A1 in the Appendix) with a paired *t*-test *p*-value of 0.482. Consequently, we assume that past behavior is a good proxy for the optimal donation in the absence of a match and we use the (maximum) past donation for the 769 past donors in our sample as such proxy.

[11] Non-giving in one or two campaigns does not necessarily reveal a basic preference against giving but might reflect high transition costs at the time of receiving the appeal, for example, because of the work load, illness, or planning for Christmas celebrations. If transaction costs vary over time, individuals might donate in some but not other campaigns (Huck and Rasul 2010). Other reasons for giving only after a second or third fundraising letter might result from increasing pressure or persuasion. All in all, Adena and Huck (2019b) have demonstrated that a careful selection of past non-donors (based on similar procedure as here) can lead to a relatively high response rate.

[12] Guided by a lasso selection procedure (using the *lars* command *in stata*), we use information on ticket purchasing behavior (from opera season 2016/17: total amount spent on tickets, log of this total, average ticket price, dummy equal to one if any tickets bought in a particular year; from opera season 2014/15: number of tickets, total amount spent on tickets, log of this total, average ticket price) and individual characteristics (dummies for living in Dresden, living in Germany, for subscription holders, female, couple, doctoral title and a professorial title).

[13] The raw predicted donation is, of course, almost never a round number, and, on average, somewhat smaller than the average donation of past donors. In order to address this issue, we ordered individuals according to their predicted donation and then assigned them to the same rank of the *actual* distribution of past donations. See Table A2 in the Appendix for the exact procedure.

We then employ a two-stage randomization procedure generating thresholds for all subjects in the same way. The procedure ensures that we have exogenous variation in thresholds oversampling thresholds at or just above past or predicted donation levels. First, subjects are randomly assigned to one of three paths. For one third of past donors and previous non-donors we set the threshold equal to the predicted amount (referred to in the tables below as “past/predicted”). For a second third we pushed the threshold to the next level on the grid (“plus”), and for the last third and all new customers we picked a grid point at random from the distribution of past donations (“doubly random”). These three groups are balanced on individual characteristics (see Table A3 for past donors and Table A4 for previous non-donors in the Appendix).[14]

The letter informed recipients that a generous lead donor had been found who would top up an individual donation with €10, if this donation met a “large donation” threshold or exceeded it.[15] This compares to a median positive donation in both previous campaigns of €25 and an average around €50. The threshold was referred to as “large donation” and was not flagged as personalized.[16] See the Appendix for the exact formulation of the mail-out. In total, we sent 10,004 letters to the subset of opera goers: 769 *past donors*, 3,859 *previous non-donors* and 5,376 *new customers*.

[14] Note that our procedure precludes balancing for each threshold increase: While a person that gave €10 in the past might receive a threshold increase of 50%, 100%, or more, past donors who gave €5 in the past will not receive a 50% higher threshold. Both will also not receive any intermediate categories (see Table A2 in the Appendix for the spectrum of possible threshold values drawn from the category past).

[15] The maximum total match amount was at €4,000 which allowed matching of up to 400 donations at or exceeding the threshold. Although the total number of donations was close to the predicted number, the total match amount was not exhausted as a substantial share of donations fell short of the assigned threshold. In addition to the match offer, a non-anonymous corporate donor provided a VW Multivan for the project unconditionally which was announced as well.

[16] Unlike Edwards and List (2014), we did not want to make the personalization obvious.

5. Main results

Among past donors, 242 of the 769 donated again. This corresponds to a response rate of 31.5%.[17] The average positive donation was €61[18] and the average return from the mailing was €19.20. Concerning donation levels relative to the threshold, 31% of donations were below the threshold, 37% hit the threshold exactly, and 32% of the observed donations were above the threshold. Among the 3,859 previous non-donors we observed 106 donations with an average gift of €58.54.[19] This amounts to a response rate of 2.7% which is more than double of what had been achieved in the first-year campaign (1.3%), although this group of customers had declined the donation ask already once or twice.

Figure 2 shows the empirical relationship between changes in the threshold and changes in out-of-pocket donations conditional on giving mirroring our main theoretical predictions depicted in Figure 1. The left panel shows the results for past donors, the right panel for previous non-donors. The figure shows how relative changes in the threshold affect relative changes in the positive donation level with a local polynomial fit and displays a 90% confidence interval for this relationship.[20] The resulting fitted curve resembles a combination of the two theoretical scenarios: lowering the threshold leads to a decrease in out-of-pocket giving like in scenario A; right at the threshold $t = x^*$ the donations given are higher than x^* like in scenario B, and, fully consistent with both scenarios, increasing the threshold above x^* first increases donations and then pulls them down towards the past level. Despite two sources of lower precision for previous non-donors (estimated optimal donations instead of past donations and a considerably smaller number of

[17] For donors who had given in the previous year (2016), the response rate was 42%, and for repeat donors it was 61%. For donors who gave in the first year of the campaign (2015) but not in the second (2016), the response rate was 14%.
[18] The average positive (maximum) donation in this group in previous campaigns was €53.70.
[19] The average predicted donation absent matching in this group was €54.29.
[20] We settle on local polynomial fit with 90% confidence intervals as it can be used for all following figures for reasons of convergence, coding, and the size of the confidence intervals.

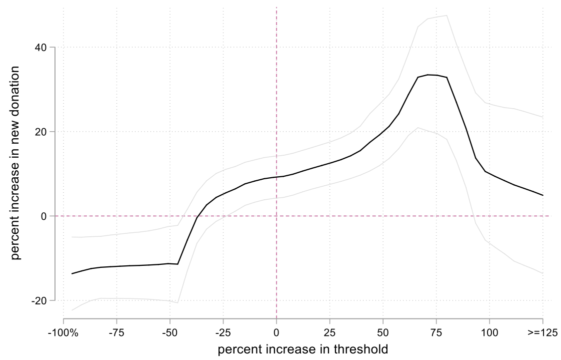
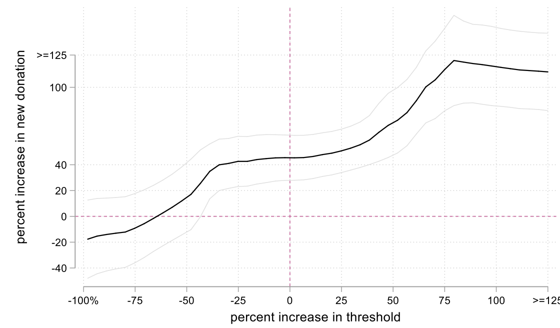
positive donations), the picture is remarkably similar indicating again the benefits of comparatively high thresholds with a peak similar to the peak for past donors.[21]

In the Appendix, we show for the sample of past donors that the results are robust to the choice of the specification. The left panel of Figure A2 shows the results of a nonparametric kernel regression with 90% confidence intervals. Furthermore, in order to address the issues of balancing conditional on the threshold increase, in the right panel of Figure A2, we present marginal effects from a parametric regression with a fifth polynomial of the threshold change variable including all available demographic controls, and, most importantly, baseline giving. Finally, in the bottom panel of Figure A2, we show a binscatter that considers each of the first-stage randomization paths separately and accounts for individual characteristics. In all cases, the figures are in line with the theoretical prediction and very similar to the left panel of Figure 2. One difference concerns the left part of the graph—in fact there is no evidence in the data that a threshold lower than past donation can lead to a donation higher than in the past as in Figure 1, scenario B. The impression in Figure 2 is simply an artefact of the smoothing algorithm. Finally, Figure A3 splits the sample of past donors in balanced samples based on baseline giving. Again, each sample's contribution is in line with the theory.

Altogether, this confirms our theoretical predictions and fulfils both our aims. With a threshold slightly higher than the individually optimal donation without the match (proxied by past donations for past donors and by the predicted donation for previous non-donors), the newly chosen out-of-pocket gifts are indeed strictly higher. In addition, we are able to identify the threshold that maximizes out-of-pocket gifts: the optimal threshold is to be found around 75% above the optimal donation without the match for past donors.

[21] Notice that just left to the origin the figures suggest a positive effect of thresholds just under the past/predicted donation level. As can be seen further below, this is an artefact of our smoothing procedure. We decided to keep these simple graphs though as none of our main conclusions hinges on the precise shape of the estimated function in this area.

Figure 2: Positive donations: Effects of changing the threshold on the out-of-pocket donation

Past donors	Previous non-donors
	

Notes: Local polynomial fit; 90% confidence intervals; x-axis left panel: (threshold - past donation)/past donation, capped at 125 percent; x-axis right panel: (threshold - predicted donation)/ predicted donation, capped at 125 percent; y-axis left panel: (new donation - past donation)/past donation conditional on giving, capped at 150 percent; y-axis right panel: (new donation - predicted donation)/ predicted donation conditional on giving, capped at 150 percent.

6. Further aspects

Contrarians

Although average behavior is in line with theoretical predictions, we discovered some behavior violating the simple theory. Zooming in on individual behavior in Figure 3 reveals, for example, a type of donor whose behavior is in direct contradiction to the theory—there are a number of individuals in the lower right quadrant of that figure who act in a contrarian way: while being implicitly asked to give more than the last time, they decide to give less.

Among individuals who received a threshold higher than their past donation, 21% gave an amount lower than the past donation.[22] It is unclear whether this behavior is systematic or rather due to some noise, e.g., because individuals are inattentive or perhaps forgot their past donation amounts or were subject to a negative income shock. However, if this was purely due to noise, we would

[22] For individuals who received a threshold equal to or higher this number is 16% and it is 10% if we account for the lower past donation if they gave twice.

expect more symmetry in Figure 3: in particular, we should also have more observations in the upper left quadrant of donors, who were asked to give less but give more. This is not the case; only 2% give more when being asked for less.[23]

We find limited guidance for understanding contrarian behavior in the literature. One possible explanation could be diffusion of responsibility (Van Teunenbroek et al. 2019): the higher threshold may convey social information that suggests that others donate more, thus, rendering the own donation less meaningful. This interpretation would also be broadly in line with a non-behavioral model of sequential contributions to public goods (Varian 1994) where giving of others crowds out own giving.[24] A further possible explanation for the observed pattern could be excuse-driven behavior (Exley and Petrie 2016; Exley 2020, 2016).[25]

Notice that the benefits of higher thresholds are substantially reduced by contrarian behavior. This raises the question whether it would be possible to predict who would respond aversely to higher thresholds such that this contrarian group can be treated differently. Hence, we compare contrarians' observable characteristics to the characteristics of those who respond positively or neutrally to a threshold increase. In Table 1 we regress an indicator dummy for contrarian behavior on a set of individual characteristics. We define a contrarian as a donor who donated less than in

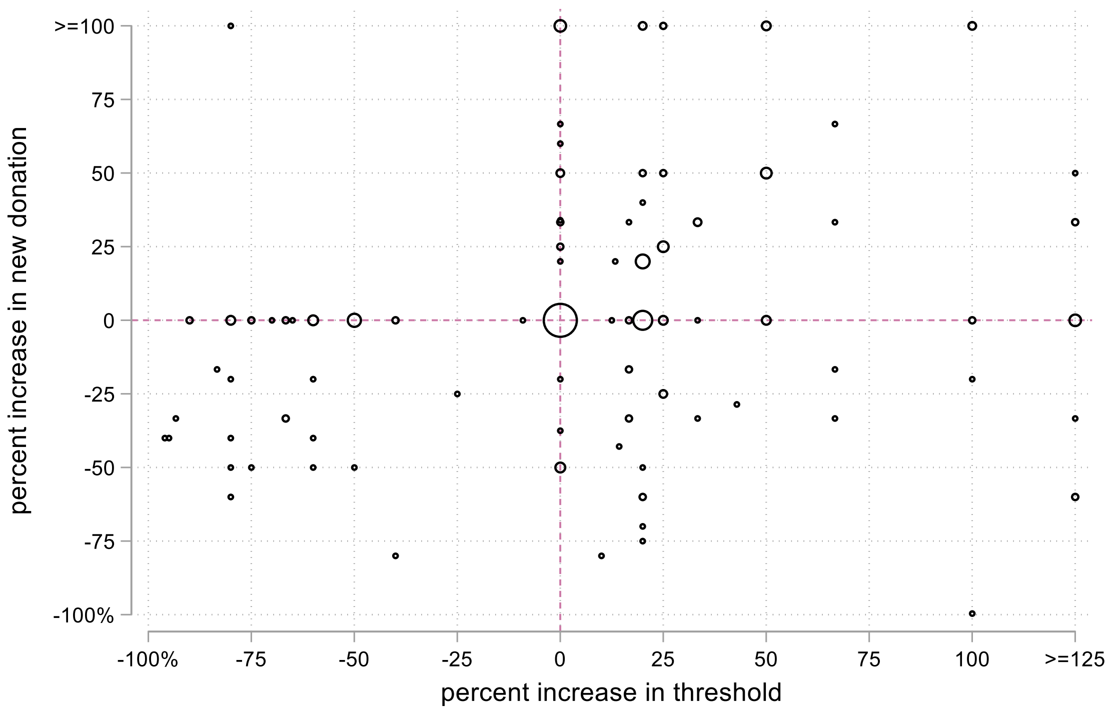
[23] Note that giving more than in the past when receiving a lower threshold is consistent with theory (scenario B in Figure 1). The share of individuals who behave at odds with our theoretical predictions and give less than in the past when being asked for more is strikingly similar to the shares of individuals who do not behave in line with a standard neoclassical choice model found in Adena, Huck, and Rasul (2017) in a similar charitable context but using a different methodology. They rely on a between-subject design and compare shares and distributions of donations between treatments with crossing budget sets. Our comparison is similar to a within-subjects design. They identify a share of at most 20% of individuals, whose behavior cannot be rationalized within a standard neoclassical choice model in which individuals have preferences defined over own consumption and their contribution towards the charitable good satisfying the axioms of revealed preference.

[24] Higher expected giving by others could lower own giving if the total giving by others enters the own utility function with a sufficient weight and the higher threshold shifts those expectations. Chlaß, Gangadharan, and Jones (2015) find that less efficient donations might lead to higher giving.

[25] If a fraction of individuals looks for any type of excuse—being asked to give less, reduction in disposable income, having donated already to another organization, etcetera—this could explain some of the observations in the lower left quadrant of Figure 3. In psychology, reactance theory (Brehm and Brehm 2013) tries to explain contrarian behavior as a reaction to a reduced decision set. In marketing, Goldfarb and Tucker (2011) and Lambrecht and Tucker (2013) find that too much personalization might backfire, for example, if ads for one company are pervasively shown after one has visited that company's website.

the past (max in the Columns I-III and min in Columns IV-VI), while being assigned a threshold equal or higher than her max past donation. We have a sample of 195 individuals who were asked to donate an amount equal or higher than in the past including 30 (19) contrarians according to the first (second) definition. Unfortunately, we cannot detect any meaningful differences with the data we have. While single coefficients turn significant at low levels, their number is in line with the expected number of false positives (we do not correct for multiple hypotheses testing in Table 1). Therefore, we rather abstain from drawing any inference from this table. Nevertheless, the opera now knows to treat this set of customers differently in the future.

Figure 3: Past donors; individual choices



Notes: The size of the dot corresponds to the number of individuals, x-axis: (threshold - past donation)/past donation, capped at 100 percent, y-axis: (new donation - past donation)/past donation, capped at 100 percent.

Given that the match amount was fixed at €10 one could worry that larger donors, for whom €10 constitutes a much lower fraction of their donation, might feel vexed and thus react differently than expected. However, Table 1 does not confirm that the probability of being a contrarian increases in the size of past donations once other individual characteristics are taken into account (Columns II-III). This is also true if, for those who donated twice in the past, we rely on the lower past donation for our definition of contrarian (Columns IV-VI).

Table 1: Individual characteristics of the contrarians

Dependent variable: dummy equal to 1 if	Donation<Past (max)			Donation<Past (min)		
	I	II	III	IV	V	VI
Past donation (log)	0.059**	0.036	0.024	0.014	-0.000	-0.019
	(0.027)	(0.031)	(0.033)	(0.023)	(0.025)	(0.026)
No. tickets 2016/17		0.006	-0.043		0.039	0.003
		(0.054)	(0.058)		(0.044)	(0.046)
Amount spent on tickets 2016/17 (log)		-0.002	0.025		-0.047*	-0.026
		(0.031)	(0.033)		(0.025)	(0.026)
Dummy active customer in the preceding season (16/17)		-0.042	-0.042		0.131	0.149
		(0.113)	(0.115)		(0.093)	(0.092)
Female dummy		0.018	0.013		0.004	0.004
		(0.055)	(0.057)		(0.045)	(0.045)
Subscription holder dummy		-0.077	-0.104		-0.048	-0.058
		(0.087)	(0.091)		(0.071)	(0.072)
Dresden dummy		0.000	0.172		-0.055	0.189
		(0.059)	(0.151)		(0.048)	(0.120)
Germany dummy		0.364	0.382		0.201	0.231
		(0.370)	(0.370)		(0.303)	(0.294)
Academic dummy		0.079	0.076		0.088	0.089
		(0.085)	(0.088)		(0.069)	(0.070)
Donated twice before dummy		0.049	0.060		-0.088*	-0.078
		(0.057)	(0.060)		(0.047)	(0.048)
Donated only in 2016 dummy		-0.115	-0.110		-0.118*	-0.120*
		(0.076)	(0.079)		(0.062)	(0.062)
Online customer dummy			0.038			0.022
			(0.084)			(0.067)
Distance in km (log) to the Opera house			0.034			0.052**
			(0.032)			(0.025)
Constant	-0.055	-0.310	-0.505	0.046	-0.003	-0.267
	(0.100)	(0.396)	(0.455)	(0.083)	(0.324)	(0.362)
Observations	195	195	182	195	195	182
R^2	0.023	0.073	0.087	0.002	0.083	0.089

Notes: OLS, sample of past donors who donated repeatedly and who received the donation ask with a threshold set equal or higher than the past donation. Dependent variable is a dummy equal to 1 if donation<past donation (max) or donation<past donation (min) respectively; Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Response rate and revenue

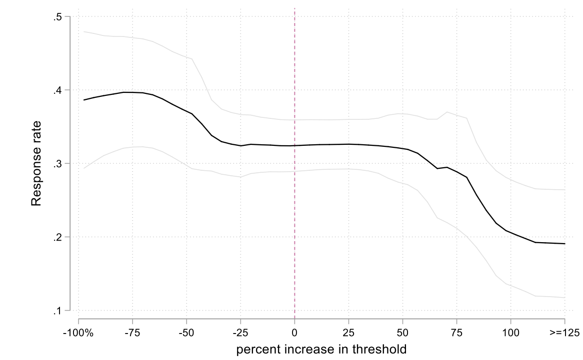
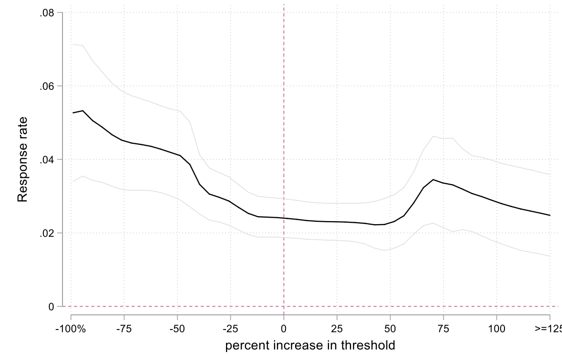
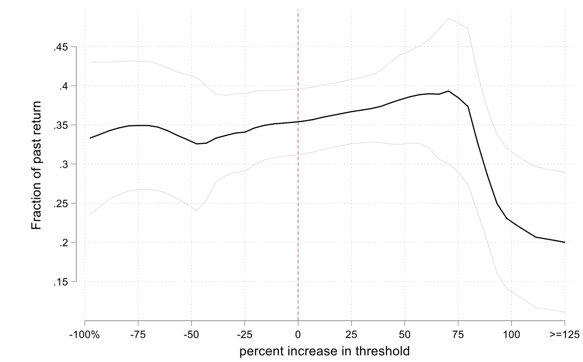
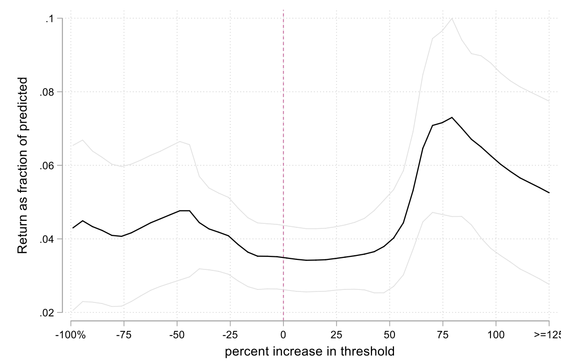
In the upper panel of Figure 4 we inspect the response rate. Theoretically, the response rate should not be affected by the threshold level (as donors can always revert to their optimal donation without matching). In practice, however, we observe a negative trend in Figure 4. In the lower panel of Figure 4 we inspect the total effect of the campaign: depending on the change in threshold, we look at the realized return as a fraction of the hypothetical return in absence of a match (using past donations for past donors and predicted donations for past non-donors).[26] The total effect of changes on the return exhibits, despite the falling response rate, the same shape that we identified for donation amounts, with peaks at increases of 75% for both past donors and previous non-donors. While for past donors the lower thresholds do not result in significantly lower overall return, thresholds that are set too high are clearly inferior.

Long-term effects

From a charity's perspective it is important to understand the long-term effect of a campaign, and a key question is whether the change in donation values induced by some manipulation is permanent (Adena and Huck 2019b) or whether there is some intertemporal crowding out (Blinder and Rosen 1985; Meier 2007). Also, in this specific application, one might wonder how the contrarians behave in the future. Will they stick to the lower donations or reverse their behavior?

[26] Note again that this presentation is necessary since different threshold changes are not available for the same set of baseline donations. Therefore, a presentation with absolute return is not meaningful. Figure A4 in the Appendix shows a parametric version of the bottom left graph in Figure 4 after controlling for individual characteristics and baseline donations.

Figure 4: Response rate and return

	Past donors	Previous non-donors
Response rate		
Return as fraction of hypothetical return absent matching		

Notes: Local polynomial fit, 90% confidence intervals; x-axis left panel: (threshold – past donation)/past donation, capped at 125 percent; x-axis right panel: (threshold – predicted donation)/predicted donation, capped at 125 percent; y-axis, top panel: share giving positive amount; y-axis, bottom panel: new donation/past or predicted donation including non-donors.

While we cannot assess the permanent effect, we can at least look at the behavior in the subsequent year. At the end of November 2018 the opera house repeated the fundraising on a much smaller scale without any treatment variation and without offering any matching (see Apendix for the mail-out 2018 and its translation). Only past donors (conditional on having donated in at least two of the three previous campaigns in 2015-2017) were asked to donate (332 individuals). Of those, 320 were in the group of past donors who received a threshold matching offer in 2017. Of those, 241 donated in 2017, 159 donated in 2018, and 132 in both years. Table 2 shows donation levels chosen in 2018 depending on the threshold setting in 2017 and the response to this threshold divided into: (i) compliers (those who increased their giving when the threshold was higher than their past donation or decreased it respectively whith a lower threshold), (ii) contrarians, and (iii) stayers (those whose donation was not affected by a higher or lower threshold relative to their past donation). The averages presented in Table 2 are conditional on positive donations before, during, and a year after the campaign. Note that despite the self-selection, the response rate in 2018 is similar in all cells with the exception of the last one—those asked for less, who repeated their donation in 2017, were more likely to give in 2018. There are four conclusions that we can draw about long-run dynamics from Table 2:

(i) Those who were asked for more and complied in 2017 (compliers) chose higher donations in 2018 again (very similar to those in 2017 and significantly higher than before ($p<0.001$)). This suggests that our campaign was successful in shifting donation amounts for this group for at least one additional year.

(ii) Those who did not change their donation in 2017 despite being asked for more or less (stayers) increased their giving slightly but not significantly in 2018.

(iii) Those who decreased their donation in 2017 when being asked for more (the contrarians), increased their giving relative to 2017 significantly ($p>0.1$) but stayed below their original donations, that is, there is some long-run harm.

(iv) Those who decreased their donation in 2017 when being asked for less (complier), increased the donation 2018 (not significantly) but stayed below their original amounts, indicating potential long-run harm of ill-designed fundraising calls.

Figure 5 shows the correlation between chosen donation values during our main campaign and in 2018. The correlation is very high (0.908 with $p<0.0001$), suggesting that the 2017 choices set a new standard rather than any intertemporal substitution taking place.

Table 2: Average giving of repeat donors in different years depending on threshold setting in 2017 and their response to that threshold

Conditional on being a donor in 2015 and/or 2016, 2017, and 2018

			Max donation before (in 2015 and 2016) x*		Donation during the campaign (2017) d		Donation after the campaign (2018)		Paired t-test p value		N (donation 2018 >0)	N received mailing 2018	Response rate
			I		II		III		I=III	II=III			
Relative to max donation in 2015 and 2016,			mean	std. error	mean	std. error	mean	std. error					
threshold in 2017 is:	donation in 2017 is:												
Higher x*<t	higher (complier) x*<d	i	43,125	7,426	61.458	10,279	61,875	10,486	0.000	0.899	24	49	0.490
	equal (stayers) x*=d	ii	48,810	7,129	48,810	7,129	54,524	9,825	0.248	0.249	21	39	0.538
	lower (contrarian) x*>d	iii	107,917	42,047	50,833	19,432	88,750	29,645	0.632	0.085	12	23	0.522
Lower x*>t	lower (complier) x*>d	iv	144,444	46,729	88,889	28,208	116,667	45,399	0.294	0.302	9	17	0.529
	equal (stayers) x*=d	ii	80,000	12,019	80,000	12,019	90,263	14,919	0.272	0.272	19	29	0.655

Notes: x* is our definition of the optimal donation without the match being given by maximum donation in 2015 and 2016, t is the threshold in 2017, and d is the donation in 2017.

7. Uniform thresholds

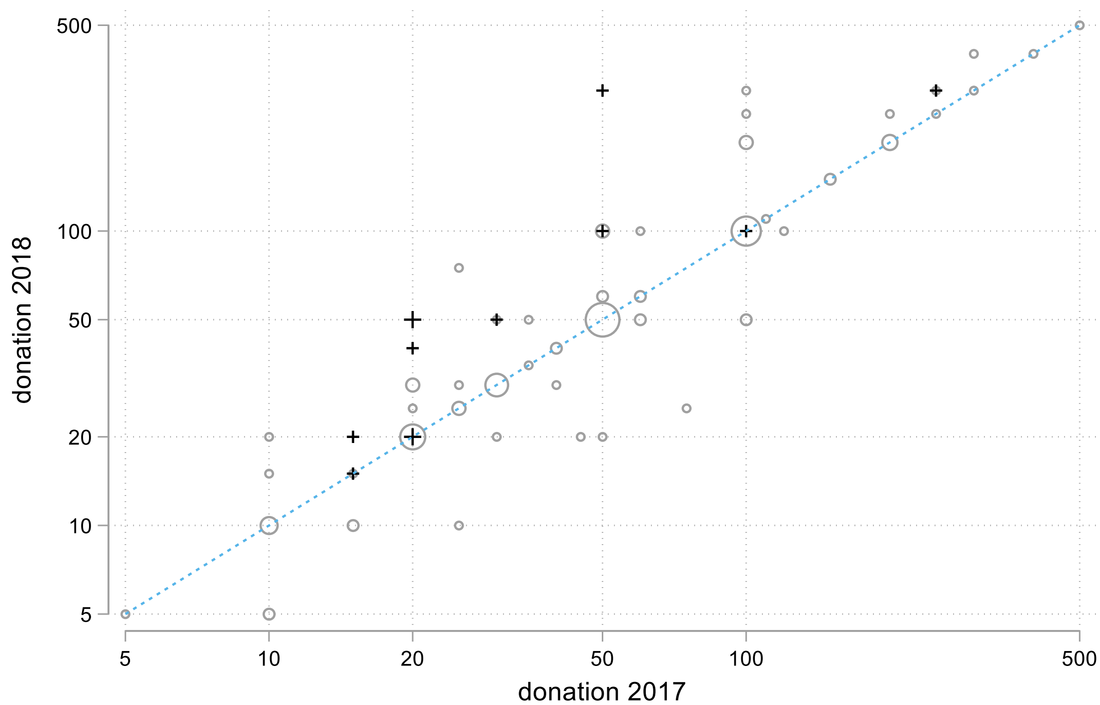
In the case when information about individual characteristics is not available to fundraisers (or cannot be used for data protection or other reasons), the question arises, which uniform threshold should be used (if any). For this reason, in Table 3, we regress our outcome variables (a donation dummy, the log of positive donations, and the return per mail-out (+1, log)) on the threshold value (log). We include available control variables including dummies for customer type and interaction of the customer type with past or predicted donation levels (except for new customers for which this is not known). For the sample of past donors and previous non-donors, we also account for the probability of the assignment of a specific threshold by using appropriate weights.[27] The linear relationship is very clear and highly statistically significant: higher uniform thresholds reduce the

[27] This accounts, for example, for the fact that one third of the past donors are assigned a threshold equal to their past donation. The results without weights are, however, very similar.

probability to donate, increase the average positive donation conditional on giving but reduce the overall return from the campaign. This resembles the effects of non-personalized suggestions in the literature (see Adena, Huck, and Rasul 2014). However, the above results seem to be in contrast with the results in Castillo and Petrie (2019). They structurally estimate an optimal uniform threshold level (with a match value equal to the threshold which is different from our study). They find a large threshold that is around eightfold of the average donation in their sample to be optimal (or with two thresholds, a second that is 35 times as large as the average donation).[28] While the optimal threshold estimated by Castillo and Petrie (2019) is out of the range of the thresholds tested in their experiment, our experiment included a threshold eight times higher (€400) than the average past donation in our sample (around €50). Since the regressions presented in Table 3 enforce a linear fit in the threshold value, this could have obscured some nonlinearities that might point to better performance of higher thresholds. Therefore, in Figure 6 we also show a local polynomial fit for our three different customer groups separately.[29] We see that random and nonpersonalized threshold values have little effect on past donors. This is in stark contrast to the personalized thresholds, which improved the outcomes of our charitable campaign. For previous non-donors and new customers, Figure 6 visualizes what can be inferred from Table 3: the response rate decreases, the positive donation increases and the return decreases in the value of the threshold. We conclude that the resulting optimal uniform threshold value for prospective donors is just the lowest possible, in our case equal to €5, which, as our previous section shows, can be outperformed by a personalized threshold value set at about 75% above the predicted donation.

[28] The average donation in their sample is $235 and the thresholds respectively $1,875 and $8,150.
[29] Again, in the case of past donors and previous non-donors, we reweight the observations by the inverse probability of the assignment of a specific threshold.

Figure 5: Correlation between donation values during and after the campaign



Notes: Symbol plus (+) marks the contrarians; donation amounts in Euros, log scale and a 45-degree line; the size of the markers corresponds to the number of gifts in each category.

Regarding the difference to Castillo and Petrie (2019), this might arise because we use a fixed match amount of €10 while they use a match amount that is equal to the threshold value. In addition, the contrasting results raise the point of external validity. Of course, our thresholds and match amount might not be appropriate for charities that target different donor types or pursue much different goals. A charity that wants to apply personalized threshold matching should adapt the match to their donor types, and it would be great to study whether thresholds at plus 75% maximize the donation values in other contexts as well.

Table 3: Uniform threshold

	donation dummy	positive donation (log)	Return: donation including zeros (+1, log)
Threshold value (log)	-0.007***	0.216***	-0.021***
	(0.002)	(0.043)	(0.008)
Controls	Yes	Yes	Yes
Observations	10004	386	10004
R^2	0.173	0.404	0.172

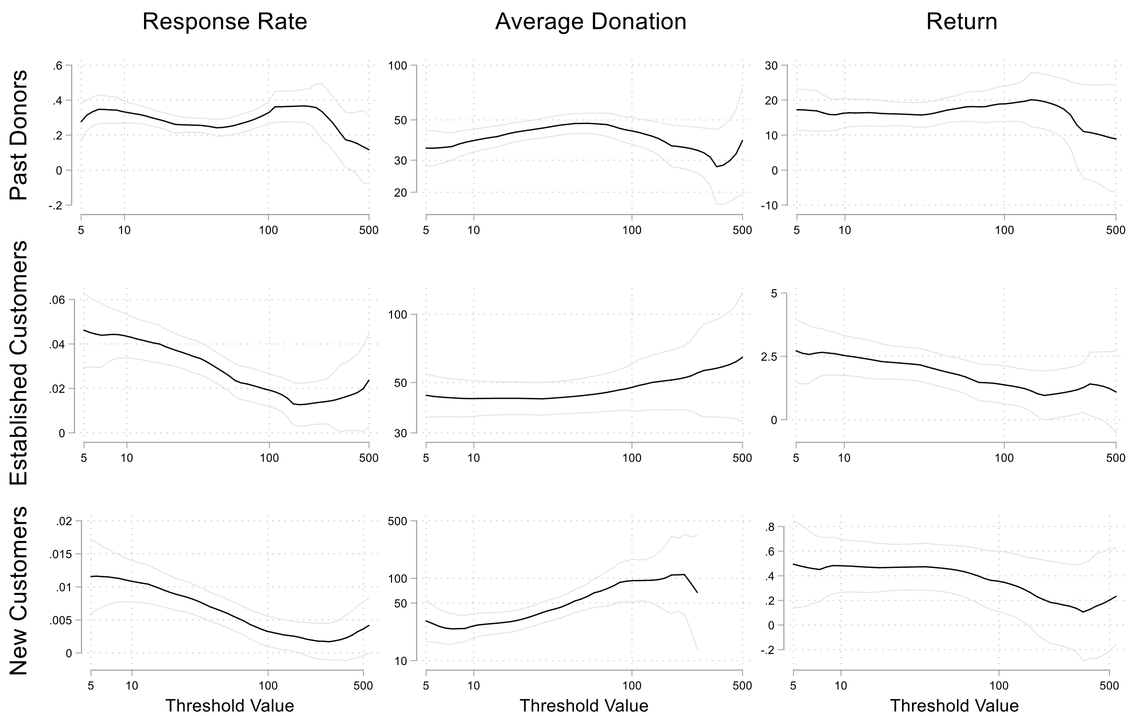
Notes: standard errors in parentheses; Controls include dummies for female, family, Dresden, Germany, and academic dummy, and the amount spent on tickets 2014/15 (log) and 2016/17 (log), dummy past donor and regular customer as well as the interaction of those dummies with the amount of past or predicted donation; for the samples of past donors and previous non-donors we correct for a probability of the assignment of a specific threshold by using appropriate weights; See Table A5 for full results; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8. Conclusions

While linear matching schemes have been shown to reduce out-of-pocket giving, they are nevertheless popular with fundraisers, presumably because of competitive pressure (Meer 2017; Scharf, Smith, and Ottoni-Wilhelm 2017). Ceteris paribus, prospective donors will always prefer to give to calls that offer some kind of matching that reduces the price of giving. Hence, it is of vital interest for fundraisers to find alternative matching schemes that are competitive in the marketplace but maximize out-of-pocket giving. In this study we propose *personalized threshold matching* for charitable giving and show, both theoretically and empirically, how it can be used to increase donations. Beyond the immediate positive effects, we find an indication of long-term gains due to considerable persistence in giving behavior. The matching scheme that we employ has the additional advantage that the amount that has to be secured for the match prior to the fundraising is much smaller than necessary for standard 1:1 linear matching and easier to predict and, thus, potentially easier to obtain.

There appears to be nothing peculiar in our setting and we expect that the fundraising scheme would work similarly for other organization pursuing similar (social) goals and with similar donor types. However, in the spirit of Maniadis, Tufano, and List (2014), it would be desirable to see replications in other contexts.

Figure 6: The effects of the uniform threshold



Notes: Local polynomial fit and 90% confidence intervals, no controls; Graphs for past donors and previous non-donors are using weights accounting for a probability of threshold assignment, see notes to Table 3. Average donation and return in Euros.

Further research could also explore other variants in which, for example, the match amount equals the value of the personalized threshold. Such variants could potentially reduce the prevalence of contrarians. Also, more research that could help to identify contrarians *ex ante* or inform a redesign of the incentive structure to avoid contrarian behavior would also be desirable. Since our paper can only be interpreted in terms of partial equilibrium, that is, abstracting from other charities, further research could study the effects of the proposed design on donations to other goals. Other interesting questions would be to test the boundaries of our proposed technique: Can personalized threshold matching be repeated with the same donors and could it increase the donations again? How often could the charity repeat this?

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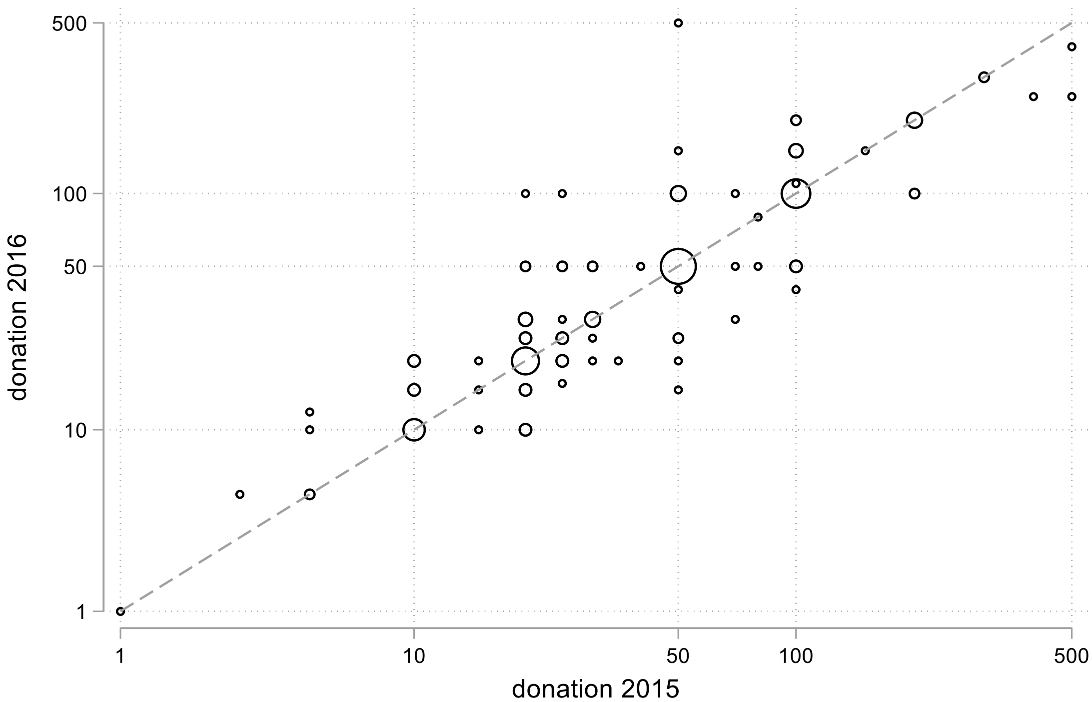
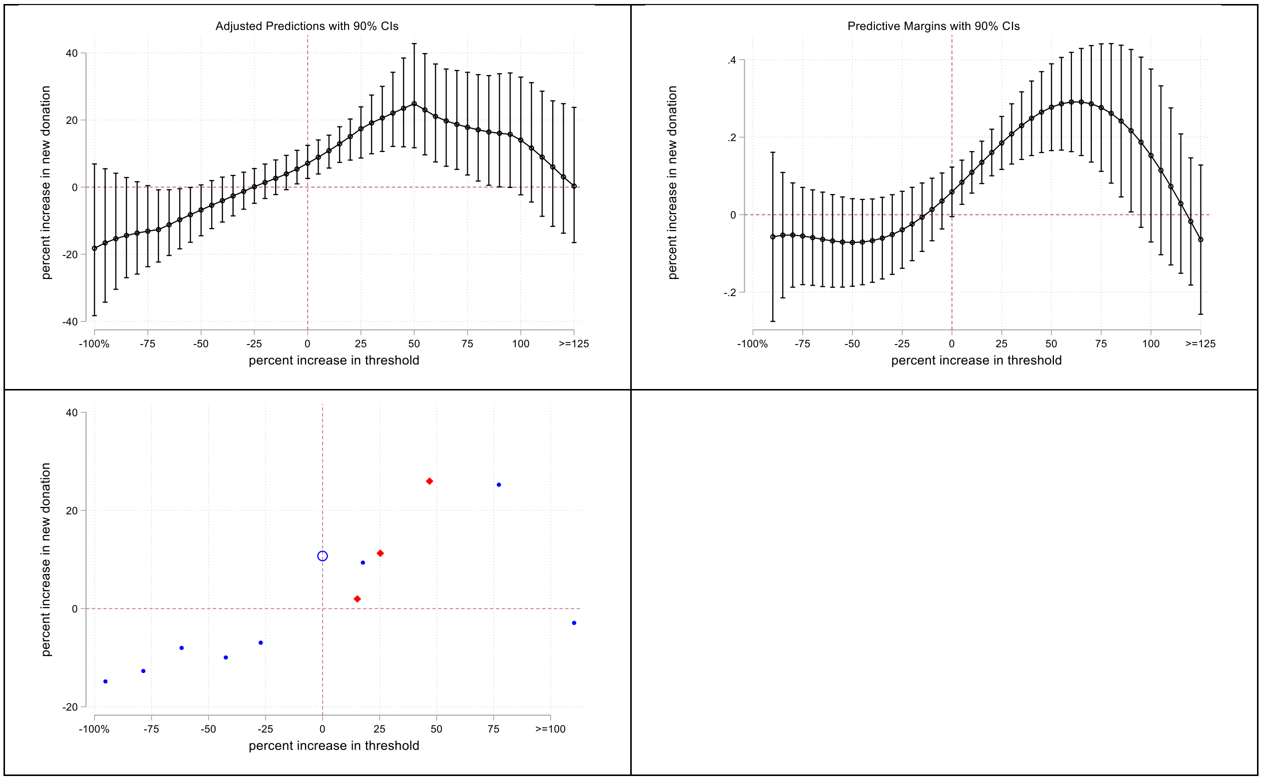
Appendix: Additional Graphs and Tables:

Figure A1: Correlation of donation values in previous campaigns



Notes: Donation amounts in Euros, log scale and a 45-degree line; the size of the bubbles corresponds to the number of gifts in each category.

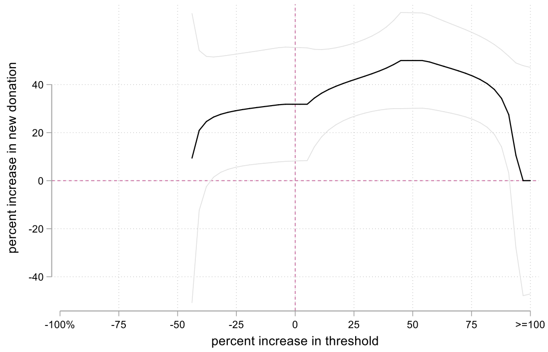
Figure A2: Past donors; positive donations; effects of changing the threshold: Alternative specifications



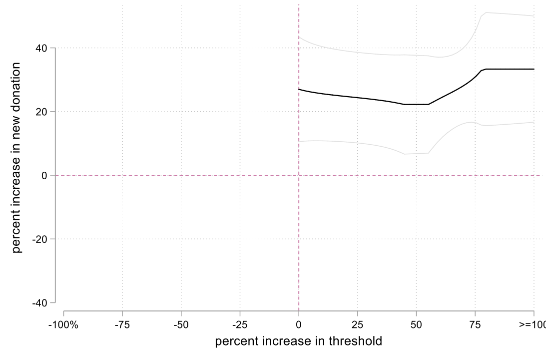
Notes: left panel: marginal effects at different values of threshold change after a nonparametric kernel regression; bootstrapped errors, 100 replications; right panel: marginal effects at different values of threshold change after an OLS regression with fifth polynomial in the variable percent increase in threshold and control variables including: (maximum) past donation value, donated twice before dummy, dummy active customer in the preceding season (16/17), amount spent on tickets 2016/17 (log), No. tickets 2016/17 (log), average ticket price, female dummy, subscription holder dummy, Dresden dummy, big city dummy, academic dummy, online customer dummy, distance in km (log) to the Opera house; bottom panel: binscatter (separate for each randomization path). X & y variables are residualized the on a small number of control variables before plotting: dummies for female, family, Dresden, Germany, academic and previous ticket spend. Dots—random path; hollow dot—past path; diamonds—plus path.

Figure A3: Past donors; positive donations; effects of changing the threshold: separate samples balanced on baseline (past maximum) donation with at least 6 new donations

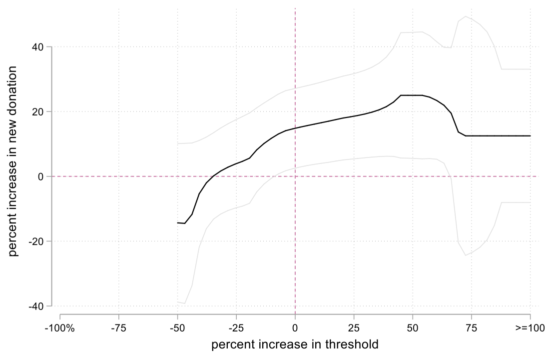
Sample of donors with (maximum) past donation equal to €10, 103 asked, 28 donated



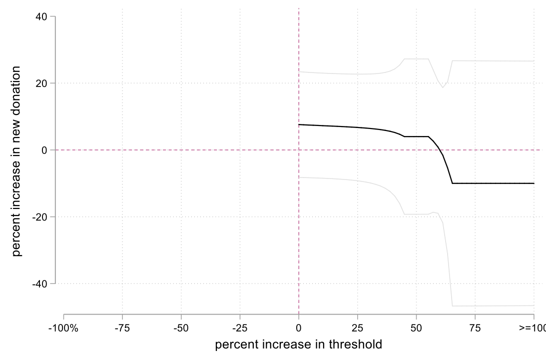
Sample of donors with (maximum) past donation equal to €15, 33 asked, 6 donated



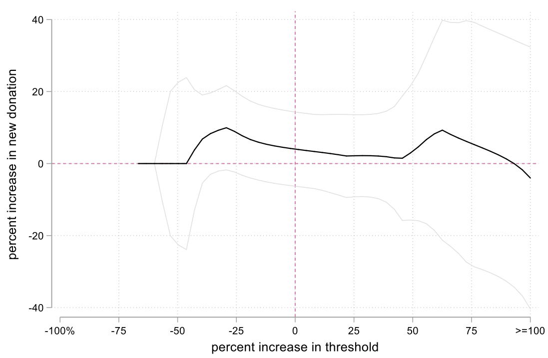
Sample of donors with (maximum) past donation equal to €20, 163 asked, 41 donated



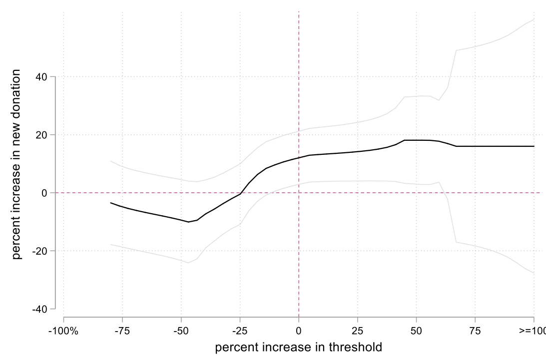
Sample of donors with (maximum) past donation equal to €25, 45 asked, 13 donated



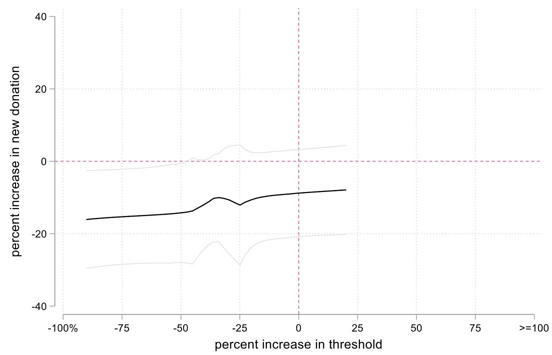
Sample of donors with (maximum) past donation equal to €30, 57 asked, 22 donated



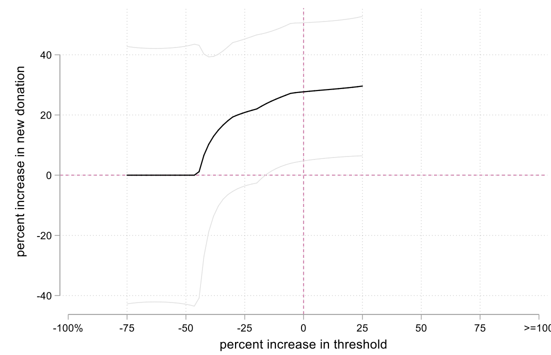
Sample of donors with (maximum) past donation equal to €50, 165 asked, 63 donated



Sample of donors with (maximum) past donation equal to €100, 91 asked, 32 donated



Sample of donors with (maximum) past donation equal to €200, 25 asked, 9 donated



Notes: 90% confidence intervals; We do not show the results for the sample of donors with (maximum) past donation equal to €5 excluded (27 asked, 5 donated): there are observations only for threshold increase of 0 and 100% and the average donation increase is zero.

Figure A4: Past donors; return as a fraction of hypothetical return: effects of changing the threshold: parametric regression with fifth polynomial and controls including past donations

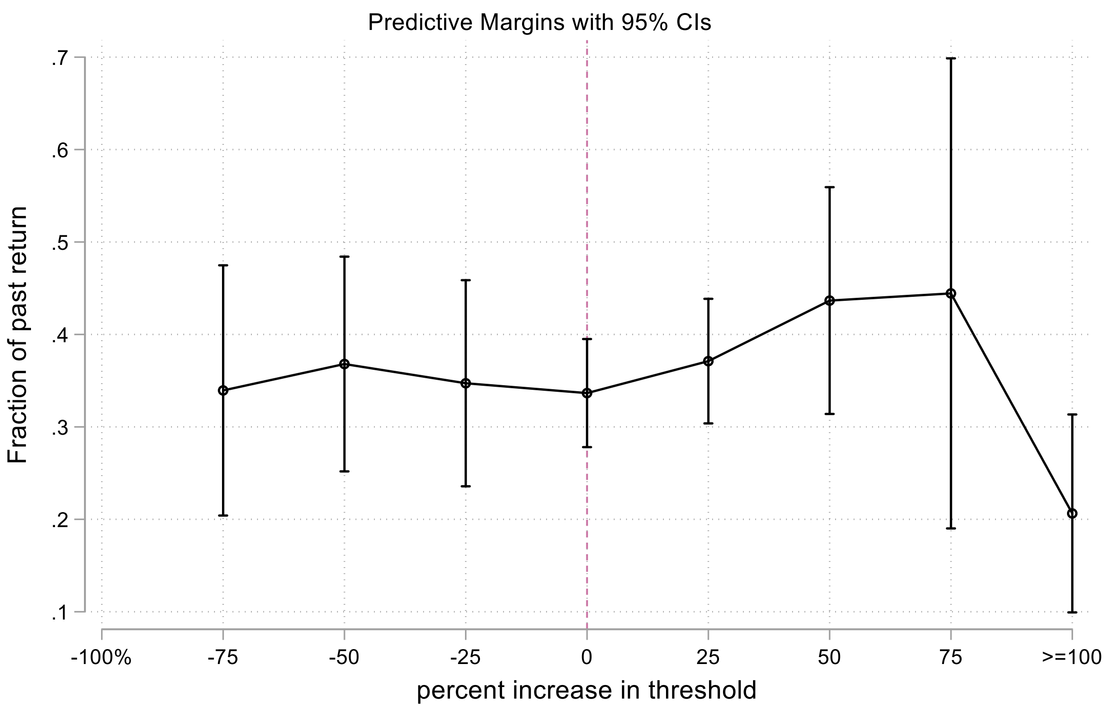
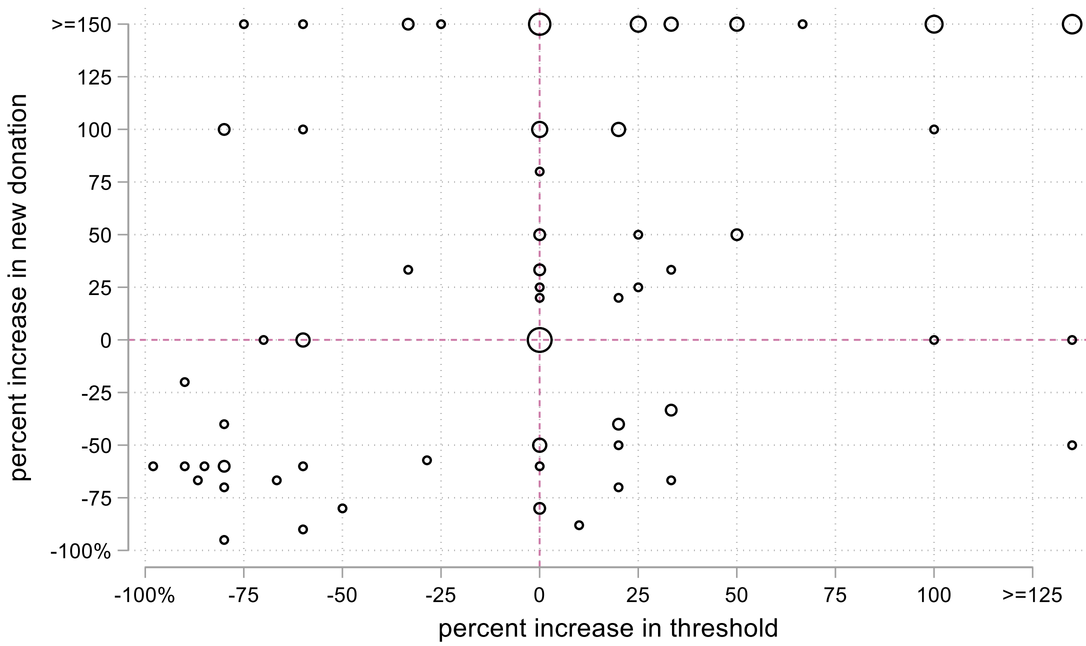


Figure A5: Previous non-donors; individual responses



Notes: The size of the dot corresponds to the number of individuals, x-axis: (threshold - predicted donation)/ predicted donation, capped at 125 percent, y-axis: (new donation - predicted donation)/ predicted donation, capped at 150 percent.

Table A1: Description of threshold assignment

	Past donors		Previous non-donors		New customers	
		share		share		share
Short description	Customers who were asked to donate in one or two last campaigns and donated at least once. We use the maximum donation as reference point.		Selected customers who attended opera house in the last three seasons and received fundraising call in the last two calls but did not donate.		Selected new customers in the season 2016/17. Not previously in the customer database.	
N	769		3,859		5,376	
Past/ predicted	Past maximum donation	1/3	Predicted donation. Prediction is based on a regression of past donation in a sample of past donors on a set of available characteristics and then out of sample prediction for previous non-donors. This raw prediction (usually non-round numbers) is transformed such to match the distribution of past donation values by past donors. This predicted donation is somewhat higher than raw prediction.	1/3	-	
Plus	Past maximum donation lifted to the next category, see Table A2.	1/3	Predicted donation lifted to the next category, see Table A2.	1/3	-	
Doubly random	Random suggestion drawn from the distribution of past donations, excluding own past donation amount.	1/3	Random suggestion drawn from the distribution of past donations, excluding own predicted donation.	1/3	All thresholds chosen at random from a distribution of past donations by past donors.	1

Table A2: Exact distribution of past donations and thresholds assigned

		Threshold in respective condition	
Actual donation (maximum)	N	Past/ predicted	Plus
1	1	5	10
2	1	5	10
5	24	5	10
5.55	1	5	10
10	102	10	15
12	2	10	15
15	33	15	20
20	161	20	25
20.2	1	20	25
25	45	25	30
30	57	30	35
35	3	35	40
40	9	40	50
50	163	50	60
55.55	1	60	70
60	5	60	70
70	2	70	80
75	4	75	85
80	2	80	90
95	1	95	105
100	90	100	120
110	1	110	130
120	1	120	140
150	13	150	200
200	25	200	250
250	6	250	300
300	6	300	350
400	1	400	450
500	8	500	550

Note: Donors who gave €1000 and more in the past campaigns (4 individuals) were excluded from the new campaign.

Table A3: Randomization in the sample of past donors

Threshold assignment:	doubly random		past		plus		t-test p-value		
	(1)		(2)		(3)				
	mean	Standard error	mean	Standard error	mean	Standard error	(1)=(2)	(1)=(3)	(2)=(3)
Threshold	50.698	4.245	54.981	4.570	65.329	5.064	0.493	0.027	0.130
Past donation (max)	54.047	4.403	54.984	4.570	53.793	4.381	0.883	0.967	0.851
Threshold - Past donation	-3.349	6.129	-0.003	0.002	11.537	0.758	0.586	0.017	0.000
Tickets 2014/15	7.283	0.446	7.132	0.607	8.043	0.524	0.841	0.270	0.256
Ticket revenue 2014/15	347.163	25.360	326.422	22.677	355.422	22.697	0.542	0.808	0.366
Ticket revenue 2014/15 (log)	5.655	0.051	5.611	0.050	5.702	0.049	0.538	0.508	0.196
Average ticket price 2014/15	52.717	2.117	56.694	2.488	53.257	2.030	0.224	0.854	0.285
Tickets 2016/17	1.081	0.074	0.915	0.069	1.058	0.080	0.100	0.832	0.175
Average price 2016/17	56.534	6.460	49.564	6.170	57.475	6.383	0.436	0.918	0.373
Two donations dummy	0.205	0.025	0.240	0.027	0.209	0.025	0.342	0.914	0.400
Dresden dummy	0.430	0.031	0.484	0.031	0.457	0.031	0.217	0.536	0.538
Abo dummy	0.295	0.028	0.329	0.029	0.353	0.030	0.393	0.159	0.578
Female dummy	0.457	0.031	0.457	0.031	0.496	0.031	1.000	0.379	0.379
Family dummy	0.000	0.000	0.004	0.004	0.004	0.004	0.318	0.318	1.000
Academic dummy	0.116	0.020	0.116	0.020	0.116	0.020	1.000	1.000	1.000
Doctor dummy	0.101	0.019	0.093	0.018	0.085	0.017	0.767	0.545	0.758
AO	0,008	0,005	0,008	0,005	0,004	0,004	1,000	0,563	0,563
AA	0,295	0,028	0,333	0,029	0,236	0,027	0,344	0,135	0,015
BO	0,004	0,004	0,004	0,004	0,008	0,005	1,000	0,563	0,563
BA	0,167	0,023	0,136	0,021	0,132	0,021	0,326	0,267	0,897
BB	0,128	0,021	0,136	0,021	0,140	0,022	0,795	0,699	0,899
CO	0,008	0,005	0,000	0,000	0,008	0,005	0,158	1,000	0,158
CA	0,136	0,021	0,132	0,021	0,120	0,020	0,897	0,599	0,691
CB	0,140	0,022	0,120	0,020	0,190	0,024	0,514	0,123	0,029
OO	0,000	0,000	0,004	0,004	0,000	0,000	0,318	-	0,318
OA	0,027	0,010	0,031	0,011	0,058	0,015	0,794	0,082	0,136
OB	0,031	0,011	0,031	0,011	0,058	0,015	1,000	0,136	0,136
OI	0,000	0,000	0,016	0,008	0,008	0,005	0,045	0,158	0,413
	N=258		N=258		N=258				

Notes: AO, AA, BO, BA, BB, CO, CA, CB, OO, OA, OB, and OI denote the treatment combination in 2015 and 2016, see Adena and Huck (2019a).

Table A4: Randomization in the sample of previous non-donors

Threshold assignment:	doubly random		predicted		plus		t-test p-value		
	(1)		(2)		(3)				
	mean	Standard error	mean	Standard error	mean	Standard error	(1)=(2)	(1)=(3)	(2)=(3)
Threshold	55.957	2.039	54.143	1.977	65.841	2.298	0.523	0.001	0.000
Predicted (raw)	40.888	0.899	40.382	0.710	40.526	0.753	0.659	0.757	0.889
Tickets 2014/15	8.615	0.211	8.838	0.223	8.564	0.223	0.467	0.870	0.386
Ticket revenue 2014/15	435.008	10.182	438.605	11.745	446.497	11.290	0.817	0.450	0.628
Ticket revenue 2014/15 (log)	5.889	0.018	5.893	0.018	5.890	0.019	0.878	0.947	0.933
Average ticket price 2014/15	61.321	0.773	60.486	0.803	62.622	0.801	0.454	0.243	0.060
Tickets 2016/17	1.983	0.020	1.998	0.019	2.016	0.022	0.581	0.265	0.544
Average price 2016/17	130.514	3.395	122.890	3.179	121.764	3.208	0.101	0.061	0.803
Dresden dummy	0.501	0.014	0.496	0.014	0.488	0.014	0.813	0.529	0.694
Abo dummy	0.463	0.014	0.462	0.014	0.440	0.014	0.969	0.235	0.251
Female dummy	0.374	0.013	0.364	0.013	0.350	0.013	0.568	0.204	0.485
Academic dummy	0.239	0.012	0.281	0.013	0.251	0.012	0.015	0.464	0.090
Doctor dummy	0.209	0.011	0.244	0.012	0.217	0.011	0.034	0.631	0.102
AO	0,074	0,007	0,071	0,007	0,067	0,007	0,761	0,488	0,697
AA	0,168	0,010	0,156	0,010	0,158	0,010	0,393	0,489	0,871
BO	0,078	0,007	0,072	0,007	0,082	0,008	0,551	0,717	0,338
BA	0,063	0,007	0,079	0,008	0,080	0,008	0,107	0,092	0,942
BB	0,088	0,008	0,095	0,008	0,081	0,008	0,495	0,523	0,187
CO	0,069	0,007	0,059	0,007	0,069	0,007	0,296	1,000	0,296
CA	0,071	0,007	0,088	0,008	0,073	0,007	0,126	0,879	0,169
CB	0,076	0,007	0,074	0,007	0,080	0,008	0,822	0,714	0,554
OO	0,172	0,011	0,179	0,011	0,184	0,011	0,642	0,411	0,721
OA	0,045	0,006	0,047	0,006	0,037	0,005	0,851	0,321	0,238
OB	0,047	0,006	0,041	0,006	0,043	0,006	0,501	0,704	0,769
OI	0,050	0,006	0,040	0,005	0,046	0,006	0,254	0,644	0,497
	N=1290		N=1290		N=1290				

Notes: see note to Table A3.

Table A5: Uniform threshold; full results

	donation dummy	positive donation (log)	donation including zeros (+1, log)
Threshold value (log)	-0.007^{***}	0.216^{***}	-0.021^{***}
	(0.002)	(0.043)	(0.008)
Female dummy	0.004	-0.254^{***}	0.005
	(0.004)	(0.071)	(0.014)
Family dummy	0.013	-0.623	0.073
	(0.023)	(0.559)	(0.089)
Dresden dummy	0.003	-0.105	-0.007
	(0.005)	(0.078)	(0.020)
Germany dummy	-0.001	-0.396	0.000
	(0.007)	(0.315)	(0.025)
Academic dummy	0.002	0.090	0.020
	(0.005)	(0.097)	(0.020)
Amount spent on tickets	-0.004	0.103^{***}	-0.002
2014/15 (log)	(0.003)	(0.028)	(0.012)
Amount spent on tickets	0.001	-0.019	0.003
2016/17 (log)	(0.002)	(0.018)	(0.006)
Past donor dummy	0.298^{***}	-1.022^{***}	0.901^{***}
	(0.020)	(0.213)	(0.075)
Past donor dummy * past	0.000^{***}	0.007^{***}	0.004^{***}
donation	(0.000)	(0.001)	(0.000)
Regular customer dummy	0.039^{**}	-0.457^{**}	0.086
	(0.018)	(0.214)	(0.070)
Regular customer dummy	0.000	-0.001	0.000
* predicted donation	(0.000)	(0.001)	(0.000)
Constant	0.027^{*}	3.581^{***}	0.084
	(0.014)	(0.358)	(0.052)
Observations	10004	386	10004
R^2	0.173	0.404	0.172

Notes: See notes to Table 3.

Mail-out 2017 translation:

Dear Sir / Madam,

Over the last two years the Semperoper team Junge Szene has been well received in class rooms, especially in the Dresden area. The main purpose is to reach elementary students through the educational theatre program and lower the threshold for the so-called "Hochkultur" ["high culture"].
With the class room friendly theatrical piece »OPERation Stern 12_acht_2« children are introduced to opera in a playful manner, get acquainted with the Ensemble members of the Semperoper and, afterwards, are invited to look behind the curtain during a visit to the Semperoper.

We are taking social responsibility very seriously and would like to better meet the encouragingly high demand "outside" the Semperoper. In the future we want to make the Junge Szene mobile for local tasks. Since we have no funds of our own available for such projects, the Semperoper relies on your contribution.

Please help with your donation! Your donation helps to expand the mobile Junge Szene program and to improve local cultural education in schools. It allows children in the Dresden area and in rural Saxony to access the exiting world of opera and help to evoke musical curiosity for opera music and dance.

A donor, who wants to remain anonymous, could already be won. He supports the Junge Szene with up to EUR 4,000 by matching big donations. For every donation of at least EUR XX he will add another EUR 10. In addition, this project is sponsored by Volkswagen AG which, as part of their sponsorship, provides the Semperoper with a Multivan for means of transportation.
As a thank you we raffle an opera visit for two people in my box.

Thank you for your support!
Sincerely,

Director Staatsoper
and Commercial Manager

Mail-out 2017 original:

Sehr geehrte/r

das Team der Semperoper Junge Szene ist seit zwei Jahren erfolgreich in den Klassenzimmern, insbesondere im Umland von Dresden unterwegs. Dezidiert sollen Grundschüler mit dem theaterpädagogischen Programm erreicht und die Hemmschwelle zur sogenannten „Hochkultur“ abgebaut werden.
Mit dem mobilen Klassenzimmerstück »OPERation Stern 12_acht_2« werden die Kinder spielerisch an die Oper herangeführt, lernen Mitglieder des Ensembles der Semperoper kennen und sind eingeladen bei einem anschließenden Besuch der Semperoper einen Blick hinter die Kulissen zu werfen.

Wir nehmen diese Aufgabe und Verantwortung „außerhalb“ der Semperoper sehr ernst, sind aber bisher nicht in der Lage der erfreulich großen Nachfrage gerecht zu werden. Das möchten wir gerne zukünftig dadurch ändern, dass wir die Junge Szene mobiler und präsenter machen. Da uns für derartige Vorhaben keine eigenen Mittel zur Verfügung stehen, ist die Semperoper hierbei auf Ihre Spende angewiesen.

Helfen auch Sie mit Ihrer Spende! Ihre Spende leistet einen Beitrag zum Ausbau des mobilen Programms der Jungen Szene und zur kulturellen Bildung in den Schulen vor Ort. Sie ermöglicht den Kindern aus dem Dresdner Umland und den ländlicheren Gebieten Sachsens einen Zugang zur spannenden Welt der Oper und hilft dabei die Begeisterung der Kinder für Oper und Musik zu wecken.

Ein Geber, der anonym bleiben möchte, konnte bereits gewonnen werden. Er unterstützt die Junge Szene mit bis zu €4.000, indem er große Spenden aufstockt. Für Ihre Spende von mindestens €XX gibt er noch weitere €10 dazu. Darüber hinaus wird das Projekt durch die Volkswagen AG unterstützt, die im Rahmen der Partnerschaft mit der Semperoper einen Multivan als Transportfahrzeug zur Verfügung stellt.
Als Dankeschön verlosen wir unter allen Spendern einen Vorstellungsbesuch für zwei Personen in meiner Loge.

Herzlichen Dank für Ihre Unterstützung!

Intendant Staatsoper
und Kaufmännischer Geschäftsführer

Mail-out 2018 translation:

Dear Sir / Madam,

With your donation last season you contributed to the fact that the Semperoper Junge Szene / Education team reached a large number of children directly in schools with the “mobile classroom piece” and was able to introduce them to the topic of music and get them excited about music.
For this, we thank you from the bottom of our hearts!

This season, likewise, we would like to recommend a project with which the Semperoper Education wants to permanently interest students in culture and engage with cultural topics, and thus make a significant contribution to cultural education in schools. Since the beginning of the current season, Semperoper Education acquired seven partner schools. In a three-year program, the students will get to know and experience the entire operation of the Saxon State Opera from ticket sales to the studios to the performance. In numerous projects and workshops, they will also be actively involved with the various dealings behind and in front of the curtain. The seven partner schools include elementary and high schools that are spread all over the city.

Unfortunately, we do not have any funds of our own for such projects. Therefore, the Semperoper depends on your donation.

You too can help with your donation! Your donation could, for example, cover the costs for the various associated projects and workshops, tickets for pupils to attend the workshops and the performances, and to enable the projects to be expanded to other schools. By donating you support us in lowering the threshold for the so-called "Hochkultur" and in giving a large number of children access to the exciting world of opera.

Thank you for your support!
Sincerely,

Director Staatsoper

Mail-out 2018 original:

Sehr geehrte,

in der vergangenen Spielzeit haben Sie mit Ihrer Spende dazu beigetragen, dass das Team der Semperoper Jungen Szene/Education mit dem »mobilen Klassenzimmerstück« eine Vielzahl Kinder direkt in den Schulen erreicht hat und so an das Thema Musik heranführen und dafür begeistern konnte.
Hierfür danken wir Ihnen von Herzen!

Auch in dieser Spielzeit legen wir Ihnen ein Projekt ans Herz, mit dem die Semperoper Education Schüler*innen dauerhaft für Kultur und die Beschäftigung mit kulturellen Themen interessieren und so einen wesentlichen Beitrag zur kulturellen Bildung an Schulen leisten möchte. Seit Beginn der aktuellen Spielzeit hat die Semperoper Education sieben Partnerschulen. In einem dreijährigen Programm werden die Schüler*innen den gesamten Betrieb der Sächsischen Staatsoper vom Kartenverkauf über die Werkstätten bis zur Aufführung kennen lernen und erleben. In zahlreichen Projekten und Workshops werden sie sich auch aktiv mit den verschiedenen Facetten hinter und vor den Kulissen beschäftigen. Die sieben Partnerschulen sind Grund- und Oberschulen über die ganze Stadt verteilt.

Leider stehen uns für derartige Vorhaben keine eigenen Mittel zur Verfügung, deshalb ist die Semperoper hierbei auf Ihre Spende angewiesen.

Helfen auch Sie mit Ihrer Spende! Mit Ihrer Spende können beispielsweise Kosten für die verschiedenen begleitenden Projekte und Workshops gedeckt, Fahrkarten für Schüler*innen zu den Workshops und den Vorstellungen finanziert und eine Ausweitung auf weitere Schulen ermöglicht werden. Sie unterstützen uns dabei, die Hemmschwelle gegenüber der sogenannten „Hochkultur“ abzubauen und einer Vielzahl von Kindern den Zugang zur spannenden Welt der Oper zu ermöglichen.

Herzlichen Dank für Ihre Unterstützung!
Mit freundlichen Grüßen

Intendant