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Online Fundraising, Self-Image, and the Long-Term Impact of Ask Avoidance

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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 for a social youth project 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 the fundraising campaign for ticket sales. “Avoiding the ask,” opera customers who faced more insistent online fundraising buy fewer tickets in the following season. Our results suggest that fundraising management should not decide in isolation about their campaigns, even if very successful. Rather broader operational concerns have to be considered.

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

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

1 Introduction

Over the last decade online fundraising has gained enormous popularity among fundraising managers. Its key advantage is, of course, 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 among the fundraising managers of arts charities: an ask at the time of checkout when customers buy tickets for an event. In our case, an opera house asks for support for a social youth project introducing disadvantaged school children to the world of opera. We study three incarnations of that ask by varying the donation interface within the booking platform of the opera house. After establishing a baseline, we pushed up the grid of suggested donations in the expectation that it would increase donations. This failed miserably. We then introduced an apparently minor change in the interface, forcing customers who want to continue without a donation to tick one of two boxes that were already present before. One box says “I have donated already,” the other “No, thank you.” As we will document, this minor change in the choice architecture has strong positive effects on 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 below). 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, List, and Malmendier (2012) and Andreoni, Rao, and Trachtman (2017) 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 entrances 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 two check boxes (“I have donated already" and "No, thank you"). Customers could always "explain" their decision not to give by saying that they had given before or adding the 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 – their (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. We provide a model sketch for such behavior in the spirit of Bodner and Prelec (2003) and Bénabou and Tirole (2006) where customers can protect their "diagnostic" or "ego utility" through self-deception.

Finally, we observe that customers "learn to avoid the ask" in the long run. One year later, customers who were forced to admit that they were non-donors buy fewer tickets through the online platform than those who were not forced to do so. Luckily, however, the total effect on tickets purchased through all the possible means (including box office, mail and phone) is smaller and not significant suggesting that customers simply changed the channel through which they acquired tickets. In other contexts where such substitution is more difficult more severe consequences could have materialized. This suggests that fundraising management has to be holistically integrated into larger operational concerns and with success measures that transcend beyond the narrow realm of net proceeds from fundraising as such.

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 a simple model with ego utility that can explain self-deception by an egoistic type. Section 4 describes the design of our study and the data. Section 5 and 6 provide the main results and Section 7 adds a discussion. Finally, Section 8 concludes.

2 Related literature

Online fundraising. With the rise of the internet, online fundraising has become ever more popular and economically important. Smith, Windmeijer, and Wright (2015) document how online fundraising has become a major source of income for many UK charities. The total revenue of the biggest individual online fundraising 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. Germany's biggest platform, Betterplace.org, collected a total of €1.17 million in revenues for charitable organizations over an eleven month period in 2012/13 (Altmann et al. 2014).

There is a growing number of online experiments and field studies that either consider donation platforms (Altmann et al. 2014; Meer 2014), environments in which the fundraiser actively asks for donations (Chen, Li, and MacKie-Mason 2006; Exley and Petrie 2016) or other forms including peer-to-peer solicitations (Bøg et al. 2012; Castillo, Petrie, and Wardell 2015; Elfenbein, Fisman, and McManus 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.

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, Weber, and Kuang (2007) individuals behave less pro-socially in the laboratory 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 through satiation in self-signaling at the earlier stage 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. In contrast, Grossman and van der Weele (2017) are able to identify the role of self-signaling in a laboratory study. Mazar, Amir, and Ariely (2008) suggest that individuals behave dishonestly when it pays but are willing to incur significant costs to maintain their self-image. Bénabou and Tirole (2006) propose a model which combines the different motives in prosocial behavior including self and social signaling and 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 as non-donors they are forced *to admit to themselves* that they are indeed 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, List, and Malmendier (2012) and Andreoni, Rao, and Trachtman (2017). 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 show the hidden costs of reminders: annoyance costs for the solicited and long-term effects on donations for the charity. Knutsson, Martinsson, and Wollbrant (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.

Defaults and donation grids. It is popular in fundraising to suggest 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, Huck, and Rasul (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. Altmann et al. (2014) 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 to support the running costs of the online platform, donations do increase with defaults. Finally, 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 of 24%.

3 A model sketch

We can capture the role of self-deception in our online environment with a model in the spirit of Bodner and Prelec (2003) and Bénabou and Tirole (2006) where decision making has two elements: a choice component based on true consumption preferences and a judgement module that also cares for diagnostic or ego utility. See also Dubé, Luo, and Fang (2016) for a similar approach in a similar context – cause marketing where the sale of an object is bundled with a charitable donation. Specifically, we consider the case where decision makers have some uncertainty about their own type, here their prosocial attitude, and derive ego utility that is increasing in their belief that they are a "good" type, that is, a type who cares about others.

Let us sketch the simplest version of such a model. We assume that there are just two types, an egoist and an (imperfect) altruist. The decision maker's consumption utility is $u(x) + v(c)$ where x denotes private consumption and c the donation to a charitable good, with $u' > 0$, $u'' < 0$ for both types, $v' > 0$, $v'' < 0$ for the altruistic type and $v' = 0$ for the egoistic type.

Consumption utility is driving choices. Total utility is modelled as:

$$U(x, c, \beta) = u(x) + v(c) + E(\beta)$$

where $E(\beta)$ is the ego utility derived from attaching a probability of $\beta \in [0,1]$ to being the altruistic type. In such a setup the decision maker can strategically manipulate his decision in order to protect his ego utility.

Let I denote the decision maker's disposable income. Then in the absence of ego utility or, to be more precise, for constant ego utility (that is, for $E' = 0$) the decision maker will make a donation if and only if $u'(I) < v'(0)$. For the egoistic type this is, of course, never the case but let us suppose that at income level I, the condition holds for the altruist such that he would make a donation of c^* in the absence of ego utility.

Once $E' > 0$, things become more interesting as the decision maker is now engaged in a self-signaling game. Let the decision maker's prior in this game be denoted by $\hat{\beta}$ and let us assume that the decision maker, once he expresses his decision not to donate cannot fool himself into believing that he did. For off-equilibrium beliefs that satisfy the intuitive criterion there are two equilibrium candidates for this game: (A) a pooling equilibrium where both types donate c^* and (B) a separating equilibrium where the altruist donates and the egoist does not. Pooling with both types not donating would not satisfy the intuitive criterion as the altruist could deviate to making a donation, increasing both, his consumption and ego utility. For our purposes the interesting equilibrium candidate is (A) where both types donate. This equilibrium exists if $u(I - c^*) + E(\hat{\beta}) > u(I) + E(0)$, that is, if the egoist's self-revelation to be the egoist weighs heavily enough on him to make a *strategic* donation. The same condition rules out equilibrium type (B).

Things change once we introduce the option for decision makers to forget a past choice or trick themselves into believing there was no choice to be made. This is exactly what a direct click on the "proceed" button – without ticking one of the two boxes explaining the choice – may achieve. In this case the egoist has the possibility to preserve his prior by clicking on the "proceed" button conveniently "overlooking" the fundraising call. In this case, the two types will separate but learning will be incomplete: while the altruist learns his type by making donation c^* and achieving total utility $u(I - c^*) + v(c^*) + E(1)$, the egoist successfully fools himself thinking that he did not make a decision achieving total utility of $u(I) + E(\hat{\beta})$. In other words, the egoist preserves his self-image by engaging in self-deception.

4 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.[1] 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 Appendix A show the exact implementation. The last period continued for 20 days and the online fundraising campaign was completely suspended afterwards.

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, Huck, and Rasul (2014) which studied the effect of nonbinding suggestions.[3]

[1] The suspension occurred during Easter holidays.
[2] The fiscal year in Germany ends in December, almost a month before the online campaign started.
[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.

4.1 Sample and empirical strategy

The sample consists of 8,442 customers that arrived at the platform in the period under study. We exclude *frequent* buyers (1,136) who arrived in at least two different treatments in order to avoid spillover effects (Appendix A4 offers some additional analysis including frequent buyers). Although there was no random assignment into treatments, the decision when to buy tickets does not depend on treatments directly. However, different compositions of customers and pools of tickets over time potentially pose a challenge for the identification of the effects of interest. Appendix A2 offers some descriptive statistic at the level of treatments and day by day. It also describes the composition of the available tickets and buyers at the platform, the numbers and the types of tickets bought and the prices in detail. Importantly, given a day by day release of new tickets, the available ticket pool remains approximately constant over time.[4] There are some differences between treatments in terms of total spent on tickets and the number of tickets bought, however, they do not seem to favor one treatment over another (see Table A1). In our empirical strategy, we make sure that any potential differences between treatments other than our experimental variation do not affect our results. First, we control for an extensive set of observables including the following variable categories: flexible ticket controls at time of purchase, past season controls, performance controls, time controls, and demographics. Second, when adding the above variable categories separately, the magnitude of coefficients of interest remains stable, which suggests that, under any correlation between observables and unobservables, unobservables are not driving our results. Third, we show that the magnitude of the coefficients of interest does not depend on the specific timing. We present results using much shorter periods around the change in treatment. Since the timing of the change in treatments was unknown to customers, those who arrived shortly before or shortly after the change landed in a particular treatment quasi randomly. Finally, we show that specific types of customers are not driving our results.

[4] The exceptions are festival tickets for which we control in the main analysis.

5 Individual-level results

In Tables 1 and 2 we regress giving behavior on our treatments at the individual level. In Table 1 the results are presented in terms of the response rates (logit specification with a donation dummy as a dependent variable) and in Table 2 in terms of the return to fundraising (OLS regression with donation value including zeros as a dependent variable).[5] The base treatment is T2, since we are primarily interested in comparisons between T1–T2 and T2–T3. Different columns present results after inclusion of different sets of controls, and Column V shows the results after the inclusion of all controls. Gender dummies for female and other (for couples and other) are included in all specifications. The OLS specification also includes corporate dummy.[6] Ticket controls at *t* reflect current prices and individual demand. They include: individual average value of tickets, individual average value of tickets squared, individual average value of tickets cubed, individual number of tickets, daily average value of tickets. Past season controls that we found to be relevant for the time of arrival at the platform include: dummy customer in previous season, number of tickets in previous season, individual average value of tickets in previous season, and dummies for means through which tickets had been ordered in previous season dummy (box office, mail, phone). Performance controls reflect individual tastes and include: separate performance dummies for five performances with the largest number of tickets in the sample (A Midsummer Night's Dream, Rigoletto, The Yellow Sound, Salome, Boris Godunow), performance type dummies (Opera North,[7] Other Opera, Ballet, Other, the excluded category is Concert), and a festival ticket dummy. Note that a number of the performances (including those listed above) were played repeatedly, and the period in which the tickets were sold spanned different treatments. By including performance dummies, we can compare the reactions to different treatments by people who decided to attend the same performance.[8] Finally, time controls relate to the timing of arrival at the platform and include: time to performance, time to performance x festival ticket dummy, day of week dummies. The coefficients on T1 and T3

[5] Last column in Table 4 additionally presents results from a Tobit regression, and Table A3 in the Appendix shows results from rare events logit.
[6] In logit specification the corporate dummy is dropped because of collinearity (no corporate is a donor in our sample).
[7] The category Opera North includes mostly German language operas by Richard Strauss, Richard Wagner, and others. The category Other Opera includes mostly Italian language operas.
[8] This approach is close to having performance fixed effects. A complete fixed effects approach is not feasible.

remain relatively stable independent of the set of controls included and strongly suggest that the effects found can indeed be attributed to the treatment variations.

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.[9] The same holds for the return per buyer, which is significantly higher in T1 by around 11 cents and in T3 by around 46 cents.

Table 1: Response to fundraising

Dependent variable: donation dummy

Specification	Logit m.e.				
	I	II	III	IV	V
T1:lower grids	0.007***	0.007***	0.007***	0.007***	0.007***
	(2.81)	(2.78)	(2.60)	(2.99)	(2.68)
T3: statement required	0.010***	0.010***	0.011***	0.009***	0.010***
	(3.24)	(3.64)	(3.48)	(3.65)	(2.86)
Ticket controls at t	yes				yes
Past season controls		yes			yes
Performance controls			yes		yes
Time controls				yes	yes
Demographics	yes	yes	yes	yes	yes
Observations	9028	9028	9028	9028	9028
Pseudo R^2	0.039	0.043	0.044	0.042	0.072
Wald Test T1≥T3, p-value	0.094	0.065	0.035	0.110	0.119

Notes: non-frequent buyers; unit of observation: buyer per day; errors clustered at the day level; z-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, m.e.: marginal effects;
Ticket controls at t include: individual average value of tickets, individual average value of tickets squared, individual average value of tickets cubed, individual number of tickets, daily average value of tickets;
Past season controls include: dummy customer in previous season, number of tickets in previous season, individual average value of tickets in previous season, box office in previous season dummy, letter in previous season dummy, phone in previous season dummy;
Performance controls include: separate performance dummies for five performances with the largest number of tickets in the sample (A Midsummer Night's Dream, Rigoletto, The Yellow Sound, Salome, Boris Godunow), performance type dummies (opera nord, other opera, ballet, other, excluded category is concert), festival ticket dummy;
Time controls include: time to performance, time to performance x festival ticket dummy, day of week dummies;
Demographics include female and other dummy.

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 rejects the null T1≥T3 at p<0.10 in all response

[9] Table A3 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.

specifications and at p<0.05 in all return specifications (except Tobit, see bottom of Table 1 and Table 2). This suggests that the loss from the introduction of higher grids was more than compensated by the change in website navigation.

Table 2: Return from fundraising

Dependent variable: donation value including zeros

Specification:	OLS					Tobit m.e. y*
	I	II	III	IV	V	VI
T1:lower grids	0.121**	0.125**	0.091	0.136***	0.110**	0.249***
	(2.24)	(2.32)	(1.47)	(2.74)	(2.04)	(2.92)
T3: statement required	0.489***	0.489***	0.481***	0.453***	0.457**	0.373***
	(2.87)	(3.18)	(2.87)	(3.10)	(2.44)	(3.16)
Ticket controls at t	yes				yes	yes
Past season controls		yes			yes	yes
Performance type controls			yes		yes	yes
Time controls				yes	yes	yes
Demographics	yes	yes	yes	yes	yes	yes
Observations	9028	9028	9028	9028	9028	9028
R^2 /Pseudo R^2	0.004	0.003	0.005	0.003	0.007	0.042
Wald Test T1≥T3, p-value	0.0204	0.0129	0.0226	0.0174	0.0417	0.2024

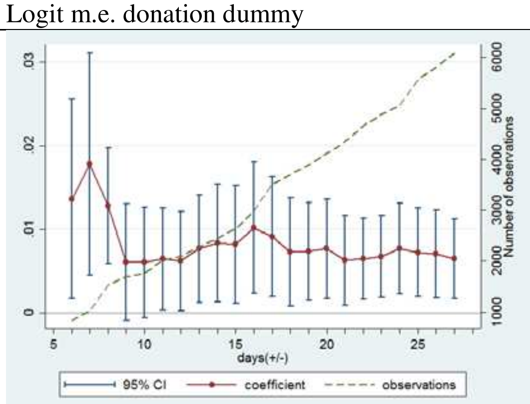
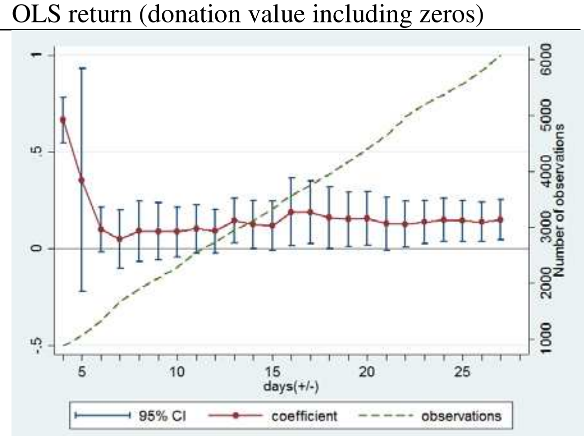
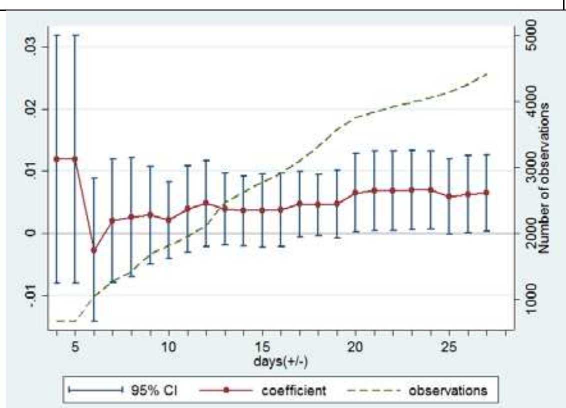
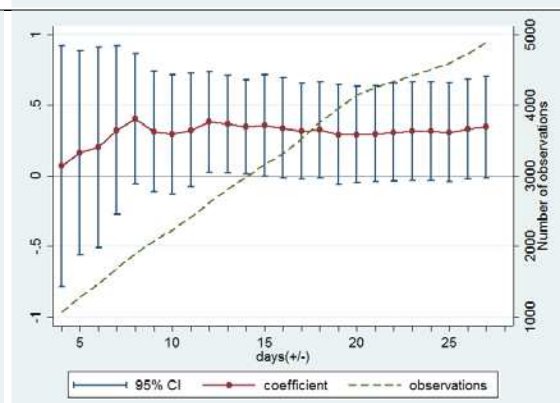
Notes: see notes to Table 1; t- and z-statistics in parentheses, Marginal effects after Tobit with lower limit set to zero in Column VI; demographics include female, corporate, and other dummy in OLS specifications.

We also show that the results do not depend on the specific timing. In order to address the additional worry about potential time trends influencing our results, we present results using much shorter periods around the change in treatment. Since the timing of the change in treatments was unknown to customers, those who arrived shortly before or shortly after the change landed in a particular treatment quasi randomly. Therefore, we repeat our analysis by looking only at individuals who arrived shortly before or after the change. Starting with 4 days before and after, we extend the sample day by day and present the coefficients on treatment dummies with confidence intervals for the donation probability and average return in Figure 1.

We see that both coefficients (for T1 and T3) are (almost) independent of the time span analyzed. Similar magnitudes to those obtained for the full sample are already estimated with a very small sample and time span. We also offer a placebo exercise showing that there is no similar effect of a fictitious treatment dummy (Figure A5 in the Appendix A). Specifically, we take the respective

T1, T2, and T3 periods separately and create a set of fictitious treatment dummies for the first 3, 4, 5, up to (n-3) days. Figure A5 in the Appendix shows the regression results analogue to the above. We see that almost all estimated coefficients (126 out of 128) are not statistically significant, and most are very close to zero. Only the coefficients for the return at the end of the T2 period and during the T3 period are somewhat larger and closer to being significant. This, however, points toward an opposite time trend (if any), that should have made finding the real T3 effect rather more difficult. Overall, we conclude that the effects that we find cannot be accounted for by any time specific trends other than implied by our treatments.

Figure 1: Regression coefficients from a series of regressions spanning an increasing number of days around the change in treatments

	Logit m.e. donation dummy	OLS return (donation value including zeros)
T1: lower grids		
T3: forced statement		

Notes: all regressions are at the individual level and include the full set of controls (exceptions: festival tickets and their interaction with time is dropped in both upper graphs since festival tickets started to be available only at the end of T2, some other are dropped in small samples), see notes to Table 1 and Table 2. Right y axis shows the number of observations used in the estimation. Days (+/-) is the number of days around the change from T1 to T2 in the upper graphs and from T2 to T3 in the lower graphs. The upper left graph starts at +/- 6 days since the smaller sample does not converge.

Table 3: Heterogeneity

	Probit m.e.: donation dummy		OLS: return (donation value including zeros)	
	I	II	III	IV
T1:lower grids	0.007*	0.008***	0.024	0.134**
	(1.84)	(2.88)	(0.41)	(2.49)
T3: statement required	0.011**	0.013***	0.478*	0.574***
	(2.41)	(3.32)	(1.88)	(2.82)
T1 x past customer	-0.005		0.121	
	(-0.69)		(0.55)	
T3 x past customer	-0.005		-0.095	
	(-0.74)		(-0.21)	
T1 x average ticket value in past season above median	0.009*		0.311	
	(1.78)		(0.92)	
T3 x average ticket value in past season above median	0.005		0.021	
	(0.86)		(0.05)	
T3 x festival ticket dummy		-0.024**		-1.098***
		(-2.50)		(-4.08)
Ticket controls at t	yes	yes	yes	yes
Past season controls	yes	yes	yes	yes
Performance type controls	yes	yes	yes	yes
Time controls	yes	yes	yes	yes
Demographics	yes	yes	yes	yes
Observations	9028	9028	9028	9028
Pseudo R^2 /R^2	0.076	0.078	0.007	0.007

See notes to Table 1 and Table 2.

Given differences in the timing of arrival of past customers presented in Appendix A2.3 and the specific timing for summer festival ticket buyers, we now analyze whether those groups are potentially driving our results. In Table 3, we add interaction terms between treatment dummies and the past customer dummy as well as between treatment dummies and the individual average ticket price in the previous season to our main specification (Column II and IV). We find no interaction effects. Importantly, the coefficients on T3 for the probability of giving and the return, and the coefficient on T1 for the probability of giving remain almost unchanged from their previous values (only the T1 coefficient for the return declines and loses significance). This leads us to the conclusion that the treatments work in a similar way for both past customers and new customers, and independently of the amount spent on tickets in the last year. Beyond that, we also test whether there are any interaction effects of festival ticket buyers with the T3 dummy (no festival tickets were sold in T1, therefore no interaction with T1, see Columns I and III). We find that festival ticket buyers respond less to T3. However, the main coefficient on T3 remains significant and even increases in magnitude.

6 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. We use the same sample of non-frequent customers (8442 individuals) that was used in the previous analysis. The base treatment is, again, T2. Specifically, we are interested in the effect of T3 relative to T2, that is, the effect of exerting more pressure on customers on ask avoidance. This is similar to the endeavours in Andreoni, Rao, and Trachtman (2017) and DellaVigna, List, and Malmendier (2012). However, in contrast to the immediate effects measured in these studies, we are interested in long-term persistence of ask avoidance.

We run a set of regressions analogous to the previous section but now with next-season outcomes, specifically, the number of tickets purchased online (Table 4), online ticket revenue (Table 5), the total number of tickets purchased (also through the box office, mail, telephone, Table 6), and the total revenue (Table 7). The specifications include exactly the same set of controls as previously, and errors are, equally, clustered on day level.[10]

The results suggests that the more intensive fundraising in treatment T3 relative to the base treatment T2 has adverse long-term effects on online tickets and online revenue. Customers who were forced to admit being a non-donor during an online fundraising buy significantly fewer tickets online in the next season. The online return from those customers is lower as well.[11] However, when accounting for all means through which tickets can be purchased the results turn non-significant in specifications with the full set of controls. This suggests substitution between different means to buy tickets. Customers avoid the online ask by purchasing tickets on the phone or at the box office.

Our results are similar to "avoiding the ask" in DellaVigna, List, and Malmendier (2012) and Andreoni, Rao, and Trachtman (2017). However, the novelty of our findings is, that the ask avoidance at the ticketing platform persists over the long-term. This should have important

[10] Refers to the purchase at *t*, for customers with multiple purchases, we take the very first day.

[11] In Tables A4-A7 in the Appendix we present analogous results from Tobit regressions. The regressions with the number of tickets as a dependent variable lead to equal conclusions. The regressions with total return as dependent variable show less significance of the coefficients that the OLS regressions.

consequences for firms and organizations for which fundraising is not the primary task like the opera house. Such firms and organizations need to understand how fundraising activities interact with other operational aspects and how they affect other sources of revenue. Of course, adverse short- and long-term effects of ask avoidance might be compensated through potential long-term positive effects stemming from those individuals who do choose to donate. In our case donors appear to be more loyal customers, buying more tickets, and spending more money in the next season (Tables 4–7).

Finally, the substitution between the tickets bought online and through other channels relates to Lacetera, Macis, and Slonim (2012). They observed that blood donors in the US left neighboring drives without incentives to attend blood drives with incentives. Our results suggest that, when studying fundraising and other interventions, we need to take a broad perspective. Partial equilibrium and short-term results might be misleading. Our evidence is the first to point to long-term effects of fundraising campaigns.

Table 4: Long-term effects on tickets online

Dependent variable: number of tickets online in the next season (including zeros)

Specification: OLS

	I	II	III	IV	V	VI
T1: lower grids	-0.305	-0.288	-0.229	-0.093	-0.358	-0.222
	(-1.11)	(-1.40)	(-1.39)	(-0.48)	(-1.51)	(-1.49)
T3: statement required	-0.622**	-1.095***	-0.369*	-0.733***	-0.646**	-0.430**
	(-2.19)	(-3.65)	(-1.93)	(-3.21)	(-2.56)	(-2.22)
Donor dummy		1.392	0.940	1.402	1.496*	1.029*
		(1.58)	(1.49)	(1.62)	(1.70)	(1.71)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
R^2	0.003	0.063	0.275	0.043	0.047	0.309

Notes: see notes to Table 1; t-statistics; demographics include female, corporate, and other dummy.

Table 5: Long-term effects on revenue online

Dependent variable: online ticket revenue in the next season (ticket value including zeros)

Specification: OLS

	I	II	III	IV	V	VI
T1: lower grids	-26.173*	-24.538**	-19.837**	-15.609	-23.148**	-19.911***
	(-1.68)	(-2.24)	(-2.07)	(-1.62)	(-2.41)	(-2.72)
T3: statement required	-22.972	-52.594***	-16.782	-34.960***	-28.290**	-16.861*
	(-1.43)	(-2.94)	(-1.54)	(-2.66)	(-2.40)	(-1.73)
Donor dummy		63.555*	43.125	63.179*	66.347**	46.780*
		(1.96)	(1.60)	(1.97)	(2.04)	(1.80)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
R^2	0.002	0.049	0.196	0.034	0.032	0.219

Notes: see notes to Table 1; t-statistics; demographics include female, corporate, and other dummy.

Table 6: Long-term effects on all tickets

Dependent variable: number of tickets (all means including online, box office, mail, and phone) in the next season (ticket value including zeros)

Specification: OLS

	I	II	III	IV	V	VI
T1: lower grids	-0.432	-0.406	-0.230	-0.083	-0.518	-0.183
	(-0.90)	(-1.13)	(-1.14)	(-0.26)	(-1.37)	(-1.07)
T3: statement required	-0.834*	-1.673***	-0.217	-1.061***	-0.899**	-0.267
	(-1.75)	(-3.15)	(-0.91)	(-2.66)	(-2.16)	(-1.13)
Donor dummy		1.584	0.721	1.619	1.746*	0.832*
		(1.48)	(1.57)	(1.56)	(1.67)	(1.86)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
R^2	0.002	0.048	0.556	0.034	0.043	0.567

Notes: see notes to Table 1; t-statistics; demographics include female, corporate, and other dummy.

Table 7: Long-term effects on whole ticket revenue

Dependent variable: ticket revenue (all means including online, box office, mail, and phone) in the next season (ticket value including zeros)

Specification: OLS

	I	II	III	IV	V	VI
T1: lower grids	-28.609	-26.563	-13.721	-11.832	-24.369	-12.439
	(-1.07)	(-1.38)	(-1.09)	(-0.72)	(-1.48)	(-1.28)
T3: statement required	-24.915	-76.145**	-5.199	-46.769**	-39.003*	-1.796
	(-0.94)	(-2.54)	(-0.36)	(-2.10)	(-1.91)	(-0.13)
Donor dummy		76.033*	26.173	74.624*	77.902*	29.492
		(1.88)	(0.70)	(1.83)	(1.90)	(0.79)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
R^2	0.001	0.054	0.400	0.042	0.041	0.410

Notes: see notes to Table 1; t-statistics; demographics include female, corporate, and other dummy.

7 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. This suggests that customers were successfully deceiving themselves in T2, behaving just as if the donation request had not been there, and thereby protecting their prior belief about their own type. When the act of declining becomes more salient, they are less likely to avoid it, and some egoistic types may now decide to give. This is related to the “avoiding the ask” phenomenon studied by DellaVigna, List, and Malmendier (2012) and Andreoni, Rao, and Trachtman (2017). In DellaVigna, List, and Malmendier (2012), individuals were less likely to be at home when they knew that a solicitor was coming. In Andreoni, Rao, and Trachtman (2017) 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 their environments. 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 per person (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, Rao, and Trachtman (2017) and DellaVigna, List, and Malmendier (2012) leads to a conclusion that, overall, the fundraising campaigns analyzed were welfare enhancing. Beyond the short-term effect of ask avoidance documented in these studies our results indicate a long-term effect, here on the number of tickets and ticket revenue for opera performances purchased online. This effect is negative for non-donors who faced the online fundraising campaign and positive for actual donors. In order to evaluate the overall success of fundraising activities such long-term costs (that potentially arise in other operational arm of an organization) should be considered.

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, Huck, and Rasul (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.

Post-Study Probability. How confident are we about our findings? The sole reliance on statistical significance can lead to false positives. As Maniadis, Tufano, and List (2014) highlight, the rate of false positives depends on statistical power, research priors, and the number of scholars exploring the question. Indeed, there has been some work done recently on image concerns in charitable giving and ask avoidance. Although our findings are novel in at least two ways (pure self-image in the field, long-term effects of ask avoidance), they are a logical continuation of previous research. In a general sense (see Levitt and List 2009), our study can be seen as a replication of the previous studies of ask avoidance: we test the previous hypotheses with new research designs. For example, in Section 6 we test the ask avoidance hypothesis in a different setting than the previous studies do, but we largely addresses the same question. Our results point in the same direction as the previous findings. Now, we provide a fourth study in favor of ask avoidance additional to DellaVigna, List, and Malmendier (2012), Andreoni, Rao, and Trachtman (2017), and Trachtman et al. (2015) (although, we do not know how many studies with null results were undertaken and not published). Following Maniadis, Tufano, and List (2014), we compute the change in the *post-study probability* after our replication (see Table A9 in the Appendix). The conclusions are that (i) even with a very low prior it is difficult to believe that all four papers find results that are a statistical artefact, (ii) our replication makes a real difference for the posterior probability if the assumed prior probability is low.

8 Conclusions

In this paper we study an online fundraising campaign introduced on a ticketing platform by an opera house. This is an important setting to study, since an increasing portion of charitable giving is moving online. But the question of "how" and foremost "whether" at all is still open. Especially, it is not clear whether the findings about more traditional fundraising channels (e.g. Landry et al. 2006; Landry et al. 2010; Adena, Huck, and Rasul 2014; Adena and Huck 2017) 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 choice architecture has unexpectedly large positive effects on giving. 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-á-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 evidence of the fundraiser's long-term costs of ask avoidance that result from more insistent fundraising. This suggests that the question of "whether" to engage in additional online fundraising is non-trivial. Overall, we conclude that fundraising management should not take place in isolation but that broader operational concerns require consideration.

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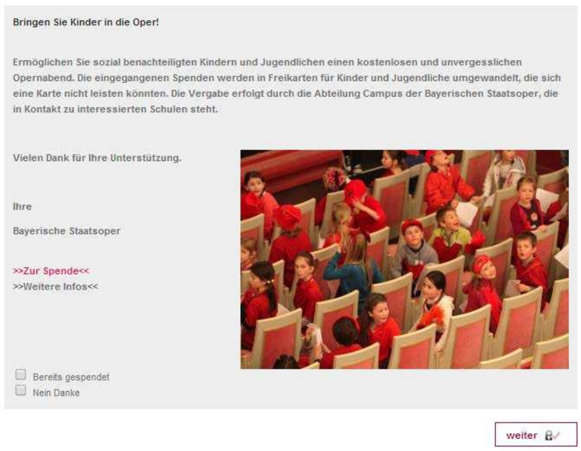
Appendix A (additional information):

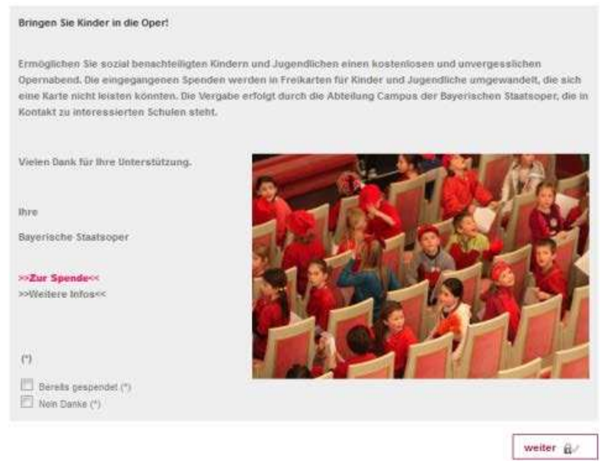
A1: Charity appeal

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

T1 and T2



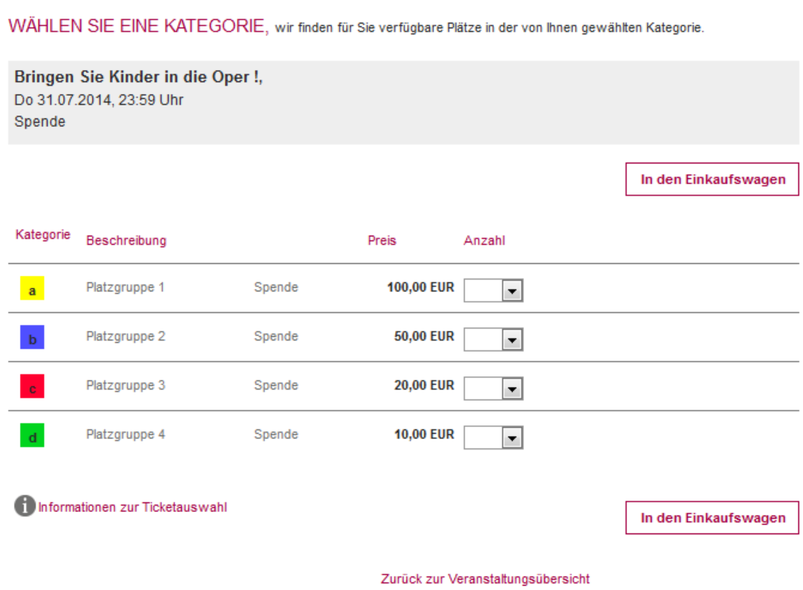
T3



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):



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

A2 Donation and ticket data

A2.1 Overall

In total, 96 donations were made adding up to €3,780 (€39.38 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 type of customers. We distinguish between *one-time buyers*[12] (dotted bars, 7,950 customers); *non-frequent* repeated *buyers* on the condition that they do so only during one distinct treatment (solid bars, additional 492 customers making a total of 8,442); and *frequent buyers* arriving in at least two distinct treatments (striped bars, 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.

For the subsequent analysis, we remove the buyers who arrived at the platform in multiple treatments. In what follows, we shall refer to the remaining customers (one-time buyers and buyers who bought repeatedly in the same treatment) as *non-frequent buyers*. In this sample, there were 8,442 customers in 9,028 visits, who made 65 donations of €33.23 on average. 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.

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

Figure A3: Donation values by Treatment

T1: lower grids

Duration: 28 days;

Grids: €10, €20, €50, €100;

Number of donations: 43

T2: higher grids

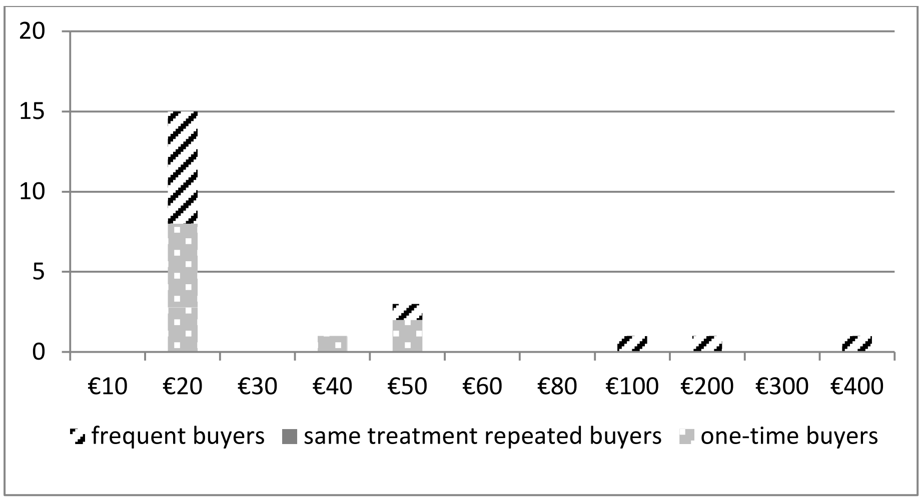
Duration: 33 days;

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

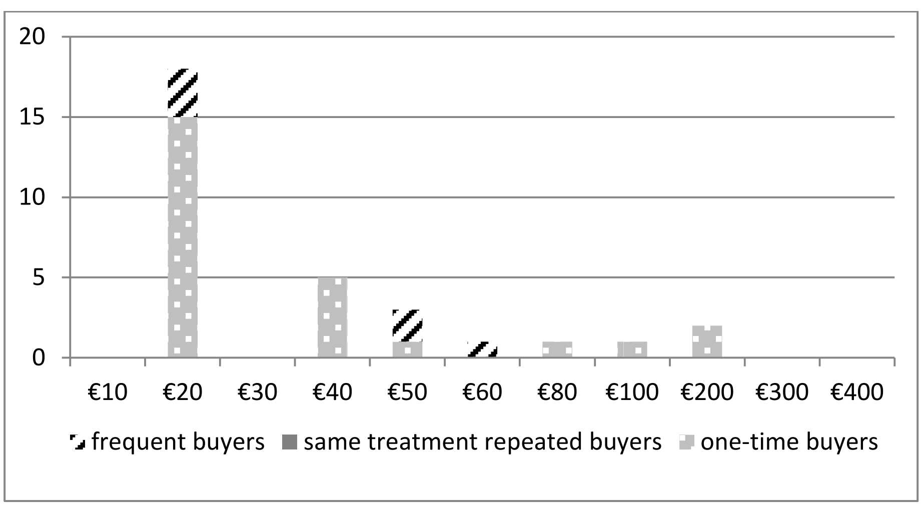


Table A1 presents averages in different treatments in the raw data. The return, average donation including zeros, is more than double in T1(with the lower grid) as in T2 (with the higher grid) (21 cents per buyer versus 9 cents). Crucially, the return increases even further in T3 (higher grids plus forced statement) – to 57 cents. 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%. 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.

Table A1: Averages in different treatments

	Treatment	T1: lower grids			T2: higher grids			T3: forced statement		
	days	28			33			20		
	N	3513			3533			1982		
		mean	s.d.		mean	s.d.		mean	s.d.	
Ticket behavior at t	Average single ticket value (in €)	53.13	0.770		54.3	0.760		64.48	1.180	
	Total money spent excluding donation, including festival tickets (in €)	112.28	2.000		115.23	1.990		139.86	3.160	
	Average number of tickets excluding donation, including festival tickets	2.15	0.018		2.15	0.021		2.18	0.025	
Ticket behavior at t1	Dummy customer	0.309	0.462		0.328	0.470		0.283	0.450	
	Number of tickets	2.737	7.996		3.223	9.374		2.006	6.928	
	Total money spent	132.025	466.404		150.970	423.183		115.516	402.622	
Donative behavior	Average donation per buyer (including zeros) (in €)	0.208	0.053		0.085	0.028		0.57	0.169	
	Dummy response rate	0.008	0.002		0.003	0.001		0.013	0.003	
	Average positive donation	25.17	4.430	N=29	27.27	3.840	N=11	45.2	10.150	N=25
	Median donation	20			20			20		

A2.2 Day-level

<u>Donations</u>

Figure 2, Panel A presents day-level donation data for the sample of non-frequent buyers. Panel B presents the numbers of no-thank-you or already-donated statements checked when choosing not to donate. Distinct treatments are marked with vertical dashed lines. The number of donors, number of donation-tickets chosen, average and total value of donations 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 seems to be reversed after the introduction of the change in website navigation (holding the higher grid constant) in T3.

Finally, we also observe a big jump in the number of "No, thank you" box checks in treatment 3 (Panel B) confirming the role of the change in website navigation.[13]

Tickets

Advance online sales of regular tickets begin at 10 am two months before a performance.[14] If the pre-sale date falls on a Sunday or holiday, the ticket sale starts on the working day before. That means that almost each day new tickets are released and that the pool of available regular tickets should remain approximately the same over time. There was one important exception since shortly before the end of T2 summer festival tickets were released all at once. The festival performances started two months after our online fundraising.

Panel C of Figure 2 presents ticket related daily data. The top left picture shows the daily number of buyers. The number of buyers falls slightly over time for regular performances. There is higher variation in the number of buyers in T1. For example, the first spike marks the release day for the ballet "A Midsummer Night's Dream" (fifth performance out of six that are sold in our period) that accounts for 52 new buyers and for two guest ballet performances "Sasha Waltz & Guests" on two subsequent days that account for 34 new buyers. The three following spikes are the release days for the opera "La traviata" with respectively 70, 113, and 100 unique buyers. On top of 70 buyers of "La traviata," there were 59 buyers of newly released tickets for the opera "Parsifal." Concerning festival ticket buyers, on the first day of the release a relatively large number of buyers arrived (more than 250). After the release day, the numbers stabilized at approximately 25 buyers per day. The top left picture in Panel C shows the number of buyers for different ticket categories separately (excluding festival tickets).[15]

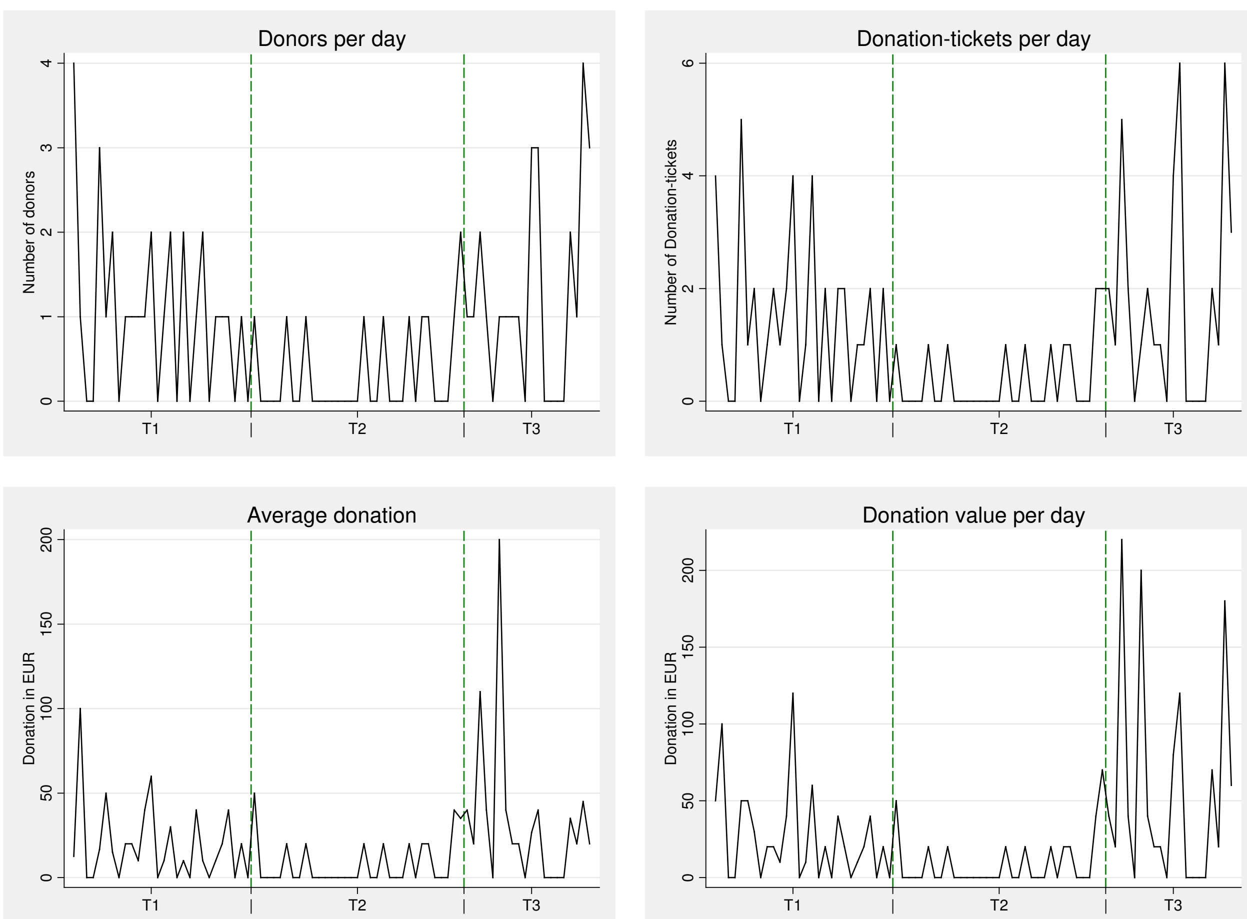
The bottom left picture presents the daily average price of tickets sold. The average for regular

[13] Unfortunately, for box checks, we have only aggregate daily data and cannot link it to the individuals.
[14] Advance sales by the mean of a letter begin three months in advance.
[15] Note that the sum is larger than in the top left picture since some visitors might buy tickets for different performance categories at one visit.

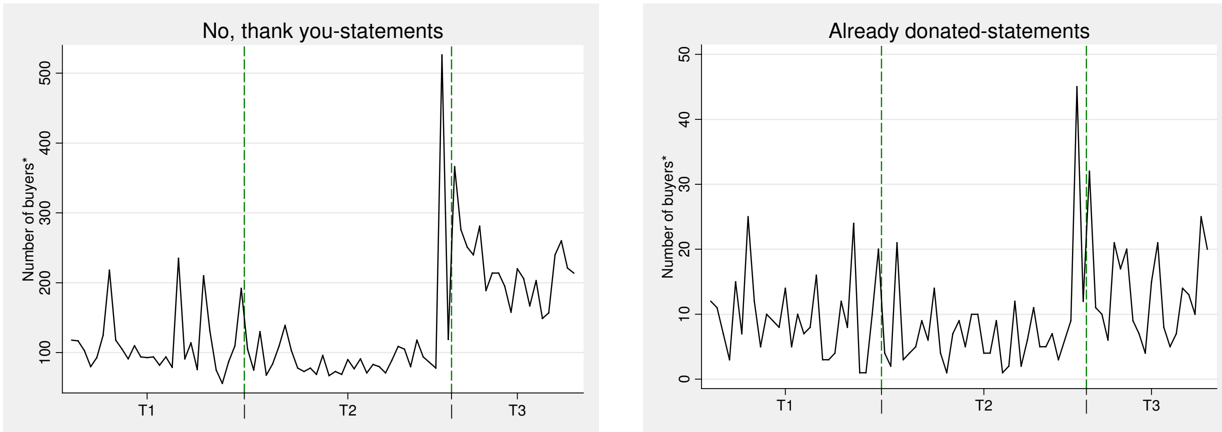
performances was slightly higher at the end of T1 and in T3. The average prices for festival tickets were appx. 50% higher than regular performances. Overall, the average regular ticket price for an opera amounted to €63.23 (ballet €37.92, concert €26.78, other €36.26). For opera tickets during the festival, the average price was €89.78.

The bottom right picture shows the length of time between the purchase and the performance date for regular performances and festival tickets separately. For regular performances there was an U-shaped pattern with most of the tickets bought at the time of release two months before the performance (the spike around 60 days before the showing). More tickets were also sold shortly before the performance date. The festival tickets were bought between 50 and 120 days before the performance (during our period) with slightly more tickets bought earlier than later.

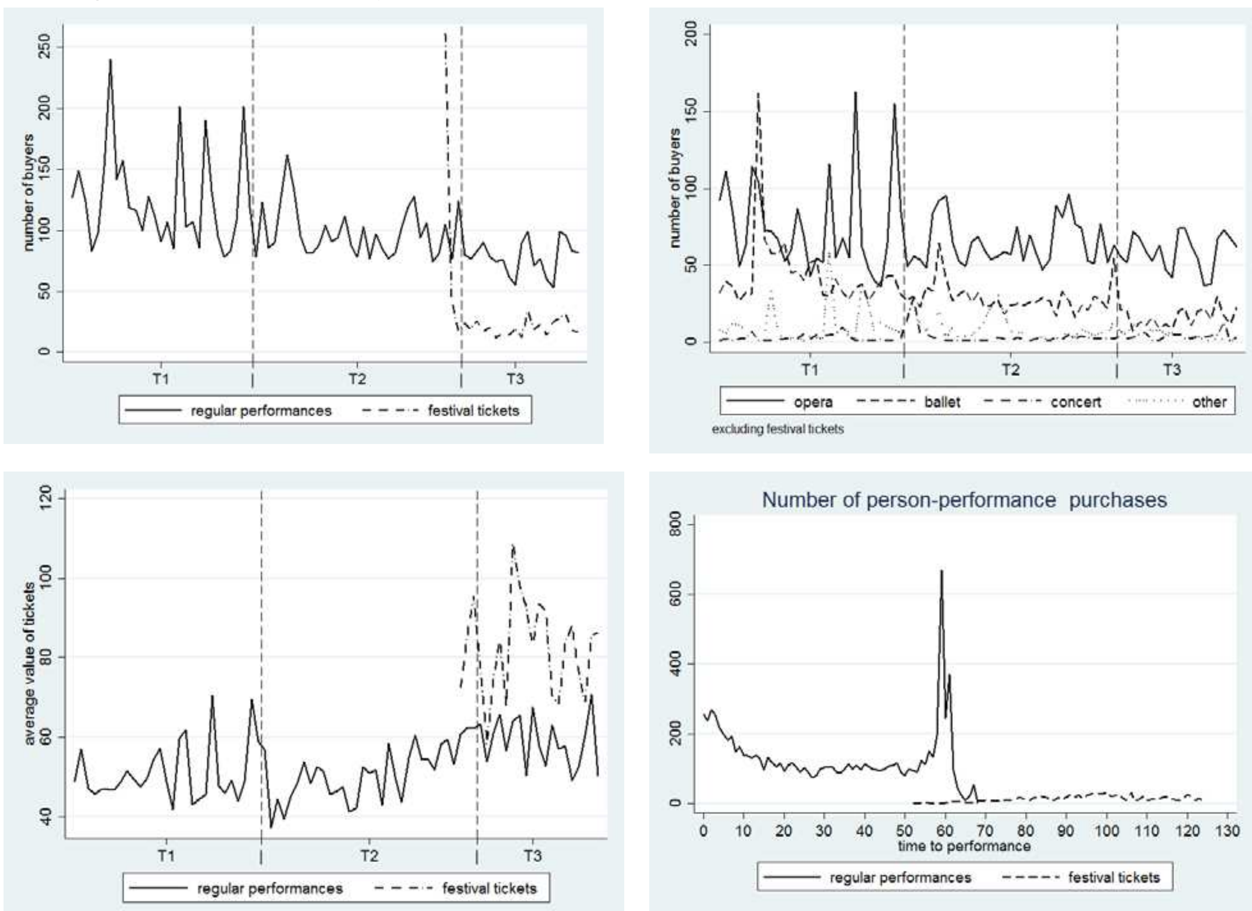
Figure A4: Day-level results
Panel A: Donative behavior



Panel B: Statements checked



Panel C: Ticket related behavior



Notes: Panel A and C are based on the sample of non-frequent buyers. Panel B is based on the full sample due to the availability at the aggregate level only, 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.

A2.3 Ticket sequencing for non-festival performances

In the preceding subsection, we saw that the timing of arrival of individuals at the platform is influenced by the release of tickets. In this subsection, we study how the timing of arrival depends on individual characteristics. In OLS regressions in Table 2 we analyze the timing of arrival at the platform depending on past characteristics of customers. We also control for gender and corporates. Overall, 45% are identified as male, 49% as female, 0.25% as corporate, and the remainder 8% is nondefined. The dependent variables are: time (days) in Column I, treatment number (1, 2, or 3) in Column II, time between purchase and performance (the maximum for those who bought more than one performance tickets) in Column III, and time between purchase and performance (the minimum for those who bought than one performance tickets) in Column IV. We see that past customers, on average, bought tickets for a particular performance 6-7 days earlier than new customers. Also, those who bought more tickets in the past were quicker in buying tickets for particular shows. Conditional on being a customer in the past season, those who spent more on average last year, arrived later and bought tickets closer to the performance date. Past customers who ordered tickets per mail last year arrived earlier. Ordering through mail has the advantage that the processing begins three months in advance in contrast to two months in advance at the online platform, which implies better access to tickets to popular shows.

Table A2: Timing of arrival

Dependent variable:	Time (days)	Treatment (1, 2, 3)	Time between max	Time between min
	I	II	III	IV
dummy customer in previous season	-1.716	-0.044	6.856***	5.886***
	(-1.64)	(-1.47)	(8.13)	(6.95)
number of tickets previous season	-0.014	-0.001	0.190***	0.186***
	(-0.31)	(-0.42)	(5.24)	(5.10)
average value of ticket previous season	0.026**	0.001*	-0.045***	-0.037***
	(2.12)	(1.82)	(-4.60)	(-3.79)
dummy box office in previous season	-1.751	-0.040	1.235	1.111
	(-0.99)	(-0.80)	(0.87)	(0.78)
dummy letter in previous season	-2.373**	-0.065**	2.099**	1.271
	(-2.10)	(-2.02)	(2.31)	(1.39)
dummy phone in previous season	2.267	0.063	-1.664	-1.625
	(1.59)	(1.56)	(-1.45)	(-1.41)
female	-1.540***	-0.040**	0.332	0.325
	(-2.59)	(-2.37)	(0.70)	(0.68)
firm	11.307**	0.250	0.307	1.044
	(2.00)	(1.56)	(0.07)	(0.23)
other	-0.295	-0.000	-3.467***	-3.503***
	(-0.26)	(-0.02)	(-3.87)	(-3.89)
Constant	38.926***	1.796***	30.015***	29.369***
	(81.79)	(133.40)	(78.46)	(76.37)
Observations	8317	8317	8317	8317
R^2	0.003	0.003	0.033	0.026

Notes: OLS regressions, t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, excluding festival ticket buyers; other means that the customer was neither identified as female, nor male, nor firm.

A3: Additional results

Table A3: Rare events logit, first differences

Dependent variable	Donation dummy		
	(I)	(II)	(III)
T1:lower grids	0.005***	0.005***	0.005***
	(2.68)	(2.69)	(2.62)
T3: statement required	0.009***	0.010***	0.011***
	(3.81)	(3.77)	(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 A4: Long-term effects on tickets online

Dependent variable: number of tickets online in the next season (including zeros)

Specification: Tobit m.e.y*

	I	II	III	IV	V	VI
T1: lower grids	-0.189	-0.163	-0.121	-0.026	-0.224	-0.121
	(-0.94)	(-1.15)	(-1.12)	(-0.18)	(-1.44)	(-1.20)
T3: statement required	-0.410*	-0.805***	-0.197	-0.502***	-0.366**	-0.253**
	(-1.83)	(-3.67)	(-1.41)	(-2.78)	(-2.05)	(-2.02)
Donor dummy		1.181***	0.749**	1.113***	1.249***	0.776***
		(2.74)	(2.49)	(2.71)	(3.00)	(2.66)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
Pseudo R^2	0.001	0.016	0.092	0.013	0.017	0.103

Notes: see notes to Table 1; z-statistics; demographics include female, corporate, and other dummy; Marginal effects after Tobit with lower limit set to zero.

Table A5: Long-term effects on revenue online

Dependent variable: online ticket revenue in the next season (ticket value including zeros)

Specification: Tobit m.e.y*

	I	II	III	IV	V	VI
T1: lower grids	-14.191	-12.457	-9.639	-5.706	-13.573*	-9.984*
	(-1.20)	(-1.58)	(-1.42)	(-0.77)	(-1.85)	(-1.84)
T3: statement required	-16.896	-39.762***	-8.928	-24.178**	-16.176*	-10.666
	(-1.33)	(-3.04)	(-1.12)	(-2.32)	(-1.79)	(-1.52)
Donor dummy		58.187***	37.700**	55.413***	61.584***	38.798**
		(3.04)	(2.43)	(3.13)	(3.34)	(2.48)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
Pseudo R^2	0.000	0.006	0.044	0.007	0.008	0.048

Notes: see notes to Table 1; z-statistics; demographics include female, corporate, and other dummy; Marginal effects after Tobit with lower limit set to zero.

Table A6: Long-term effects on all tickets

Dependent variable: number of tickets (all means including online, box office, mail, and phone) in the next season (ticket value including zeros)

Specification: Tobit m.e.y*

	I	II	III	IV	V	VI
T1: lower grids	-0.380	-0.331	-0.185	-0.073	-0.410	-0.135
	(-1.00)	(-1.27)	(-1.13)	(-0.30)	(-1.58)	(-1.07)
T3: statement required	-0.586	-1.298***	-0.117	-0.793***	-0.516*	-0.175
	(-1.50)	(-3.19)	(-0.59)	(-2.60)	(-1.73)	(-0.96)
Donor dummy		1.875***	0.932***	1.821***	2.017***	0.978***
		(3.03)	(2.96)	(3.15)	(3.46)	(3.09)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
Pseudo R^2	0.000	0.012	0.127	0.011	0.016	0.134

Notes: see notes to Table 1; z-statistics; demographics include female, corporate, and other dummy; Marginal effects after Tobit with lower limit set to zero.

Table A7: Long-term effects on whole ticket revenue

Dependent variable: ticket revenue (all means including online, box office, mail, and phone) in the next season (ticket value including zeros)

Specification: Tobit m.e.y*

	I	II	III	IV	V	VI
T1: lower grids	-23.566	-20.689	-11.335	-7.295	-20.950	-9.312
	(-1.07)	(-1.42)	(-1.06)	(-0.56)	(-1.64)	(-1.20)
T3: statement required	-22.326	-64.788***	-3.053	-37.755**	-23.163	-4.296
	(-1.00)	(-2.77)	(-0.25)	(-2.16)	(-1.47)	(-0.37)
Donor dummy		99.170***	51.076**	96.561***	105.833***	52.146**
		(3.32)	(2.08)	(3.38)	(3.61)	(2.06)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
Pseudo R^2	0.000	0.006	0.056	0.007	0.008	0.059

Notes: see notes to Table 1; z-statistics; demographics include female, corporate, and other dummy; Marginal effects after Tobit with lower limit set to zero.

Table A8: Long-term effects on the probability of being an online customer next season

Dependent variable: internet customer next year (dummy)

Specification: Logit m.e.

	I	II	III	IV	V	VI
T1: lower grids	-0.012	-0.009	-0.004	0.004	-0.016	-0.003
	(-0.54)	(-0.58)	(-0.29)	(0.26)	(-0.95)	(-0.27)
T3: statement required	-0.027	-0.073***	-0.003	-0.038*	-0.023	-0.017
	(-1.15)	(-2.95)	(-0.19)	(-1.89)	(-1.16)	(-1.02)
Donor dummy		0.125***	0.081**	0.127***	0.139***	0.088**
		(2.77)	(1.99)	(2.89)	(3.25)	(2.13)
Ticket controls at t		yes				yes
Past season controls			yes			yes
Performance type controls				yes		yes
Time controls					yes	yes
Demographics		yes	yes	yes	yes	yes
Observations	8442	8442	8442	8442	8442	8442
Pseudo R^2	0.000	0.021	0.192	0.022	0.028	0.204

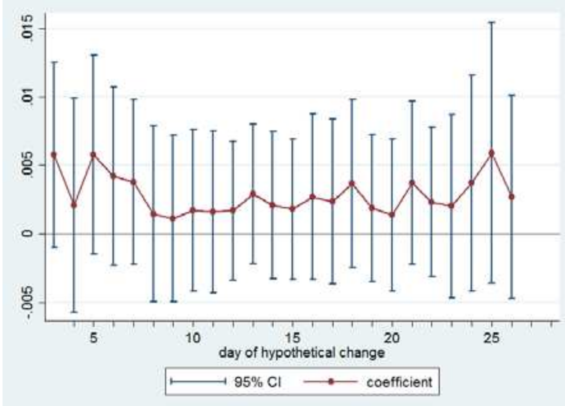
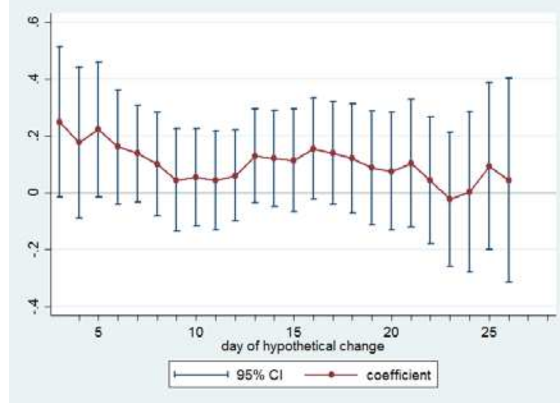
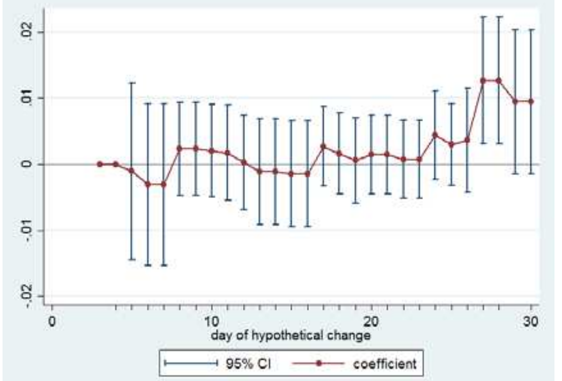
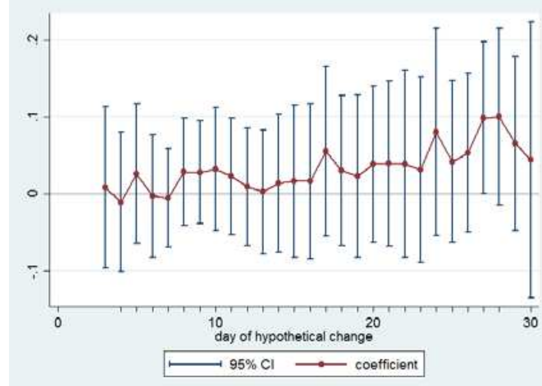
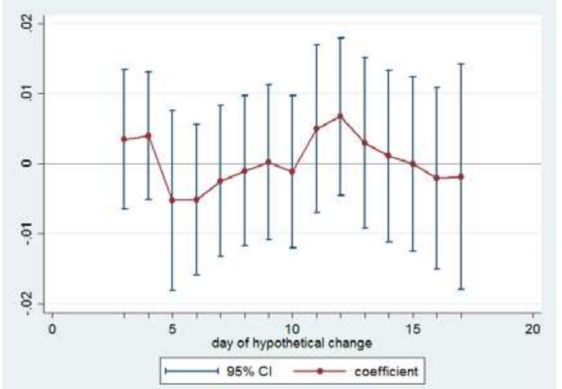
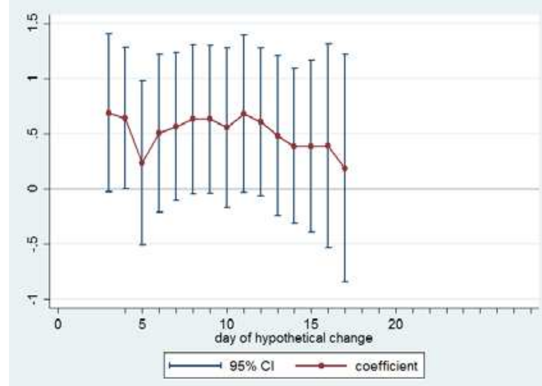
Notes: see notes to Table 1; z-statistics; m.e. marginal effects.

Table A9: The Post-Study Probability given 2 replications and adding our study as a function of prior probability and power.

prior probability:	Power=0.80	Power=0.50
low (0.01)	0.47 ->0.91	0.45->0.89
Medium (0.10)	0.91->0.99	0.90->0.99
High (0.55)	0.99->1.00	0.99->1.00

Note: The table displays a relevant subset of Table 4 in Maniadis et al. 2014. For relatively large effects as found in our study and over 8,000 subjects, the power of our study is high.

Figure A5: Results of a placebo exercise – estimating effects of a fictive treatment

<table>
<tr><td></td><td>Logit m.e. donation dummy</td><td>OLS return (donation value including zeros)</td></tr>
<tr><td>Fictive treatment in the first part of T1 period</td><td>
</td><td>
</td></tr>
<tr><td>Fictive treatment in in the first part of T2 period</td><td>
</td><td>
</td></tr>
<tr><td>Fictive treatment in in the first part of T3 period</td><td>
</td><td>
</td></tr>
<tr><td colspan="3">Notes: all regressions are at the individual level and include the full set of controls (some are dropped in small samples), see notes to Table 1 and Table 4. All observations in the respective (T1, T2, or T3) period are used. The day of hypothetical change is shifted starting at three and going stepwise up to the maximum number of day minus three.</td></tr>
</table>

A4: 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 A10: Regression analysis: including frequent buyers

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

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.