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Personalized fundraising: a field experiment on threshold matching of donations

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Abstract

Personalized fundraising: a field experiment on threshold matching of donations*

While increasing the number of small donors, standard linear matching schemes have been shown to cause considerable crowding out in charitable giving with pronounced effects on large gifts. We propose a form of threshold matching where donations above a certain, potentially personalized, 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. We find that the optimal choice of thresholds is rather bold, approximately 60–75% 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 general thresholds applying to all recipients of a fundraising call.

Keywords: Charitable giving, field experiments, matching donations

JEL classification: C93; D64; D12

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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. Tackling these challenges U.S. charities received an estimated $410.02 billion in 2018 from individuals, bequests, foundations and corporations (*Giving USA* 2018). And charities do their best to increase this number. However, it turns out that some of the mechanisms and incentive structures they use appear suboptimal as documented in some recent studies.

One such example is linear donation matching where each dollar someone donates is topped up with another dollar or at some other fixed rate. Linear matching is widely used by charities in fundraising campaigns, in particular in Anglo-Saxon countries. It has been shown to increase the response rate by crowding in small donations but it has also been shown to reduce out-of-pocket donations for those who would have contributed anyway. Such crowding out harms the performance of fundraising campaigns that rely on relatively large gifts (Eckel and Grossman, 2003, Karlan and List, 2007, or Huck and Rasul, 2011). In order to address the shortcomings of linear matching, we propose and test an alternative matching scheme where donations above a personalized threshold are matched with a fixed amount and show how they can *crowd in* donations.

We believe that our matching scheme has excellent potential in improving the effectiveness of fundraising drives where some information on individual characteristics of donors or their past donations are known. It combines the attractiveness of matching for donors in environments where charitable organizations compete while at the same time not only avoiding its major pitfall, crowding out, but actually reversing it. 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 that would be chosen 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 crowding in.

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 have not donated in the past but for whom we observe some characteristics that correlate with giving behavior among donors. Observed behavior largely mirrors 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 giving. The maximum increase is achieved at a threshold of around 60-75% above the past donation. Thresholds below past donations result in lower donations. For recipients who have not yet donated, we first show that we can predict their optimal donation fairy well. Second, on the basis of this prediction, we can set the threshold in the same way as with past donors and obtain similar results. The most effective threshold is around 75% above the predicted donation in the absence of a match.

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. Consequently, thresholds that are too low or much too high decrease giving and are to be avoided. Still, accounting for both caveats, the return is still maximized if the threshold is set around 60% (for past donors) or 75% (for other customers) above the past or predicted donation.

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 made a donation 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 strong 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 an unpersonalized random threshold and the donation return.

We proceed as follows. In Section 2 we relate our paper to the existing literature and in Section 3 we outline the basic theory. Section 4 presents the design and implementation of the experiment and Sections 5, 6 and 7 the 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 donations that are received by the charity, that is, larger donations *including* the match. However, most studies on matching show that charitable donations behave very much like a normal good. As the price falls, consumers demand more but spend less on it. In other words, matching causes crowding out reducing out-of-pocket donations (Eckel and Grossman 2003; Karlan and List 2007; Huck and Rasul 2011).[1] As a consequence, charitable organizations would be better off to announce the funds provided for matching as *unconditional* lead gifts (Huck, Rasul, and Shephard 2015).[2] In both cases, the funds serve as a strong signal of charities' quality (Vesterlund 2003; Andreoni 2006; Huck and Rasul 2011). The reasons why matching is still widely used in practice might include competition among charities or heterogeneity in preferences.

[1] See Adena, Hakimov, and Huck (2019) for a review of the degree of crowding out in field experiments on matching. For some other recent studies on matching, see Diederich et al. (2019) and Gallier et al. (2019).
[2] For studies on lead donations or seed money, see List and Lucking-Reiley (2002), Gneezy, Keenan, and Gneezy (2014), and Rondeau and List (2008).

The literature has proposed some alternative forms of matching, which include matching money 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. By varying the menu of the thresholds, they are able to structurally estimate the optimal menu of thresholds. They conclude that optimal uniform thresholds would have to be set very high.

Defaults, suggestions, and donation grids

Our scheme involves an announcement of a threshold for the match, which creates 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. 2018) or even detrimental effects (Adena and Huck 2019a; 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 earlier literature on suggestions, see Bekkers and Wiepking 2010).[3]

[3] 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).

Personalization

A number of studies include some element of personalization of suggested amounts or grids.[4] Edwards and List (2014) conduct a field experiment where 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 the participants gave more often $20.00-$20.08 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 response rate and a decrease in average donation. There were no overall differences in 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 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.[5] Lee and Feinberg (2018) study personalized grids and concluded 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 than an optimal default should be set at a double of a past donation level. Our study is the first to combine elements of personalization with matching rather than defaults or grids.

[4] 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).

[5] 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.

3. Theory sketch

Consider a potential donor who has to allocate her income between private consumption and a charitable good. She cares about the donation *received* by the charity and about her own consumption.[6] We assume that her indifference curves are strictly convex. We denote her out-of-pocket donation (or donation given) by x and her optimal 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 $x \geq t$ 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, such 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 denoted by x' and, for all t, 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 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 leads then 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

[6] If total giving enters into a donor's utility function our analysis requires that total giving is not perceived as a function of the threshold.

donation without matching. In scenario B, a further increase of t first results in a constant higher level of the donation given, $x' \geq x^*$, then starts to 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.

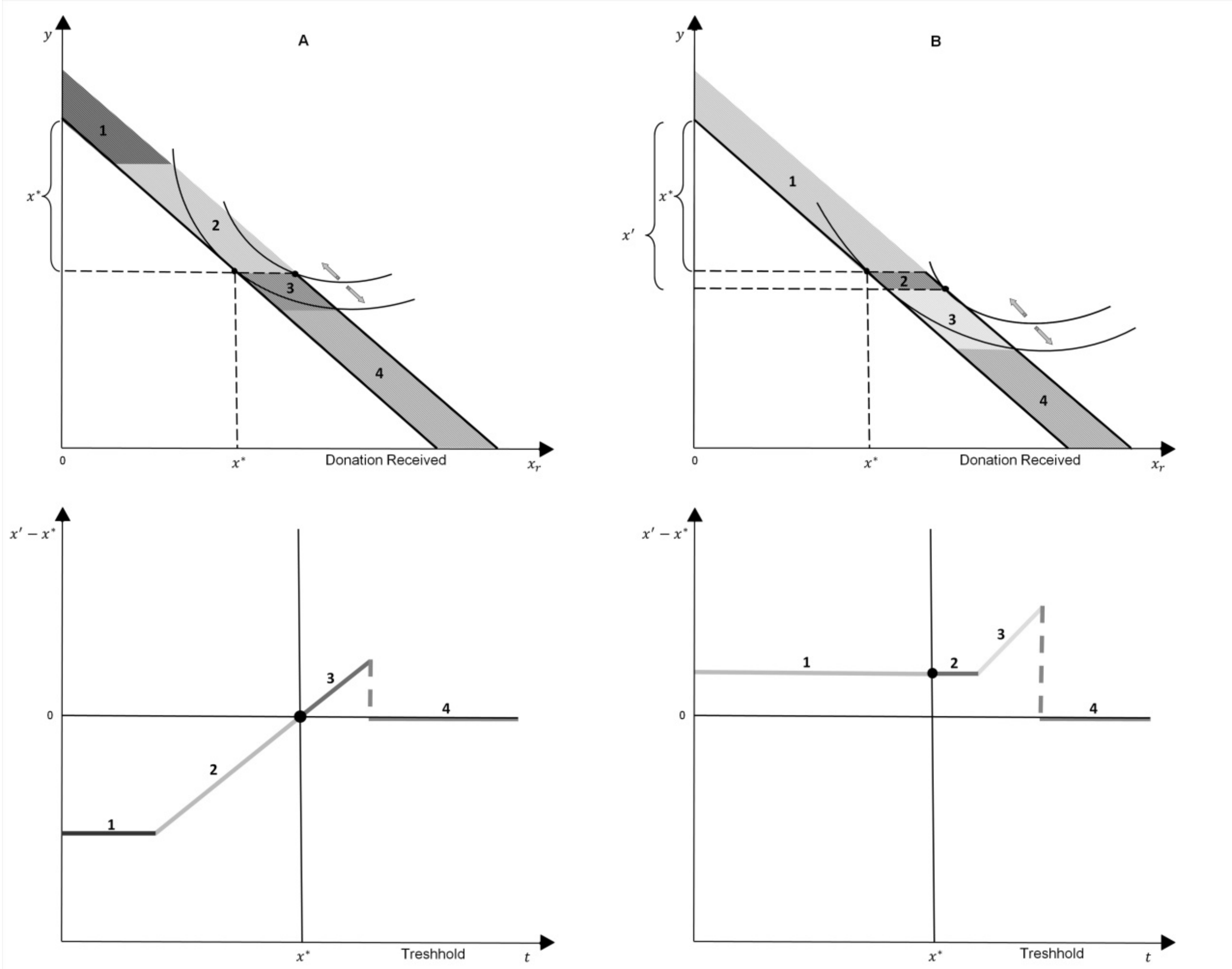
From these theoretical considerations we establish two aims for our field experiment:

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.

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

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.

4. Design of the experiment and implementation

We partnered with an opera house that provides a social youth program for children from disadvantaged rural areas offering access to culture and music. The project is financed through donations and the recipients of the donation ask were individuals from the database of opera customers. 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. Thus, we have a (small) set of past donors we can draw on and previous non-donors who can be partitioned into a set of regular customers and a set of new customers. For the regular customers we know a 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*.

Unlike the personalization studied in Edwards and List (2014), we did not want to make the connection between the personal characteristics and the threshold obvious. Therefore, we offered a fixed matching of €10 for donations exceeding a specific threshold that was referred to as "large donation" and was not flagged as personalized. In total, we sent 10,004 letters to the subset of opera goers who purchased at least one opera ticket in the last season and, based on their past purchasing behavior, were expected to donate the largest amounts, including all past donors. The recipients consisted of three groups: those who had donated at least once in the two last fundraising campaigns (769 *past donors*), customers who had attended the opera house in the last three seasons and who had received a fundraising call in the last two calls but did not donate (3,859 *regular customers*), and *new customers* (5,376) for whom it was the first fundraising call from the opera house.

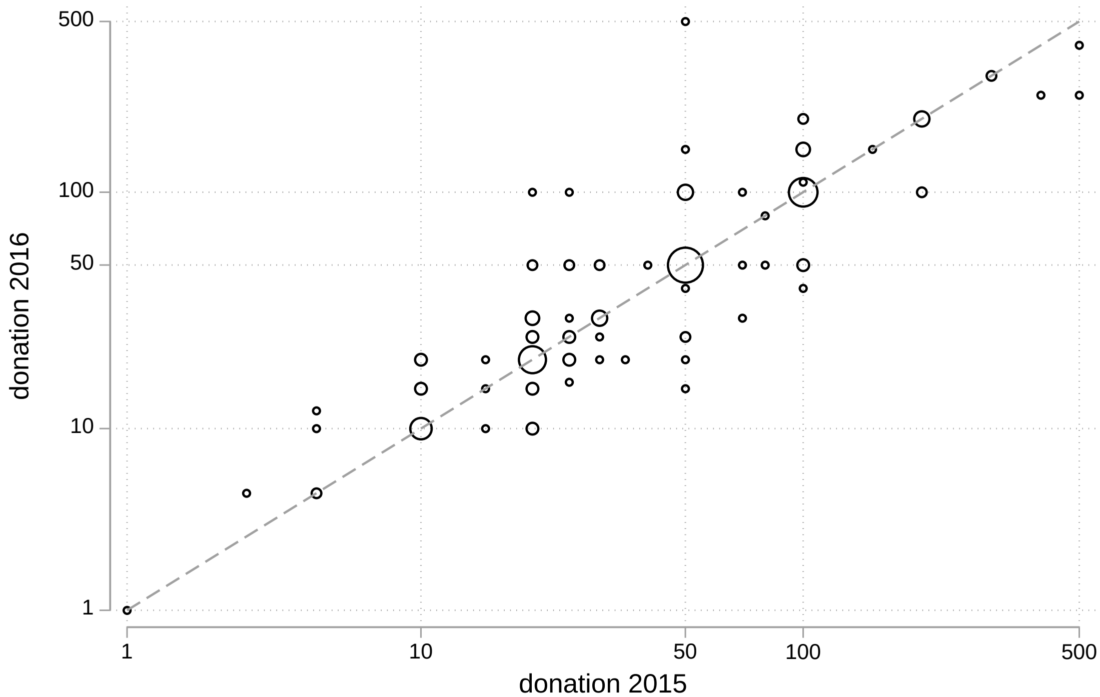
The letter informed the recipients that a generous lead donor had been found who would top up an individual donation with €10 if this donation met a minimum threshold (called "large donation") or exceeded it.[7] See the Appendix for the exact formulation of the mail-out.

The literature has documented sizable persistence in donative choices. Charitable giving in one year is the best predictor for giving next year (Meier 2007; Landry et al. 2010) and the amounts chosen are usually very close to previous amounts (Adena and Huck 2019). 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). There is a high correlation between the gift levels of repeat donors (0.778, see Figure 2) 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.

For established customers (past non-donors) we predict optimal donations by extrapolating from the estimated giving equation of past donors. More specifically, guided by a lasso selection procedure, we use information on ticket purchasing behavior (from 2016: ticket revenue, ticket revenue (log), average price, dummy equal to one if any tickets bought in a particular year; from 2015: number of tickets, ticket revenue, ticket revenue (log), average price) and individual characteristics (dummies for living in Dresden, living in Germany, for subscription holders, female, couple, an academic and a professorial title). 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. We shall simply refer to the resulting amount as the predicted donation.

[7] 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.

Figure 2: 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.

We assigned the following thresholds: For one third of past donors and regular customers the threshold was set equal to either the maximum past donation (for donors) or to the predicted donation (for non-donors). For another third of these recipients the above thresholds were lifted up to the next "category" of previously observed donations (see Table A1 in the Appendix for the exact procedure). With few exceptions this resulted for past donations below €40 in threshold increases of €5, for donations up to €95 in increases of €10, for donations up to €120 in increases of €20, and for higher donations in increases of €50. For the remaining past donors, established customers and all new customers, the threshold values were drawn at random from the distribution of past donations (for the first two groups excluding own past or predicted donations).

5. Main results

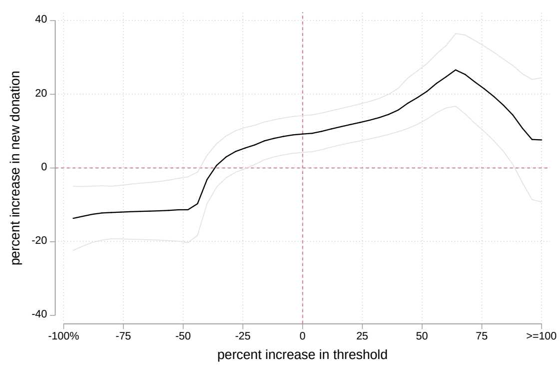
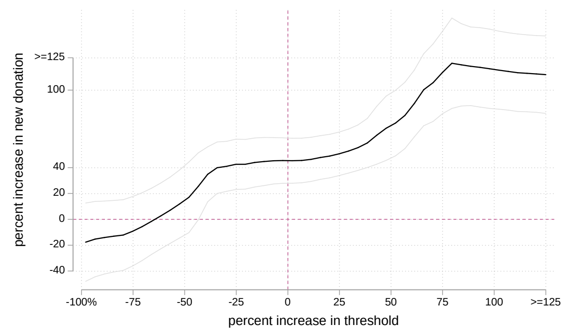
Overall, 242 of the 769 past donors donated again. This corresponds to a response rate of 31.5%.[8] The average positive donation was €61[9] and the average return from the mailing was €19.20. Concerning donation levels relative to the threshold, 31% of donations were below the set threshold, 37% exactly hit the threshold, and 32% of the observed donations were above the threshold. In the group of the 3,859 previous non-donors with a predicted optimal donation absent matching of €54.29, we observe 106 donations with an average gift of €58.54. This equates to a response rate of 2.7%.

Figure 3 shows the empirical relationship between changes in the threshold and changes in out-of-pocket giving, mirroring our main theoretical predictions depicted in Figure 1. The left panel shows the results for past donors, the right panel for regular customers. 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.[10] 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 precisions (estimated optimal donations instead of past donations and a considerably smaller number of observations) for regular customers who have not donated previously, the picture is remarkably similar indicating again the benefits of comparatively high thresholds with a peak close to the peak for past donors.

[8] For donors who had given in the previous year the response rate was 42% and for repeat donors even 61%. For donors who gave in year 1 but not in year 2 the response rate was 14%.
[9] The average positive (maximum) donation in this group in previous campaigns was €53.70.
[10] Alternatively, we show in the Appendix the results of nonparametric kernel regression for past donors with 95% confidence intervals, Figure A1. While the shape remains very similar independent of the chosen approach (median plot, fractional polynomial plot, median spline plot, and locally weighted regression are available for past donors sample on request) 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.

Altogether, we can confirm our theoretical predictions. 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 regular customers), the newly chosen out-of-pocket gifts are strictly higher, fulfilling our first aim. We also find a threshold level that maximizes out-of-pocket gifts, fulfilling our second aim: the optimal threshold is to be found around 60% above the optimal donation without the match for past donors and around 75% above the predicted donation for regular customers. While both numbers are not equal, they might be statistically not different, arise through the imprecision of the prediction stage for past non-donors, and are subject to the usual external validity concerns. If they are indeed higher for past non-donors a potential explanation might lie in persistence of donative behavior—those who have donated in the past might be more difficult to push further from their past choices.

Figure 3: Positive donations: Effects of changing the threshold on the out-of-pocket donation

<table>
<tr><th>Past donors</th><th>Regular customers, past non-donors</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Notes: Local polynomial fit, 90% confidence intervals; x-axis: (threshold - past donation)/past donation, capped at 100 percent, y-axis: (new donation - past donation)/past donation conditional on giving, capped at 100 percent.</td><td>Notes: Local polynomial fit, 90% confidence intervals; x-axis: (threshold - predicted donation)/ predicted donation, capped at 125 percent, y-axis: (new donation - predicted donation)/ predicted donation conditional on giving, capped at 125 percent.</td></tr>
</table>

6. Further aspects: Contrarians and the response rate

Although average behavior is in line with our theoretical predictions, we discover some behavior contradicting the simple theory. Zooming in on individual behavior in Figure 4 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 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.[11] It is unclear whether this behavior is systematic or rather due to some noise, e.g. because the 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 a noise, we would expect more symmetry in Figure 4: in particular, we should also have a sizeable number of 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.[12]

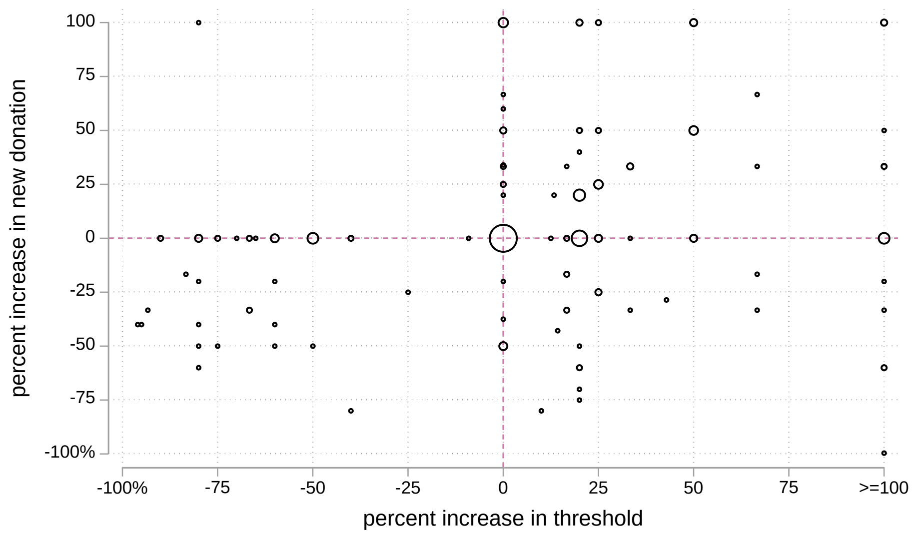
Notice that the benefits of higher thresholds are substantially reduced by the contrarian behavior we identified above. This raises the question whether it would be possible to predict who would respond aversely to higher thresholds such that this contrarian group can be treated differently. Hence, we 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

[11] 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.

[12] Note that giving more than in the past when receiving a lower threshold is consistent with theory. 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 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.

who donated less than in 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. Unfortunately, we cannot detect any statistically meaningful differences with the data we have. But, of course, the opera now knows to treat this set of customers differently in the future.

Figure 4: 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 which €10 amounts to 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 past donation once other individual characteristics are taken into account (Columns II-III) or the fact that defining the contrarian with the max past donation might oversee that they are actually of a lower type (Columns IV-VI).

We find limited guidance for understanding contrarian behavior in the literature. Van Teunenbroek et al. (2019) suggest diffusion of responsibility: the higher threshold may convey social information that suggests that others donate more, thus, rendering the own donation as 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.[13]

Table 1: Individual characteristics of the contrarians

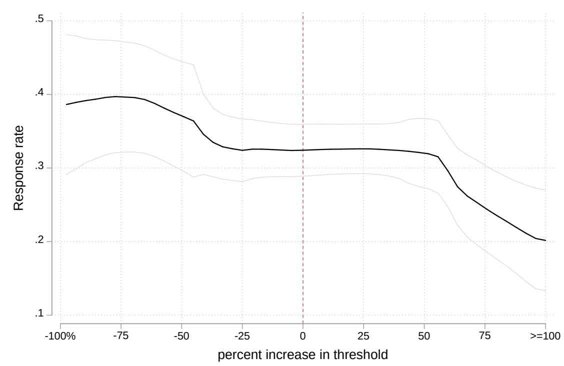
Dependent variable: dummy equal to 1 if	Donation<Past (max)			Donation<Past (min)		
	I	II	III	IV	V	VI
Past donation (log)	0.059**	0.039	0.028	0.014	0.004	-0.014
	(0.027)	(0.031)	(0.033)	(0.023)	(0.025)	(0.027)
No. tickets 2016		0.009	-0.043		0.042	0.003
		(0.054)	(0.059)		(0.044)	(0.047)
Amount spent on tickets 2016 (log)		-0.003	0.025		-0.049*	-0.026
		(0.031)	(0.033)		(0.025)	(0.026)
Dummy tickets December 2016-June 2017		-0.032	-0.037		0.141	0.153*
		(0.114)	(0.115)		(0.093)	(0.092)
female dummy		0.013	0.005		-0.002	-0.004
		(0.055)	(0.057)		(0.045)	(0.046)
Subscription holder		-0.079	-0.108		-0.050	-0.063
		(0.087)	(0.091)		(0.071)	(0.073)
Dresden dummy		0.006	0.162		-0.049	0.178
		(0.059)	(0.151)		(0.049)	(0.121)
Germany dummy		0.362	0.379		0.199	0.228
		(0.372)	(0.371)		(0.305)	(0.296)
Academic dummy		0.085	0.080		0.094	0.093
		(0.085)	(0.088)		(0.070)	(0.071)
donated twice before		0.079	0.094*		-0.057	-0.041
		(0.054)	(0.056)		(0.044)	(0.045)
Online customer			0.060			0.046
			(0.082)			(0.066)
distance in km (log)			0.030			0.048*
			(0.032)			(0.025)
Constant	-0.055	-0.357	-0.552	0.046	-0.051	-0.318
	(0.100)	(0.397)	(0.455)	(0.083)	(0.325)	(0.364)
Observations	195	195	182	195	195	182
R^2	0.023	0.062	0.076	0.002	0.065	0.069

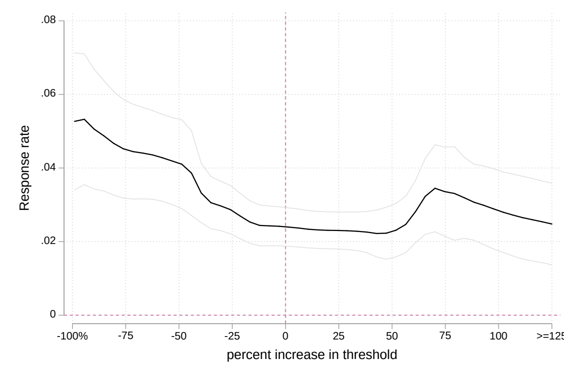
Notes: OLS, sample of past donors who donated repeatedly and who received the ask with a threshold set equal or higher than the past donation. Dependent variable is a dummy equal to 1 if donation<past donation (max) or donation<past donation (min) respectively; Standard errors in parentheses; * $p <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

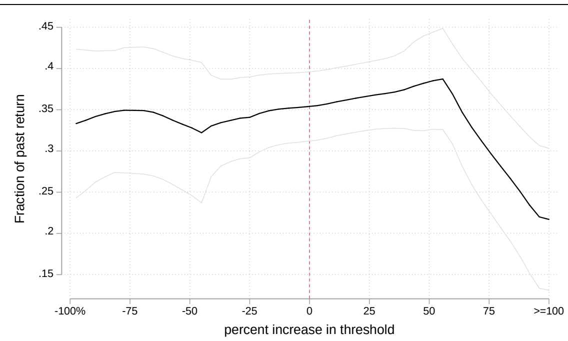
[13] Higher expected giving by others could lower own giving if the total giving by others enters ones utility function with a sufficient weight and the higher threshold shifts those expectations. Chlaß, Gangadharan, and Jones (2015) find that less efficient donations might lead to higher giving. In psychology, the reactance theory (Brehm and Brehm 2013) could explain this type of 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.

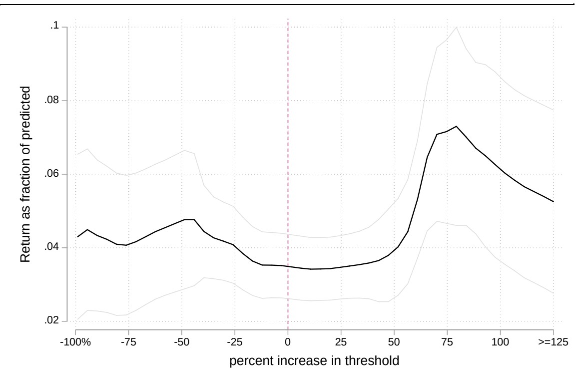
In Figure 5, upper panel, we inspect the response rate. Theoretically, the response rate should not be affected by the threshold level (as donors can always go back to their optimal donation without matching). In practice, however, we observe a somewhat negative trend in Figure 5. The total effect of changes on the extensive and intensive margins on the return exhibits, however, still the same shape with peaks at increases of 60% for past donors and 75% for regular customers. The former is, however, no longer statistically significant. See Figure 5, bottom panel, in which we show the increase in return relative to the hypothetical return absent matching, that is, relative to the past or predicted donations.

Figure 5: Response rate and return

<table>
<tr><th></th><th>Past donors</th><th>Regular customers, past non-donors</th></tr>
<tr><td>Response rate</td><td>


</td><td>


</td></tr>
<tr><td>Return as fraction of hypothetical return absent matching</td><td>


</td><td>


</td></tr>
</table>

Notes: Local polynomial fit, 90% confidence intervals; x-axis: (threshold - past donation)/past donation, capped at 100 percent; y-axis, top panel: share giving positive amount; y-axis, bottom panel: new donation/past or predicted donation including non-donors-

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 2, we regress our outcome variables (donation dummy, log of positive donations, and return per mail-out (+1, log)) on the threshold value (log) in the sample of previous non-donors (including new customers). Additionally, Figure 6 shows the local polynomial fit for our three different customer groups in order to demonstrate effects of different threshold values.[14] 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 established and new customers Figure 6 visualizes what can be inferred from Table 2: the response rate decreases, the positive donation increases and the return decreases in the value of threshold. 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.

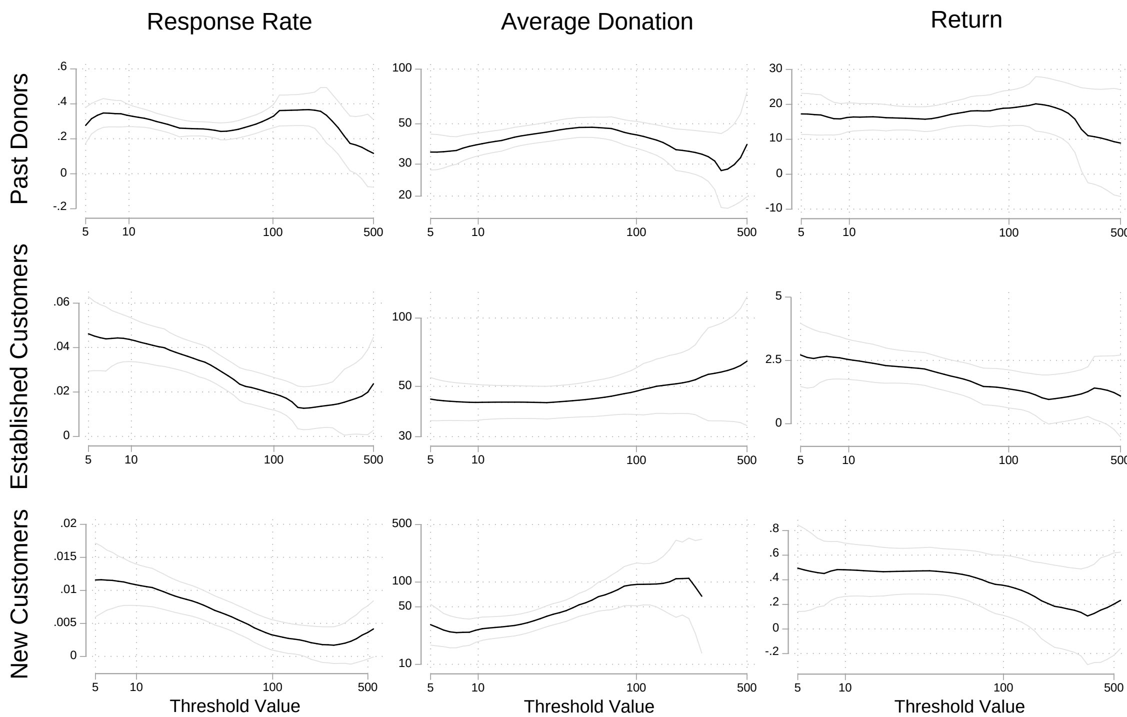
Table 2: Uniform threshold, previous non-donors

	donation dummy	positive donation (log)	Return: donation including zeros (+1, log)
Threshold value (log)	-0.006***	0.212***	-0.019***
	(0.001)	(0.077)	(0.006)
Controls	Yes	Yes	Yes
Observations	9235	144	9235
R^2	0.010	0.111	0.009

Notes: Sample of previous non-donors, both regular and new customers; standard errors in parentheses; Controls include female, family (dropped in Column II), Dresden, Germany, and academic dummy, and the amount spent on tickets 2015 (log) and 2016 (log); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[14] In the case of past donors and established customers, we reweight the observations by the inverse probability of the assignment of a specific threshold.

Figure 6: the effects of the uniform threshold



Notes: Local polynomial fit and 90% confidence intervals; Graphs for past customers and established customers are using weighted observations accounting for a probability of threshold assignment. Average donation and return in Euros.

At first sight our results are in contrast to Castillo and Petrie (2019) who structurally estimate an optimal uniform threshold level (with a match value equal to the threshold). They find a large threshold of over $1,000 optimal (or with two thresholds, a second that is even higher). However, these predictions are out of sample and, of course, their match amount is much larger than ours.

8. Conclusions

While linear matching schemes have been shown to induce crowding out, 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. Hence, it is of vital interest for fundraisers to find alternative matching schemes that are competitive in the marketplace but avoid crowding out. In this study we propose *personalized threshold matching* for charitable giving and show, both, theoretically and empirically how it can be used to crowd in donations. Beyond the immediate increase in the donation revenue that we document, long-term gains may also be expected as there is much persistence in giving behavior (Adena and Huck 2019b). 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 for standard 1:1 linear matching and easier to predict and, thus, potentially easier to obtain.

Further research could explore 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.

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Appendix: Additional Graphs and Tables:

Figure A1: Past donors; positive donations; effects of changing the threshold: nonparametric kernel regression

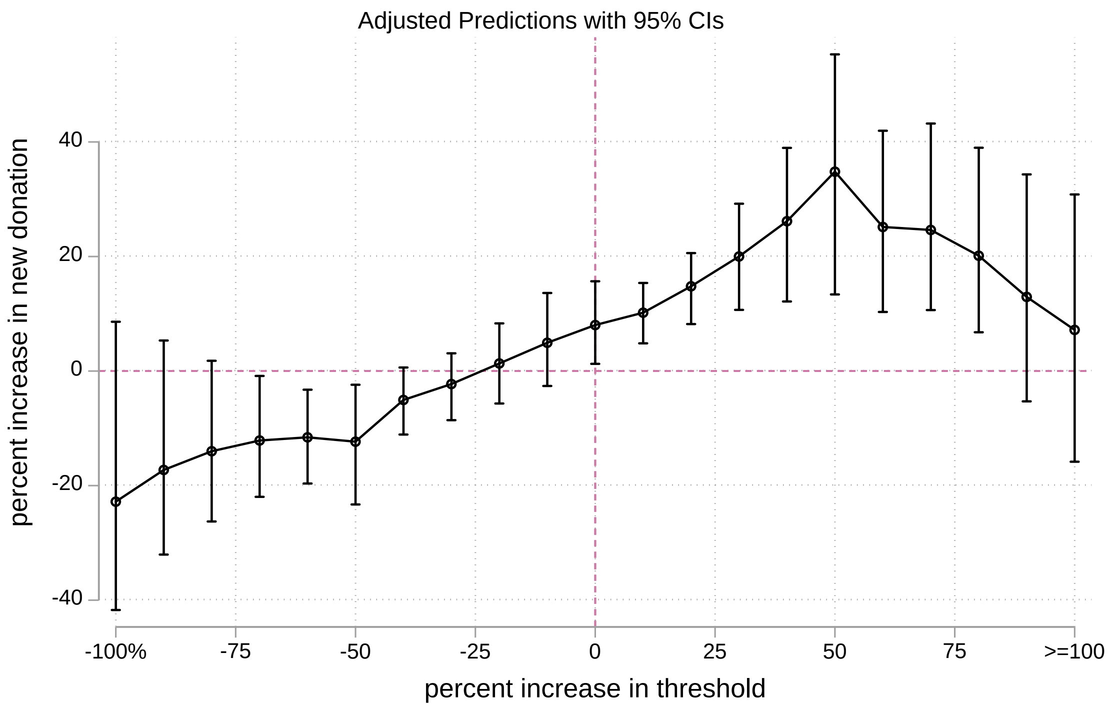
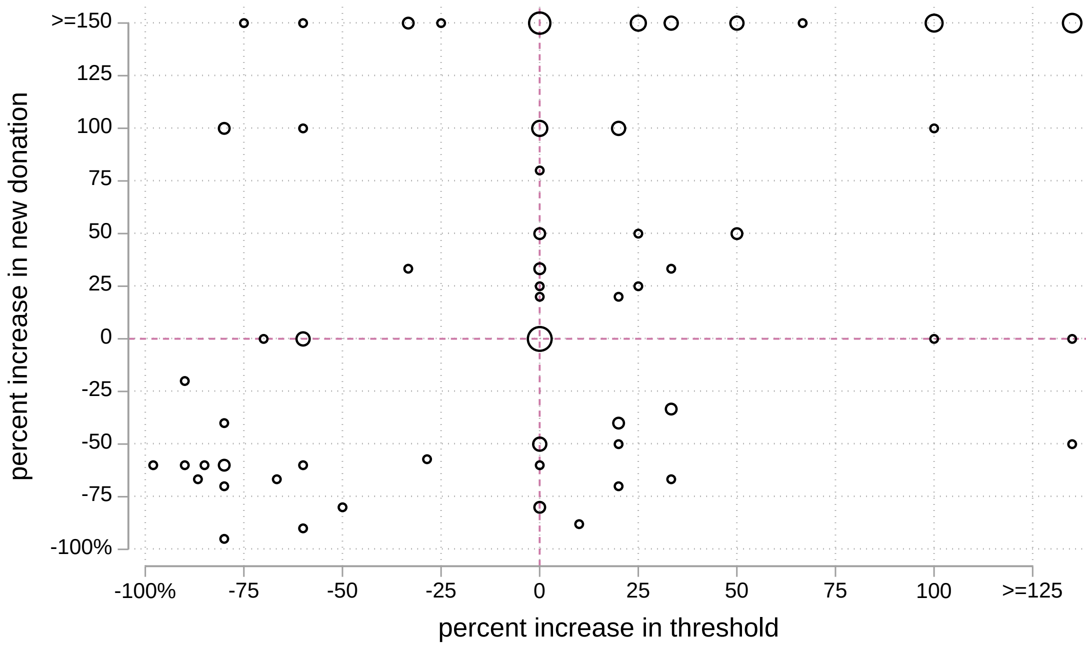


Figure A2: Established customers; individual responses



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

Table A1: Exact distribution of past donations and thresholds assigned

		Threshold in respective treatment	
Actual	N	Past	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	162	20	25
20.2	1	20	25
25	45	25	30
30	57	30	35
35	3	35	40
40	9	40	50
50	165	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	91	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	9	500	550

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

Table A2: Uniform threshold, non-donors: Full results

	donation dummy	positive donation (log)	donation including zeros (+1, log)
Threshold value (log)	-0.006***	0.212***	-0.019***
	(0.001)	(0.077)	(0.006)
Female dummy	0.002	-0.119	0.005
	(0.003)	(0.140)	(0.010)
Family dummy	-0.008	-	-0.028
	(0.016)		(0.063)
Dresden dummy	0.002	-0.228	0.002
	(0.004)	(0.159)	(0.015)
Germany dummy	-0.000	-0.091	0.001
	(0.005)	(0.589)	(0.018)
Academic dummy	0.007*	0.138	0.028*
	(0.004)	(0.159)	(0.014)
Amount spent on tickets 2015 (log)	0.003***	0.028	0.013***
	(0.001)	(0.029)	(0.002)
Amount spent on tickets 2016 (log)	-0.002	0.120	-0.006
	(0.002)	(0.079)	(0.006)
Constant	0.038***	2.535***	0.115***
	(0.010)	(0.702)	(0.040)
Observations	9235	144	9235
R^2	0.010	0.111	0.009

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Further tables:

Table A3: Description of treatments

	share	Past donors	Established customers	New customers
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.	Customers who attended opera house in the last three seasons and received fundraising call in the last two calls but did not donate.	
N		774	5*774	7*774
Exact	1/3	Past maximum donation	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 the established customers. 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.	-
Plus	1/3	Past maximum donation lifted to the next category defined as plus €5 for donations up to €35, plus €10 for donations up to €95, plus €20 for donations up to €120, plus €50 for remaining donations	Above lifted to the next category, see left cell.	-
random	1/3	Random suggestion drawn from the distribution of past donations excluding own past amount	See left cell, excluding own predicted donation.	All thresholds chosen at random from a distribution of past donations by past donors.

Table A4: Randomization in the sample of past donors

Treatment	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 2015	7.283	0.446	7.132	0.607	8.043	0.524	0.841	0.270	0.256

Ticket revenue 2015	347.163	25.360	326.422	22.677	355.422	22.697	0.542	0.808	0.366
Ticket revenue 2015 (log)	5.655	0.051	5.611	0.050	5.702	0.049	0.538	0.508	0.196
Average ticket price 2015	52.717	2.117	56.694	2.488	53.257	2.030	0.224	0.854	0.285
Tickets 2016	1.081	0.074	0.915	0.069	1.058	0.080	0.100	0.832	0.175
Average price 2016	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
Couple 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
Past treatment AA	0.174	0.024	0.182	0.024	0.151	0.022	0.819	0.475	0.346
Past treatment OB	0.031	0.011	0.031	0.011	0.058	0.015	1.000	0.136	0.136

Table A5: Randomization in the sample of past customers

Treatment	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	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 2015	8.615	0.211	8.838	0.223	8.564	0.223	0.467	0.870	0.386
Ticket revenue 2015	435.008	10.182	438.605	11.745	446.497	11.290	0.817	0.450	0.628
Ticket revenue 2015 (log)	5.889	0.018	5.893	0.018	5.890	0.019	0.878	0.947	0.933
Average ticket price 2015	61.321	0.773	60.486	0.803	62.622	0.801	0.454	0.243	0.060
Tickets 2016	1.983	0.020	1.998	0.019	2.016	0.022	0.581	0.265	0.544
Average price 2016	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

Table A6: Share of donations above, equal, or lower to past donation in different treatments

	donation		
Treatment	new<past	new=past	new>past
Past	8%	70%	22%
Plus	18%	38%	44%
Random<Past	36%	62%	2%
Random>Past	29%	29%	42%

Mail out
Letter:

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

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!