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DEFAULTS AND DONATIONS: EVIDENCE FROM A FIELD EXPERIMENT

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Abstract—We study the effects of defaults on charitable giving in a large-scale field experiment on an online fundraising platform. We exogenously vary default options along two choice dimensions: the charitable donation decision and the "co-donation" decision regarding how much to contribute to supporting the platform. We document a strong effect of defaults on individual behavior but nevertheless find that aggregate donation levels are unaffected by defaults. In contrast, co-donations increase in the default amount. We complement our experimental results with a structural model that investigates whether personalizing defaults based on individuals' donation histories can increase donation revenues.

I. Introduction

ONLINE fundraising constitutes a sizable and rapidly growing segment of the market for charitable giving.[1] A pervasive feature on the websites of charities and online fundraising platforms is default options that specify the amount to be donated unless a donor actively enters a different contribution level. The ubiquity of default donation amounts in online fundraising is likely to stem from a common presumption that "defaults matter." This presumption, buttressed by famously documented examples of the importance of defaults for decisions on retirement saving or organ donation (Madrian & Shea, 2001; Johnson & Goldstein, 2003; Thaler & Sunstein, 2008), has generated a lively discussion in the practitioner community regarding best practice for setting default donation amounts. Yet this discussion lacks rigorous evidence.[2]

This paper takes a step toward closing this evidence gap with the help of a field experiment on Germany's largest online platform for making charitable contributions. We study two main questions. First, do defaults affect individual behavior; in other words, do they influence the distribution of individuals' contributions? Second, do defaults influence overall donation revenues?

To address these questions, we exogenously vary default options in two distinct choice dimensions: the main donation decision and an add-on choice, which is a gratuity to support the providers of the online platform. Regarding the first dimension, website visitors are randomly assigned to default donation amounts of 10, 20, and 50 euros. These values correspond, respectively, to the 25th, 50th, and 75th percentile of donations on the platform in the six months prior to our experiment. This allows us to examine whether defaults have stronger or weaker effects on behavior when they are set relatively high or low compared to what most people would donate otherwise. We also implement an additional treatment in which the donation field is initially set to 0, such that people who want to make a donation have to make an active decision on their contribution level. In our second treatment dimension, we randomly assign donation-page visitors to percentage add-ons of 5%, 10%, or 15% of their main donation. The corresponding contributions, or "co-donations," are used to support and maintain the online platform, which itself operates as a nonprofit organization.

Over the course of our experiment, we collected data on roughly 680,000 donation-page visits and almost 23,000 donations, yielding a total of 1.17 million euros in terms of revenues for charitable organizations on the platform. Our data show that defaults have a strong impact on individual donor behavior. In each of our treatments, the modal positive contribution invariably corresponds to the default specification. This holds for the main donation decision, as well as for the add-on contribution to the online platform, indicating that defaults are important poles of attraction for donors' behavior in both decision dimensions.

Despite the substantial effects on the distribution of donations, defaults in our experiment do not significantly alter overall donation revenues. For all treatment comparisons, we find no systematic differences in average contribution levels. The difference between our individual- and aggregate-level results can be explained by countervailing changes in the distribution of donations due to defaults. We find that relative to the active-decision environment, defaults induce some people to donate more while others donate less or not at all, such that the two effects cancel each other out at the aggregate level. For default contributions of 10 and 20 euros, the changes in the donation distribution operate entirely on the intensive margin. At the 50 euro default, we observe an additional extensive-margin effect, with more people opting out of the donation process altogether. As a result of this higher donor attrition, average donations once again do not differ

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[1] In 2017, online giving accounted for 7.6% of the total—multibillion—fundraising volume in the U.S. nonprofit sector (see Blackbaud, 2018). In line with the positive trend from previous years, online giving grew strongly in absolute terms as well as compared to the overall increase in charitable giving (the yearly growth rates were 12.1% and 4.1%, respectively).

[2] Perhaps the best existing evidence comes from a disaster relief donation drive conducted by Google.com in 2009 (see https://goo.gl/1ZvALr). While there is no information on sample sizes and statistical significance, results indicate that, with the exception of a drop in average donations at a $20 default, donation revenues did not differ strongly for different default donation levels.

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significantly from those in the other treatments. By contrast, we do observe strong average treatment effects in the add-on dimension. Co-donation revenues increase monotonically in the percentage add-on that is set as the default. This is because the dominant change in the distribution of co-donations at higher default values is an intensive-margin movement toward the default from lower co-donations.

In the final part of our analysis, we examine whether personalized defaults could help to raise donation revenues. We start by exploring heterogeneous treatment effects based on individual-level characteristics such as gender and the type of donation. Consistent with a number of earlier findings (Madrian & Shea, 2001; Levav et al., 2010; Altmann et al., 2013), we observe that some donor groups are especially prone to stick to defaults. Our estimates, however, also indicate that there is little scope for making use of this tendency to systematically increase donations. To further explore whether the platform could increase donations by differentiating defaults based on individuals' prior donation levels, we estimate a simple structural model in which individuals behave as if deviating from the default were costly (motivated by Carroll et al., 2009, and Bernheim, Fradkin, & Popov, 2015). Counterfactual simulations based on our model estimates indicate that there is at best modest scope for successfully using personalized defaults in a setting like ours, in which information on (potential) donors is sparse.

A. *Related Literature*

Our paper contributes to two main strands of the literature. First, we add to the body of literature that analyzes the impact of defaults on a variety of economic decisions, such as retirement saving (Madrian & Shea, 2001; Beshears et al., 2008; Carroll et al., 2009), organ donor registration (Johnson & Goldstein, 2003; Abadie & Gay, 2006), or the choice of insurance contracts (Johnson et al., 1993).

An important difference between the mentioned studies and ours is that they consider applications in which consumers who remain entirely inactive automatically stick to the default. In contrast, potential donors in our setting must actively confirm the transaction for the default to affect outcomes. This is similar to how default options are used in Web interfaces for configuring computers, cars, and other customizable products (Levav et al., 2010, Ebeling, 2013). As we explain in section IIID, the difference between the two types of settings is important, as some common explanations for default effects, such as procrastination in making choices, are unlikely to play an important role for our results. These differences notwithstanding, we find that the workhorse model for capturing default effects in the retirement savings literature—a model involving fixed costs of deviating from the default (see Carroll et al., 2009; Bernheim et al., 2015)—does remarkably well in fitting the key features of the donation distributions in our experiment. At the same time, our estimates indicate that in our setting, a much smaller fraction of potential donors is affected by these as-if costs, which is in line with the intuition that procrastination is indeed an important factor behind the default effects observed in the retirement savings context (Carroll et al., 2009).

Our experiment differs from previous studies on "Web defaults" in other economic applications (Johnson, Bellman, & Lohse, 2002; Löfgren et al., 2012; Ebeling, 2013) in that we examine a setup where consumers not only face a binary opt-in versus opt-out decision but have a continuum of decision alternatives. This allows us to study a rich set of reactions to defaults along both the intensive and extensive margins of the donation distribution. Our findings demonstrate that defaults can have manifold—and, in our case, countervailing—effects, highlighting the importance of a detailed assessment of distributional effects of defaults for nonbinary choices. In particular, our results indicate that a strategy that attempts to boost donation revenues through higher defaults based on a simplistic notion that "defaults work" might backfire for charitable organizations.[3]

The second strand of the literature to which our paper contributes is that on charitable giving and nonprofit fundraising. While defaults are widely observed on online donation platforms and many practitioners presume that appropriately specified defaults will help them increase donations, there has been a lack of rigorous evidence on the causal effects of default options on donation behavior. A notable exception are two recent papers by Fiala and Noussair (2017) and Goswami and Urminsky (2016), who study default effects on charitable giving in lab experiments and online surveys, with mixed results. While Fiala and Noussair (2017) observe no significant differences in overall donation levels under different defaults, Goswami and Urminsky (2016) report a small, positive effect of higher defaults.[4] One has to bear in mind, however, that these findings are based on relatively small samples and arguably rather weak incentives.

Beyond defaults, a voluminous literature has examined the impact of other fundraising interventions (see Andreoni, 2006, as well as Bekkers & Wiepking, 2011, for comprehensive reviews of the literature). Our paper is related to these studies in that some of the potential mechanisms behind default effects can also play a role for other fundraising interventions. Specifically, to the extent that potential donors interpret the default option as a recommended contribution to the charitable cause, our paper is related to studies that examine how giving is affected by directly requesting (Fraser, Hite, & Sauer, 1988; Edwards & List, 2014) or explicitly suggesting (Adena et al., 2014; Goswami & Urminsky, 2016) specific donation levels during solicitation. Similarly, the literature on "appeal scales" (i.e., providing donors with a vector of

[3] This is related to a recent result by Haggag and Paci (2014), who analyze tipping behavior in New York City cabs and find that customers are more likely to leave no tip at all when the payment interface features a high default tip.

[4] More distantly related, Smith and Ottoni-Wilhelm (2018) further document that defaults may systematically affect fundraisers' choices of fundraising goals.

multiple suggested contribution levels; see Weyant & Smith, 1987; Desmet & Feinberg, 2003; Adena & Huck, 2016; Reiley & Samek, 2017) is related in that there is a partial overlap in the channels through which appeal scales and defaults may affect behavior (e.g., recommendations or anchoring). Finally, interventions based on statements like "every penny helps" (Cialdini & Schroeder, 1976; Fraser, Hite, & Sauer, 1988) or the provision of information about other donors' behavior (Frey & Meier, 2004; Shang & Croson, 2009) are potentially related to defaults, as they may also affect behavior by transmitting information or shaping social norms. Since all of these interventions, however, also introduce aspects that are unrelated to defaults[5] and since defaults, in turn, may work through mechanisms that have little or no relevance for the other interventions, it is difficult to directly compare the results of these studies to our setting.

The paper proceeds as follows. In the next section, we describe the setup of our experiment. Section III presents our main empirical results, and section IV examines whether the platform could increase aggregate donation revenues by personalizing defaults. Section V concludes.

II. The Experiment

A. *The Donation Platform*

We study the effect of default options on betterplace.org, Germany's largest platform for making charitable donations over the Web. At the time of the experiment, the platform hosted about 6,000 "project pages" through which charities collect funds for their activities. The aid projects on the platform cover the whole gamut in terms of geography, charitable cause, and scale. They range from after-school help for a handful of children in Berlin, to supporting orphanages in Kenya, to humanitarian aid for victims of natural disasters. Charities that are present on Betterplace include small, local NGOs as well as organizations like UNICEF and the International Committee of the Red Cross. The platform also hosts pages for "fundraising events," which offer individuals, firms, or other organizations the possibility of collecting donations for one of the aid projects by organizing charity runs, benefit concerts, or similar fundraising campaigns.

Visitors to the donation platform can browse individual fundraising or project pages, which describe the project and overall budget needed to fund it, as well as the amounts of money that are required for the specific elements of which the overall project consists. Figure 1A provides an example of a project page (see figure B.1 in the online appendix for an English translation). The project title, "Typhoon Haiyan: Emergency Relief in the Philippines," is displayed at the top of the page, followed by a picture, a location map, and a project description. The number of previous donors, the proportion of the overall project budget that has already been funded, and the amount that is still required for the project are displayed in the upper right part of the page. Potential donors can contribute directly to the aid project or to one of the specific project elements—in this example, relief packages for the catastrophe zone—displayed at the bottom right of the figure and further below on the screen (suppressed in figure 1A).[6]

By clicking on either of two buttons on the screen—the large button, which reads "Jetzt spenden," translates to "Donate now," and the smaller one at the bottom right, which reads "Hierfür spenden," translates to "Donate for this"—the potential donor is redirected to the donation page for the project. A screenshot is depicted in figure 1B (see figure B.3 in the online appendix for an English translation). On this page, the donor specifies the amount that she wishes to contribute to the charitable cause by filling in the "Project donation" ("Projektspende") field on the top left part of the screen. In what follows, we refer to this amount as the *donation* or *donated amount*.

In addition to specifying the donation to the charitable cause, donors can make a contribution to support the online platform. In this secondary choice dimension, contributions can be determined as a percentage add-on or as an absolute euro amount that is added to the project donation. By clicking the field below the "Support betterplace.org" ("Fördere betterplace.org") label on the right side of the screen, a dropdown menu appears that allows donors to choose among the options: "not this time" (i.e., no contribution), 5%, 10%, 15%, 20%, 25%, or "other amount." The last of these options gives the donor the possibility of entering any absolute euro amount. We refer to the add-on contributions in support of the platform as *co-donations*. Co-donations are used to cover the costs for developing and sustaining the platform, which itself operates as a nonprofit organization.

The sum of the donation and co-donation amount determine the donor's "total donation" (*Gesamtspende*), which is automatically calculated in the second line on the left of the donation form. In the bottom part of the donation page (suppressed in figure 1B), donors are asked to provide further information that is required to finalize the transaction, including their name and payment details. After having completed the donation form, donors confirm the transaction by clicking a "Donate Now" button at the end of the page.

B. *Treatments*

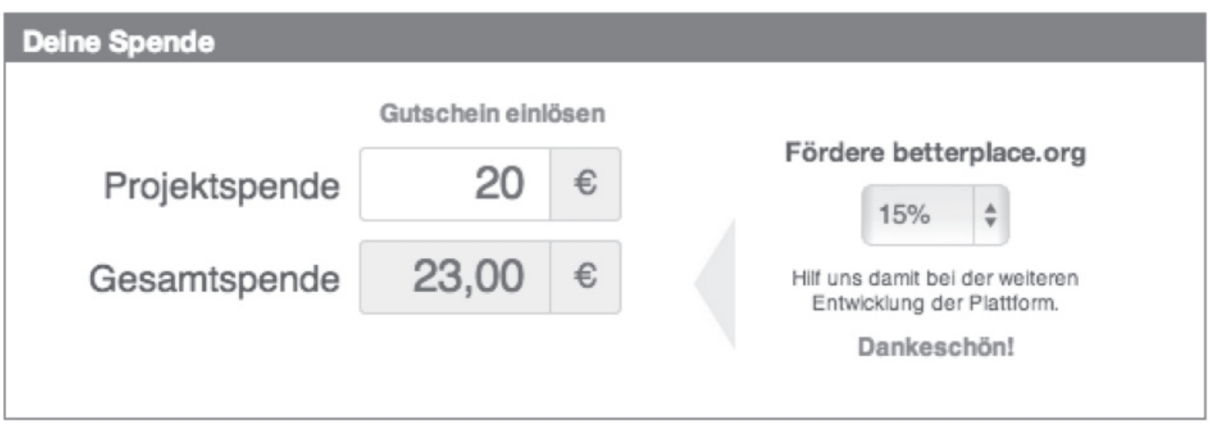
Our experimental intervention pertains to the donation page depicted in figure 1B. For each website visitor who enters the donation page, we exogenously vary the donation

[5]For instance, the studies on explicit requests typically provide additional contextual information or employ relatively strong framing. Similarly, appeal scales open the possibility for "decoy" or "compromise effects" (Simonson, 1989; Ekström, 2018).

[6]The corresponding page for fundraising events has a slightly different layout (see figure B.2 in the online appendix for an example). The donation page on which our experimental intervention takes place, however, is exactly the same for all types of donations (see figure 1B).

FIGURE 1.—SCREEN SHOTS OF A PROJECT PAGE AND THE DONATION PAGE

(A) Project Page



(B) Donation Page

and co-donation amounts that are displayed by default in the respective fields of the donation form. We randomize independently in both treatment dimensions. In the donation dimension, we assign potential donors to one of four different treatments. Specifically, when arriving at the donation page, the amount displayed in the project donation field is either 0 or corresponds to a prespecified donation level of 10, 20, or 50 euros. Note that in each case, donors are free to contribute any positive amount by simply typing in the desired contribution level into the donation field.

The three positive default values correspond, respectively, to the 25th, 50th, and 75th percentile of all donations on the platform during the six months before our experiment started. This allows us to examine whether defaults have stronger or weaker effects on behavior when they are set relatively high or low compared to what most people would donate otherwise.[7] In contrast to the positive donation defaults, the 0 treatment implements an active decision or forced-choice environment: a user who wants to make a donation in this treatment has to actively specify the amount she wishes to contribute. If a donor tries to finalize the transaction while the donation field is set to 0, an error message appears and the donor is redirected to the donation form. Active-decision environments are sometimes argued to have desirable properties (e.g., if preferences in the population are very diverse; see Carroll et al., 2009, or Sunstein, 2013). In our empirical analysis, this treatment will provide us with a benchmark of actively determined donations, against which we can compare donors' behavior in the treatments with positive donation defaults.

There is a second sense in which our setting involves active decision making: contributions, and thus potentially also the default donation levels, become effective only after users actively confirm the transaction. While this is typical for how defaults—or, more specifically, default options—are implemented in a wide variety of online applications, it differs from the use of defaults in other settings like organ donor registration or 401(k) savings plans. In these environments, defaults—or what might be coined "default rules"—are typically implemented as a set of rules that are relevant for the decision maker even if she remains entirely passive. While this difference may seem subtle, it is potentially important for understanding the channels through which defaults can affect behavior. In particular, as we will discuss in detail in section IIID, the degree to which present-biased preferences and procrastination of active decisions might affect outcomes differs between the two different types of default regimes.

In our second treatment dimension, co-donations, we independently vary the prespecified percentage add-on to support the online platform. Specifically, we randomly assign donation page visitors to co-donation defaults of 5%, 10%, or 15%. These treatments were chosen based on historical values and heuristics. Five percent was the value originally used by the platform. It was retained in the experiment as a "control group" representing the status quo before the beginning of the intervention. The remaining two values were chosen based on the intuition that the co-donation is likely to be perceived as a "tip" to Betterplace. The co-donation defaults of 10% and 15% were implemented as they correspond to the tipping conventions in Germany and places like North America, respectively.

C. *Implementation of the Experiment*

The experiment was conducted over an eleven-month period from June 8, 2012, to April 19, 2013. We observe roughly 680,000 donation page visitors during this period, distributed over the twelve different treatment cells in our 4×3 design (see table B.1 in the online appendix for a detailed breakdown). Some aspects of our data and procedures are worth noting. First, to avoid technical errors in the settlement of payments, our experiment is confined to situations where the remaining required budget for the respective project element is at least 50 euros (i.e., the highest possible default). Second, to rule out that a small number of extreme contributions may distort our results, we drop the top 0.2% of donors ($n = 41$) for our analysis.[8]

Third, we randomize website visitors into treatments at the "website session" level, such that they remain in the same treatment throughout their visit to the platform. This minimizes the possibility that a potential donor who visits more than one donation page—because she wishes to make multiple donations or browses several project and donation pages before ultimately making a donation decision—is exposed to different treatments. More precisely, we assign treatments when a user enters a donation page for the first time. Subsequently, a browser cookie ensures that the user keeps being exposed to the same treatment. While we cannot perfectly ensure that a donor never faces another treatment (e.g., when she makes donations from two different devices), this procedure minimizes donors' awareness of the experiment and possible treatment spillovers.

Our final sample covers 683,910 observations—roughly 57,000 in each treatment cell (see table B.1 in the online appendix). In 99.7% of cases, one observation corresponds to a unique website visitor or "session": the 683,910 observations correspond to 681,660 unique sessions. This is the case since relatively few donors make more than one donation. Table A.1 in the appendix indicates that observations are balanced in terms of baseline characteristics for which we have information: whether the potential donation was for a fundraising event, a project, or element within the project, and whether potential donations to a given project are tax deductible, which is typically the case when the charity is registered in Germany.

[7] Coincidentally, rather than by design, the different defaults also correspond to modes in the historical distribution of donations. This is the case since many donors contribute "round" amounts (e.g., 5, 10, or 20 euros; see section III). It is unclear how this may affect the impact of defaults on behavior. On the one hand, defaults may have little traction to increase the mass of donations at these modes, since many people are already giving these amounts. On the other hand, it may be easier for defaults to attract donors from more unusual donation levels to the common default amounts or to make potential donors jump from one prominent amount to another.

[8] Each of these donors contributes 2,165 euros or more. This compares to a median donation level of 20 euros. Some of the figures reported below (e.g., the exact values of the average donation and codonation amounts) naturally depend on the specific cutoff used. Unless explicitly noted otherwise, however, our main results and conclusions remain unchanged when applying different cutoff levels (e.g., excluding the top 0.1%, 0.5%, or 1% of donors).

In total, we observe 22,792 donations coming from 20,542 different participants. Among those who do make a positive donation, 92.5% ($n = 19{,}010$) make a single donation in the period of our intervention, 5.5% ($n = 1{,}125$) make two donations, and the remaining 2% ($n = 407$) make three or more donations. In what follows, we separately include the different individual donations as our unit of analysis for participants who make multiple donations within a session. To control for possible dependencies of observations, all estimation results reported below are clustered at the website-session level. This clustering has almost no bearing on our empirical findings. Results are also robust to using alternative approaches to account for donors with multiple contributions (e.g., using the sum of donations or focusing only on the first decision for each donor).

Over the course of the experiment, the fraction of participants who make a donation (denoted as the "donation rate" in what follows) is 3.33%. At first glance, this rate seems relatively low, given that participants in our experiment are all individuals who visited the online platform, browsed through the website, and at some point clicked on the "Donate Now" button. According to the platform providers, however, this figure is in line with historical levels of the donation rate on the platform. Relatively low donation rates are common in the charitable giving literature in general (Karlan & List, 2007; Falk, 2007; Huck & Rasul, 2011) and in online fundraising more specifically. In a study based on the online fundraising sites of 84 nonprofit organizations, for instance, M + R Benchmarks (2015) reports a median overall conversion rate on the charities' websites of 0.76%. Conditional on visiting the organizations' main donation page, the median donation rate reported in the study is 13%. We can only speculate on what drives the relatively lower donation rate in our setting compared to the last figure. One possible explanation is that we are studying a "marketplace" for charitable projects where platform visitors may have more diffuse donation intentions compared to potential donors who visit the website of a specific charitable organization. The latter might also attract a relatively higher fraction of donors who arrive at the website in response to solicitation emails or other fundraising drives of the charity. Indeed, we also observe considerably higher donation rates for participants who come to the platform through an organized "fundraising event" (see section IIA)—in this case, donation rates are roughly 10% to 11%.[9]

As a consequence of the low donation rate, the modal action of participants in our experiment is not to donate. This holds for all of our treatments (see table A.1 in the appendix for a detailed overview of summary statistics by treatment). Conditional on making a donation, the average (median) donation level in our sample is 51.27 euros (20 euros). The corresponding values for co-donations are 2.00 and 0.25 euros, respectively. In sum, these numbers yield a total of 1.17 million euros in terms of donations and roughly 45,500 euros in co-donations over the course of our experiment.

[9]Reassuringly, our main findings (i.e., strong distributional effects for both donations and co-donations, but significant average treatment effects only in terms of co-donations) hold for participants who respond to fundraising events as well as those who visit the donation pages of aid projects or project elements. Our empirical analysis in section III thus concentrates on the pooled data set that includes all participants. In cases where we find systematic differences between different donor types for more specific results, we note this explicitly.

III. Empirical Results

In this section, we present the results of our experiment. We begin, in section IIIA, by studying treatment effects in terms of individual donor behavior. In particular, we analyze how the different defaults affect the distributions of donations and co-donations in the experiment. In sections IIIB and IIIC, we turn to an aggregate-level perspective and examine the influence of defaults on average donation and co-donation revenues, respectively. We also explore how treatment differences on the intensive and extensive margin of the donation and co-donation distributions can account for the observed aggregate-level outcomes. We conclude, in section IIID, by discussing which psychological mechanisms may account for donors' reactions to defaults in our experiment.

A. *Do Defaults Affect Individual Donor Behavior?*

In a first step, we examine how defaults influence individual donations and co-donations across treatments. Do defaults cause systematic bunching of donors at the respective default amounts? The answer to this question is a clear yes. To illustrate this point, we examine the distributions of donations and co-donations, focusing first on the 22,792 cases in which participants in our experiment actually make a donation. Panel A of table 1 summarizes the distribution of donations across treatments. Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for the donation amount and co-donation percentage, (d€, c%). In the rows of panel A, we depict the fraction of donations in a given treatment that correspond to one of the default donation levels, 10, 20, and 50 euros, as well as the fraction of donations that differ from these values. Panel B in the bottom half of the table pertains to co-donations, which we will discuss shortly.

The highlighted cells in panel A reveal a strong impact of defaults on individual donations. The likelihood of making a donation of 10, 20, or 50 euros is considerably more pronounced when the respective amount is selected as the default donation level. For instance, 22.9%, 22.8%, and 21.7% of donors make a contribution of 10 euros in the three treatment cells where this amount is the default donation value (see columns 1–3 of table 1). This compares to only 12% to 14% of donors making a 10 euro contribution when facing a default of 20 or 50 euros (columns 4 to 9). Similar effects can be found for each of the nine treatments that involve a positive default contribution. Comparing the highlighted fractions of donors who stick to the different defaults to the

TABLE 1.—DONATIONS AND CO-DONATIONS BY TREATMENT

	Treatment (d€, c%)											
Amount	(10,5) (1)	(10,10) (2)	(10,15) (3)	(20,5) (4)	(20,10) (5)	(20,15) (6)	(50,5) (7)	(50,10) (8)	(50,15) (9)	(AD,5) (10)	(AD,10) (11)	(AD,15) (12)
	A. Donated amount											
€10	**.229**	**.228**	**.217**	.128	.128	.124	.135	.139	.132	.173	.164	.146
€20	.124	.109	.114	**.233**	**.211**	**.238**	.105	.109	.110	.119	.124	.132
€50	.106	.115	.104	.094	.110	.095	**.196**	**.183**	**.176**	.122	.115	.122
Other	.541	.549	.565	.546	.552	.544	.564	.569	.582	.586	.597	.600
	B. Co-donation											
0	.421	451	.439	.413	.432	.448	.427	.494	.475	.455	.480	.486
5%	**.530**	.138	.121	**.532**	.147	.133	**.530**	.122	.141	**.503**	.125	.144
10%	.033	**.384**	077	.023	**.399**	.082	.022	**.363**	.071	.022	**.373**	.071
15%	0	.004	**.337**	.003	.002	**.309**	.001	.005	**.290**	.001	.003	**.280**
Other	.017	.022	.026	.029	.019	.029	.021	.016	.023	.019	.019	.019

Panel A depicts the proportion of donors in a given treatment who contribute 10, 20, or 50 euros, as well as the fraction of donors who donate a different amount ("other"). Panel B depicts the proportion of donors in a given treatment who make a co-donation of 0, 5%, 10%, 15%, as well as the fraction of donors who co-donate a different amount ("other"). Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for donations and co-donations.

corresponding numbers in the treatments where donors have to make an active decision (AD in columns 10 to 12) shows that setting the default to a certain value increases the proportion of donors who actually contribute this amount by roughly 5 to 10 percentage points. Given that the observed baseline values for the different donation levels in the active-decision environment lie between 10% and 17%, this implies that defaults increase donors' propensity to make the corresponding contribution by 30% to 90%.

The strong influence of defaults on individual donor behavior is also evident in the overall distribution of donations. In figure 2, we present histograms for the active-decision regime and the three different donation defaults. To facilitate illustration, we right-censor the x-axis of the graphs at 100 euros and focus our attention on the donation-default dimension. More precisely, we plot the histograms for subsamples in which we pool observations across the different co-donation treatments, holding the treatment assignment in the donation dimension constant.

The histograms underscore the strong impact of defaults on donations. While the distributions otherwise look relatively similar (e.g., we observe more or less pronounced spikes at multiples of 5 euros), there is a marked difference in the proportion of donations at the default values (indicated by the dashed lines). Indeed, the figure shows that the modal contribution always corresponds to the default donation level. Kolmogorov-Smirnov tests indicate that the distributions of donations differ significantly across the four different default regimes ($p < 0.01$ for all pairwise tests).

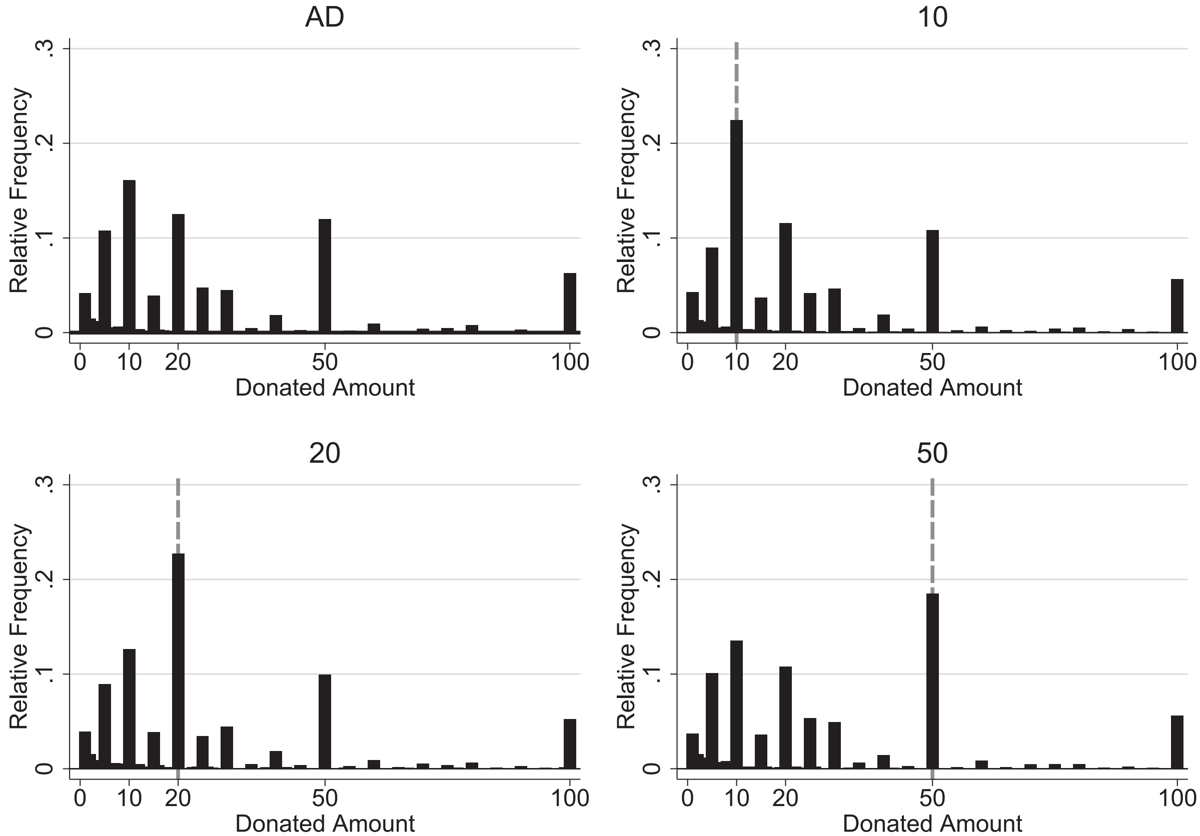
The systematic influence of donation defaults on the distribution of donations is also evident when considering the twelve individual treatment cells separately. Figure B.4 in the online appendix depicts the full set of histograms for all individual treatment cells. When comparing the distributions of treatment pairs that differ in terms of donation defaults but have identical co-donation defaults (i.e., when testing across "columns" within a given "row" of figure B.4), all treatment comparisons, but one, are statistically significant ($p = 0.148$ when comparing (AD,5) versus (10,5); $p < 0.05$ for all other pairwise treatment comparisons). At the same time, the distributions of donations generally do not differ significantly when holding the donation default constant but varying the default in the co-donation dimension (i.e., comparing the rows within a given column of figure B.4): only one out of twelve pairwise treatment comparisons turns out to be significant at the 10% level (Kolmogorov-Smirnov tests; $p = 0.084$ when comparing the (20,5) and (20,10) treatments).

In a next step, we study how defaults affect behavior in our second treatment dimension: the add-on contribution to support the online platform. Panel B of table 1 depicts the co-donation frequencies across treatments, mirroring the analysis of donations in panel A.[10] The highlighted cells indicate that defaults also have a pronounced impact on individuals' behavior in terms of add-on contributions. For instance, moving from a 5% to a 10% default increases the proportion of donors who make a 10% contribution from roughly 2–3% to 35–40% (see the third row of panel B). Another noteworthy feature is that participants' choices in the co-donation dimension exhibit a bimodal pattern, with 40% to 50% of donors in a given treatment making no co-donation at all and another 30% to 50% of donors sticking exactly to the respective default amount. Comparing differences in the distributions of co-donations using Kolmogorov-Smirnov tests shows that the distributions differ significantly for all pairwise tests of individual treatments that differ in the co-donation default but have the same default donation ($p < 0.01$ in all cases).

Our data also indicate that donors' propensity to stick to defaults in the two choice dimensions is highly correlated. In

[10]Co-donation histograms can be found in figure B.5 in the online appendix. We display histograms for individual treatment cells instead of pooling data across donation defaults, since Kolmogorov-Smirnov tests indicate a number of significant differences between the distributions (e.g., the co-donation distribution for the (10,15) treatment in the third row of figure B.5 turns out to differ significantly from the (AD,15) as well as the (50,15) treatment; $p < 0.01$ in both cases).

FIGURE 2.—DONATION DISTRIBUTIONS BY DEFAULT DONATION LEVEL



The figure depicts the relative frequencies of donations for each of the treatments in the donation dimension (indicated by the panel titles). Default donation levels are highlighted by the dashed lines. The x-axes of the graphs are censored at 100 euros (the underlying data are not).

particular, the conditional likelihood of donating the default amount is almost 80% higher for donors who also stick to the default in the co-donation dimension (the respective likelihoods are 28.7% versus 16.1%; $p < 0.01$). This suggests that some people in our sample are systematically more affected by defaults than others. It is not to say, however, that we generally observe no default effects for participants who actively deviate from the default in one of the decision dimensions. For instance, among donors who actively opt out of the co-donation default, we still observe bunching at the default for donations: relative to the active-decision environment, their propensity to donate the stipulated default amount increases by 10% to 40%.[11] We return to the discussion of types that are generally more likely to stick to defaults in section IV.

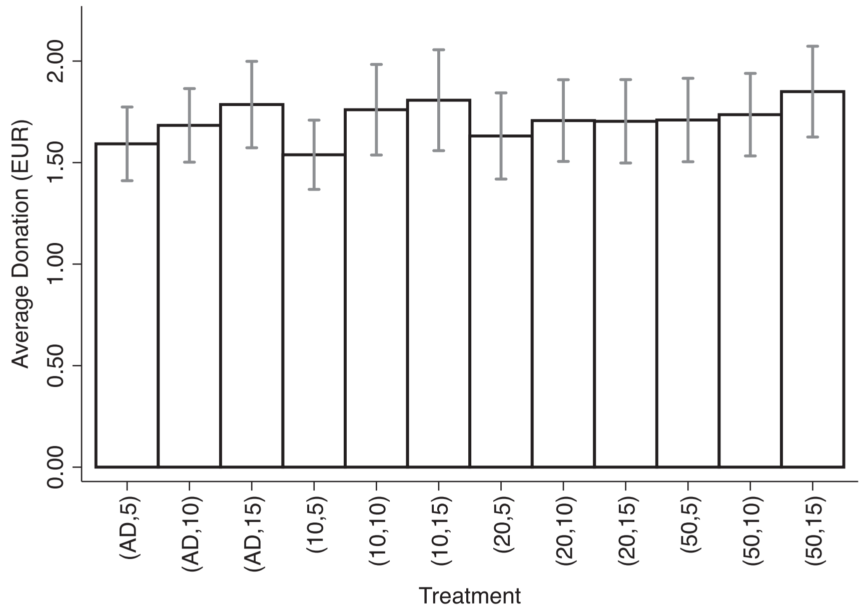
B. *Do Defaults Affect Average Donation Levels?*

In a next step of our analysis, we explore how defaults affect average donation amounts at the aggregate level. Figure 3 presents average donation levels across treatments, calculated based on all 683,910 observations in our data set (i.e., including donors as well as participants who opted out of the donation process without making a contribution). Average donations in the different treatments lie in a range between 1.54 and 1.85 euros (for more details, see table A.1 in the appendix). The confidence intervals marked at the top of each bar indicate that the observed differences across treatments are generally insignificant. If we consider all pairwise treatment comparisons that are possible given our twelve different treatment cells, we find that only 1 out of the 66 pairwise t-tests is significant at the 5% level and three further treatment pairs differ at the 10% level. Specifically, the average donation level in the (10,5) treatment is significantly lower than in the (50,15) treatment and weakly lower than in the (AD,15) and the (10,15) treatment (t-tests accounting for clustering of standard errors at the session level; $p = 0.030$, $p = 0.076$, and $p = 0.081$, respectively). In addition, contributions in the (50,15) treatment are marginally higher than in the (AD,5) treatment ($p = 0.080$). The p-values of all other 62 treatment comparisons, however, are well above conventional levels of significance.

Most important, we observe no systematic influence of different donation defaults on average contribution levels. For instance, average donations under a 10 euro donation default

[11] For further illustration, figure B.6 in the online appendix depicts separate donation histograms for individuals who do versus do not stick to the co-donation default. In section B.1 of the online appendix, we further discuss how people are affected by the specific default tuples in different treatment cells.

FIGURE 3.—AVERAGE DONATION BY TREATMENT



The figure depicts average donation levels across the twelve different treatments, calculated based on all participants in the experiment. Ninety-five percent confidence intervals, accounting for clustering of standard errors at the session level, are presented at the top of each bar.

TABLE 2.—SUMMARY STATISTICS BY DEFAULT DONATION LEVEL

	Treatment (Donation Default)			
	AD	€10	€20	€50
1. Donation rate (%)	3.35	3.39	3.35	3.23
2. Average donation (overall)	1.69	1.70	1.68	1.77
3. Average donation (donors only)	50.29	50.16	50.17	54.59
4. Median donation (donors only)	20	20	20	25
5. Number of observations	170,660	170,770	170,977	171,503
6. Number of donors	5,725	5,795	5,727	5,545

The table gives an overview of donation behavior for different donation defaults (subsamples pooled across co-donation treatments).

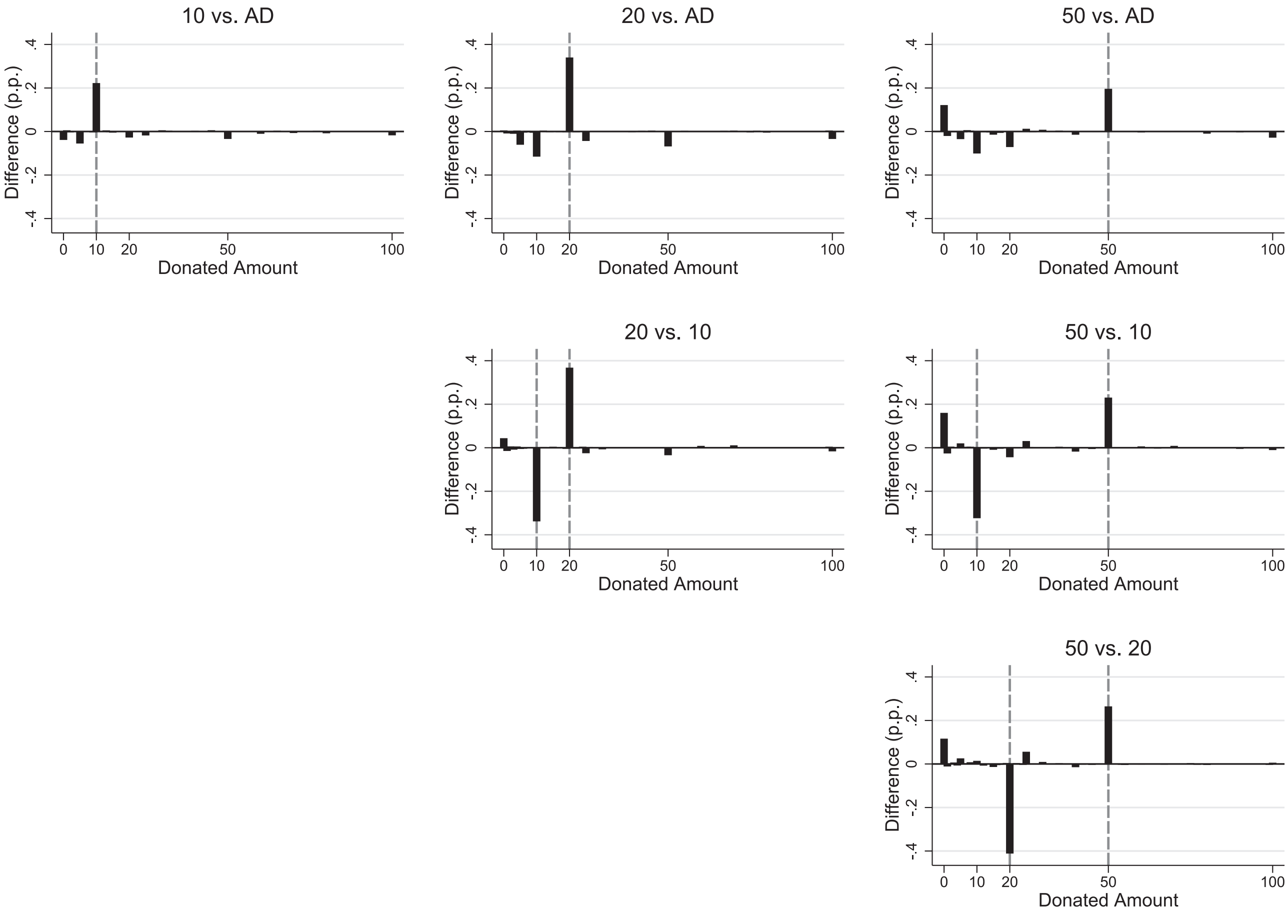
(bars 4–6 in figure 3) are very similar to those in the active-decision environment (see the three leftmost bars in figure 3). On average, participants in the AD treatments contribute 1.69 euros. This compares to 1.70, 1.68, and 1.77 euros in the treatments with a 10, 20, and 50 euro donation default, respectively (see table 2). As is the case for the comparison of individual treatment cells, these differences in average contributions for the "pooled" subsamples are not statistically significant ($p > 0.3$ for all treatment comparisons).

Interestingly, some of the bars in figure 3 seem to suggest that for a given donation default, average donation levels tend to increase in the codonation default. While the effect is relatively modest and generally not statistically significant, it turns significant for one treatment comparison if we pool observations across the different default donation levels. In particular, donations under a 15% co-donation default turn out to be significantly higher than under a 5% default ($p = 0.025$) in pooled data.

One might worry that the overall low donation rate in our sample (i.e., the high number of zero contributions from platform visitors who end up making no donation) could bias our results toward not finding statistically significant treatment differences at the aggregate level. To address this potential concern, we repeat our analysis with restricted subsamples in which we drop x% of observations for each treatment (all of which involve contributions of 0). One way to interpret this exercise is to assume that x% of participants in our experiment were only browsing the online platform without an inclination to actually make a donation. Doing so for various cutoff levels (e.g., $x = 10$, 25, or 50), we generally find no significant differences in average donation levels across treatments (see figure B.7 in the online appendix for a more detailed summary of our analysis). In the most extreme scenario, we keep only 3.39% of participants per treatment. This implies that we solely retain the 5,795 actual donors in the 10 euro treatment (where the donation rate is exactly 3.39%; see table 2), and no more than 275 nondonors in each of the remaining treatments. Nevertheless, we still cannot reject the null hypothesis of no difference in average donation levels at different donation defaults (the lowest p-value for all pairwise treatment comparisons in this case is 0.282).

Despite the substantial individual-level reactions described in section IIIA, we observe no systematic impact of defaults on average donation levels. Figure 4 explains how both of these findings can be reconciled. In the figure, we show how behavior under a given donation default changes relative to the active-decision environment and relative to the treatments involving other default specifications. The three frames in the top row of the figure depict the differences in the distributions of donations between the active-decision environment and the 10, 20, and 50 euros default, respectively. Simply put, we "subtract" the upper-left panel of figure 2 from the three other

FIGURE 4.—CHANGE IN DONATION DISTRIBUTIONS DUE TO DEFAULTS



Each panel of the figure depicts differences (in percentage points) between the distributions of donations under different donation defaults (as indicated in the panel titles). Default donations are indicated by the dashed lines. Extensive-margin differences in the proportion of nondonors are depicted at 0.

histograms depicted in figure 2, while additionally taking into account potential differences in the proportion of nondonors (i.e., a bar at 0). This allows us to examine how defaults affect the distributions of donations along both the intensive and extensive margin, relative to the active-decision environment. The frames in the second and third row of figure 4 depict the corresponding pairwise differences in the distributions of donations (and nondonors) for different donation defaults.

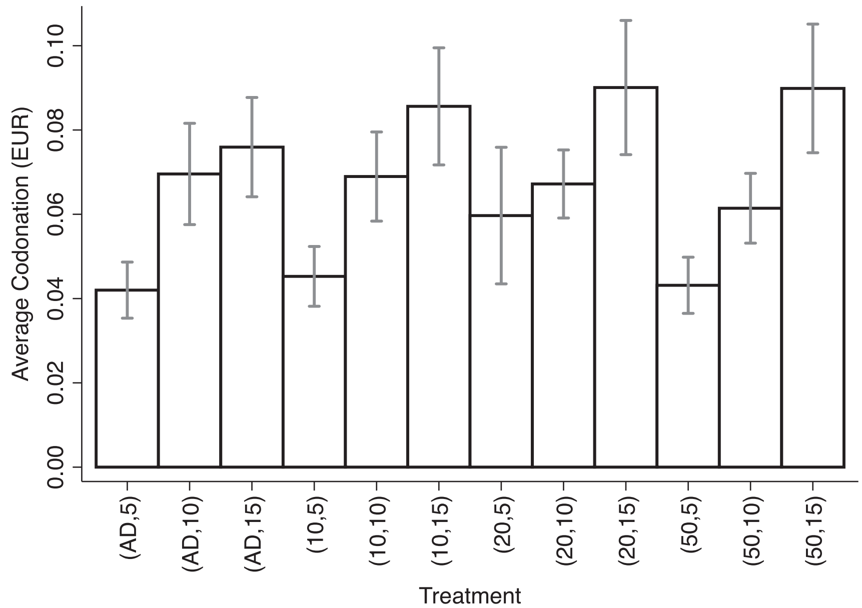
If defaults are poles of attraction for people's behavior but there are no significant differences in average donation levels, then it must be the case that defaults induce some people to donate more than they otherwise would have, while others donate less or not at all, such that the two countervailing effects cancel each other out at the aggregate level. This is exactly what we find. Figure 4 demonstrates that relative to the active-decision environment, people move toward the default from both above and below for each of the different default donation levels.[12] For instance, the spike of additional people donating 20 euros when this is the default (middle panel in the top row of figure 4) comes "at the cost" of fewer people donating 5, 10, 25, 50, and 100 euros.

Notably, at higher default values, the mass of people who can be "pulled down" by the default becomes smaller and smaller (recall that the 50 euros default corresponds to the 75th percentile in the distribution of historical donations, as well as in the AD treatments). As a result, one might reasonably expect average donation levels to go up. The panels in the right-most column of figure 4, however, show a second countervailing effect that works against such an increase. In particular, under a 50 euro default, we observe a higher fraction of participants opting out of the donation process altogether. The donation rate in the treatment with a 50 euro default is 3.23%. This compares to values of 3.35% to 3.39% in the remaining treatments (see row 1 of table 2).

Linear-probability models that analyze the propensity of making a donation across treatments show that the drop in the donation rate at the 50 euro default is statistically significant. The corresponding p-values are $p = 0.018$ when comparing the 50 euro treatment to all other treatments and $p = 0.077$ (50 euros versus AD), $p = 0.022$ (50 euros versus 10 euros), and $p = 0.093$ (50 euros versus 20 euros), respectively, for individual treatment comparisons. While the drop in the

[12]The statistical significance of these movements toward the default is further examined in section B.2 of the online appendix.

FIGURE 5.—AVERAGE CO-DONATION BY TREATMENT



This figure describes average co-donation levels across the twelve different treatments. Ninety-five percent confidence intervals, accounting for clustering of standard errors at the session level, are presented at the top of each bar.

donation rate might seem modest in size, it suffices to offset the increase in donations at the intensive margin that we observe at the 50 euro default.[13] As a result, we again observe no significant treatment differences in average donation levels.[14]

In sum, our analysis shows that defaults are important poles of attraction for donors' contribution decisions. We observe strong bunching of donations exactly at the respective default in a given treatment but no systematic changes in the frequency of contributions in the neighborhood of the default amount. Defaults tend to push up the contributions of some donors, even if they do not induce nondonors to become donors. At the same time, they tend to pull others' donations down. At relatively low default values, these two effects seem to operate entirely on the intensive margin. At higher defaults, we find that defaults can also lead to a reduction in donation rates on the extensive margin. In both cases, the countervailing effects essentially cancel each other out, leading to small and statistically insignificant average treatment effects for the different donation defaults in our experiment.

C. *Do Defaults Affect Average Co-Donations?*

The picture is quite different when considering overall co-donation levels. Figure 5 presents average co-donation amounts by treatment for our full sample (for further information on co-donation levels in the subsample of participants who make positive donations, see table A.1 in the appendix). The saw-shaped pattern shows that holding the donation default constant, co-donation revenues increase monotonically for higher co-donation defaults. The 95% confidence intervals presented at the top of each bar indicate that for most of the relevant pairwise comparisons, these differences are statistically significant. In particular, holding the donation default constant, average co-donation levels are always significantly higher at the 15% relative to the 5% co-donation default (t-tests accounting for clustering at the session level, $p < 0.01$ in all cases). With the exception of the treatments that involve a 20 euro donation default, this also holds when comparing the 10% and the 5% co-donation treatments ($p = 0.417$ for (20,5) versus (20,10); $p < 0.01$ in the remaining cases). When comparing the 15% and the 10% co-donation treatments, we find that co-donations do not differ significantly in the active-decision environment ($p = 0.458$), whereas the differences are significant for the treatments with positive donation defaults ($p = 0.062$, $p = 0.012$, and $p = 0.001$ for the 10, 20, and 50 euro donation default, respectively).[15]

[13] Focusing only on the subset of participants who do make a donation (row 3 of table 2), we indeed find a significant increase in the average donation level at the 50 default euro ($p = 0.068$, $p = 0.064$, and $p = 0.061$ when comparing the 50 euro treatment to the 10 euro, 20 euro, and AD treatment, respectively).

[14] Interestingly, while this aggregate-level result holds for all of the different donation types, the mechanisms behind the result are somewhat different for the group of participants who come to the platform in response to an organized fundraising event (see section 2.1). In particular, within this group of participants, we observe no significant drop in the donation rate at the 50 euro default. Instead, the countervailing effects in this treatment also operate entirely on the intensive margin—a decrease in the number of donors who give even higher amounts.

[15] When comparing average co-donation levels under different donation defaults, we find no systematic evidence for a spillover from donation defaults to co-donation behavior. In only one case are co-donations significantly higher than in another treatment that features the same co-donation default but a different donation default, specifically, co-donations in the

The magnitude of the observed differences in co-donation levels is substantial. For the 15% co-donation default, overall co-donation levels are roughly 80% higher than under the 5% default and still lie about 30% above the values for the 10% treatments. Comparing the co-donation revenues to the overall donation levels in the corresponding treatments underscores this effect. When facing a 5% co-donation default, participants on average make an add-on contribution to the online platform that amounts to 2.94% of their donation. This value increases to 3.88% and 4.78%, respectively, under the 10% and 15% co-donation defaults. Given that the donation levels themselves are not lowered by higher co-donation defaults (see figure 3), our findings indicate that higher defaults in the co-donation dimension increase overall revenues for the online platform without hampering donations to the charitable cause.

Panel B of table 1, as well as figure B.5 in the online appendix, illustrate how participants' reactions to co-donation defaults bring about this positive overall effect. Notably, we find that donors essentially never deviate from a co-donation default in order to make a higher contribution to the platform. Across all treatments, the fraction of donors doing so is at most 6%. Furthermore, we observe only a modest increase in the proportion of donors who opt out of making a co-donation altogether when facing higher default values. The corresponding fraction changes from 42.9% in case of a 5% default to 46.4% and 46.2% for the 10% and 15% default, respectively. While this increase of about 3 percentage points is statistically significant ($p < 0.01$ in both cases),[16] it is far from being able to offset the boost in co-donations that is caused by the roughly 30% to 35% of additional donors who make a 10% or 15% co-donation when facing these values as a default contribution (see the bold numbers in panel B of table 1). This implies that most of the behavioral reactions to defaults in the co-donation dimension happen on the intensive margin, with movements to the default from below. As a result, we observe not only strong individual-level effects of defaults but also substantial increases in overall revenues in the co-donation dimension.

D. Why Do Defaults Affect Behavior?

A natural question to ask in view of our empirical findings is why defaults matter in our setting. Although our experiment is not designed to pin down the precise mechanisms through which defaults affect behavior, our data do permit some informed speculation regarding the psychological mechanisms at work. The literature on default effects has identified numerous mechanisms that may cause people to stick to defaults, such as status quo biases, attentional limitations, or a tendency to procrastinate (see Dinner et al., 2011, and Sunstein, 2013, for comprehensive reviews of the literature). In what follows, we briefly assess the relevance of some frequently discussed candidates in light of our empirical findings. (A more detailed discussion of various mechanisms and their predictions for our setting is in section C in the online appendix.)

First, while our data look as if deviating from the default were costly for some agents, it seems highly unlikely that the treatment differences in our experiment can be explained by direct (neoclassical) transaction costs of opting out of the default. For one thing, these costs are essentially 0 in online applications, since consumers are in an environment where alternative choices are just one click away. For another, the direct costs of altering the donation amount seem negligible in comparison to the other costs that donors incur in order to finalize the transaction, such as filling out the payment details in the donation form.

Second, since we are dealing with an environment where defaults become relevant only in the final stage of a sequence of active choices, explanations based on present-biased preferences and procrastination seem of limited relevance in our setting. Specifically, while a tendency to procrastinate active decision making may contribute to the low overall donation rate that we observe, it seems unlikely that consumers bear the short-run costs of actively going to the platform, selecting a project, and so on, but then procrastinate on determining the actual donation amount.

Third, the finding that defaults have no effect on overall donation revenues is inconsistent with a class of psychological mechanisms that predict a monotone increase in average donation levels at higher default values. As we explain in section C in the online appendix, these mechanisms include explanations based on anchoring as well as simple models of reference-dependent preferences, consumer inattention, or information transmission and recommendations. More involved variants of these models—for example, featuring nonlinear gain-loss utility or allowing for more general information structures—may be able to rationalize our data. The same holds for some formalizations of the idea that defaults may signal or directly shape prevailing social norms. All of these more involved formulations, however, can rationalize a very wide range of behavioral responses. In this sense, they lack meaningful predictive power.

In sum, none of the predictive mechanisms mentioned above are able to account for all of our main empirical findings. Yet our data suggest that defaults systematically affect people's choices and that some individuals are systematically more prone to stick to defaults than others. These individuals thus behave as if deviating from the default were costly.[17] In the next section, we examine this more closely by analyzing

(20,5) treatment are higher than in (AD,5) [$p = 0.048$] and weakly higher than in (50,5) [$p = 0.064$].

[16] These tests are based on linear-probability estimations that compare the propensity of making an add-on contribution for the different co-donation defaults, controlling for potential differences across the donation-default treatments. Standard errors are clustered at the session level.

[17] A fixed as-if cost of deviating from the default could also rationalize why we observe stronger aggregate-level effects in the co-donation dimension in which stakes are smaller and people have a relatively low baseline inclination to contribute (see section IIIC).

whether the platform could make use of the heterogeneity in individuals' reactions to defaults in order to increase donation revenues.

IV. Personalized Donation Defaults

Our results above show that defaults can be used to increase co-donations but not donations. Defaults in the donation dimension serve as strong attractors, but they make some people donate more than they would otherwise have, and others donate less or not at all. On aggregate, it is a wash. This problem would obviously not arise if the online platform could personalize defaults so that some donations are pushed up but none are pulled down.

In this section, we ask whether Betterplace could make use of such a personalization strategy to increase donation revenues. A natural starting point is a reduced-form approach, investigating whether some types of donors are more likely to stick to defaults than others and whether there are heterogeneous treatment effects in donation levels under different defaults, which might in principle be exploited to target defaults based on trackable individual characteristics. A drawback to this approach is that many personal characteristics of interest are observable only for individuals who end up making a donation but not for potential donors who visit the website. More generally, the scope for personalizing defaults is limited on (publicly accessible) online fundraising sites since charities—often motivated by privacy and transparency concerns—typically cannot observe, or do not track, potentially relevant individual characteristics. This is in contrast to some offline settings (such as alumni fundraising), and it is certainly a limiting factor given the data architecture of Betterplace. In focusing on donor characteristics, our reduced-form approach is therefore bound to ignore responses along the extensive margin. That being said, for all realized donations, we can track the time stamp of the donation; whether the donation went toward a fundraising event, a project, or an element within the project; and whether the donor had logged in as a registered user. In addition, in the donation form, donors provide their first names, from which we use a name recognition algorithm to deduce their gender.

We explore donors' propensities to stick to defaults by estimating linear probability models in which the dependent variable is a dummy variable equal to 1 if a donor sticks to a positive donation default or—in an alternative specification—if she sticks to both the donation and the co-donation defaults. The estimates (presented in table B.2 of the online appendix) indicate that donors are not significantly more likely to stick to positive donation defaults in the year-end holiday season (December); donors who contribute as part of a group fundraising event are 3 to 4 percentage points less likely to stick to the default relative to those who contribute to a particular element or project ($p < 0.01$); female donors are about 4 percentage points more likely to stick to a donation default than males ($p < 0.01$); and registered users are roughly 2 percentage points less likely to stick to donation defaults than their unregistered counterparts ($p < 0.05$). This pattern is qualitatively identical when it comes to sticking to both the donation and co-donation defaults, indicating again that some types of donors are generally more likely to stick to defaults than others.

These findings suggest some scope for personalizing defaults on the basis of gender, donation type, and user registration. But it does not say much about what that default should be. Heterogeneous responses to different defaults in terms of donation levels are potentially more informative, but our reduced-form results are not very promising in this regard. More specifically, although we observe statistically significant level effects—women, notably, donate 9 euros less on average than men and donations are 26 euros higher in December than at other times of year—none of the interactions between these characteristics and the donation defaults are statistically significant at the 5% level (see table B.3 in the online appendix).[18]

Our reduced-form results indicate that it may in principle be possible to increase donations by targeting defaults based on personal characteristics, but that this strategy requires substantially richer data on donation histories and personal characteristics, not to mention large sample sizes. More generally, personalizing defaults in this manner is unlikely to be a successful strategy given the data constraints on Betterplace and other charitable-giving websites. In the remainder of this section, therefore, we adopt a structural approach that has more modest and arguably more realistic data requirements for the personalization of donation defaults. The model we build requires that the charity can store historical data on individual donations. The thought experiment we wish to conduct is the following. Suppose that the platform can first track individuals' donations in a default-free environment akin to the active-decision treatment (the status quo for Betterplace prior to our experiment).[19] This information can be used to recover the donors' underlying "generosity"—how much they are inclined to donate in the absence of a default. The platform can then use this information to personalize defaults, ensuring that they never set a default that is below a donor's baseline generosity level.

To personalize defaults in this manner, one needs to predict how individuals would respond to different default donation levels. The structural exercise accomplishes this by setting up a model, in section IVA, in which donors differ in their generosity levels. They also differ in terms of the "as-if" costs they face when either deviating from the default to a different donation amount or opting out of donating altogether.

[18]In line with our aggregate-level results for the subset of participants who make a donation (see table A.1 and note 13), contributions under the 50 euro default are significantly higher than in the AD treatment in some specifications of table B.3. This result, however, neglects the extensive-margin reduction in donation rates under the 50 euro default, illustrating again the limitations of focusing only on the intensive margin of donations.

[19]This kind of tracking is technically feasible in many online settings, by requiring one-step logins on website entry (e.g., through linked social media accounts) or, as a second-best alternative, using cookies to track IP addresses.

Structural estimates of the distributions of donors' underlying generosity and as-if costs, described and derived in sections IVB and IVC, are then used to make counterfactual predictions of donations under different defaults, which are personalized as a function of a potential donor's underlying generosity, as captured by his or her past contribution in the AD environment. Based on these predictions, we are able to examine, in section IVD, whether Betterplace could increase aggregate donation revenues by personalizing defaults.

A. *A Simple Model of As-if Costs*

In this section, we study a stylized model to derive a potential donor's optimal contribution in the presence and absence of a default. In so doing, we remain agnostic about individuals' behavioral motivations for adhering to defaults (see section IIID for a discussion of these). Instead, we set up a simple model of "costly opt-out"—in the tradition of Carroll et al. (2009) and Bernheim et al. (2015)—in which individuals who deviate from the default incur as-if costs that can stem from a variety of possible underlying psychological or economic mechanisms.

In order for this model to be useful, its predictions must match three key empirical features of our data regarding distributional differences under different defaults, summarized at the end of section IIIB. First, defaults generate bunching at the default but not in its neighborhood, and movements to the default come from both sides of the default. Second, donation rates in the AD environment are not lower than those in the different default treatments. Defaults do not induce non-donors to become donors. Third, high, but not low, defaults lead to movements along the extensive margin, reducing the donation rate by inducing some potential donors to opt out of the donation process altogether.

Formally, let $x \geq 0$ be the donation made by an individual to the charitable cause. We suppose that there is a stable underlying trait—donor generosity ρ—that determines how much an individual donates in the absence of a default.[20] In the AD environment, without defaults, an individual of type $\rho \geq 0$ maximizes her donation utility $V(x, \rho)$. We suppose that

$$V(x, \rho) = \rho x - \frac{x^2}{2}. \tag{1}$$

This structure enables us to uncover the generosity type ρ from observing the chosen donation x in the AD environment, as the utility-maximizing donation in this case is simply $x = \rho$.

Now consider an agent who faces a default $d > 0$. We suppose that independent of the default, an ungenerous type ($\rho = 0$) obtains a utility of 0 when opting out of donating altogether. Conversely, a generous type ($\rho > 0$) receives a fixed "opt-out utility" of $-\alpha$ when making no donation (with $\alpha \geq 0$). Intuitively, a generous type may feel bad when donating nothing. An individual who deviates from the default ($x \neq d$) but still donates a positive amount ($x > 0$) incurs a deviation cost $\delta \geq 0$, so that her overall utility is $V(x, \rho) - \delta$.

Note that this structure allows us to capture the three key features of the empirical donation distributions in the different treatments of our experiment. First, a person donating a positive amount will either stick to the default, thus avoiding the deviation cost δ, or donate an amount equal to her generosity level ρ. This implies that defaults increase the frequency of donations exactly at the default amount from above or below the default, but that donors are not drawn to other positive donation amounts. Second, an ungenerous agent ($\rho = 0$) cannot be induced to give a positive amount. This is in line with our observation that positive defaults do not increase the observed number of donors. Third, defaults may induce donors to opt out of the donation process altogether. This is the case when the fixed cost of doing so (α) is low relative to both the utility $V(\rho, \rho) - \delta$ of giving one's preferred amount and the utility $V(d, \rho)$ of sticking to the default. This captures the extensive-margin reduction in donation rates at higher defaults.

Simple algebra establishes that the optimal donation $x^o \geq 0$ for a generous agent with $\rho > 0$ in the presence of a default option $d > 0$ is given by

$$x^o = \begin{cases} d & \text{if } V(d, \rho) > V(\rho, \rho) - \delta \text{ and } V(d, \rho) \geq -\alpha \\ \rho & \text{if } V(\rho, \rho) - \delta \geq V(d, \rho) \text{ and } V(\rho, \rho) - \delta \geq -\alpha. \\ 0 & \text{if } \max\{V(\rho, \rho) - \delta, V(d, \rho)\} < -\alpha \end{cases} \tag{2}$$

To simplify notation, let

$$\Delta(\rho, d) \equiv V(\rho, \rho) - V(d, \rho) = \frac{\rho^2 + d^2}{2} - \rho d.$$

We assume that there is a share λ_1 of agents who act as if deviating from the default is costless. These agents experience no deviation costs δ and therefore always donate their preferred amount ρ.[21] The remaining $1 - \lambda_1$ share of agents has positive deviation costs. The optimal donation decision of agents who face deviation costs will depend on their generosity level. For relatively generous agents, it is never optimal to opt out of making a donation altogether. Specifically, for agents with a generosity level $\rho \geq d/2$, sticking to the default yields utility $\rho d - d^2/2 \geq 0$, whereas the utility from opting out and making no donation is $-\alpha < 0$. These relatively generous agents will therefore either stick to the default or donate their preferred amount ρ, depending on whether their

[20] Inasmuch as this trait is not stable, we are bound to overestimate the benefits from personalizing defaults based on donors' past donations under an active-decision policy.

[21] Note that these agents might still be subject to opt-out costs (α), but the latter are irrelevant for agents' choices. This is because agents can costlessly deviate from the default to their preferred donation amount ρ, which guarantees strictly positive utility.

deviation costs δ are larger or smaller than $\Delta(\rho, d)$. Agents with relatively low generosity, $0 < \rho < d/2$, also determine their choice of sticking to the default or deviating to their preferred amount depending on which side of the cutoff, $\Delta(\rho, d)$, their δ lies. For low-generosity agents, however, the utility of donating d and the utility of deviating to ρ may both be smaller than the opt-out utility $-\alpha$. When this is the case, it is optimal for low-generosity agents to opt out of donating altogether. Finally, ungenerous agents with $\rho = 0$ will never make a positive donation.

B. Estimation

There are three unknown parameters in this model: generosity types ρ, deviation costs δ, and opt-out costs α. A key advantage of our data is that we can identify the distribution function $f(\rho)$ nonparametrically from the observed donation distribution in the AD treatment, which features no default and therefore entails no deviation costs.

Modeling costs requires more structure, since costs are not directly observed. In keeping with Bernheim et al. (2015), we allow for heterogeneous deviation costs that follow an exponential distribution. Specifically, we assume that conditional on belonging to the share $1 - \lambda_1$ of agents with positive deviation costs (whom we index by $z = 1$), the cost δ of deviating from the default to a positive donation amount is distributed according to the cumulative distribution function Φ, where

$$\Phi(\delta|z = 1) = \begin{cases} (1 - e^{-\lambda_2 \delta}), & \text{for } \delta \geq 0, \\ 0, & \text{for } \delta < 0. \end{cases}$$

Once again following Bernheim et al. (2015), we further assume that ρ and δ are independently distributed. As for the costs of opting out of the donation process altogether, we assume that making no donation entails no costs for ungenerous types ($\alpha = 0$ for agents with $\rho = 0$). For generous types ($\rho > 0$), the opt-out cost α is distributed according to the cumulative distribution function Ω, where

$$\Omega(\alpha|\rho > 0) = \begin{cases} (1 - e^{-\lambda_3 \alpha}), & \text{for } \alpha \geq 0, \\ 0, & \text{for } \alpha < 0, \end{cases}$$

and is distributed independently of δ and ρ.

Given that $f(\cdot)$ is already nonparametrically identified from the AD treatment, the estimation problem boils down to identifying the three parameters of the model that define the cost distributions: a proportion λ_1, which is inured to deviation costs, and the parameters of the exponential distributions λ_2 and λ_3, which define the deviation costs and opt-out costs, respectively. We estimate these parameters by maximizing a log-likelihood function of the following form:

$$L(\lambda) = \sum_{i=1}^{N} \log(\Pr(x_i|d, \lambda, f(\cdot))),$$

where $i = 1, \ldots, N$ are the individual observations in the treatments with positive donation defaults. Section D.1 in the online appendix provides a detailed derivation of the log-likelihood function. In essence, the likelihood function in our setting consists of the different cases involved in the optimal donation decision described in equation (2), weighted by the corresponding probabilities with which they occur, given the (estimated) model parameters. For example, the probability of observing a person donating 15 euros, in a treatment with a 50 euro default depends on the prevalence of people with a generosity type $\rho = 15$, the fraction of individuals who are subject to deviation costs $(1 - \lambda_1)$, as well as the distributions of the deviation and opt-out costs (determined by λ_2 and λ_3).

Note that the log-likelihood function is defined only if $f(\rho)$ takes on positive values for all ρ. As the empirically observed donations in the AD treatment take discrete values and the data become sparse at donations above 300 euros, we restrict the sample in our estimation to $\rho \in [0, 300]$ and "smooth" our data by assigning donations to integer bins, such that each bin has positive mass. The observations used in the estimation amount to 99.9% of the total sample. Parameters $\lambda = (\lambda_1, \lambda_2, \lambda_3)$ are identified through changes in the donation distribution under the different donation defaults in our experiment, relative to the AD treatment (see figure 4).

C. Estimation Results

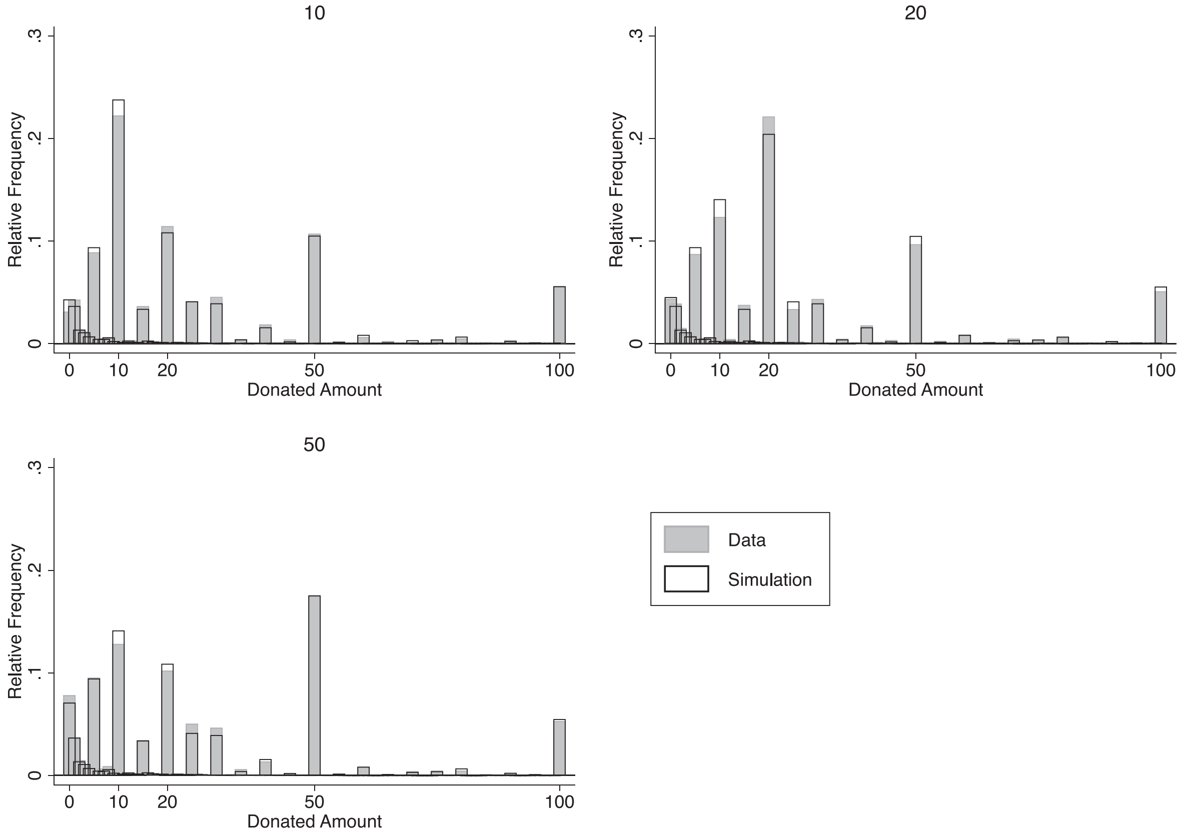
Our estimate for λ_1 indicates that 89% of potential donors are inured to, or simply ignore, the default (see table D.1 in the online appendix for an overview of the maximum likelihood estimates for λ). This proportion, though seemingly high, is entirely in line with the empirically observed responses to defaults in our experiment. In particular, recall that the proportion of donors who contribute the default amount under different donation defaults increased by roughly 5 to 10 percentage points relative to the AD environment (see table 1). Default options thus substantially affect the behavior of some individuals, but they leave a majority of potential donors untouched.[22]

Among the 11% of potential donors who do incur costs, the estimates for λ_2 and λ_3 indicate that deviation costs and opt-out costs are rather high (see table D.1).[23] High

[22]This finding might seem surprising in light of the evidence that defaults affect a large share of the population in applications like retirement savings or organ donor registration. Note, however, that some of the potential mechanisms behind default effects in these settings are, by design, less relevant in ours (such as hassle costs of opting out or present-biased procrastination; see section IIID). Hence, our relatively high estimate for λ_1 may indicate that procrastination is indeed a major driver of default effects in those other settings.

[23]These costs are measured in utils and are therefore not directly interpretable in monetary terms. Figure D.1 in the online appendix, however, gives a sense of what "high" means in this context by plotting the $\Delta(\rho, d)$ functions under the three different defaults, as well as the mean and median of δ implied by our estimates. The figure shows that for agents of type $\rho \leq$ €158 (168) [198], the median deviation costs are high enough to make the agents stick to a default of €10 (€20) [€50], rather than donating their preferred amount ρ.

FIGURE 6.—FITTED VERSUS ACTUAL DONATION DISTRIBUTION



The figure compares the empirically observed distributions of donations in the experiment to (simulated) fitted distributions, using the nonparametric distribution $f(\cdot)$ from the AD treatment for integer values of ρ and the maximum likelihood estimates of λ from table D.1 in the online appendix. For the simulated ρ's, a random sample of the distribution function $f(\rho)$ is drawn with $N = 500{,}000$. For illustrative reasons (i.e., to avoid extreme spikes at 0 due to the high share of nondonors), the analysis focuses on a subsample containing 3.5% of the overall sample in each treatment (all actual donations and the corresponding number of zero contributions per treatment), excluding donations above 300.

deviation costs imply that agents who are subject to these costs are inclined to stick to the default, generating modes in the distributions of donations at the corresponding default values. At the same time, the estimate for λ_3 is larger than the estimate for λ_2, indicating that opt-out costs tend to be smaller than deviation costs. The upshot of this is that opting out of donating altogether may be preferable to donating a non-default amount, especially for potential donors who are less generous. At high enough defaults, this generates movements along the extensive margin.

The model with these parameter estimates performs remarkably well. As figure 6 shows, the fitted model successfully reproduces all of the key features of the data from our experiment: it generates the empirically observed modes at the 10, 20, and 50 euro defaults; reproduces the decrease in the donation rate (i.e., the spike at zero) under the 50 euro default; and closely matches the empirical distributions elsewhere.

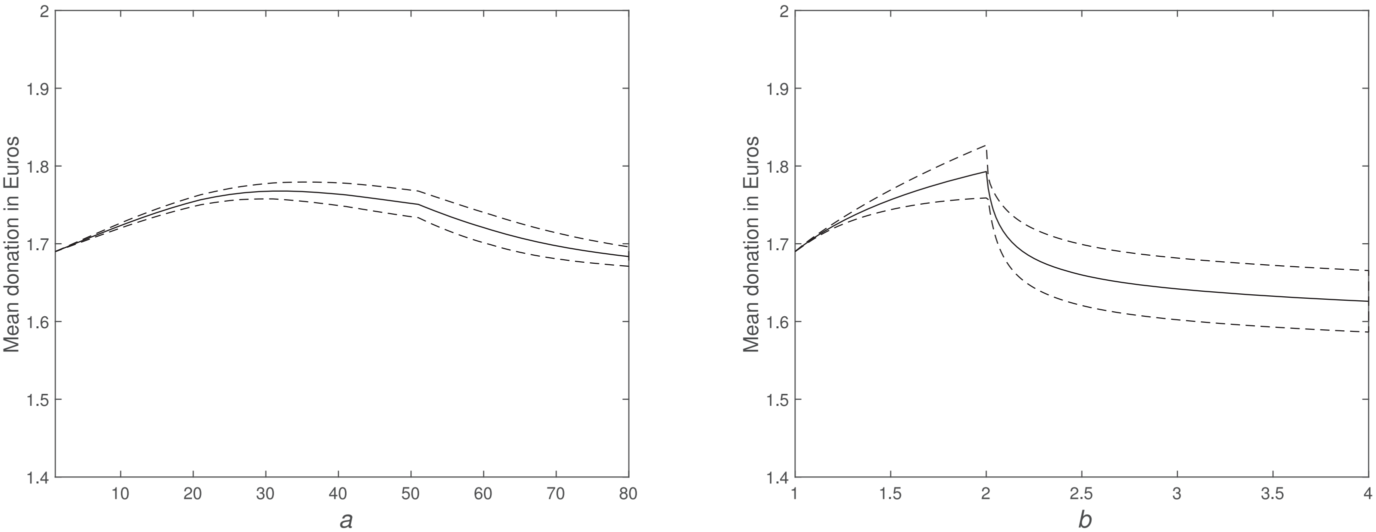
D. *Personalized Defaults*

Using the parameter estimates for λ, we can now make counterfactual predictions regarding how donation revenues would change under a system of personalized defaults. Specifically, we examine how the platform could optimally condition defaults on an individual's (past) donation level in the absence of defaults, captured in our model by the parameter ρ. As is immediately clear from our derivations above, as well as from the empirical observation that defaults pull some donors' contributions down relative to the AD treatment, it never makes sense to set the donation default for a given individual below his or her generosity type ρ. We therefore simulate two types of personalized defaults. The first is additive: an individual of type ρ is assigned a default of $\rho + a$, where $a \geq 0$. The second is proportional: an individual of type ρ is assigned a default of $\rho \cdot b$, where $b \geq 1$.

Figure 7 furnishes our model's predictions of mean donation levels under personalized defaults for the additive (panel A) and proportional case (panel B). Under the additive default option, donations are maximized at $a^* = 31.3$. The optimal scaling factor for the proportional personalized default is $b^* = 2.0$.[24] Under these defaults, our model predicts that overall donation revenues would increase by at most 6.2%

[24]The optimal add-on and scaling factor may seem high, but they follow naturally from our parameter estimates in the previous section, our model specification, and the empirical results from section III. Since a majority of potential donors is generally inured to defaults, it does not matter for them when this default is high. For the rest, a high personalized default may lead some to completely opt out of the donation process, but those who

FIGURE 7.—DONATIONS UNDER PERSONALIZED DEFAULTS



(A) Additive: $d(\rho) = \rho + a$

(B) Proportional: $d(\rho) = \rho \cdot b$

This figure plots means and confidence intervals of donations under different personalized default-setting policies, based on simulated data. Personalized defaults are determined by adding a constant a to the agent's baseline generosity level ρ (left panel) or multiplying it with a factor b (right panel). Agents' response to the personalized default is simulated for a range of different values of a and b. The confidence interval accounts for uncertainty in the estimated parameters. We reestimate the λ parameters with bootstrap samples from the 10, 20, and 50 euro default treatments and replicate this 1,000 times. For each of these estimated λ parameters, we simulate the agents' response to the personalized defaults and construct a confidence interval around these means. The simulations are carried out with a large sample of ρ's drawn from the AD treatment to approximate well the distributions of the as-if costs.

relative to the AD environment (4.7% in the additive and 6.2% in the proportional case). While this increase in donation revenues seems economically relevant, we think of it as an upper bound for the potential gains to be made from personalization in our setting. Specifically, if the donors' generosity level fluctuates over time or varies by project, the gains from personalized defaults are bound to be lower. Moreover, our simple functional form of individuals' donation utility $V(\cdot)$ implies that increasing a potential donor's default to up to twice her preferred amount does not trigger an extensive-margin reaction. The fact that we see a sharp drop in predicted revenues for proportional scaling factors above 2 suggests that individuals may drop out somewhat earlier if we allowed for a more flexible specification of their preferences. Hence, despite our model's ability to replicate key data patterns of our experiment, the potential benefits of personalizing defaults in our setting seem rather limited.

V. Conclusion

We conclude by discussing practical implications of our findings for charitable organizations and providers of online donation platforms. Most important, our results highlight the possibility that defaults may have both desired and undesired effects on the distribution of donations and overall donation revenues. They also demonstrate that defaults may have an influence on people's decisions, even if this influence might not be directly apparent in aggregate-level data.

Both observations caution against a simplistic use of defaults based on the notion that "defaults work." This, of course, does not imply that positive defaults may never increase donation revenues. The use of personalized or adaptive defaults seems promising in this respect, but our results from section IV suggest that it is challenging to successfully increase donations through personalized defaults in a setting like ours. While our reduced-form results indicate heterogeneity across groups in terms of potential donors' proclivity to stick to defaults as well as in the overall propensity to contribute, we find no compelling evidence of heterogeneous donation responses to defaults. The results from our structural estimates are not much more encouraging. They indicate that personalized defaults have the potential to avert downward movements in donations by setting defaults neither too high nor too low for a given donor, but they also suggest that successful personalization requires much richer data. While the data constraints that limit our analysis in this respect are, at present, shared by many other online charitable giving platforms, better tracking of data from donors and their reactions to different features of the platforms, as well as linked data from other sources, might eventually make such an approach feasible.

do not are induced to contribute a higher amount. Optimal personalized defaults are those that best manage the trade-off between driving some people out and others up. This can be readily seen in the case of proportional personalization. The scaling factor of 2 implies that nobody is induced to opt out entirely under their personalized default, since individuals with $\rho \geq d/2$ always stay in the donation process (see section IVA). At the same time, individuals with high deviation costs δ will stick to the default, thereby generating higher revenues for the charity.

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Appendix Table

TABLE A.1.—SUMMARY STATISTICS

		Treatment (D€, C%)												
		(AD,5) (1)	(AD,10) (2)	(AD,15) (3)	(10,5) (4)	(10,10) (5)	(10,15) (6)	(20,5) (7)	(20,10) (8)	(20,15) (9)	(50,5) (10)	(50,10) (11)	(50,15) (12)	F-test (13)
		Donations												
(1)	Donation rate (%)	3.34	3.27	3.45	3.35	3.45	3.38	3.31	3.39	3.35	3.14	3.35	3.21	
(2)	Av. donation (overall)	1.59	1.68	1.79	1.54	1.76	1.81	1.63	1.71	1.70	1.71	1.74	1.85	
(3)	Av. donation (donors only)	47.65	51.44	51.76	45.90	51.10	53.44	49.31	50.33	50.85	54.53	51.82	57.54	
(4)	Median donation (donors only)	20	20	20	20	20	20	20	20	20	23	25	25	

TABLE A.1.—*Continued*.

		Treatment (D€, C%)												
		(AD,5) (1)	(AD,10) (2)	(AD,15) (3)	(10,5) (4)	(10,10) (5)	(10,15) (6)	(20,5) (7)	(20,10) (8)	(20,15) (9)	(50,5) (10)	(50,10) (11)	(50,15) (12)	F-test (13)
		Codonations												
(5)	Donation rate (%, all)	1.82	1.70	1.77	1.94	1.89	1.90	1.94	1.93	1.85	1.80	1.69	1.69	
(6)	Donation rate (%, donors only)	54.50	52.04	51.43	57.91	54.89	56.12	58.68	56.77	55.25	57.39	50.55	52.52	
(7)	Av. co-donation (€, all)	0.042	0.070	0.076	0.045	0.069	0.086	0.060	0.067	0.090	0.043	0.061	0.090	
(8)	Av. co-donation (€, donors only)	1.26	2.13	2.20	1.35	2.00	2.53	1.80	1.98	2.69	1.38	1.83	2.80	
		Project background characteristics												
(9)	Fundraising event	0.118	0.116	0.117	0.118	0.116	0.116	0.115	0.116	0.117	0.114	0.117	0.118	0.658
(10)	Project	0.339	0.339	0.338	0.338	0.338	0.338	0.340	0.340	0.336	0.337	0.339	0.336	0.827
(11)	Element	0.542	0.544	0.545	0.544	0.545	0.546	0.545	0.543	0.548	0.549	0.544	0.546	0.620
(12)	Tax deductible	0.661	0.657	0.655	0.659	0.660	0.658	0.660	0.655	0.660	0.658	0.657	0.656	0.317
(13)	Number of observations	56,894	56,959	56,807	56,739	57,014	57,017	56,777	57,083	57,117	57,138	56,985	57,335	
(14)	Number of donors	1,901	1,864	1,960	1,903	1,964	1,928	1,878	1,936	1,913	1,793	1,909	1,843	

The top and middle panel provide an overview of key outcome variables in the different treatments. The bottom panel provides an overview of observed project background characteristics. Rows 9 to 11 report the proportion of observations in a given treatment that pertain to a fundraising event (e.g., a birthday or charity run), an aid project, or a specific element within a project (e.g., a first aid kit within a Red Cross Project), respectively. Row 12 pertains to the proportion of observations per treatment group that were eligible for a tax deduction (typically the case when the charity is registered in Germany). The final column reports p-values from F-tests for treatment differences in background characteristics, based on separate regressions of each of the characteristics on dummies for the different treatments.