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Online fundraising, self-image, and the long-term impact of ask avoidance

Maja Adena and Steffen Huck*

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Abstract

We provide the first field evidence for the role of pure self-image, independent of social image, in charitable giving. In an online fundraising campaign run on an opera ticket booking platform we document how individuals engage in self-deception to preserve their self-image. In addition, we provide evidence on stark adverse long-run effects of fundraising campaigns for ticket selling entities. “Avoiding the ask,” opera customers buy fewer tickets in the following season. Ticket sales per person fall by €16–32, while average charitable income from the same group during the campaign is just €0.26.

Keywords: online fundraising, quasi-experiment, self-image.

JEL classifications: D64, D03, D12, C93, L31.

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1 Introduction

The key advantage of online fundraising is that it is tremendously cheap. Transaction costs for internet-based fundraising, in particular those borne by the fundraisers, are easily one order of magnitude lower than for more traditional campaign forms. However, the reduction in costs goes hand in hand with an increase in social distance and, thus, reduced “social pressure,” potentially diminishing the return of a fundraising campaign.

In this paper we study a form of online fundraising that has become popular with many arts charities: an ask at the time of checkout when customers buy tickets for an event. We study three incarnations of that ask by varying the donation interface within the booking platform of an opera house. After establishing a baseline, the grid of suggested donations was pushed up in the expectation that it would increase donations. This failed miserably. We then introduced an apparently minor change in the interface, now simply forcing customers who want to continue without a donation to tick one of two boxes (also available before): one box says “I have donated already”, the other “No, thank you.” As we will document, this minor change in framing has stark positive consequences for giving.

There are a number of recent papers that examine the role of social pressure and social rewards for giving (which we briefly discuss in a literature section further below) but the closest relatives to our investigation are recent studies investigating why and how people might want to avoid being asked for a donation in the first place. As impressively documented by DellaVigna *et al.* (2012) and Andreoni *et al.* (2016) people are willing to exert costly effort to avoid the social pressure and emotional triggers from direct interaction with fundraisers. They choose “not to be at home” when a fundraiser has announced his arrival at their doorstep or choose different exits in supermarkets to avoid the ask. In our setting, this type of social interaction was absent. People interacted with the ticketing website without being talked to or being directly observed. Rather, they could choose not to give by clicking on a button to “proceed” without further ado. In all our settings, the interface contained the two check boxes mentioned above. Customers could always “explain” their decision not to give by saying that they had given before or adding a courteous “No, thank you.” But in the first two settings they were not forced to. That is, they could click on

the “proceed” button ignoring – vis-à-vis themselves – the (implicit) decision not to give. This is what we changed in our third treatment which forced customers to check one of the two boxes if they wanted to proceed without a donation. Notice that this changes nothing in the relationship between the customer and the opera house. The opera house observes the customer’s decision in all settings. The boxes do not contain any extra information. Regardless of whether a customer donates or not, it will be known by the opera house in all conditions. There is no change in social pressure, no change in the substance of the interaction between potential donor and fundraiser. The only thing that does change is that the non-donor is forced to make a choice between two boxes. As this choice has neither social nor material consequences, it can affect behavior only through its impact on *self-image*. Clicking on “proceed” without ticking one of the two boxes allows, after all, for some potentially attractive self-deception. The “proceed” button might be perceived as an invitation simply to proceed with the purchase and the fact that the decision to proceed implies the decision not to donate can potentially be conveniently overlooked. Non-donors are not forced to admit to themselves that they are non-donors.

Forcing customers to tick one of the two boxes (the first of which equates to an outright lie for the vast majority of customers) shuts down this option of self-deception. Now, non-donors have no other option but to admit to themselves that they are non-donors. As it turns out, there is a substantial share of customers for whom this admission is sufficiently costly, such that they choose to donate when otherwise they would not have. On average, they also donate higher amounts.

Finally, we observe how customers “learn to avoid the ask.” Non-frequent customers who faced the online fundraising campaign return less often to the opera in the next season and spend on average €16–32 less on tickets than those who were not exposed to the fundraising campaign. This compares to donations of just €0.26 from the same group of customers raised during the campaign. We present evidence that this effect is not fading over time but become permanent.

The remainder of our paper is organized as follows. Section 2 contains a brief discussion of related literature, focusing on our four main themes: online fundraising; the role of defaults and donation grids; the role of image for prosocial behavior; and ask avoidance. In Section 3 we present the design of our study and in Section 4 its results. Section 5 concludes.

2 Related literature

Online fundraising. With the rise of the internet, online fundraising has become ever more popular and economically important. Smith *et al.* (2015) document how online fundraising has become a major source of income for many UK charities. The total revenue of the biggest individual online fund-raising website recently crossed the £1 billion mark. According to Meer (2014), Kickstarter.com, a leading US crowd funding website, crossed the \$1 billion threshold in March 2014.¹ Germany's biggest platform collected a total of €1.17 million in revenues for charitable organizations over an eleven month period in 2012/13 (Altmann *et al.* 2016). These shifts towards online giving call for experimentation and there is a growing number of online experiments and field studies that either consider donation platforms (Altmann *et al.* 2016, Meer 2014), environments in which the fundraiser actively asks for donations (Exley and Petrie 2016) or other forms including peer-to-peer solicitations (Castillo *et al.* 2014, Elfenbein *et al.* 2012). We study the second type – a situation in which individuals come to the website to buy opera tickets and are not expecting to be asked for donations, since the opera house has never used online fundraising before.

Defaults and donation grids. It is popular in fundraising to use suggestions for amounts that can be donated. Suggestions offer guidance in choosing contributions and transmit information about how much is needed. In practice, suggestions can be implemented in different ways – they can be more or less binding and there is either one suggestion (usually a default which may be changed) or a menu to choose from (donation grids). There are a number of studies concerned with donation grids or defaults and the conclusions are mixed. For an extensive literature review and a discussion, see Adena *et al.* (2014) who study the effect of nonbinding suggestions in a field experiment. They find that suggestions of €100 and €200 increase the average positive donation significantly as compared to a treatment without suggestions. The overall revenue effect is, however, non-significant due to reductions in the response rates. Altman *et al.* (2016) study defaults and conclude that although they do change the distribution of donations, they do not have an effect on aggregate donations. This is because the defaults exert pulling effects, both increasing and decreasing donations. However, in a secondary choice dimension, a contribution

¹ As of December 2015, the website names \$2.1 billion.

to support the running of the online platform, donations do increase with defaults. Reiley and Samek (2015) find that increasing donation grids by 20% leads to a decrease in response rate by 15–16% and a similar average positive donation. Approximately doubling the donation grids leads to a drop in response rate by 16% and 11% lower average donation, yielding an overall decrease in return by 24%.

Image motives in charitable giving. Ariely *et al.* (2009) distinguish between three broad categories of motives for charitable giving: intrinsic, extrinsic and image motivation. The third of these includes “the desire to be liked and respected by others and by one-self.” The authors show that individuals donate more when they can publicly signal their pro-sociality. Allowing for public signals of pro-sociality has also been confirmed by other authors to be effective in increasing charitable giving (see the literature cited in Glazer and Konrad (1996) who offer a theoretical model of signaling as an explanation for giving). The psychology literature has recognized self-signaling as an important behavioral force, see e.g. Bodner and Prelec (2003) and a number of laboratory experiments have sought to understand its relevance. In Dana *et al.* (2007) individuals behave less pro-socially if they can make their actions less transparent to both others and themselves. In a lab experiment by Tonin and Vlassopoulos (2013) individuals choose their donation and their choice is implemented with some probability. At the final stage they can withdraw their donation choice. The authors explain numerous observed revisions by a satiation in self-signaling and higher monetary cost at the end. By varying the probability of the implementation and the observability of a chosen allocation, Grossman (2015) aims at disentangling self- and social signaling. He finds little evidence for self-signaling and stronger evidence for social signaling. Mazar *et al.* (2008) suggest that individuals behave dishonestly when it pays but are willing to incur significant costs to maintain their self-image. Bénabou and Tirole (2007) propose a model which combines the different motives in prosocial behavior including self and social signaling and they point out the complex interplay of both. In our context, individuals appear to deceive themselves by overlooking the donation request when possible but donate non-negligible amounts if forced to admit to themselves that they are non-donors.

Social pressure, ask avoidance, and unintended consequences of fundraising. While allowing for signaling of one’s pro-sociality, a public ask creates social pressure when individuals do not want

to appear greedy or have difficulties in turning down the fundraiser. This creates costs for the individuals who may, in response, take measures to avoid the ask. This has been documented in DellaVigna *et al.* (2012) and Andreoni *et al.* (2016). These studies have in common that there is some direct social interaction between fundraiser and donor or between different donors – rendering social signaling and social pressure possible. In an online fundraising campaign (without direct social interaction), Exley and Petrie (2016) vary whether an upcoming ask is expected or not. The additional time to deliberate leads to a 22% lower rate at which the individuals agree to be forwarded to the donation pages. This difference is strongly reduced if subjects receive additional information about projects which they cannot avoid. Exley and Petrie conclude that individuals are searching for excuses not to donate if given the opportunity to do so. Damgaard and Gravert (2016) document that reminders in fundraising – while increasing donations in the short term – also substantially increase unsubscriptions from the mailing list. The authors also point to hidden costs of reminders: annoyance costs for the solicited and long-term effects of unsubscriptions on donations for the charity. Knutsson *et al.* (2013) find that the introduction of a donation button at recycling machines in a chain store in Sweden led to a reduction in the recycling amount at those machines. The authors conjecture that customers shifted locations for their recycling since the overall material recovered had not decreased over the analyzed period.

3 Description of the quasi-experiment

An opera house in Germany introduced an online fundraising tool for a period of approximately three months. When individuals sought to buy tickets, they first logged in/registered, selected tickets, and then decided to proceed with the payment. At this point they were asked to support a charitable project aimed to introduce school children from socially disadvantaged areas to classical music and opera. Customers could contribute to a fund that pays for children who would otherwise have no access to opera. When deciding on the amount they wanted to donate they could choose a number of “tickets” in different price categories. This had mainly technical reasons as the ticketing tool employed by the opera house can only accept payments for tickets. Hence, the charitable project had to feature as a “performance” in the ticketing system for which donors could buy arbitrarily many tickets in different “price categories,” the sum of which generated their total donation. This is similar to introducing a number of possible defaults

through a donation grid (see, for example, Reiley and Samek 2015) with the small difference that our donors could choose “multiple tickets” in one or multiple price categories at the same time.

There were two subsequent changes in the design of the online fundraising tool. The first change occurred after 28 days and involved roughly a doubling of the donation categories from €10, €20, €50, and €100 to €20, €50, €100, and €200 Euros respectively. The second change occurred after a further 33 days of operation and an additional 11 days of suspension. The higher grid remained in place but now the buyers were forced to tick either the “I have donated already” or the “No, thank you” box if they decided to proceed to the payment stage without making a donation. These two checking boxes had also been available in the previous treatments, but one could click the button “proceed” without checking them. Figures A1 and A2 in the Appendix A show the exact implementation. The last period continued for 20 days and the online fundraising campaign was suspended afterwards.

Although there was no random assignment into treatments, the decision when to buy tickets and the timing of arrival at the platform can be assumed to be independent of treatments. Importantly, we can distinguish between one-time buyers and individuals who bought tickets in several periods. In most of our analysis, we exclude the latter group in order to avoid spillover effects between treatments. We also confirm that the periods are indeed very similar with just one difference. The later into the opera season, the more expensive are the tickets that customers buy. This is due to the fact that better seats in cheaper price categories are sold out first. In our analysis we control, of course, for ticket prices.

We do not expect giving behavior to be affected by any major holiday. Indeed, the Easter holiday fell into the suspension period between treatment 2 and treatment 3, and if at all, we would have expected it to affect the donations at the end of treatment 2 positively, which was not the case. Also, the online fundraising campaign did not coincide with the end of the fiscal year.² In what follows we shall refer to the three treatments as T1, T2, and T3. The choice of the grids for the current study was based on evidence from a fundraising campaign with a similar sample of opera-goers – a field experiment documented in Adena *et al.* (2014) which studied the effect of

² The fiscal year in Germany ends in December, almost a month before the online campaign started.

nonbinding suggestions.³

4 Results

4.1 Overall

In total, 96 donations were made adding up to €4,130 (€39.33 on average) over 81 days. In the same time period 9,578 buyers purchased 27,787 tickets (not counting the donation “tickets”) in 13,041 visits to the booking platform.

Figure 1 shows the numbers of donations in different monetary categories by treatment. The bars are subdivided by the frequency of purchases by customers at the time of the online fundraising. The dotted part of the bars accounts for one-time buyers⁴ only (7,950 customers); the solid part adds repeated buyers on the condition that they do so only during one distinct treatment (additional 492 customers making a total of 8,442); the striped part adds the remaining buyers arriving in at least two distinct treatments (a further 1,136 customers making a grand total of 9,578). It is immediately evident that the frequency of donations is much lower in T2 although it spanned the longest time period of 33 days. The numbers of top donations do not vary much between treatments. In all treatments there are exactly three donations equal to or higher than €100.

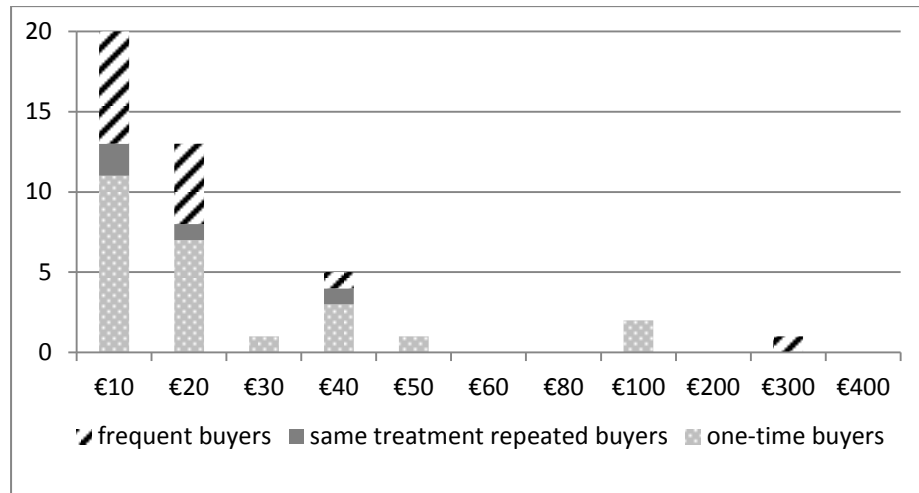
³ In that study, one treatment involved a €100 suggestion and another €200 suggestion. The first suggestion was followed by over 50% of donors, and the second by over 20%. The median donations were €100 in both treatments. In view of that, and given the average spending on opera tickets at each visit in similar range, the suggested grids are not particularly high.

⁴ Note that it does not mean that they are first-time buyers. Indeed, around one quarter of them purchased tickets in the previous season.

Figure 1: Donation values by Treatment

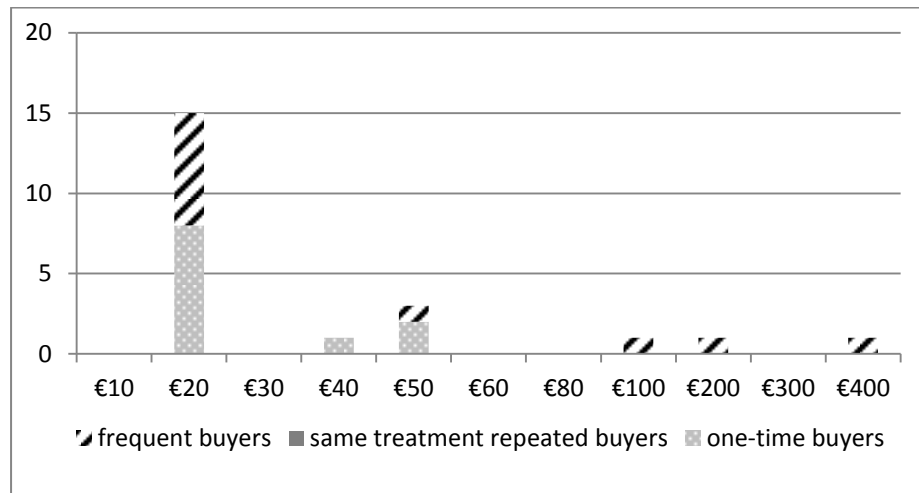
T1: lower grids

Duration: 28 days;
 Grids: €10, €20, €50, €100;
 Number of donations: 43



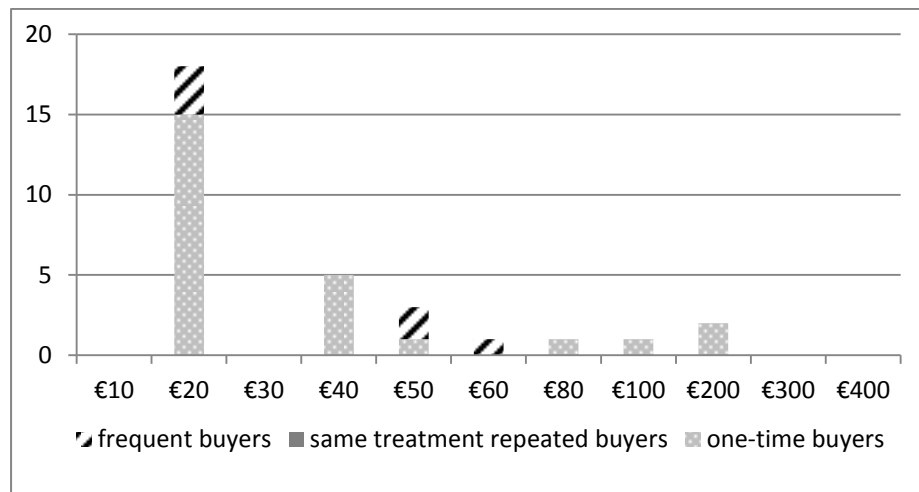
T2: higher grids

Duration: 33 days;
 Grids: €20, €50, €100, €200
 (donation of €10 and €30 was not possible);
 Number of donations: 22



T3: higher grids + forced statement

Duration: 20 days;
 Grids: €20, €50, €100, €200
 (donation of €10 and €30 was not possible);
 Number of donations: 31



For the subsequent analysis, we remove the buyers who arrived at the platform in different treatments. In what follows, we shall refer to the remaining customers as *non-frequent buyers* (8,442 customers). By adopting this approach, we avoid possible spillovers between treatments but, at the same time, do not account for *frequent buyers*, who may differ in their reaction to the treatments. Appendix C provides some additional analysis for frequent buyers. By concentrating on non-frequent buyers (as opposed to one-time buyers) we get closer to the representative sample and thus to the better overall evaluation of the intervention. Appendix D repeats the analysis for *one-time buyers* only (7,950), however, these results do not differ much from those presented below (note that the additional donations occur in T1 only, thus yielding the comparison between T2 and T3 unaffected). After removing buyers present in more than one treatment we are left with 65 donations of €33.23 on average and 8,442 customers in 9,028 visits.

4.2 Day-level results

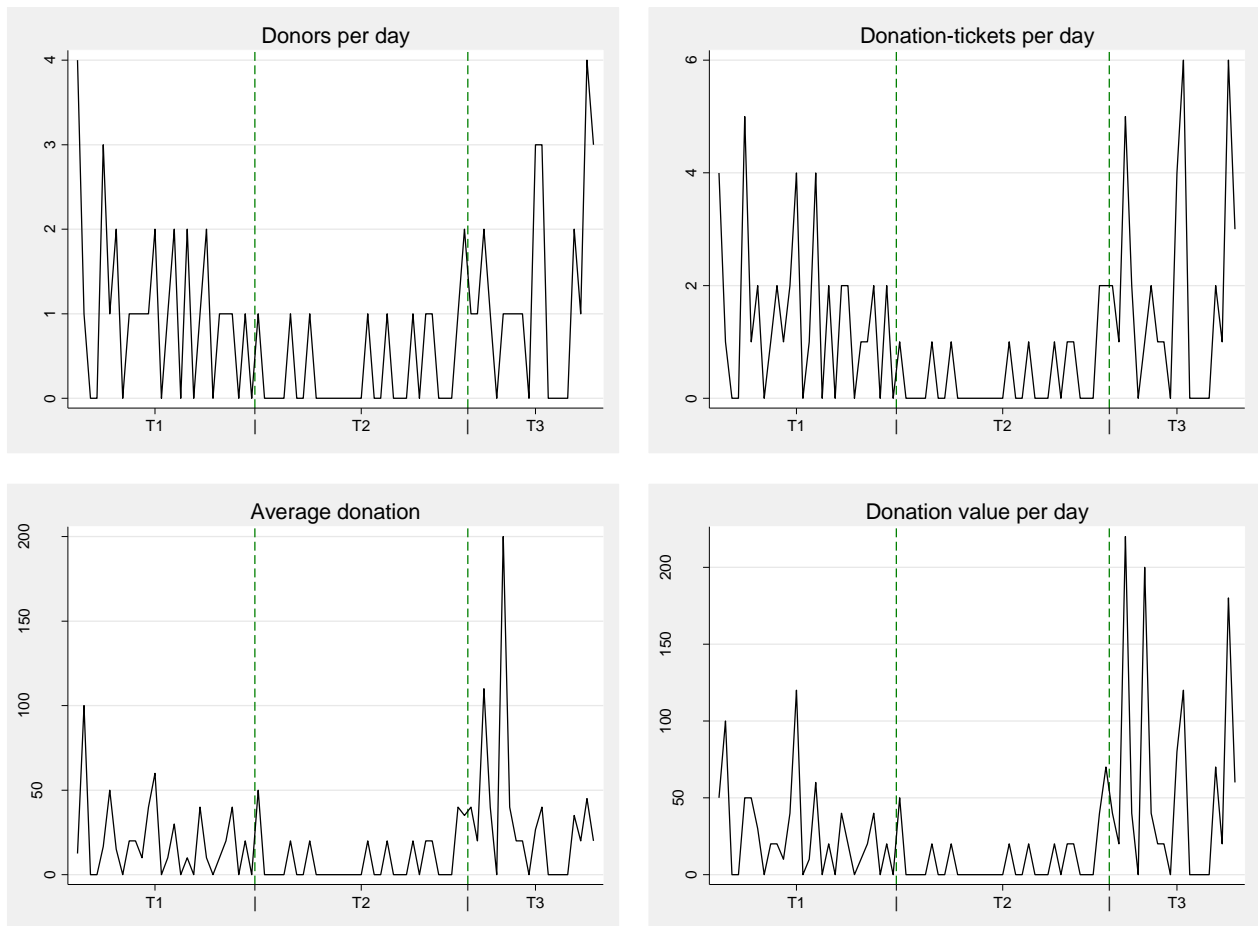
Figure 2 presents day-level results for charitable giving (Panel A), ticket purchases (Panel B), and numbers of statements checked (Panel C). Distinct treatments are marked with vertical dashed lines. In terms of giving (Panel A), the number of donors, number of donation-tickets chosen, average and total value of donation per day decline visibly from T1 to T2, i.e., from the lower to the higher grid. Although the reduction in the response rate might have been expected, we would instead have expected an increase in the value of donations in T2.

The overall decrease in contributions in T2 is reversed after the introduction of the change in website navigation (holding the higher grid constant) in T3. While we observe differences in giving between treatments, notice that ticket related behavior does not exhibit any sharp changes related to treatments (Panel B). In particular, the number of buyers per day seems to be similar in all treatments; however, there is higher day variation in T1 and one spike in T2. The spike at the end of the second period marks the beginning of the sale of the remaining tickets for the summer festival that the opera company holds every year, starting two months later.

While ticket prices are on average higher during T3, notice that both the lowest and highest values per day are observed in T2. In general, the upward trend in ticket prices tends to be related to how far advanced the opera season is, such that fewer and fewer inexpensive tickets with

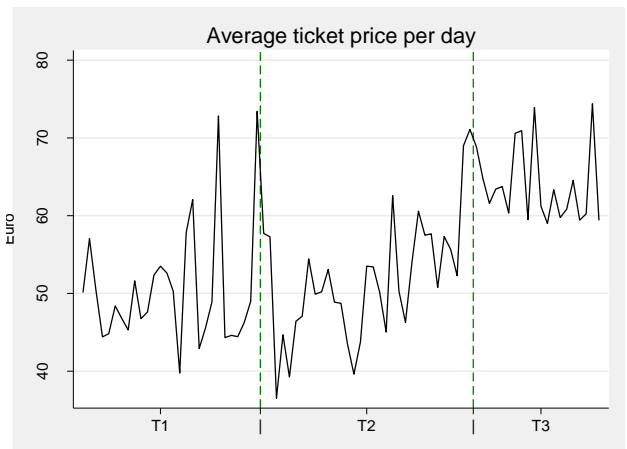
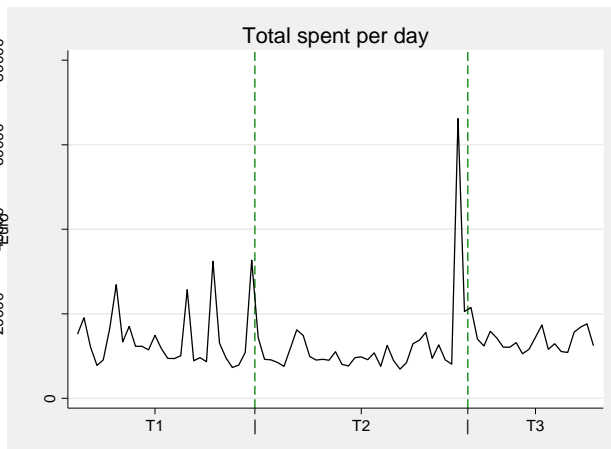
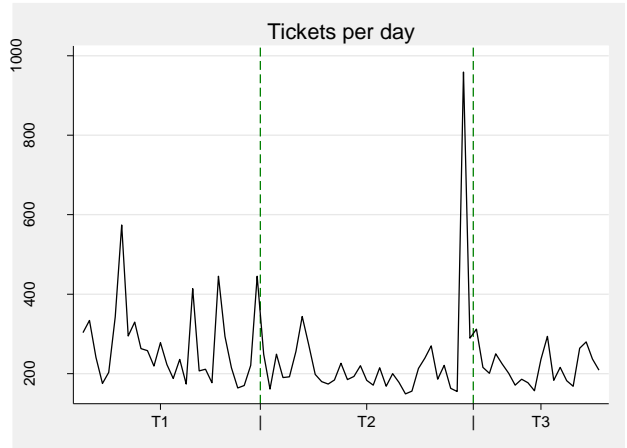
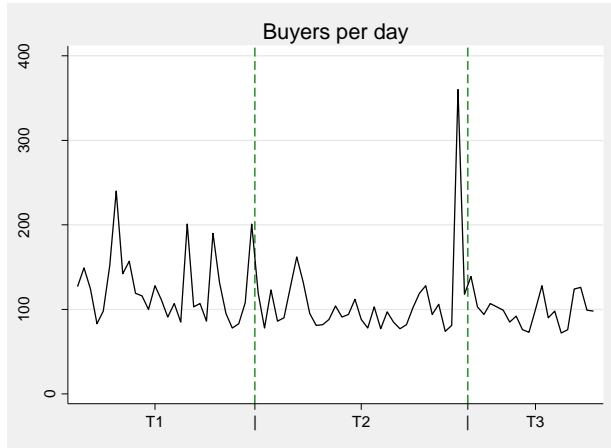
sufficiently good views (and sound) are available. Finally, we also observe a big jump in the number of “No, thank you” box checks in treatment 3 (Panel C) confirming the role of the change in website navigation.⁵

Figure 2: Day-level results
Panel A: Donative behavior

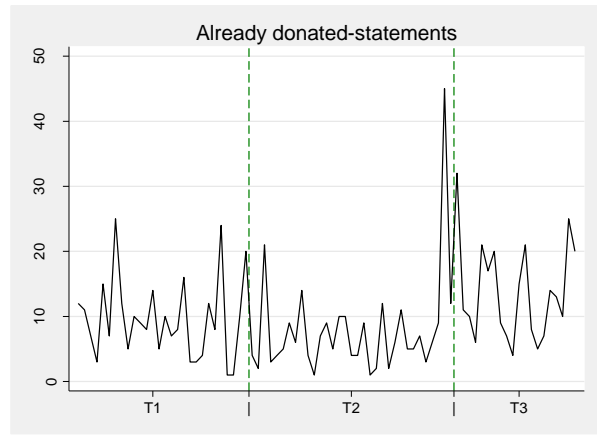
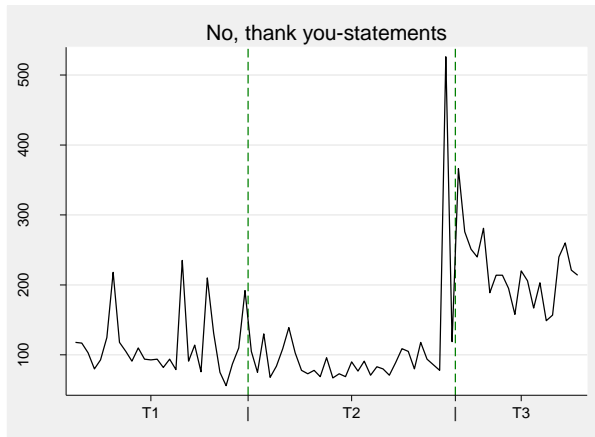


Panel B: Ticket related behavior

⁵ Unfortunately, for box checks, we have only aggregate daily data and cannot link it to the individuals. Therefore this data is available for the full sample only.



Panel C: Statements checked



Notes: Panel A and B are based on the sample of non-frequent buyers. Panel C is based on the full sample, i.e. including frequent buyers. The spike at the end of the second period marks begin of the sale of the remaining tickets for the summer festival starting two month later. The suspension period between T2 and T3 has been cut-off.

4.3 Individual-level results

Table 1 presents averages by treatment in the raw data (without any controls) and the results of T-tests and MWU-test for comparisons between T1–T2 and T2–T3. The return – average donation including zeros – in T1 compared to T2 (a lower versus a higher grid) is more than double (21 cents per buyer versus 9 cents). However, crucially it increases even further in T3 (higher grids plus forced statement) – to 57 cents. These differences are statistically significant. A similar pattern is observed for the response rate, which is more than double in T1 than in T2 (0.8% versus 0.3%), and increases further in T3 to 1.3%. Again, these differences are statistically significant. In terms of the average positive donation the values in T1 and T2 are similar (€25, €27 respectively) but in T3 the average positive donation increases to €45. There are differences between treatments in terms of ticket-related behavior, but they are not as meaningful as the differences in giving behavior. However, there are statistically significant differences between T2 and T3 which is why we now turn to a regression analysis, controlling for ticket-related information.

Table 2 presents the regression results at the individual level. The results are presented in terms of the response rates (logit specification with a donation dummy as a dependent variable), return (OLS regression with donation value including zeros as a dependent variable), and average positive donation (OLS regression with donation value excluding zeros as a dependent variable).⁶ The base treatment is T2, since we are primarily interested in comparisons between T1–T2 and T2–T3. The coefficients on T1 and T3 remain relatively stable whether or not we include controls.⁷ The most extensive specifications (third, sixth and ninth column) include controls for current ticket-related behavior (number of tickets, average value of tickets, and performance type dummies), and, crucially, also past-season ticket related behavior (dummy for being a customer in previous season, number of tickets and average ticket value) as well as day-of-week dummies.

⁶ Tables A1 and A2 in the Appendix A present additional results from alternative specifications.

⁷ This is not the case for the coefficient on T3 in the OLS regression but there the coefficients are not significant except in one specification.

Table 1: Individual level comparisons

Treatment	days	N	Ticket related behavior			Giving behavior				
			Average single ticket value (in €)	Average total money spent excluding donation (in €)	Average number of tickets (without donation)	Average donation per buyer (including zeros) (in €)	Dummy-response rate	Average positive donation	Median donation	
T1: lower grids	(1)	28	3513	53.13 (0.77)	112.28 (2.00)	2.15 (0.018)	0.208 (0.053)	0.008 (0.002)	25.17 (4.43)	20 N=29
T2: higher grids	(2)	33	3533	54.30 (0.76)	115.23 (1.99)	2.15 (0.021)	0.085 (0.028)	0.003 (0.001)	27.27 (3.84)	20 N=11
T3: forced statement	(3)	20	1982	64.48 (1.18)	139.86 (3.16)	2.18 (0.025)	0.570 (0.169)	0.013 (0.003)	45.20 (10.15)	20 N=25
T-test, p-value	(1)=(2)			0.277	0.295	0.789	0.039	0.004	0.784	
MWU-test, p-value	(1)=(2)			0.136	0.301	0.119	0.004	0.004	0.088	
T-test, p-value	(2)=(3)			0.000	0.000	0.248	0.000	0.000	0.259	
MWU-test, p-value	(2)=(3)			0.000	0.000	0.026	0.000	0.000	0.446	

Notes: Sample of non-frequent buyers; unit of observation: buyer per day; individuals arriving in different treatments are excluded; standard errors in parentheses. Table A1 in the Appendix A presents the analogous results for one-time buyers only.

Table 2: Regression analysis

Dependent variable:	Logit m.e. donation dummy			OLS return (donation value including zeros)			OLS positive donations		
	T1:lower grids	0.007*** (2.62)	0.007*** (2.63)	0.007** (2.57)	0.123** (2.06)	0.123** (2.05)	0.111* (1.91)	-2.100 (-0.36)	-1.760 (-0.31)
T3: forced statement	0.010*** (3.51)	0.010*** (3.48)	0.011*** (3.66)	0.485*** (2.83)	0.495*** (2.71)	0.491*** (2.74)	17.927 (1.65)	19.686* (1.92)	13.506 (1.25)
Controls I		yes	yes		yes	yes		yes	yes
Controls II			yes			yes			yes
Observations	9028	9028	9028	9028	9028	9028	65	65	65
Pseudo R2 /R2	0.023	0.025	0.045	0.002	0.002	0.005	0.069	0.086	0.205
Wald Test	0.125	0.133	0.060	0.041	0.050	0.040	0.076	0.038	0.119
T1=T3, p-value									
Wald Test	0.062	0.067	0.030	0.020	0.025	0.020	0.038	0.019	0.059
T1≥T3, p-value									

Notes: non-frequent buyers; unit of observation: buyer per day; errors clustered at the individual level; z- and t- statistics in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01, m.e.: marginal effects; controls I include number of tickets and average value of ticket at t=0; controls II include dummy customer, number of tickets, and average value of ticket at t-1, performance type dummies, and day of week dummies at t=0; full results in the Appendix B, Table B1.

The results confirm the impression from the raw individual and day-level data. Compared to T2, the response rate is significantly higher in T1 with an additional 0.7 percentage point and it is significantly higher in T3 by 1 percentage point.⁸ The same holds for the return per buyer, which is significantly higher in T1 by around 11–12 cents and in T3 by around 49 cents. In terms of average positive donation, only the coefficient on T3 in the specification which includes controls for the number of tickets and the average value of ticket is significant suggesting an increase in the value of positive donations by €20 relative to T2. There is only a small and nonsignificant decrease of donation values in T1.

The experiment is not designed to directly compare T1 with T3 since it includes a twofold change. Still, it is interesting to see whether the loss from the higher grid was reversed by the change in the navigation. A Wald test of equality between coefficients on T1 and T3 rejects the null in each full specification and in all OLS specifications, and the null, $T1 \geq T3$, is rejected in all specifications. This suggests that the loss from the introduction of higher grids was more than compensated by the change in website navigation.

Table A3 in the Appendix A shows the results of the interaction of T1 and T3 with three customer type categories in the past season: non-customers (0 tickets), non-frequent customers (1–4 tickets), and frequent customers (>4 tickets).⁹ The results are very close to those of Table 2, i.e. all types of customers react similarly to the treatments, however, the coefficients on T1 and T3 are highest for the non-frequent category in the response and return regressions.

4.4 Long-term impact of fundraising on ticket-related behavior

We now analyze long-term effects of online fundraising by looking at ticket-related behavior in the following opera season that started 4 months and ended 15 months after the campaign. For this purpose we concentrate on the customers that came to the platform at the time of the online fundraising campaign and those that arrived just days before or after the campaign (with a two-

⁸ Table A2 in the Appendix A presents the results of rare events logit (King and Zeng 2001). Those results suggest an increase in T1 relative to T2 by 0.5 percentage point. The increase in T3 relative to T2 is estimated to 0.9–1.1 percentage points.

⁹ The median of the number of positive tickets in the past season is 4.

week window in both directions). We identify one-time buyers in the grand period¹⁰ and compare those treated (facing the online fundraising) to the control group (who were not exposed to online fundraising) in the next season.¹¹ All these customers are likely to be non-frequent, occasional opera goers (Table A4 in the Appendix A provides descriptive statistics). Admittedly, this approach suffers from one problem. The customers arriving during the online campaign might already be affected and be less likely to return until the end of our grand period. This might result in including in the group of treated individuals customers who would otherwise be classified as frequent buyers. But given that more frequent customers spend more on tickets this would imply that we underestimate the studied effects.

Table 3 presents regression results for the next ticketing season in terms of the probability that a customer is coming back to the opera next season; the overall return from tickets (including non-buyers); and ticket revenue per returning buyer. We account for tickets bought through all means: internet, box office, on the phone or by mail. In the next ticketing season around 30% of identified one-time buyers from the grand period returned to the opera. It turns out that there are stark differences between those who faced the online campaign and those who did not. Those who were exposed to the fundraising campaign returned less often to the opera, and those who returned spent €46–69 less on tickets.¹² Overall, the revenue from the exposed group is lower by €16–32. The magnitude of this effect is in dismal contrast to the return from the online fundraising campaign, which generated just €0.26 in donations from the same group of customers (see Table A4 in the Appendix A).

In order to make sure that the effect is not driven by the immediate responses to the campaign, we separately analyze ticket outcomes in the earlier and in the later part of the next season. In the earlier part (7 months) 24% and in the later part (4 months) 19% of considered customers returned to the opera.¹³ Table 4 (earlier part of the next season) and Table 5 (later part of the next season) show similar responses with a decrease in positive spending on tickets in the later part apparently even stronger. Most importantly, the negative effect of avoiding the ask is not fading over time; on the contrary, it seems to have become permanent. Table A6 (Appendix A) shows

¹⁰ Note that those are not necessarily first time buyers. Indeed, 26% were customers in the previous season.

¹¹ We exclude the buyers arriving at the day of the sale of the remaining tickets for the summer festival, the break between treatments and the start and end days.

¹² The number of tickets by returning buyer decreased not significantly for those facing online campaign, see Table A5 in the Appendix A.

¹³ The granularity of the available data does not allow us a more equal split.

similar results for outcomes even later – in the first part of the season after next (months 16–24).¹⁴

In Table A7 we also document a placebo exercise in which we look at the effects of a fictive “treatment” a year later on ticket behavior in the subsequent year. Since, as expected, the estimated coefficients are not significant (and small and of the opposite sign), we conclude that our results are not due to some regular time patterns.

Table 3: Ticket-related behavior in the next season – regression results

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.025**	-0.023**	-0.010	-32.140**	-31.197**	-16.534*	-68.985*	-59.357	-45.638*
	(-2.18)	(-2.07)	(-0.97)	(-2.56)	(-2.50)	(-1.75)	(-1.87)	(-1.64)	(-1.65)
Controls I		yes	yes		yes	yes		yes	yes
Controls II			yes			yes			yes
Observations	8900	8900	8900	8900	8900	8900	2771	2771	2771
Pseudo R^2 / R^2	0.000	0.001	0.190	0.001	0.015	0.438	0.001	0.049	0.444

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; controls I include number of tickets and average value of ticket at $t=0$; controls II include dummy customer, number of tickets, and average value of ticket at $t-1$; full results in the Appendix B, Table B2.

Table 4: Ticket-related behavior in the earlier part of the next season

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.018*	-0.017*	-0.006	-15.065**	-14.679*	-6.790	-39.891	-29.645	-13.003
	(-1.74)	(-1.65)	(-0.60)	(-2.00)	(-1.95)	(-1.13)	(-1.40)	(-1.07)	(-0.59)
Controls I		yes	yes		yes	yes		yes	yes
Controls II			yes			yes			yes
Observations	8900	8900	8900	8900	8900	8900	2124	2124	2124
Pseudo R^2 / R^2	0.000	0.001	0.179	0.000	0.010	0.368	0.001	0.061	0.411

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; controls I include number of tickets and average value of ticket at $t=0$; controls II include dummy customer, number of tickets, and average value of ticket at $t-1$; earlier part: months 4 through 10; full results in the Appendix B, Table B4.

¹⁴ At the time of the analysis the season was not yet finished.

Table 5: Ticket-related behavior in the *later part of the next season*

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.018*	-0.016*	-0.006	-17.075***	-16.518***	-9.744*	-59.426**	-65.258**	-51.115**
	(-1.91)	(-1.74)	(-0.69)	(-2.69)	(-2.62)	(-1.89)	(-2.00)	(-2.28)	(-2.19)
Controls I		yes	yes		yes	yes		yes	yes
Controls II			yes			yes			yes
Observations	8900	8900	8900	8900	8900	8900	1663	1663	1663
Pseudo R^2 / R^2	0.000	0.002	0.190	0.001	0.015	0.346	0.002	0.077	0.392

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; controls I include number of tickets and average value of ticket at $t=0$; controls II include dummy customer, number of tickets, and average value of ticket at $t-1$; later part: months 11 through 15; full results in the Appendix B, Table B5.

What is the mechanism behind the reduction in the likelihood of returning to the opera and the reduction in the amount spent on tickets? The theoretical model of ask avoidance put forward by DellaVigna *et al.* (2012) assumes a *direct effect* of social pressure. Social pressure is assumed to generate a direct utility cost which decreases in the donation and which can be avoided by “avoiding the ask.” Andreoni *et al.* (2016) propose a model in which the ask is not a direct cost, but rather triggers an emotional reaction which makes it difficult to resist the solicitor. If one can resist, one feels guilt. The individuals who know that they will not be able to resist try to avoid the ask as a mean of self-control. In line with these models, one explanation for our results could be that some opera customers who were facing the online fundraising expect to be asked again and therefore abstain from going to the opera. Note, however, that there was no possibility to avoid the ask during the online campaign.

DellaVigna (2009) presents a survey of experiments suggesting that individuals project their emotions onto economic fundamentals. In line with Andreoni *et al.* (2016), we assume that the ask and individuals’ responses to the ask trigger an emotional response. The fact that we observe a reduction in the positive amount spent on tickets by those who were facing the online campaign points to an *indirect effect* which interacts with the utility from visiting opera performances. Some individuals switch from more expensive to cheaper tickets, and those who are closer to zero net-of-cost utility refrain from buying tickets at all. Of course, those who do not buy at all might simply display direct ask avoidance. Table A8 in the Appendix A presents results analogous to those in Table 4 but for purchases made next season *on the internet only*. If there

was a long-term direct effect of deliberate ask avoidance, rational individuals should have reduced the number of tickets bought online, and possibly increase the number of tickets purchased through other means. Table A4 does not confirm this intuition which speaks against direct ask avoidance, and in favor of an indirect effect. This does not mean, however, that there is no direct effect at all. We rather believe the direct effect to be short-lived and not measurable in our context.

Why is there reduced expected utility from visiting the opera for those who faced online campaign? Note that all treated individuals were asked and that only very few responded (0.7%). One explanation is rooted retrospective feelings of guilt, the other in prospective (possibly unconscious) projections of past emotional states onto the expected utility from spending a night at the opera. In case of retrospective feelings of guilt we should expect stronger reactions to T3 as compared to treatments T1 and T2 which did not require the explicit admission that one is a non-donor. Table A9 in the Appendix A presents results analogous to Table 4 but with treatment dummies. We do not see any support for retrospective guilt. This suggests that the effect is due to prospective projections of emotional states onto the enjoyment of a (lavish) night at the opera. Listening to fine sopranos and sipping a glass of champagne in the interval is just not as much fun anymore.

This conjecture is in line with findings about the role of self-image. Direct ask avoidance requires that individuals admit to themselves that they are non-donors. In contrast, a change in the valuation of opera performances results in an effective excuse. This effect may be relevant in many very different contexts. For example, individuals asked for donations for environmental projects can possibly reduce their valuation of environmentally friendly behavior in general and, as a result, pollute more.¹⁵

It appears psychologically plausible that this effect may work in reverse for those who decided to make a donation and who, as a self-justification of their donation, may increase their valuation of a (lavish) night at the opera. We cannot assess this directly since we do not know the identity of the would-be-donors who have just not been asked. However, Table 7 shows that donors (relative to treated non-donors and non-treated) return much more often to the opera.

¹⁵ Knutsson et al. (2013) suppose that “avoiding the ask” leads store chain customers to use recycling machines at other locations without the donation button. But it might also be the case that they reduce their recycling behavior. Note that in our opera context there is no close substitute available in reasonable distance.

Table 6: Ticket-related behavior of donors in the next season

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.026**	-0.025**	-0.011	-32.653***	-31.622**	-17.172*	-69.035*	-58.045	-46.022*
	(-2.30)	(-2.19)	(-1.09)	(-2.60)	(-2.53)	(-1.82)	(-1.87)	(-1.60)	(-1.66)
Dummy: facing online fundraising *donor dummy	0.160***	0.155**	0.131**	68.604	55.095	82.349	4.215	-106.413	31.346
	(2.64)	(2.55)	(2.56)	(0.95)	(0.76)	(1.51)	(0.02)	(-0.62)	(0.24)
Controls I		yes	yes		yes	yes		yes	yes
Controls II			yes			yes			yes
Observations	8900	8900	8900	8900	8900	8900	2771	2771	2771
Pseudo R^2 / R^2	0.001	0.002	0.191	0.001	0.015	0.438	0.001	0.050	0.445

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; there are 50 donors in this sample (only treated); z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; controls I include number of tickets and average value of ticket at $t=0$; controls II include dummy customer, number of tickets, and average value of ticket at $t-1$; full results in the Appendix B, Table B4.

The reduction in ticket revenue in the following season in range of €16–32 contrasts with the revenue from donations of just €0.26. Unless the effect of online fundraising goes in the opposite direction for more frequent buyers, the online campaign would have to be judged as detrimental for the main business of the opera house. A cost benefit analysis analogous to the one presented by Andreoni *et al.* (2016) is as follows. The costs from reduced ticket sells in the next season are in range of €16–32 per individual, and since there is no decline over time, those costs must be assumed to be the same for a number of years t . The actual donors received some positive utility from the act of giving, say y , and 0.7% of those who were asked turned into donors. The recipients received a marginal utility μ per received Euro. Altogether, the online fundraising is to be judged welfare detrimental unless $0.007 * y + \mu * €0.26 \geq t * €16$ which seems unlikely to hold.¹⁶

¹⁶ This calculation does not account for more frequent customers, who were more likely to give (1.9%) and gave, on average €1.43. The formula can be easily extended by a discount rate (here assumed to be zero for simplicity).

4.5 Discussion

Self-image. Why do we observe more giving in T3? Individuals are more likely to donate and they donate higher amounts when they have to check a “No, thank you” box in order to get around donating. This suggests that customers were successfully deceiving themselves in T2, behaving just as if the donation request had not been there. When the act of declining becomes more salient, they are less likely to avoid it. This is related to the “avoiding the ask” phenomenon studied by DellaVigna *et al.* (2012) and Andreoni *et al.* (2016). In DellaVigna *et al.* 2012, individuals were less likely to be at home when they knew that a solicitor was coming. In Andreoni *et al.* (2016) some individuals chose other exit doors from a supermarket to avoid being asked. However, these papers’ primary concern is with social pressure to give and social interaction, although both, social and self-image may play a role in this kind of context. It is difficult to tell where self-image ends and social-image begins. Even if it appears that social image requires an audience, it is unclear what is in people’s minds when they are asked for donations online. They might still feel observed by the opera house, a partner or spouse, or might like to talk about their choices to other opera goers. In our case, however, there were no changes in social interaction between treatments, rendering the social-image concern irrelevant for treatment differences. Consequently, the check-box effect that we observe must stem from the self-image motive. For some individuals declining donations is difficult to reconcile with their self-image, and saying “No, thank you” makes the decline apparent to themselves. In our context, the magnitude of the self-image motive in charitable giving is economically meaningful – increasing the return from fundraising six- to sevenfold or by 49 cents (after controlling for confounders). To our knowledge, our study is the first to disentangle this motive in the field.

Costs of “avoiding the ask.” In contrast to the literature concerned with immediate ask avoidance, we are able to measure long-term effects. The short-term cost-benefit analysis in Andreoni *et al.* (2016) and DellaVigna *et al.* (2012) leads to a conclusion that, overall, the fundraising campaigns analyzed were welfare enhancing. In our case, the net effect of the campaign is most likely to be negative for, both, the opera house and overall welfare.

Beyond the short term direct effect of ask avoidance documented in other studies (which we are not able to measure here), we document a long-term indirect effect which interacts with the utility from opera going. This effect is negative for those who faced the online fundraising campaign

and positive for actual donors. This finding has potential implications for many other contexts, e.g. campaigns for environmental projects and individuals' environmental behavior.

Donation grids. Grids seem to exert multiple effects. On the one hand, grids serve as a reference point and convey information about the range of donations expected. Thus, grids that are set too high will deter small donors; grids set too low will lower the perceived expectation and induce lower donations. But the question about what is too high or too low might be an individual one, and for prospective donors it might be only resolved by means of trial and error. On the other hand, the number, the spread and the skewness of the grids chosen affects prospective donors and these effects are even less well understood. As discussed above, the literature on donation grids is not conclusive. While Adena *et al.* (2014) found promising effects of non-binding suggestions in a similar environment, Reiley and Samek (2015) found negative effects of increasing grids and no better performance of tailored grids. Here we find dramatic effects of higher grids for non-frequent users: they donate less often and the overall return from them is significantly lower.

5. Conclusions

In this paper we study an online fundraising campaign introduced on a ticketing platform by an opera house. This is an interesting setting to study, since an increasing portion of charitable giving is done online and no arts company wants to lose the momentum and be left behind. But the question of “how” and foremost “whether” at all is still open. Especially, it is not clear whether the findings from more traditional fundraising channels carry over to the new environment. We contribute to a better understanding of “how” in online fundraising by studying donation grids and navigation structures. Against our expectations, we find that higher donation grids result in a substantially lower response rate, similar positive donations and consequently much lower returns. Then we demonstrate that a small, apparently superficial, change in the design of the campaign has unexpectedly large consequences (offsetting the effects of changes in the choice architecture). Not allowing for the possibility of conveniently overlooking the ask increases both, the response rate and positive donations – resulting in a substantial increase in return. The aversion to admit vis-à-vis oneself that one is a non-donor provides evidence for a self-signaling motive in charitable giving. This is, to our knowledge, the first field study to

measure such a self-image effect. Finally, we provide an estimate of the fundraiser's long-term costs of donors "avoiding the ask" which, in case of our opera house, are in range of €16–32 per person and opera season. This suggests that the question "whether" is a non-trivial one. We also make a first step towards understanding the mechanism behind the revenue reduction, and conclude that this stems from an indirect effect of ask avoidance which interacts with the valuation of opera performances by a solicited customer.

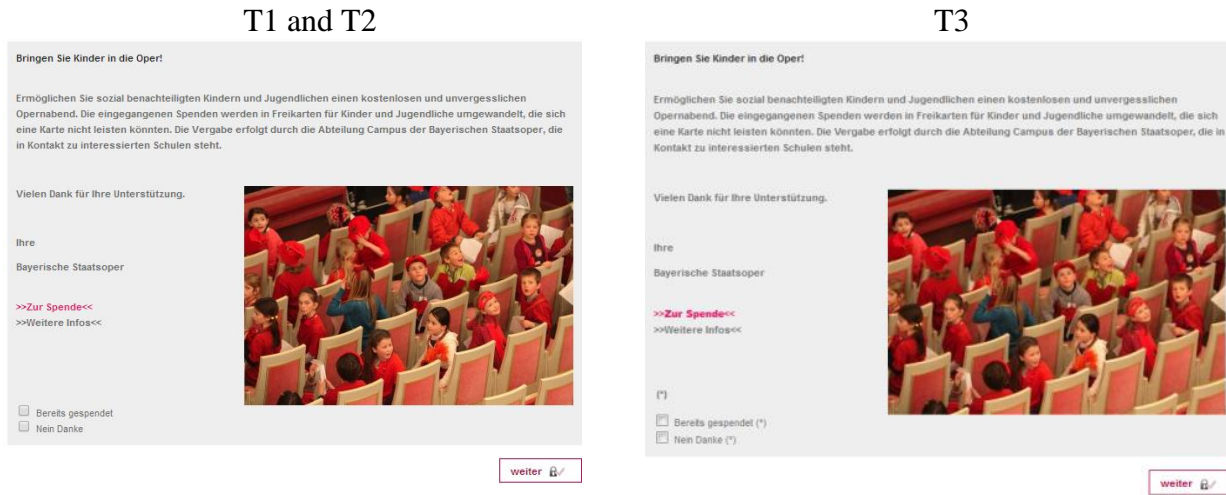
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Appendix A (additional information):

Figure A1: Charity appeal (first screen) and how the checkboxes were incorporated



Notes: In Treatment 1 and 2 the (*) was missing and it was possible to click the button “weiter” (proceed, in the bottom right corner) without checking one of the boxes. In Treatment 3 one had to check either box before proceeding.

Translation: Get children to the opera! Give socially disadvantaged children and adolescents an unforgettable evening at the opera house free of charge. The donations received are converted into free tickets for children and adolescents that cannot afford to buy a ticket. The allocation is made by the Campus department of the Bavarian State Opera, which is in contact with interested schools. Thank you very much for your support! Your Bavarian State Opera

Figure A2: Charity appeal (second screen):

WÄHLEN SIE EINE KATEGORIE, wir finden für Sie verfügbare Plätze in der von Ihnen gewählten Kategorie.

Bringen Sie Kinder in die Oper !,
Do 31.07.2014, 23:59 Uhr
Spende

[In den Einkaufswagen](#)

Kategorie	Beschreibung	Preis	Anzahl
a	Platzgruppe 1	Spende 100,00 EUR	<input type="text"/>
b	Platzgruppe 2	Spende 50,00 EUR	<input type="text"/>
c	Platzgruppe 3	Spende 20,00 EUR	<input type="text"/>
d	Platzgruppe 4	Spende 10,00 EUR	<input type="text"/>

[i Informationen zur Ticketauswahl](#)

[In den Einkaufswagen](#)

[Zurück zur Veranstaltungübersicht](#)

Notes: Those were the grids in Treatment 1. In Treatment 2 and 3 the grids were respectively 200, 100, 50 and 20 EUR.

Table A1: Individual-level regression analysis (alternative specifications)

	Probit m.e.: donation dummy			Tobit m.e. y*: return (donation value including zeros)			OLS: log of positive donations		
T1:lower grids	0.007*** (2.70)	0.007*** (2.72)	0.007*** (2.69)	0.242** (2.49)	0.243** (2.50)	0.237** (2.48)	-0.288 (-1.62)	-0.296* (-1.97)	-0.260 (-1.38)
T3: statement required	0.010*** (3.67)	0.010*** (3.65)	0.010*** (3.86)	0.378*** (3.05)	0.379*** (3.05)	0.387*** (3.27)	0.250 (1.34)	0.364** (2.05)	0.236 (1.00)
number of tickets		-0.001 (-0.87)	-0.001 (-0.79)		-0.044 (-0.93)	-0.033 (-0.83)		-0.071 (-1.16)	-0.022 (-0.35)
average value of ticket		-0.000 (-0.01)	0.000 (0.31)		-0.000 (-0.06)	0.000 (0.41)		0.004** (2.51)	0.008*** (3.90)
dummy customer in previous season			0.003 (1.04)			0.113 (1.08)			0.319 (0.99)
number of tickets previous season			-0.000 (-0.04)			-0.000 (-0.02)			0.031*** (4.05)
average value of ticket previous season			0.000 (0.12)			-0.000 (-0.01)			-0.006* (-1.74)
Performance type dummies			yes			yes			yes
Day of week dummies			yes			yes			yes
Observations	9028	9028	9028	9028	9028	9028	65	65	65
Pseudo R ²	0.023	0.025	0.044	0.014	0.015	0.026	0.121	0.185	0.418
Wald Test T1=T3, p-value	0.124	0.131	0.062	0.105	0.109	0.057	0.008	0.002	0.009
Wald Test T1≥T3, p-value	0.062	0.066	0.031	0.052	0.054	0.028	0.004	0.001	0.004

Notes: sample of non-frequent buyers (without buyers present in different treatments); z- and t- statistics in parentheses; errors clustered at the individual level; * p < 0.10, ** p < 0.05, *** p < 0.01, m.e.: marginal effects.

Table A2: Rare events logit, first differences

Dependent variable	Donation dummy			
T1:lower grids		0.005*** (2.68)	0.005*** (2.69)	0.005*** (2.62)
T3: statement required		0.009*** (3.81)	0.010*** (3.77)	0.011*** (4.01)
Controls I		no	yes	yes
Controls II		no	no	yes
Observations		9028	9028	9028

Notes: sample of non-frequent buyers (without buyers present in different treatments); treatment dummies set at 0 and other control variables at mean; controls I include number of tickets and average value of ticket at t=0; controls II include dummy customer, number of tickets, and average value of ticket at t-1, performance type dummies, and day of week dummies; * p < 0.10, ** p < 0.05, *** p < 0.01; z-statistics from relogit in parentheses.

Table A3: Regression analysis – interactions with customer type (past season ticket related behavior)

	Probit m.e.: donation dummy			Tobit m.e. y*: return (log of donation+1)			OLS: log of positive donations		
T1 * 0 tickets in t-1 dummy	0.005* (1.89)	0.005* (1.91)	0.005* (1.89)	0.043 (0.90)	0.043 (0.90)	0.025 (0.51)	-7.898 (-1.53)	-7.574 (-1.45)	-10.164 (-1.44)
T1 * 1–4 tickets in t-1 dummy	0.010*** (2.80)	0.010*** (2.81)	0.010*** (2.75)	0.501* (1.75)	0.498* (1.74)	0.492* (1.75)	17.013 (1.13)	17.474 (1.07)	13.605 (0.74)
T1 * >4 tickets in t-1 dummy	0.009** (2.33)	0.009** (2.35)	0.008** (2.35)	0.112 (1.17)	0.113 (1.18)	0.123 (1.24)	-8.939 (-1.48)	-8.175 (-1.37)	8.545 (0.49)
T3 * 0 tickets in t-1 dummy	0.009*** (3.30)	0.009*** (3.28)	0.010*** (3.42)	0.513** (2.29)	0.525** (2.21)	0.514** (2.21)	22.727 (1.47)	23.277 (1.62)	14.180 (1.13)
T3 * 1–4 tickets in t-1 dummy	0.012*** (3.14)	0.012*** (3.13)	0.013*** (3.27)	0.576* (1.85)	0.578* (1.85)	0.585* (1.89)	9.394 (0.94)	10.635 (0.99)	1.072 (0.07)
T3 * >4 tickets in t-1 dummy	0.007 (1.29)	0.007 (1.31)	0.008 (1.40)	0.179 (0.90)	0.184 (0.93)	0.185 (0.93)	2.727 (0.32)	5.436 (0.69)	-8.804 (-0.63)
Controls I		yes	yes		yes	yes		yes	yes
Controls II			yes			yes			yes
Observations	9028	9028	9028	9028	9028	9028	65	65	65
Pseudo R ² /R ²	0.028	0.030	0.044	0.003	0.003	0.005	0.123	0.137	0.209

Notes: sample of non-frequent buyers (without buyers present in different treatments); z- and t- statistics in parentheses respectively; errors clustered at the individual level; * p < 0.10, ** p < 0.05, *** p < 0.01; m.e.: marginal effects; controls I include number of tickets and average value of ticket at t=0; controls II include performance type dummies and day of week dummies at t=0.

Table A4: Descriptive statistics: one-time customers in the period of online fundraising, two weeks before, and two weeks after

	Time	Facing online fundraising			Control			difference	T-statistics p-value
		mean	Standard error	N	mean	Standard error	N		
Return from donations	0	0.261	0.056	6694	-	-	2203	-	-
Share of donors	0	0.007	0.001	6694	-	-	2203	-	-
	1	115.408	4.883	6694	147.549	16.099	2203	-32.140	0.011
Ticket revenue	0	121.076	1.472	6694	118.298	2.585	2203	2.778	0.349
	-1	89.542	4.195	6694	115.831	14.398	2203	-26.290	0.017
	1	0.306	0.006	6694	0.330	0.010	2203	-0.025	0.029
Share customers	0	1	0	6694	1	0	2203		
	-1	0.250	0.005	6694	0.279	0.010	2203	-0.028	0.008
	1	4.042	0.110	2047	3.912	0.177	728	0.130	0.542
Number of opera tickets>0	0	2.156	0.013	6689	2.047	0.019	2202	0.109	0.000
	-1	6.484	0.227	1676	6.702	0.478	614	-0.217	0.646

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; t=0 spans only the period of online fundraising + 2 weeks before and after; t=1 is the complete next opera season (11 months); t=-1 is the complete previous opera season (11 months).

Table A5: Ticket-related behavior in the next season

Dependent variable	OLS		
	number of positive tickets next season		
Dummy: facing online fundraising	-2.425 (-1.24)	-0.190 (-0.13)	-0.141 (-0.10)
Controls I		yes	yes
Controls II			yes
Observations	2771	2771	2771
R^2	0.001	0.443	0.496

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; controls I include number of tickets and average value of ticket at t=0; controls II include dummy customer, number of tickets, and average value of ticket at t-1

Table A6: Ticket-related behavior two seasons later – regression results

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer at t+2			Ticket revenue at t+2 (including zeros)			Ticket revenue at t+2 (excluding zeros)		
Dummy: facing online fundraising	-0.022** (-2.13)	-0.022** (-2.10)	-0.010 (-1.10)	-15.431** (-2.34)	-15.353** (-2.34)	-7.979 (-1.49)	-37.397 (-1.53)	-35.456 (-1.50)	-28.442 (-1.46)
Number of tickets at t		-0.002 (-0.50)	-0.000 (-0.03)		7.459*** (2.65)	6.918*** (3.01)		29.743*** (3.09)	24.483*** (3.09)
average value of ticket at t		0.000 (1.02)	-0.000 (-0.01)		0.677*** (11.37)	0.291*** (5.60)		2.731*** (12.46)	1.491*** (6.94)
dummy customer at t-1			0.164*** (11.41)			-156.095*** (-17.62)			-292.946*** (-11.16)
average value of ticket at t-1			0.000** (2.03)			2.407*** (22.98)			3.522*** (12.29)
number of tickets at t-1			0.021*** (13.09)			25.606*** (56.39)			25.652*** (28.93)
Constant				77.024*** (13.45)	22.440** (2.53)	-0.496 (-0.07)	303.007*** (14.44)	80.130*** (2.60)	70.957** (2.48)
Observations	8900	8900	8900	8900	8900	8900	2113	2113	2113
Pseudo R^2 / R^2	0.000	0.001	0.181	0.001	0.016	0.345	0.001	0.073	0.377

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; t+2 are months 16–24 after the online fundraising (at the time of the analysis the opera season was not yet finished); standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; m.e.: marginal effects.

Table A7: Placebo exercise: the effect of a fictive “treatment” on ticket-related behavior

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer at t+1			Ticket revenue at t+1 (including zeros)			Ticket revenue at t+1 (excluding zeros)		
Dummy fictive “treatment” at t=0	0.018 (1.61)	0.017 (1.47)	0.012 (1.18)	6.375 (1.27)	3.204 (0.65)	0.063 (0.02)	7.369 (0.48)	5.222 (0.35)	-3.132 (-0.25)
Controls I		yes	yes		yes	yes		yes	yes
Controls II			yes			yes			yes
Observations	9581	9581	9581	9581	9581	9581	2658	2658	2658
Pseudo R^2 / R^2	0.000	0.001	0.128	0.000	0.025	0.305	0.000	0.093	0.367

Notes: the assignment of customers to the fictive “treatment” versus control is constructed in exactly the same way as in the previous analysis (see notes to table 3) but shifted by a year; the next season comprises of 8 months since at the time of analysis the season was not yet over; controls I contain the total spending at t=0, controls II include dummy customer, number of tickets, average value of ticket in t-2, i.e. in the season before the online fundraising; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; m.e.: marginal effects.

Table A8: Ticket-related behavior in the next season-tickets purchases on the internet only

Dependent variable	logit m.e.			OLS			OLS		
	Dummy customer next season (internet only)			Ticket revenue next season (including zeros, internet only)			Ticket revenue next season (excluding zeros, internet only)		
Dummy: facing online fundraising	-0.013 (-1.29)	-0.013 (-1.23)	-0.002 (-0.19)	-8.108* (-1.69)	-7.774 (-1.63)	-3.228 (-0.73)	-19.234 (-1.16)	-12.899 (-0.84)	-12.261 (-0.82)
Number of tickets at t		-0.009* (-1.88)	-0.006 (-1.42)		3.969* (1.94)	5.151*** (2.70)		22.914*** (3.60)	24.591*** (4.00)
average value of ticket at t		-0.000* (-1.73)	-0.000** (-2.15)		0.587*** (13.59)	0.352*** (8.17)		2.614*** (18.38)	2.018*** (12.45)
dummy customer at t-1			0.217*** (15.55)			7.309 (0.99)			-43.332** (-2.20)
average value of ticket at t-1			0.000 (0.27)			1.293*** (14.86)			1.664*** (7.53)
number of tickets at t-1			0.014*** (9.94)			6.297*** (16.69)			4.962*** (7.10)
Constant				65.157*** (15.63)	22.947*** (3.57)	-2.244 (-0.36)	258.167** * (18.11)	60.180*** (2.99)	33.796 (1.57)
Observations	8900	8900	8900	8900	8900	8900	2155	2155	2155
Pseudo R ² / R ²	0.000	0.001	0.155	0.000	0.021	0.147	0.001	0.140	0.197

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$;

Table A9: Ticket-related behavior in the next season by past treatments

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
T1	-0.028** (-2.16)	-0.027** (-2.04)	-0.015 (-1.30)	-30.437** (-2.11)	-27.671* (-1.93)	-17.507 (-1.61)	-58.927 (-1.37)	-47.247 (-1.12)	-43.755 (-1.36)
T2	-0.029** (-2.18)	-0.028** (-2.08)	-0.012 (-1.06)	-37.438** (-2.53)	-32.599** (-2.21)	-16.973 (-1.52)	-80.877* (-1.83)	-54.380 (-1.26)	-42.302 (-1.28)
T3	-0.006 (-0.39)	-0.006 (-0.37)	0.008 (0.58)	-24.869 (-1.36)	-36.609** (-2.01)	-13.275 (-0.96)	-67.776 (-1.26)	-96.014* (-1.83)	-56.426 (-1.41)
Number of tickets at t		-0.010** (-2.07)	-0.007 (-1.64)		6.760 (1.26)	4.544 (1.12)		29.966** (1.96)	17.785 (1.52)
average value of ticket at t		0.000 (1.05)	-0.000 (-0.27)		1.293*** (11.37)	0.601*** (6.54)		3.940*** (11.83)	2.257*** (7.57)
dummy customer at t-1			0.192*** (11.23)			- 346.829*** (-22.20)		- 526.614*** (-14.10)	
average value of ticket at t-1			0.000*** (2.64)			4.432*** (24.01)		5.397*** (13.09)	
number of tickets at t-1			0.030*** (12.11)			57.840*** (72.25)		57.576*** (41.58)	
Constant				147.549*** (13.54)	58.629*** (3.48)	14.308 (1.09)	447.111*** (14.09)	148.643*** (3.10)	112.979*** (2.79)
Observations	8900	8900	8900	8900	8900	8900	2771	2771	2771
Pseudo R^2 / R^2	0.001	0.001	0.190	0.001	0.015	0.438	0.001	0.051	0.445

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B (full results of the tables from the text):

Table B1 (full results of Table 2): Regression analysis

Dependent variable:	Logit donation dummy			OLS return (donation value including zeros)			OLS positive donations		
T1:lower grids	0.007*** (2.62)	0.007*** (2.63)	0.007** (2.57)	0.123** (2.06)	0.123** (2.05)	0.111* (1.91)	-2.100 (-0.36)	-1.760 (-0.31)	-0.358 (-0.04)
T3: statement required	0.010*** (3.51)	0.010*** (3.48)	0.011*** (3.66)	0.485*** (2.83)	0.495*** (2.71)	0.491*** (2.74)	17.927 (1.65)	19.686* (1.92)	13.506 (1.25)
number of tickets	-0.001 (-0.82)	-0.001 (-0.70)		-0.069 (-1.11)	-0.029 (-0.76)			-3.544 (-1.03)	-1.315 (-0.44)
average value of ticket	-0.000 (-0.20)	0.000 (0.04)		-0.001 (-0.55)	-0.000 (-0.08)			0.066 (1.08)	0.224** (2.39)
dummy customer in previous season			0.003 (0.91)			0.115 (0.72)			13.076 (0.74)
number of tickets previous season			-0.000 (-0.16)			-0.001 (-0.26)			0.851** (2.29)
average value of ticket previous season			0.000 (0.38)			-0.000 (-0.17)			-0.284 (-1.61)
Performance type dummies			yes			yes			yes
Day of week dummies			yes			yes			yes
Observations	9028	9028	9028	9028	9028	9028	65	65	65
Pseudo R2 /R2	0.023	0.025	0.045	0.002	0.002	0.005	0.069	0.086	0.205
Wald Test	0.125	0.133	0.060	0.041	0.050	0.040	0.076	0.038	0.119
T1=T3, p-value									
Wald Test	0.062	0.067	0.030	0.020	0.025	0.020	0.038	0.019	0.059
T1≥T3, p-value									

Notes: without buyers present in different treatments, t- statistics in parentheses; errors clustered at the individual level; * p < 0.10, ** p < 0.05, *** p < 0.01, m.e.: marginal effects.

Table B2 (full results of Table 3): Ticket-related behavior in the next season – regression results

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.025** (-2.18)	-0.023** (-2.07)	-0.010 (-0.97)	-32.140** (-2.56)	-31.197** (-2.50)	-16.534* (-1.75)	-68.985* (-1.87)	-59.357 (-1.64)	-45.638* (-1.65)
Number of tickets at t		-0.010** (-2.05)	-0.007 (-1.62)		6.771 (1.26)	4.552 (1.12)		29.797* (1.95)	17.693 (1.51)
average value of ticket at t		0.000 (1.18)	-0.000 (-0.14)		1.290*** (11.38)	0.603*** (6.59)		3.915*** (11.80)	2.250*** (7.56)
dummy customer at t-1			0.192*** (11.28)			-346.767*** (-22.20)			-526.496*** (-14.10)
average value of ticket at t-1			0.000*** (2.62)			4.431*** (24.01)			5.396*** (13.09)
number of tickets at t-1			0.029*** (12.07)			57.836*** (72.26)			57.586*** (41.61)
Constant				147.549*** (13.54)	58.803*** (3.49)	14.153 (1.08)	447.111*** (14.09)	150.477*** (3.15)	113.550*** (2.81)
Observations	8900	8900	8900	8900	8900	8900	2771	2771	2771
Pseudo R ²	0.000	0.001	0.190	0.001	0.015	0.438	0.001	0.049	0.444

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3 (full results of Table 4): Ticket-related behavior in the earlier part of the next season

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.018* (-1.74)	-0.017* (-1.65)	-0.006 (-0.60)	-15.065** (-2.00)	-14.679* (-1.95)	-6.790 (-1.13)	-39.891 (-1.40)	-29.645 (-1.07)	-13.003 (-0.59)
Number of tickets at t		-0.012** (-2.48)	-0.009** (-2.25)		4.068 (1.26)	2.656 (1.03)		28.679** (2.43)	16.472* (1.76)
average value of ticket at t		-0.000** (-2.08)	-0.000*** (-2.87)		0.636*** (9.32)	0.290*** (4.98)		2.992*** (11.48)	1.732*** (7.06)
dummy customer at t-1			0.180*** (12.73)			-189.595*** (-19.06)			-357.129*** (-12.13)
average value of ticket at t-1			0.000 (1.33)			2.270*** (19.31)			3.430*** (10.37)
number of tickets at t-1			0.020*** (12.52)			32.412*** (63.59)			33.959*** (33.52)
Constant				79.185*** (12.10)	33.949*** (3.35)	9.421 (1.13)	313.748*** (12.80)	81.140** (2.20)	80.532** (2.46)
Observations	8900	8900	8900	8900	8900	8900	2124	2124	2124
Pseudo R ² / R ²	0.000	0.001	0.179	0.000	0.010	0.368	0.001	0.061	0.411

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; earlier part: moths 4 through 10.

Table B4 (full results of Table 5): Ticket-related behavior in the later part of the next season

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.018* (-1.91)	-0.016* (-1.74)	-0.006 (-0.69)	-17.075*** (-2.69)	-16.518*** (-2.62)	-9.744* (-1.89)	-59.426** (-2.00)	-65.258** (-2.28)	-51.115** (-2.19)
Number of tickets at t		-0.013*** (-2.87)	-0.010*** (-2.76)		2.703 (1.00)	1.895 (0.86)		27.440** (2.34)	17.402* (1.82)
average value of ticket at t		0.000*** (2.72)	0.000 (1.39)		0.654*** (11.41)	0.313*** (6.28)		2.905*** (11.33)	1.666*** (6.67)
dummy customer at t-1			0.143*** (11.24)			-157.171*** (-18.45)			- 324.866*** (-10.25)
average value of ticket at t-1			0.000** (2.57)			2.161*** (21.47)			3.589*** (10.79)
number of tickets at t-1			0.016*** (13.47)			25.424*** (58.24)			26.087*** (27.11)
Constant				68.364*** (12.41)	24.854*** (2.92)	4.732 (0.66)	340.738* (13.39)	114.077*** (3.11)	107.960*** (3.18)
Observations	8900	8900	8900	8900	8900	8900	1663	1663	1663
Pseudo R ² / R ²	0.000	0.002	0.190	0.001	0.015	0.346	0.002	0.077	0.392

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; later part: moths 11 through 15.

Table B5 (full results of Table 6): Ticket-related behavior of donors in the next season

Dependent variable	Logit m.e.			OLS			OLS		
	Dummy customer next season			Ticket revenue next season (including zeros)			Ticket revenue next season (excluding zeros)		
Dummy: facing online fundraising	-0.026** (-2.30)	-0.025** (-2.19)	-0.011 (-1.09)	-32.653*** (-2.60)	-31.622** (-2.53)	-17.172* (-1.82)	-69.035* (-1.87)	-58.045 (-1.60)	-46.022* (-1.66)
Dummy: facing online fundraising * donor dummy	0.160*** (2.64)	0.155** (2.55)	0.131** (2.56)	68.604 (0.95)	55.095 (0.76)	82.349 (1.51)	4.215 (0.02)	-106.413 (-0.62)	31.346 (0.24)
Number of tickets at t		-0.010** (-1.99)	-0.007 (-1.55)		6.878 (1.28)	4.707 (1.16)		29.653* (1.94)	17.735 (1.52)
average value of ticket at t		0.000 (1.13)	-0.000 (-0.19)		1.288*** (11.37)	0.601*** (6.57)		3.927*** (11.82)	2.246*** (7.54)
dummy customer at t-1			0.192*** (11.26)			-347.004*** (-22.22)			-526.554*** (-14.10)
average value of ticket at t-1			0.000*** (2.63)			4.431*** (24.01)			5.397*** (13.09)
number of tickets at t-1			0.029*** (12.10)			57.850*** (72.28)			57.593*** (41.60)
Constant				147.549*** (13.54)	58.680*** (3.48)	14.013 (1.07)	447.111*** (14.09)	150.050*** (3.14)	113.661*** (2.81)
Observations	8900	8900	8900	8900	8900	8900	2771	2771	2771
Adjusted R ²	0.001	0.002	0.191	0.001	0.015	0.438	0.001	0.050	0.445

Notes: sample of one-time buyers at the time of the online fundraising campaign, 2 weeks before, and 2 weeks after; z- and t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; there are 50 donors in this sample.

Appendix C: frequent buyers

Figure 1 illustrates the importance of the 1,136 more frequent buyers, 22 of which made 31 donations, yielding an overall response rate of 1.9% and return per frequent buyer of €1.43. In the following, we include frequent buyers in our regression analysis but also add interactions of the treatment dummies with a frequent buyer dummy (Table C1). The coefficients on the frequent buyers dummy are positive in all specifications but significant only in some. This suggests an overall higher response rate, higher donations and higher returns from frequent buyers.

Interestingly, the coefficients on the interaction between T3 and frequent buyers are negative in all specifications and they are similar in magnitude to the T3 coefficients (all significant except in the OLS specifications). Based on a Wald test we cannot reject the equality between the (absolute value) coefficients on T3 and the T3*frequent buyer interaction dummy. This suggests that T3 had no effect on frequent buyers, although this may be a spillover effect.

Table C1: Regression analysis: including frequent buyers

Dependent variable:	Logit m.e. donation dummy			OLS return (donation value including zeros)			OLS positive donations		
T1:lower grids	0.007*** (2.63)	0.007*** (2.63)	0.007*** (2.59)	0.123** (2.06)	0.123** (2.06)	0.112* (1.89)	-2.100 (-0.36)	-5.409 (-0.70)	-6.475 (-0.53)
T3: forced statement	0.010*** (3.53)	0.010*** (3.47)	0.010*** (3.57)	0.485*** (2.83)	0.458** (2.51)	0.474*** (2.63)	17.927 (1.64)	20.282 (1.38)	8.621 (0.51)
T1* frequent buyer	-0.004 (-1.12)	-0.004 (-1.12)	-0.004 (-1.22)	-0.285* (-1.81)	-0.275* (-1.76)	-0.298* (-1.89)	-42.380* (-1.98)	-26.258 (-1.34)	-19.505 (-0.93)
T3* frequent buyer	-0.010** (-2.01)	-0.010** (-2.00)	-0.010** (-2.14)	-0.745** (-2.20)	-0.715** (-2.24)	-0.763** (-2.28)	-62.170 (-1.62)	-49.971** (-2.07)	-35.610 (-1.58)
frequent buyer	0.005 (1.53)	0.005 (1.52)	0.007 (1.63)	0.432 (1.59)	0.471 (1.53)	0.676 (1.46)	53.636 (1.46)	40.866* (1.98)	36.554* (1.67)
number of tickets		-0.000 (-0.22)	0.000 (0.17)		0.213 (0.87)	0.275 (1.00)		15.183 (1.42)	18.826* (1.98)
average value of ticket		-0.000 (-0.03)	-0.000 (-0.29)		0.002 (0.85)	0.002 (0.77)		0.068 (0.75)	0.071 (0.61)
dummy customer in previous season			0.000 (0.07)			-0.089 (-0.52)			-1.396 (-0.08)
number of tickets previous season			-0.000 (-1.59)			-0.003 (-1.42)			-0.160 (-0.32)
average value of ticket previous season			0.000 (0.86)			0.001 (0.35)			-0.018 (-0.11)
Performance type dummies			yes			yes			yes
Day of week dummies			yes			yes			yes
Observations	13041	13041	13041	13041	13041	13041	96	96	96
Pseudo R ² /R ²	0.017	0.017	0.034	0.001	0.003	0.006	0.084	0.290	0.420
Wald test	0.8491	0.8505	0.9676	0.3742	0.3724	0.3142	0.2316	0.1371	0.1906
T3-- T3* frequent buyer									

Notes: full sample (with buyers present in different treatments), z- and t- statistics in parentheses, errors clustered at the individual level; * p < 0.10, ** p < 0.05, *** p < 0.01, m.e.: marginal effects.

Appendix D: one-time buyers

Table D1: Individual level comparisons (analogue to Table 1 but with one time buyers only):

				Ticket-related behavior			Giving behavior			
		Number of days	N	Average single ticket value (in €)	Average total money spent excluding donation (in €)	Average number of tickets (without donation)	Average per buyer return (including zeros) (in €)	response rate	Average positive donation	Median donation per donor
T1: lower grids	(1)									
T2: higher grids	(2)	39	3063	55.722 (0.826)	120.31 (2.20)	2.18 (0.02)	0.098 (0.032)	0.004 (0.001)	27.27 (3.83) N=11	20
T3: forced statement	(3)	20	1825	65.346 (1.224)	143.30 (3.35)	2.19 (0.03)	0.619 (0.184)	0.014 (0.003)	45.20 (10.15) N=25	20
T-test, p-value	(1)=(2)			0.349	0.139	0.749	0.087	0.019	0.875	
MWU-test, p-value	(1)=(2)			0.244	0.315	0.322	0.020	0.019	0.111	
T-test, p-value	(2)=(3)			0.000	0.000	0.651	0.000	0.000	0.259	
MWU-test, p-value	(2)=(3)			0.000	0.000	0.135	0.000	0.000	0.446	

Table D2: Individual level comparisons (analogue to Table 2 but with one time buyers only):

Dependent variable:	Logit m.e. donation dummy			OLS return (donation value including zeros)			OLS positive donations		
T1:lower grids	0.006** (2.19)	0.006** (2.19)	0.006** (2.07)	0.114* (1.71)	0.113* (1.68)	0.096 (1.47)	-1.273 (-0.20)	-0.923 (-0.15)	-1.456 (-0.15)
T3: statement required	0.010*** (3.37)	0.010*** (3.34)	0.010*** (3.38)	0.521*** (2.80)	0.530*** (2.68)	0.516*** (2.67)	17.927 (1.65)	19.617* (1.92)	12.576 (1.11)
number of tickets		-0.001 (-0.74)	-0.001 (-0.55)		-0.078 (-1.09)	-0.030 (-0.69)		-3.682 (-1.04)	-2.088 (-0.64)
average value of ticket		-0.000 (-0.18)	0.000 (0.07)		-0.001 (-0.56)	-0.000 (-0.08)		0.064 (1.00)	0.213** (2.25)
dummy customer in previous season			0.004 (1.22)			0.179 (0.92)			24.816 (1.18)
number of tickets previous season			-0.000* (-1.70)			-0.007** (-2.29)			-1.103 (-0.66)
average value of ticket previous season			0.000 (0.48)			-0.000 (-0.18)			-0.324* (-1.69)
Performance type dummies			yes			yes			yes
Day of week dummies			yes			yes			yes
Observations	7950	7950	7950	7950	7950	7950	61	61	61
Pseudo R^2 / R^2	0.022	0.024	0.054	0.002	0.003	0.006	0.062	0.081	0.201

Notes: sample of one-time buyers only, z- and t- statistics in parentheses, robust errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, m.e.: marginal effects.