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Abstract

We study how website defaults affect consumer behavior in the domain of charitable giving. In a field experiment that was conducted on a large platform for making charitable donations over the web, we exogenously vary the default options in two distinct choice dimensions. The first pertains to the primary donation decision, namely, how much to contribute to the charitable cause. The second relates to an "add-on" decision of how much to contribute to supporting the online platform itself. We find a strong impact of defaults on individual behavior: in each of our treatments, the modal positive contributions in both choice dimensions invariably correspond to the specified default amounts. Defaults, nevertheless, have no impact on aggregate donations. This is because defaults in the donation domain induce some people to donate more and others to donate less than they otherwise would have. In contrast, higher defaults in the secondary choice dimension unambiguously induce higher contributions to the online platform.

JEL-Code: C930, D030, D640.

Keywords: default options, charitable giving, online platforms, field experiment.

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1 Introduction

Pre-defined default specifications are a pervasive feature of web interfaces in online platforms and marketplaces. In many cases, website visitors face multiple different default options, pertaining both to the main attributes of the products and services that are being offered as well as to other "add-on" choices such as shipping and handling options, modes of payment, or extended warranties. Relative to their prevalence, systematic empirical evidence on how web defaults affect consumer behavior is surprisingly scarce. This is a serious gap, given that policy makers have already begun to regulate the use of defaults in online markets, based on an intuition that "defaults matter" and that they may be set in a way that potentially harms consumers.[1]

In this paper, we study how website defaults affect consumer behavior in the domain of charitable giving. We report results from a natural field experiment that we conducted on Germany's largest platform for making charitable contributions over the web. Our setting has a number of features that make it ideally suited to study the impact of web defaults on behavior. First, online fundraising platforms constitute a sizable and rapidly growing segment of the market for charitable giving. Over the course of our experiment, for instance, we collected data on roughly 680,000 donation-page visits and almost 23,000 donations, yielding a total of €1.17 million in terms of revenues for the charitable organizations on the platform. Second, by exogenously varying the default options on the platform, we can identify the direct causal impact of defaults on consumers' choices. Moreover, as the transaction costs of opting out of defaults in our setup are essentially zero, we can rule out an important class of mechanisms through which defaults might affect behavior. Finally, our setup allows us to systematically vary defaults in two distinct choice dimensions. In particular, we independently randomize default specifications for the main donation decision—the primary purpose of people's website visit—and for an add-on choice, which is a gratuity to support the providers of the online platform. While this is interesting in itself, given that both types of defaults are frequently observed, it can also help to shed light on the question of why people stick to defaults in our setup.

[1]The 1995 European Union Data Protection Directive, for instance, gives consumers the right to opt-in rather than opt-out of any program that collects personal information. Similarly, the EU recently enacted rules requiring airline companies to offer optional booking supplements exclusively on an opt-in basis (Regulation (EC) No. 1008/2008).

In the primary decision dimension of how much to contribute to the charitable cause, we randomly assign website visitors to default donation amounts of €10, 20, and 50. These values correspond, respectively, to the 25th, 50th, and 75th percentile of donations on the platform during 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 zero 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 independently vary defaults for the add-on contribution to the online platform. Specifically, we randomly assign donation-page visitors to percentage add-ons of 5%, 10%, or 15% of their main donation. The corresponding contributions, or "codonations", are used to support and maintain the online platform, which itself operates as a nonprofit organization.

Our data show a strong impact of defaults 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 these strong individual-level effects, defaults in our experiment do not affect aggregate giving to the charitable cause. We neither find systematic differences in average contributions across the different donation defaults, nor when comparing overall donation levels to the environment where donors have to actively decide on their contribution. The striking 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 countervailing effects cancel each other out at the aggregate level. For default contributions of €10 and €20, the changes in the donation distribution operate entirely on the intensive margin. At the €50 default, we observe an additional extensive-margin effect of more people opting out of the donation process altogether. As a result of this higher donor attrition, overall donation levels are again very similar to those in the remaining treatments. By contrast, we do observe strong aggregate-level effects of defaults in the add-on dimension. Codonation revenues are increasing monotonically in the percentage add-on that is set as the default.

This is because the dominant change in the distribution of codonations at higher default values is an intensive-margin movement towards the default from lower contribution levels. As a result, we not only observe strong individual-level effects of defaults, but also substantial increases in overall revenues in the codonation dimension.

A number of previous studies have explored how default specifications affect a variety of economic decisions, such as choices of insurance or retirement saving plans (Johnson et al. 1993, Madrian and Shea 2001, Choi et al. 2004, and Carroll et al. 2009), organ donor registration (Johnson and Goldstein 2003 and Abadie and Gay 2006), and tipping behavior in New York City cabs (Haggag and Paci 2014). We add to this literature by examining default options in one of the decisions environments where they are most widely used—the web interfaces of online platforms. Despite being relatively easy to manipulate and a cost-effective way to obtain large samples, this type of defaults has received comparably little attention so far.

Levav et al. (2010) examine the effect of defaults on consumers' customization choices at car dealerships. In contrast to our setting, however, they do not vary default options, but manipulate the ordering of attribute menus on the dealership's interface, while keeping defaults constant. Johnson et al. (2001) study default settings for a classical add-on choice—mailing-list subscriptions—and find that defaults as well as the framing of the web interface matter for subscription rates. Löfgren et al. (2012) and Ebeling (2013) study defaults for carbon offsetting and "green energy" on a conference registration page and an electricity provider's website, respectively. While Löfgren et al. (2012) observe no systematic impact of defaults, Ebeling (2013) finds that a very high fraction of consumers stick to the default electricity contract. In contrast to the latter studies, we examine a setup where consumers do not only face a binary opt-in vs. opt-out decision, but have a continuum of decision alternatives available. This allows us to study a rich set of individual-level reactions to defaults along both the intensive and extensive margin of the donation distribution. Our findings demonstrate that defaults can have manifold—and, in our case, countervailing—effects in both dimensions, highlighting the importance of a detailed assessment of individual- and aggregate-level effects of defaults. In particular, our results show 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.

Studying default options in online settings is also interesting since the mechanisms through which defaults affect behavior might differ from those in other contexts. Importantly, defaults in our setup (and in online contexts more generally) are only put into effect after a user actively comes to the online platform, decides on a project to which he wants to donate, fills out the remainder of the donation form, and confirms the transaction. Explanations based on procrastination of making active decisions that have featured prominently in the discussion of default effects in organ donor registration or 401(k) savings plans (e.g., Johnson and Goldstein 2003, Carroll et al. 2009) thus seem to be of limited relevance for our results. Instead, some of our findings suggest that defaults in our setting are behaviorally relevant because consumers exhibit limited attention (Hossain and Morgan 2006, Chetty et al. 2009, Caplin and Martin 2013) or perceive defaults as norms or recommended actions (Madrian and Shea 2001, McKenzie et al. 2006, Altmann et al. 2013).

A voluminous literature has examined the impact of different fundraising interventions on charitable giving (see Andreoni 2006 as well as Bekkers and Wiepking 2011 for comprehensive reviews of the literature). These studies have typically used direct mailings, door-to-door, or telephone solicitations. Given the growing importance of online fundraising, it is surprising that none has explored interventions in an online setting. Insofar as potential donors interpret default specifications as suggested contributions to the charitable cause, our study is related to Adena et al. (2014) and Edwards and List (2013) who explore how giving is affected by explicitly suggesting specific donation levels during solicitation.[2] In contrast to our

[2]There are three additional suggestion interventions commonly used in the literature, which are more peripherally related to our paper. First, several studies have examined how the statement "every penny helps" affects donation behavior (e.g., Brockner et al. 1984, Cialdini and Schroeder 1976, Reeves et al. 1987, and Reingen 1978). These studies have generally found a positive effect on average revenues (although Fraser et al. 1988 finds otherwise). Second, a number of studies in the marketing literature have explored whether offering different scales for suggested donation grids alters the incidence and level of donations (see Weyant and Smith 1987, Schibrowsky and Peltier 1995, Doob and McLaughlin 1989, Prokopec and De Bruyn 2009, Desmet and Feinberg 2003 and De Bruyn and Prokopec 2013). The results are often inconclusive: many of the earlier studies have low power and no compelling pattern emerges with respect to compliance and average donations across different donation grids. The last four studies, however, indicate that grids which are tailored to donors' previous donation behavior can increase overall donation levels. Finally, a number of studies have analyzed whether providing potential donors with information about other people's behavior affects charitable giving. Specifically, Frey and Meier (2004) show that information about past donation rates influences donors' propensity to make a contribution themselves. Shang and Croson (2009) demonstrate that informing potential donors about particularly high contributions of others can lead to an increase in overall donation revenues.

experiment, these papers employ relatively strong framing of the suggested contribution amounts.[3]

Our paper is also related to the recent empirical literature on add-on pricing. Most closely related, Hossain and Morgan (2006) and Chetty et al. (2009) find that variations in add-on costs such as shipping-and-handling fees or sales taxes have a smaller effect on consumer behavior than equivalent variations in the primary price of the product. Their findings are in line with more general evidence suggesting that consumers are unaware of or underestimate the role of non-primary price components.[4] The fact that we find particularly strong effects of defaults for the add-on contribution to the online platform is consistent with donors focusing more on the primary dimension. At the same time, our data shows that defaults also have substantial (albeit countervailing) effects on the main donation decision. An explanation that is purely based on attentional limitations or focusing would thus also need to extend to the primary decision dimension, at least for a subsample of our participants.

On a more general level, our paper is related to the literature that analyzes the conditions under which "non-standard" preferences or bounded rationality in individual behavior translate into differences in aggregate-level outcomes. Becker (1962) argues that irrationality on the individual level can be consistent with rationality on the aggregate level in the context of the compensated law of demand. Conversely, of course, Becker's finding illustrates that "rational" behavior in the aggregate does not imply rational behavior on the individual level. In line with this intuition, we observe no aggregate default effects for donations and yet can identify strong effects of defaults at the individual level. In terms of codonations, on the other hand, we find that systematic changes in individual behavior due to defaults also affect aggregate-level outcomes. This illustrates that aggregation may attenuate individual-level effects in some situations, but not in others.[5]

[3]For example, Adena et al. (2014) examine the following contribution-level suggestions in solicitation letters for a social youth program of an opera house: "With a donation of €100 [€200] you will [already] give a child [two children] the possibility to participate in the programme."

[4]For example, studies of credit card demand have found that consumers do not take various credit card fees into account (Agarwal et al., 2008) and tend to overvalue introductory "teaser (interest) rates" (Ausubel 1999 and Shui and Ausubel 2004) when choosing a credit card. In the banking sector, Woodward and Hall (2012) finds that borrowers underestimate broker compensation, and Cruickshank (2000) documents that retail bank customers do not know specific banking fees. Similarly, Hall (1997) shows that most customers have very little knowledge about the price of ink cartridges when buying a printer.

[5]More distantly, there is a large literature studying whether market forces eliminate or exacerbate non-

The paper proceeds as follows. In the following section, we describe the setup, treatments and procedures of our experiment. Section 3 presents our empirical results, and Section 4 concludes by discussing the relationship between our empirical findings and existing theoretical explanations of default effects.

2 The Experiment

2.1 The Donation Platform

We study the effect of default options on betterplace.org—Germany's largest platform for making charitable donations over the web. The platform hosts 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 immigrant children in Berlin, to humanitarian aid for victims of the typhoon in the Phillippines, to supporting orphanages in Kenya; charities that are present on Betterplace include small local NGOs as well as organizations like UNICEF or the International Committee of the Red Cross. In addition to the aid projects themselves, the platform also hosts pages for "fundraising events" that offer individuals, firms, or other organizations the possibility to collect donations for one of the aid projects by organizing charity runs, benefit concerts, or similar fundraising campaigns.

Visitors to the online platform can browse individual fundraising or project pages, which describe the overall project and the budget needed to fund it, as well as the amounts of money that are required for specific "needs" of the project, i.e., the precisely defined elements of which the overall project consists. Figure 1 provides an example of a project page (a full English translation of the original screen shot can be found in Figure A.1 in the appendix). 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

classical behavior by consumers or firms. Dufwenberg et al. (2011), for example, provide conditions under which agents with social preference behave as-if selfish in competitive markets. On the other hand, many recent competitive market-models with non-classical consumers demonstrate that aggregate outcomes can be affected when consumers make mistakes or are time-inconsistent (see, e.g., Laibson and Yariv 2007, Gabaix and Laibson 2006, DellaVigna and Malmendier 2004, Heidhues and Kőszegi 2010, Heidhues et al. 2014, and Heidhues and Kőszegi 2014).

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 overall aid project or to various 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 1).[6]

Figure 1: Screen shot of a project page.

By clicking on either of two red 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 (Figure 2; see Figure A.2 in the appendix for a full English translation). On this page, the donor specifies the amount that she wishes to contribute to

[6]The corresponding page for fundraising events has a slightly different layout (see Figure A.3 in the 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 2). Over the course of our experiment, 41.4% of donors contribute directly to the overall aid projects, 20.7% contribute to specific project elements, and 37.9% of donations are made through fundraising events. Since we observe no interaction effects between our treatments and the different donation channels, our empirical analysis in Section 3 concentrates on the pooled data set that includes all donations.

Figure 2: Screen shot of the donation page.

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 also 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 drop-down menu appears that allows donors to choose between 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 to enter any absolute Euro amount. We refer to the add-on contributions in support of the platform as *codonations*. Codonations are used to cover the costs for sustaining and further developing the online platform, which itself operates as a nonprofit organization.

The sum of the donation and codonation amount determine the donor's "Overall donation" ("Gesamptspende"), 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 2), 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.

2.2 Treatments

Our experimental intervention pertains to the donation page depicted in Figure 2. For each donor who enters the donation page, we exogenously vary the donation and codonation amounts that are displayed by default in the respective fields of the donation form. We randomize independently in the two different treatment dimensions. In the *donation dimension*, we assign each donor to one of four different treatments. Specifically, when arriving at the donation page, the amount displayed in the project-donation field is either zero, or corresponds to a pre-specified donation level of €10, €20, or €50. Note that in each case, donors are free to contribute any positive amount by simply typing in the desired contribution level into the project-donation field.

The three different default donation levels were chosen based on historical donation patterns, and 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 analyze whether defaults have a stronger or weaker impact on behavior if they are relatively high or low compared to what most people would typically donate. The zero treatment, by contrast, 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 zero, 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 below, 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.[7]

There is a second sense in which our setting involves active decision-making: contributions, and thus potentially also the default donation levels, only become effective 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 web-based 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

[7] An alternative way to implement an active-decision environment in our setup would be a treatment where the donation field is initially left blank. For technical reasons, it was not possible to implement this additional treatment on the web interface of Betterplace. Note that the donation distributions resulting from the two different active-decision frameworks might differ slightly, e.g., if donors use the number in the donation field as an "anchor" for their decisions (Tversky and Kahneman 1974). As we will explain in further detail in Section 3, however, anchoring only seems to play a limited role (if any) in our setting.

remains entirely passive. While this difference might seem subtle, it is potentially important for understanding the channels through which defaults can affect behavior. In particular, the degree to which present-biased preferences and procrastination of active decisions might affect outcomes differs between the two different types of default regimes.

An important feature of our setting is that we have precise information on the incidence as well as on the level of donations for each visitor of the donation page. This allows us to compare the entire distribution of donations across treatments, including non-donors, and thereby examine how default options affect donor behavior both on the extensive and the intensive margin. It also allows us to provide a detailed picture of how individual-level differences in behavior caused by variations in defaults translate into differences in aggregate outcomes in terms of overall donation revenues.

In our second treatment dimension, *codonations*, we independently vary the pre-specified percentage add-on to support the online platform. Specifically, we randomly assign donation-page visitors to codonation defaults of $5\%, 10\%$, or 15%. This second treatment dimension is interesting for two main reasons. First, the codonation decision is a typical example of an add-on choice that consumers face on top of their main purchasing decisions, and defaults for such add-on decisions are widespread in web-based commercial activities (e.g., travel insurance and other supplements for flight bookings, seat reservations for rail tickets, and shipping options on online retail platforms). Second, the mechanisms through which defaults affect behavior in our setting might differ between the primary donation decision and the secondary codonation decision. In particular, the salience of the different defaults and the degree of attention that people devote to them might differ between the two decision dimensions. For instance, it is well established that people tend to underappreciate variations in add-on costs such as shipping and handling, sales taxes, etc. (Hossain and Morgan 2006, Chetty et al. 2009) relative to the variation in the primary purchase price. Based on these previous findings and an intuition that donors may pay less attention to (Chetty et al. 2007) or focus less on the secondary dimension (Kőszegi and Szeidl 2013), one may expect default effects to be particularly pronounced for codonations.[8] In contrast, it seems likely

[8]Most donors are unlikely to completely overlook the existence of the codonation, given that it is displayed right next to the main donation field, and given that the calculation of the "total donation" amount makes it salient that there is a difference between the donation to the aid project and the overall amount contributed. Donors, nevertheless, may focus less on differences in the codonation amounts due to defaults, e.g., because these differences are smaller in absolute size compared to those in the primary donation decision (see Chetty

that potential donors are attentive to defaults in the donation dimension: since the donation decision is the primary reason why people visit the online platform, the choice of the actual donation amount is likely to be part of a deliberate decision process.

2.3 Implementation of the Experiment

The experiment was conducted over an 11-month period from June 08, 2012 to April 19, 2013. Overall, we observe roughly 680,000 visitors on the platform during this period, distributed over the 12 different treatment cells in our 4×3 design (see Table 1 for an overview). 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 (i.e., the highest possible default). Second, note that a user can make multiple donations during the same "session" or platform visit, or browse through various project and donation pages before eventually making a donation. We randomize users into treatments at the website-session level, such that a donor is always exposed to the same treatment while visiting the platform. 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 control that a donor never faces another treatment (e.g., when she makes donations from two different computers), this procedure minimizes donors' awareness of the experiment and possible treatment spillovers.[9] Finally, to preclude the possibility that a few extreme contributions are driving our results, we drop the top 0.2% of donors (n=41) for our empirical analysis.[10]

This leaves us with a total of 683,910 observations—roughly 57,000 in each of the 12

et al. 2007, Bordalo et al. 2013, and Kőszegi and Szeidl 2013 for recent theoretical models of how attention, salience, and focusing affect consumers' choices).

[9] 7.5% (n=1549) of donors in our sample make more than one donation within a given session. In what follows, we use individual donations as our unit of analysis. To control for possible dependencies of observations within sessions, all estimation results reported below are clustered at the website-session level. Our empirical results are 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).

[10] While the median donation in our sample is €20, each of these donors contributes €2,165 or more. All estimation results reported below are robust to employing different cutoff values, e.g., excluding the top .1%, .5%, or 1% of donors.

Donation default	Codonation default 5%	10%	15%	Total
AD	56,894	56,959	56,807	170,660
€10	56,739	57,014	57,017	170,770
€20	56,777	57,083	57,117	170,977
€50	57,183	56,985	57,335	171,503
Total	227,593	228,041	228,276	683,910

Table 1: Treatments and number of observations per treatment. *Notes:* "AD" denotes the active-decision environment.

treatments (see Table 1). Except for the cases in which a donor makes multiple donations within the same session, each observation in Table 1 corresponds to one website visitor.

In our empirical analysis in Section 3, we focus on three main outcome variables: the number of donations, the amount donated to the charitable cause, and the level of the codonation. Table 2 provides an overview of these variables. Over the course of the experiment, we observe 22,792 donations, corresponding to an overall donation rate of 3.3%. According to the platform providers, this figure is in line with historical levels of the donation rate. Regardless of the treatment, therefore, the modal action of of participants in our experiment is not to donate. Conditional on donating, the average (median) donation level in our sample is €51.27 (€20). The corresponding values for codonations are €2.00 and €0.25, respectively. In sum, these numbers yield a total of €1.17 million in terms of donations and roughly €45,500 in codonations over the course of our experiment.

Variable	No. Obs.	Mean	Median	SD
Donated?	683,910	0.033	0	0.18
Donation amount	22,792	51.274	20	117.17
Codonation amount	22,792	1.998	0.25	7.02

Table 2: Summary Statistics.

3 Empirical Results

The discussion of our empirical results proceeds as follows. We begin, in Section 3.1, by analyzing treatment effects in terms of individual donor behavior. In particular, we demonstrate how the different defaults affect the distributions of donations as well as codonations in our experiment. In Section 3.2 and Section 3.3, we turn to an aggregate-level perspective and examine the influence of defaults on overall donation and codonation revenues, respectively. We also discuss how a mix of individual-level changes in donor behavior on the intensive and extensive margin explains the observed outcomes at the aggregate level.

3.1 Do Defaults Affect Individual Behavior?

The answer to this first question is a clear yes. To demonstrate this point, we first examine differences in the distributions of donations and codonations across treatments, focussing on the 22,792 cases in which participants in our experiment actually make a donation. Table 3 summarizes the distributions of donations in the different treatments. Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for the donation amount and codonation percentage, (D€, C%). In the rows of the table, we depict the fraction of donations in a given treatment that correspond to one of the default donation levels, €10, €20, and €50, as well as the fraction of donations that differ from these values.

The highlighted cells reveal a strong impact of defaults on individual donations. The likelihood of making a donation of €10, €20, or €50 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 in the three treatment cells where this amount is the default donation value (see columns 1-3 of Table 3). This compares to only 12-14% of donors making a €10-contribution when facing a default of €20 or €50 (columns 4-9). 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 corresponding numbers in the treatments where donors have to make an active decision (AD in columns 10-12) shows that setting the default to a certain value increases the proportion of donors who actually contribute this amount by roughly 5-10 percentage points.

	Treatment (D€, C%)											
	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)	(AD,5)	(AD,10)	(AD,15)
Donated amount	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
€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

Table 3: Donations by treatment. *Notes:* The table depicts the proportion of donors in a given treatment who contribute €10, €20, or €50, as well as the fraction of donors who donate a different amount ("other"). Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for donations / codonations.

	Treatment (D€, C%)											
	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)	(AD,5)	(AD,10)	(AD,15)
Codonation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
0	.421	.451	.439	.413	.432	.448	.426	.495	.475	.455	.480	.486
5%	**.530**	.138	.121	**.532**	.147	.133	**.530**	.121	.141	**.502**	.125	.144
10%	.033	**.385**	077	.023	**.399**	.082	.022	**.363**	.071	.022	**.373**	.071
15%	0	.003	**.337**	.003	.002	**.308**	.001	.005	**.290**	.001	.003	**.280**
other	.017	.024	.027	.029	.020	.030	.021	.017	.023	.020	.020	.019

Table 4: Codonations by treatment. *Notes:* The table depicts the proportion of donors in a given treatment who make a codonation of 0, 5%, 10%, 15%, as well as the fraction of donors who codonate a different amount ("other"). Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for donations / codonations.

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 30-90%.

The strong influence of defaults on individual donor behavior is also evident in the overall distribution of donations. In Figure 3, we present histograms for the active-decision regime and the three different default donation treatments. To facilitate illustration, we right censor the x-axis of the graphs at €100 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 codonation treatments, holding the treatment assignment in the donation dimension constant.[11] Pooling over codonation defaults is appropriate given that the donation distribution for a given *donation default* does not vary systematically across *codonation treatments*: comparing donation distributions for different codonation defaults using Kolmogorov-Smirnov tests reveals that only one out of twelve tests indicates a significant difference in distribution at the 10% level ($p=0.077$ when comparing the (20,5) and (20,10) treatments).

The histograms underscore the strong impact of defaults on donation patterns. While the distributions otherwise look relatively similar—e.g., we observe more or less pronounced spikes in donations at multiples of €5—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. This is not only true for the "pooled" histograms in Figure 3, but holds more generally for each of the 12 treatment cells (see Figure A.4 in the appendix). Furthermore, Kolmogorov-Smirnov tests indicate that the distributions of donations differ significantly across the four different default regimes ($p<0.01$ for all pairwise tests). Except for one treatment comparison, this also holds for all pairwise tests of individual treatments that differ in terms of donation defaults, but have identical codonation defaults (i.e., testing across "columns" within a given "row" of Figure A.4; $p=0.138$ when comparing (AD,5) vs. (10,5); $p<0.05$ for all other pairwise treatment comparisons).

In a next step, we study how defaults affect behavior in our second treatment dimension—the add-on contribution to support the online platform. Table 4 depicts the codonation fre-

[11]Figure A.4 in the appendix depicts the full set of histograms for the 12 individual treatment cells.

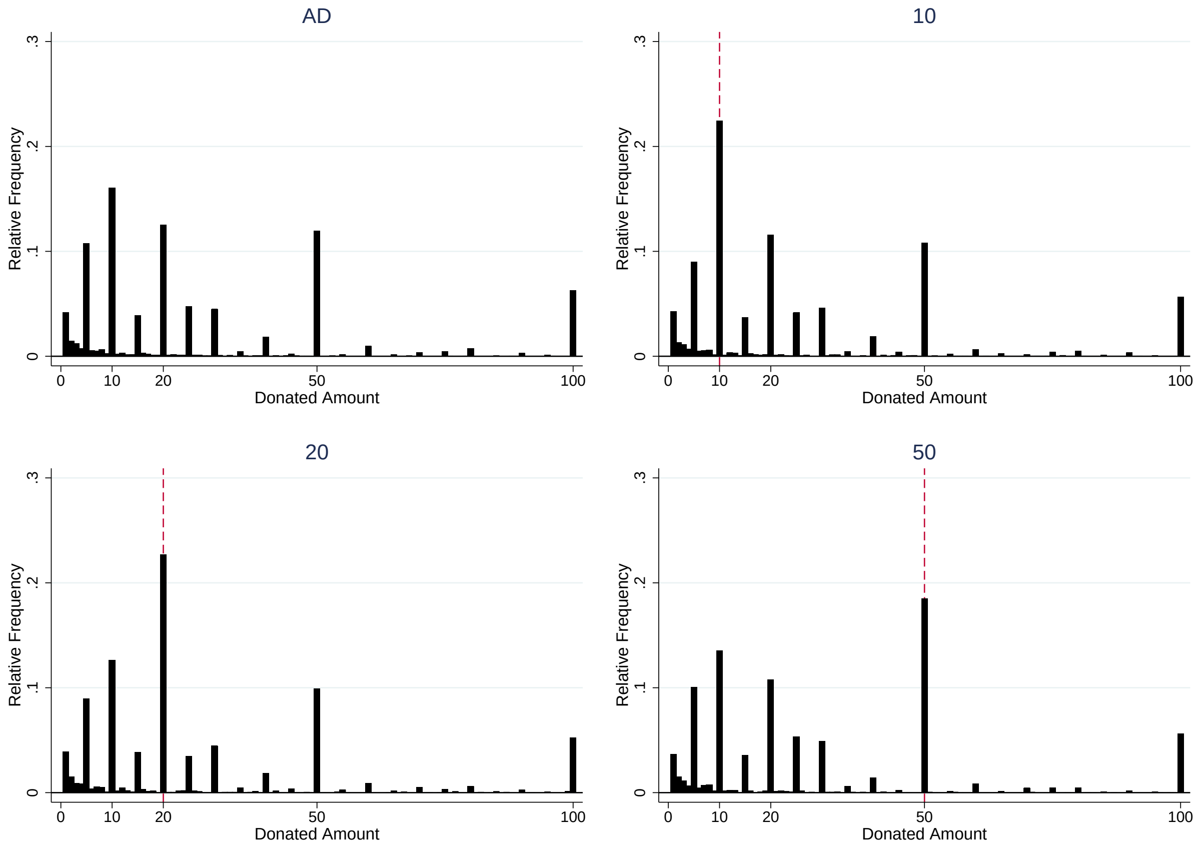

Figure 3: Donation distributions by default donation level. *Notes:* The figure depicts the relative frequencies of donations for each of the treatments in the donation dimension (indicated by the panel titles). Default donation levels are highlighted by the dashed lines. The x-axes of the graphs are censored at €100 (the underlying data are not).

quencies across treatments, mirroring the analysis of donations in Table 3.[12] The highlighted cells indicate that, as is the case for donations, defaults also have a pronounced impact on individuals' behavior in terms of add-on contributions. Among those participants who make a positive codonation, the modal contribution in all of the 12 treatments again corresponds exactly to the respective default value. Comparing differences in the distributions of codonations using Kolmogorov-Smirnov tests shows that the distributions differ significantly for all pairwise tests of individual treatments that differ in the codonation default, but have

[12]The corresponding codonation histograms for the individual treatments can be found in Figure A.5 in the appendix. We refrain from displaying codonation histograms based on subsamples that pool across donation defaults, since Kolmogorov-Smirnov tests indicate a number of significant differences between individual distributions (e.g., the codonation distribution for the (10,15) treatment in the third row of Figure A.5 turns out to differ significantly from the (AD,15) as well as the (50,15) treatment; p<0.01 in both cases).

the same default donation (p<0.01 in all cases).

The numbers in Table 4 exhibit drastic changes in the codonation patterns due to variations in defaults. For instance, moving from a 5% to a 10% default leads to a more than 10-fold increase in the proportion of donors who make a 10% contribution (see third row of Table 4). Similarly, while practically nobody makes a codonation of 15% when the default contribution is 5% or 10%, almost a third of participants do so when the 15% add-on is set as the default (see fourth row of Table 4). This is not to say that donors are completely insensitive to the size of the add-on contribution. Indeed, the magnitude of the modal effect tapers off as defaults increase: while at the 5% default slightly more than half of all donors stick to the default, only about 40% and 30% do so when the codonation default is set to 10% and 15%, respectively.

Another striking feature of the codonation patterns in Table 4 is that we observe a bimodal distribution of choices for each of the treatments, with 40-50% of donors making no codonation at all and another 30-50% of donors sticking to the respective default amount. In contrast, only about 2-3% of donors choose a codonation other than 5, 10, or 15 percent (recall that, besides the options displayed in rows 1-4 of Table 4, the drop-down menu for codonations offered a 20% and 25% add-on, as well as the option to freely specify a different codonation amount). This indicates that, although donors face a continuum of alternatives in both choice dimensions, they tend to use a coarser grid for their decisions in the add-on dimension.

Compared to our previous findings for donations, the figures in Table 4 also suggest that defaults are somewhat more "powerful" in the codonation dimension. While people's propensity to contribute exactly the default amount increases by about 5-10 percentage points in the donation dimension (see Table 3), we observe a 30-40 percentage point increase in the incidence of codonations at the different default values. The strong impact of codonation defaults is also evident when considering donors who stick to the default in one treatment dimension, but make an active decision in the other. In Table 5, we depict the fraction of donors who follow none of the defaults, just one of them, or both of them.[13] The numbers show that about 10% of donors follow the donation default, while at the same time opting out of the default in the codonation dimension. In contrast, the fraction of donors opting

[13]In Section A.2 in the appendix, we provide more detailed information and an additional test that illustrates how people are affected by the specific default tuples in different treatments.

out of the default donation, but sticking to the codonation default is almost three times as high (29.1%).[14]

Donation default	Codonation default Accept	Opt out
Accept	0.117	0.096
Opt out	0.291	0.497

Table 5: Fraction of donors sticking to defaults. *Notes:* The table depicts the fraction of donors who stick to defaults in the two treatment dimensions. Observations from the active-decision treatments are excluded.

Both the strong default effects for codonations and the fact that choices are less spread out in the codonation dimension are broadly in line with an attention-based explanation of default effects in which donors devote less attention to the secondary, add-on decision where less is at stake (Hossain and Morgan 2006, Chetty et al. 2009, Caplin and Martin 2013). Another possible mechanism that is consistent with these findings is that donors are more uncertain about their preferences in the—arguably less familiar—codonation dimension, and are therefore more prone to follow a default that is perceived as a norm or recommended action (Madrian and Shea 2001, McKenzie et al. 2006, Altmann et al. 2013).

The data depicted in Table 5 also indicate that some people are systematically more affected by defaults than others, supporting a "type-based" interpretation of default effects. In particular, we find that the conditional likelihood of accepting the codonation default is almost 50% higher for those donors who also stick to the default in the donation dimension (the respective likelihoods are 55.0% vs. 36.9%; $p<0.01$). While our data do not allow us to determine what makes the first group of donors particularly prone to stick to defaults, attentional limitations or a propensity to follow what is perceived as a recommended action are again likely candidates.

[14]Note that this is not driven by the active-decision treatments where donors have to actively determine their donation level. The corresponding treatments are excluded from the calculations in Table 5.

3.2 Do Defaults Affect Aggregate Donation Levels?

Given our findings so far, an important next question is how the different treatments affect donation amounts at the aggregate level. Do defaults influence the overall level of donations? Can they be used to boost charitable giving? The answer to these questions turns out to be "no". Figure 4 presents the average level of donations across treatments, calculated based on all 683,910 observations in our data set, which includes also those users who made no positive contribution and opted out of the donation process altogether. In all treatments, average donations lie in a relatively narrow range between €1.54 and €1.85 (for more details, see also Table A.2 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 12 different treatment cells, we find that only 1 out of the 66 pairwise t-tests is significant at the 5% level, and 3 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.

Perhaps most importantly, we observe no systematic impact of the different donation defaults on overall contribution levels. For instance, average contributions at the €10 donation default (bars 4-6 in Figure 4) are very similar to the active-decision environment (cp. the three leftmost bars in Figure 4). More specifically, the users in the AD-treatments who have to actively decide on their donation on average contribute €1.69. This compares to €1.70, €1.68, and €1.77 in the treatments with a €10, €20, and €50 donation default, respectively (see also Table A.1 in the appendix). 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).

Why do we observe such a strong and systematic influence of defaults on individual behavior and at the same time no effects in terms of aggregate donation revenues? Figure 5 explains how both findings can be reconciled with each other. In the figure, we show how behavior under the different donation defaults changes relative to the active-decision

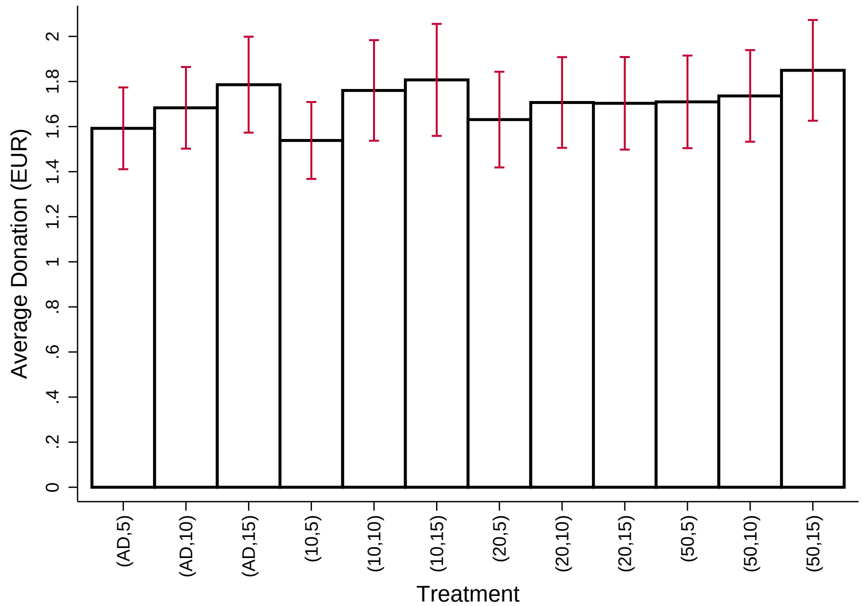

Figure 4: Average donation by treatment. *Notes:* The figure depicts average donation levels across the 12 different treatments, calculated based on all participants in the experiment. 95% confidence intervals, accounting for clustering of standard errors at the session level, are presented at the top of each bar.

environment. In particular, the three frames in the figure depict the differences in the distributions of donations between the active-decision environment and the €10, €20, and €50 default, respectively. To put it simply, we "subtract" the upper-left panel of Figure 3 from the three other histograms depicted in Figure 3, while additionally taking into account potential differences in the proportion of non-donors (i.e., a bar at 0). This allows us to examine how defaults affect the distribution of donations along both the intensive and extensive margins.

If defaults are poles of attraction for people's behavior but there is no effect on overall 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 5 demonstrates that, for each of the different default donation levels, people move towards the default from both above and below. For instance, the spike of additional people donating €20 when this is the default (top right panel) comes "at the cost" of fewer people donating €5, €10, €25, and €50. Notably, at higher default levels, the mass of people who can be "pulled down" by the default becomes smaller and smaller (recall that the €50

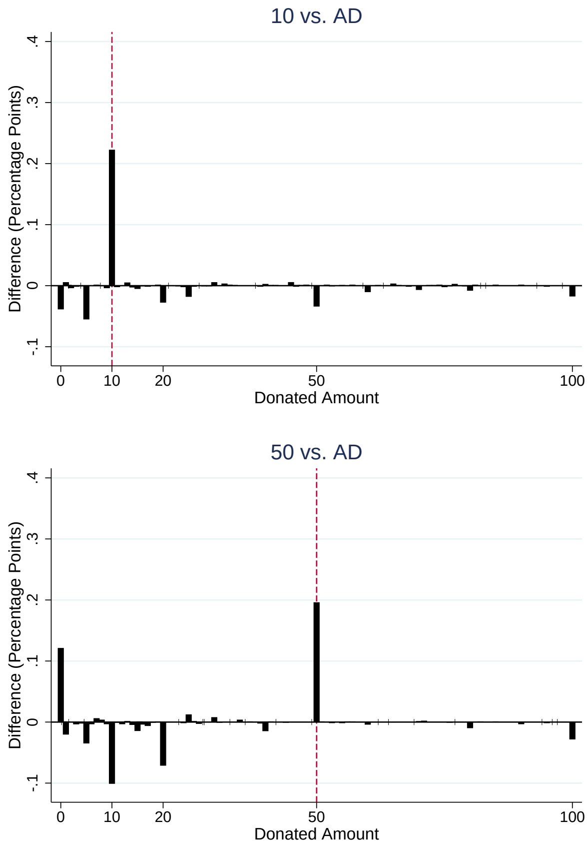

Figure 5: Change in donation distributions due to defaults. *Notes:* Each panel of the figure describes the change in the distribution of donations under a given donation default (indicated in the panel titles), relative to the active-decision environment. Default donations are indicated by the dashed lines. (Extensive-margin) differences in the proportion of non-donors are depicted at zero.

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 revenues to go up. The figure, however, shows that there is a second countervailing effect that works against such an increase. Specifically, at the €50 default we observe a higher fraction of participants who opt out of the donation process altogether, offsetting the increase in donations along the intensive margin (see also rows 1 and 3 in Table A.1 in the appendix).[15]

[15]The relevance of such extensive-margin reactions has also been pointed out in other contexts that involve voluntary contributions. For instance, Adena et al. (2014) find that fewer people respond to a fundraising call of an opera house when the solicitation letter contains a relatively high suggested contribution level. Haggag and Paci (2014) provide evidence that taxi customers are less likely to leave a tip when being confronted with higher default tipping levels. Finally, Gneezy et al. (2012) show that "pay-what-you-want" pricing schemes can lead consumers to abstain from purchasing the product altogether.

Another aspect of Figure 5 that is worth noting is that defaults lead to an increase in the proportion of donations *exactly at* the default, but not for contribution levels "in the neighborhood" of the default amount. In line with the observation that we find no increase in average donation levels at higher defaults, this indicates that people do not predominantly treat defaults as an "anchor" around which they take their decisions (Tversky and Kahneman 1974, Johnson and Schkade 1989, Ariely et al. 2003).

Table 6 demonstrates that the observed movements towards the donation defaults are not only sizable, but also statistically significant. In each row of the table, we estimate different models that compare the relative frequencies in contributions between one of the donation-default regimes and the active-decision environment. Column 1 denotes the default donation treatment that we consider in a given row. Column 2 depicts the increase in the fraction of donations at the corresponding default amount, relative to the active-decision environment. The figures in column 2 show that the proportion of donations at the different defaults increases by a statistically significant 0.2-0.3 percentage points for our full sample (top panel of Table 6), and by 6.4-10.2 percentage points for the subsample of participants who make positive donations (bottom panel). The former figures coincide exactly with the heights of modes in Figure 5, whereas the latter correspond to the increases in the spikes at the different default amounts depicted in Figure 3.

While column 2 confirms that defaults are statistically and economically significant poles of attraction for individuals, columns 3 and 4 address the question of where the increased mass of donations at the default is coming from. The two columns disaggregate the figures in column 2 into (net) movements from below the default (column 3) and movements from above the default (column 4), relative to the active-decision treatment. For the full sample of participants, the numbers indicate that, across all treatments, the shift in the distributions to the default amounts comes in roughly equal shares from people who would otherwise have donated less and those who would have donated more than the default. This can be seen by the 0.1-0.2 percentage-point reduction in the proportions of observations both below and above the default (see columns 3 and 4 in the upper panel of Table 6).

In case of the €10 and €20 treatments, a similar pattern can also be observed for the subsample of participants who make positive donations (see columns 3 and 4 in the bottom part of Table 6). Furthermore, these defaults do not systematically affect participants' overall propensity to make a donation. The corresponding donation rates of 3.39% (€10) and 3.35%

	Change in proportion of donations:			
	Exactly at the	Below the	Above the	
Treatment	treatment amount	treatment amount	treatment amount	No. Obs.
(1)	(2)	(3)	(4)	(5)
		Full sample		
€10	0.002***	-0.001*	-0.001***	341,430
	(0.000)	(0.001)	(0.000)	
€20	0.003***	-0.002***	-0.001***	341,637
	(0.000)	(0.000)	(0.000)	
€50	0.002***	-0.001***	-0.001**	342,163
	(0.000)	(0.000)	(0.000)	
		Donors only		
€10	0.064***	-0.021***	-0.043***	11,520
	(0.007)	(0.007)	(0.009)	
€20	0.102***	-0.060***	-0.042***	11,452
	(0.007)	(0.009)	(0.009)	
€50	0.065***	-0.054***	-0.011	11,270
	(0.007)	(0.009)	(0.007)	

Table 6: Movements to default donation. *Notes:* The table describes the change in the fraction of donations exactly at, below, and above the default donation amount, relative to the active-decision environment. Column 1 lists the default donation treatment. Column 2 describes the difference in the proportion of donations corresponding exactly to the amount mentioned in column 1. The subsequent two columns disaggregate the number in column 2 into movements from strictly below the default (column 3) and movement from strictly above the default (column 4). The number of observations is indicated in column 5 and pertains to observations from either the active-decision treatment or the treatment indicated in column 1. The top panel of the table includes all observations; the bottom panel is based on the subsample of participants who make positive donations. Standard errors are clustered at the session level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(€20) are very similar and do not differ significantly from the 3.35% observed under active decisions (t-test accounting for potential clustering at the session level, p=0.581 and p=0.942, respectively; see also Table A.1 in the appendix). This indicates that at these default values the wash in terms of aggregate donations operates entirely on the intensive margin. At the €50 default, however, we observe that 5.4 percentage points of the 6.4 percentage-point increase at the default comes from donors who would have given less, whereas only 1.1 percentage points of donors reduce their donation relative to the active-decision treatment.

As already seen in Figure 5, however, there is now an additional extensive-margin effect of people who opt out of donating altogether. Relative to the active-decision treatment, the donation rate drops from 3.35% to 3.23% (p=0.077), corresponding to roughly 200 fewer donations in the €50 treatment (see rows 1 and 6 in Table A.1 in the appendix). While this additional attrition might seem modest in size, it suffices to offset the increase in donations at the intensive margin, such that the overall level of donations remains unaffected.

In sum, we observe that default donations are important poles of attraction for people's behavior. They tend to push up the contributions of some donors, while pulling others' donations down. At relatively low default values, these two effects seem to operate entirely on the intensive margin. At higher defaults, our findings indicate that defaults can also lead to an reduction in donation rates on the extensive margin. In both cases, the countervailing effects essentially cancel each other out, leaving overall donation levels unchanged for the different default regimes in our experiment.

3.3 Do Defaults Affect Aggregate Codonations?

The picture is quite different when it comes to overall codonation levels. Figure 6 presents average codonation amounts by treatment for our full sample (for further information on codonation levels in the subsample of participants who make positive donations, see also Table A.2 in the appendix). The saw-shaped pattern indicates that, holding the donation default constant, codonation revenues increase monotonically for higher codonation 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, average codonation levels are always significantly higher at the 15% relative to the 5% codonation 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 donation default, this also holds when comparing the 10% and the 5% codonation treatments (p=0.417 for (20,5) vs. (20,10); p<0.01 in the remaining cases). When comparing the 15% and the 10% codonation treatments, we find that codonations 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 donation default, respectively).

The magnitude of the observed differences in codonation levels is substantial. For the 15% codonation default, overall codonation levels are roughly 80% higher than under the

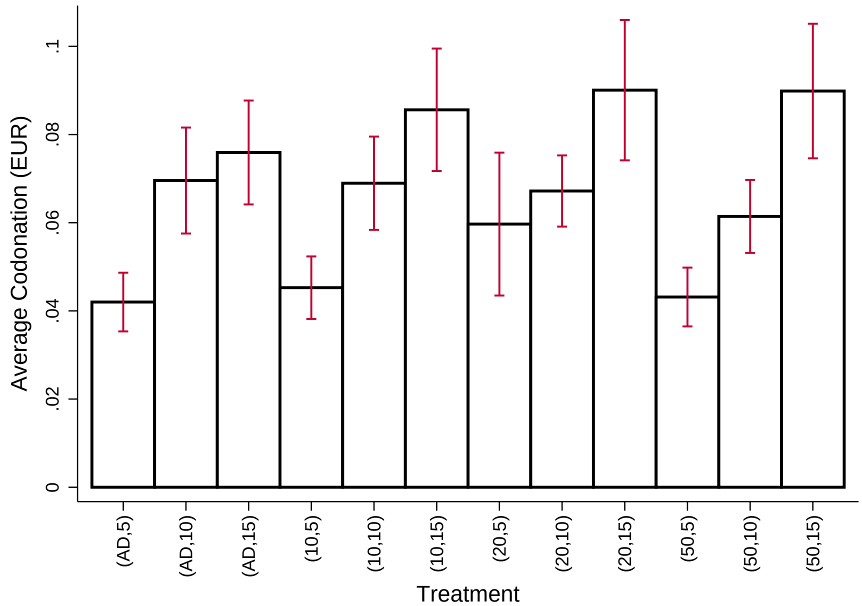

Figure 6: Average codonation by treatment. *Notes:* This figure describes average codonation levels across the 12 different treatments. 95% confidence intervals, accounting for clustering of standard errors at the session level, are presented at the top of each bar.

5% default and still lie about 30% above the values for the 10% treatments. Comparing the codonation revenues to the overall donation levels in the corresponding treatments underscores this effect. When facing a 5% codonation 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% codonation defaults. Given that the donation levels themselves are not affected by the codonation treatments (see Figure 4), our findings suggest that higher codonation defaults increase overall revenues for the online platform without hampering donations to the charitable cause.

Table 4 in Section 3.1 as well as Figure A.5 in the appendix illustrate the reasons why our findings for overall codonation revenues differ substantially from the ones for aggregate donation levels. For both types of defaults, the modal positive contribution always corresponds exactly to the default amount. In the case of codonations, however, we find that at most 6% of donors make a contribution that is *higher* than the default amount in a given treatment. Furthermore, we only observe a modest increase in the proportion of donors who opt out of making a codonation 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 codonations that is caused by the roughly 30-35% of additional donors who make a 10% or 15% codonation when facing these values as a default contribution (see the bold figures in Table 4). This implies that, as with donations, defaults act as strong attractors in the add-on dimension. Most of the action in terms of changing individual donor behavior in terms of codonations, however, operates on the intensive margin, with movements to the default from below. As a result, we not only observe strong individual-level effects of defaults, but also substantial increases in overall revenues in the codonation dimension.

4 Discussion and Conclusions

We have studied how website defaults affect consumer behavior in the domain of charitable giving. Our findings demonstrate a strong causal impact of defaults on people's behavior, in terms of both whether and how much they donate. Despite these strong individual-level effects, defaults in our experiment do not affect aggregate giving to the charitable cause, because of countervailing changes in the distribution along the intensive and extensive donation margins. In case of the add-on contributions to support the web platform, higher defaults do generate higher overall revenues, as the dominant reaction to an increase in defaults is a shift from lower to higher codonations along the intensive margin. It seems fair to speculate, however, that yet higher defaults than the ones in our experiment may eventually backfire, yielding lower revenues for both the charitable cause and the web platform due to donor attrition.

Given the prevalence of default options in online fundraising and other web-based commercial applications, our results provide potentially important insights for operators of online platforms, policy makers, and other practitioners. Most importantly, our findings demonstrate that defaults can have a strong influence on people's choices, even if this influence might not be directly apparent in aggregate-level data. Practitioners who want (or have) to implement default options in online forms should thus be aware that these can have manifold effects along the entire distribution of choices, especially in decision environments that involve

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

relatively large choice sets. Regulators who are concerned about the consequences of defaults for people's behavior should not simply rely on an aggregate-level perspective, but carefully examine the individual-level effects of default options with the help of randomized controlled trials or other appropriate empirical techniques. Furthermore, since in our setting the overall expenditure—including codonations—are automatically calculated and immediately visible for the user, our findings suggest that regulatory interventions that impose transparency regarding add-on costs are unlikely to eliminate default effects.

Although our experiment was not designed to pin down the precise mechanisms through which defaults affect behavior, our data do permit some informed speculation as to whether some candidates put forward in the literature are more relevant in our setup than others (see Dinner et al. 2011 and Sunstein 2013 for comprehensive reviews). First, it seems highly unlikely that the observed effects can be explained by direct transaction costs related to opting out of the defaults (e.g., Schwartz and Scott 2003). For one thing, these costs are essentially zero in online applications, since consumers are in an environment where alternative choices are just "one click away". For another, the opt-out costs in our setup 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 only become relevant 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 (e.g., Carroll et al. 2009). Specifically, while a tendency to procrastinate active decisions might contribute to the high overall attrition rate that we observe, it seems unlikely that consumers bear the short-run costs of actively going to the platform, selecting a project, etc., but then procrastinate on determining the actual donation amount. Furthermore, even in the final stage of the decision process, the default options in our setting are only put into effect after consumers fill out the remainder of the donation form and actively confirm the transaction.

Our findings also speak against an anchoring-based explanation of the observed default effects. Most importantly, we find no evidence that overall donation levels go up if donors face higher default contributions. Since an increase in the anchor should on average lead to higher choices, this is hard to reconcile with pure anchoring (Tversky and Kahneman 1974, Johnson and Schkade 1989, Ariely et al. 2003). Moreover, while many donors contribute exactly the default amount, we find no increase in donation frequencies "in the neighborhood" of the default.

This leaves us with a class of mechanisms where defaults are behaviorally relevant because consumers exhibit perceptual limitations (Hossain and Morgan 2006, Chetty et al. 2009, Caplin and Martin 2013) or are uncertain about their choices (Madrian and Shea 2001, McKenzie et al. 2006, Altmann et al. 2013).

At first blush, our aggregate-level findings are reminiscent of the evidence on limited attention to add-on price components (e.g., Hossain and Morgan 2006, Chetty et al. 2009). Our individual-level data, however, shows that defaults also have substantial effects on the main donation decision. To fully account for our empirical findings, a limited-attention- or focusing-based explanation would thus need to apply to the primary decision dimension, at least for a subsample of the population. Furthermore, one would need to explain why people who are less focused on a certain decision would automatically be more likely to stick to the default amount (rather than, say, use a rule of thumb such as "always give zero" or make another active, though potentially biased, choice).

An alternative explanation that is broadly in line with our findings is that donors perceive the stipulated default amounts as a recommended action (e.g, Adena et al. 2014, Edwards and List 2013) and follow them because they are uncertain about what is best for them (Madrian and Shea 2001, McKenzie et al. 2006, Altmann et al. 2013) or because they do not want to deviate from a social norm that defaults might convey (e.g., Altmann and Falk 2011). To be consistent with all of our findings, a recommendation-based mechanism would need to explain why defaults are particularly powerful in the codonation dimension. A possible candidate for this effect is that people are more uncertain about the appropriate contribution to the platform, while having relatively precise prior plans for their main contribution to the charitable cause (see Shang and Croson 2009 and Bronchetti et al. 2013 for related evidence on how individuals' prior experience and predetermined consumption plans influence their propensity to follow social information and to stick to default options, respectively). A strict desire not to deviate from a social norm may also explain why we find no increase in the proportion of donations around the default, which is otherwise puzzling for a recommendation-based explanation in which the default is just one out of multiple signals that an individual receives. Furthermore, in the context of charitable giving, social norms might be particularly relevant due to image concerns and (self-)signaling motives (e.g., Benabou and Tirole 2006, Ariely et al. 2009, Gneezy et al. 2012).

In our setup in which consumers undergo a sequence of other choices before deciding on the contribution level, cognitive depletion might be an additional factor that makes donors less attentive or more prone to accept recommendations at the point where they make the donation decision (Levav et al. 2010). Exploring the interplay of social norms, the informational content of defaults, and cognitive as well as attentional limitations in more detail thus seems to be an interesting avenue for future research on the behavioral implications of web defaults.

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Appendix

A.1 Additional Figures and Tables

Figure A.1: Translation of Figure 1.

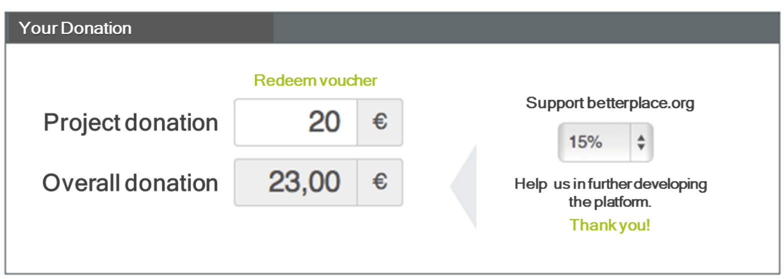

Figure A.2: Translation of Figure 2.

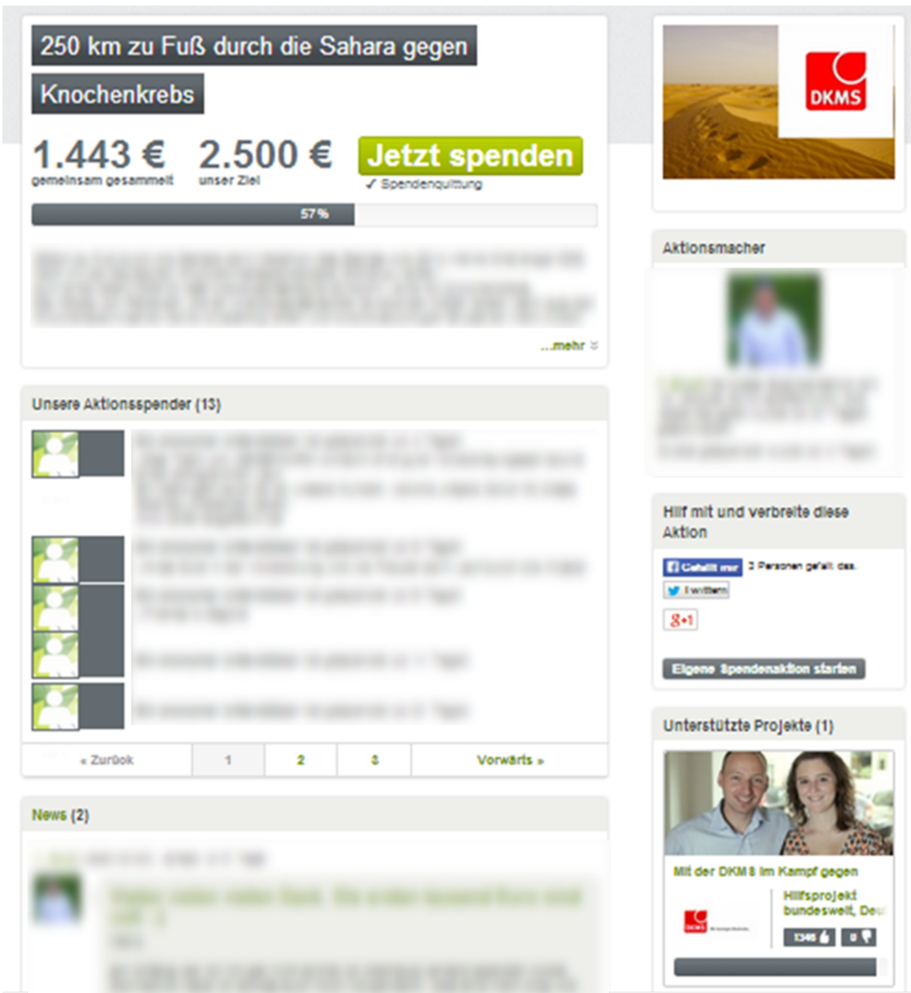

Figure A.3: Page of a fundraising event. *Notes:* The example displays a 7-day charity run through the Sahara (described in more detail at the top of the page) in support of an aid project by the German unit of "Delete Blood Cancer" (described and linked at the bottom right part of the page).

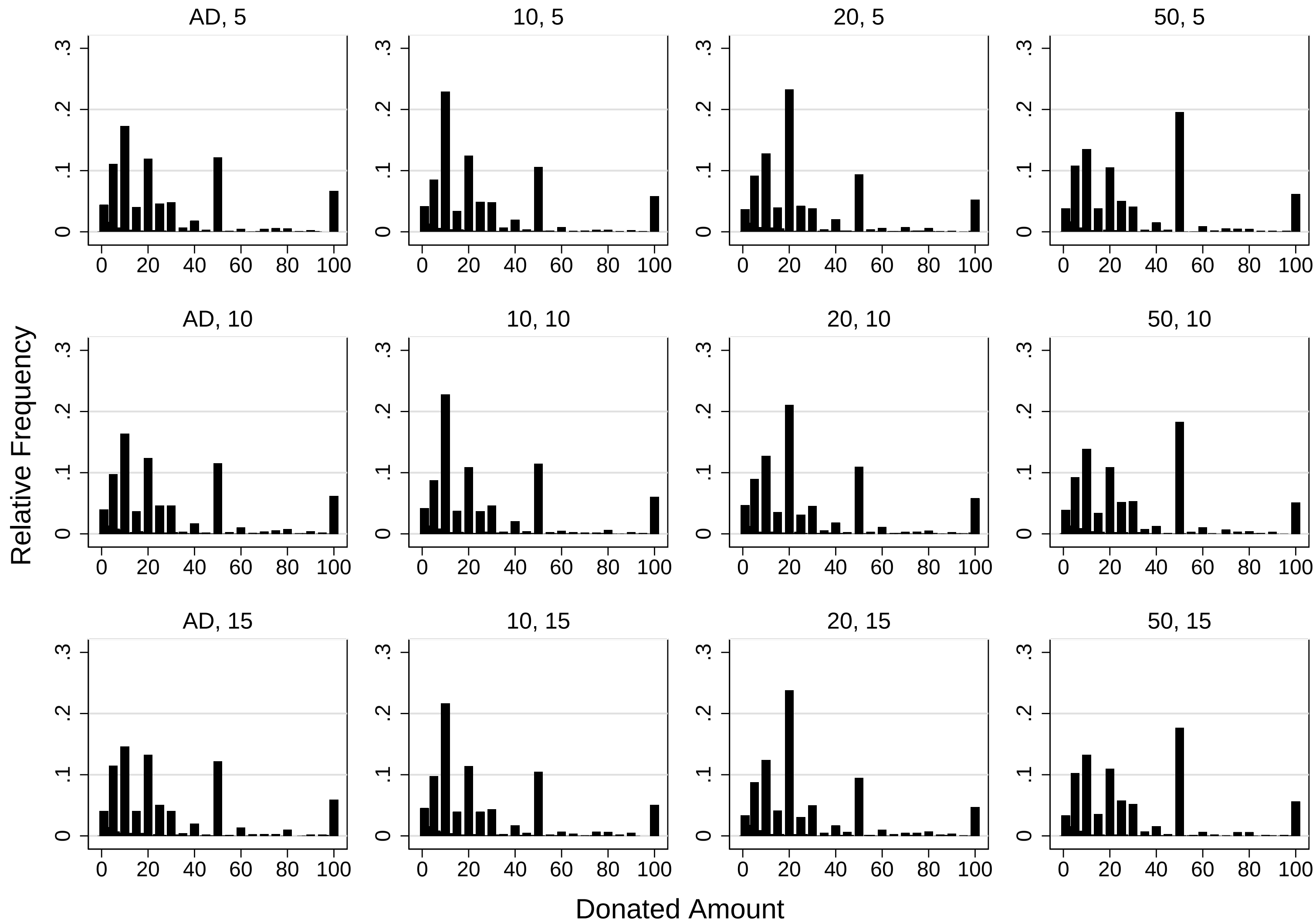

Figure A.4: Donation distributions by treatment. *Notes:* This figure describes the relative frequencies of donations in the different treatments, denoted by their respective donation / codonation default.

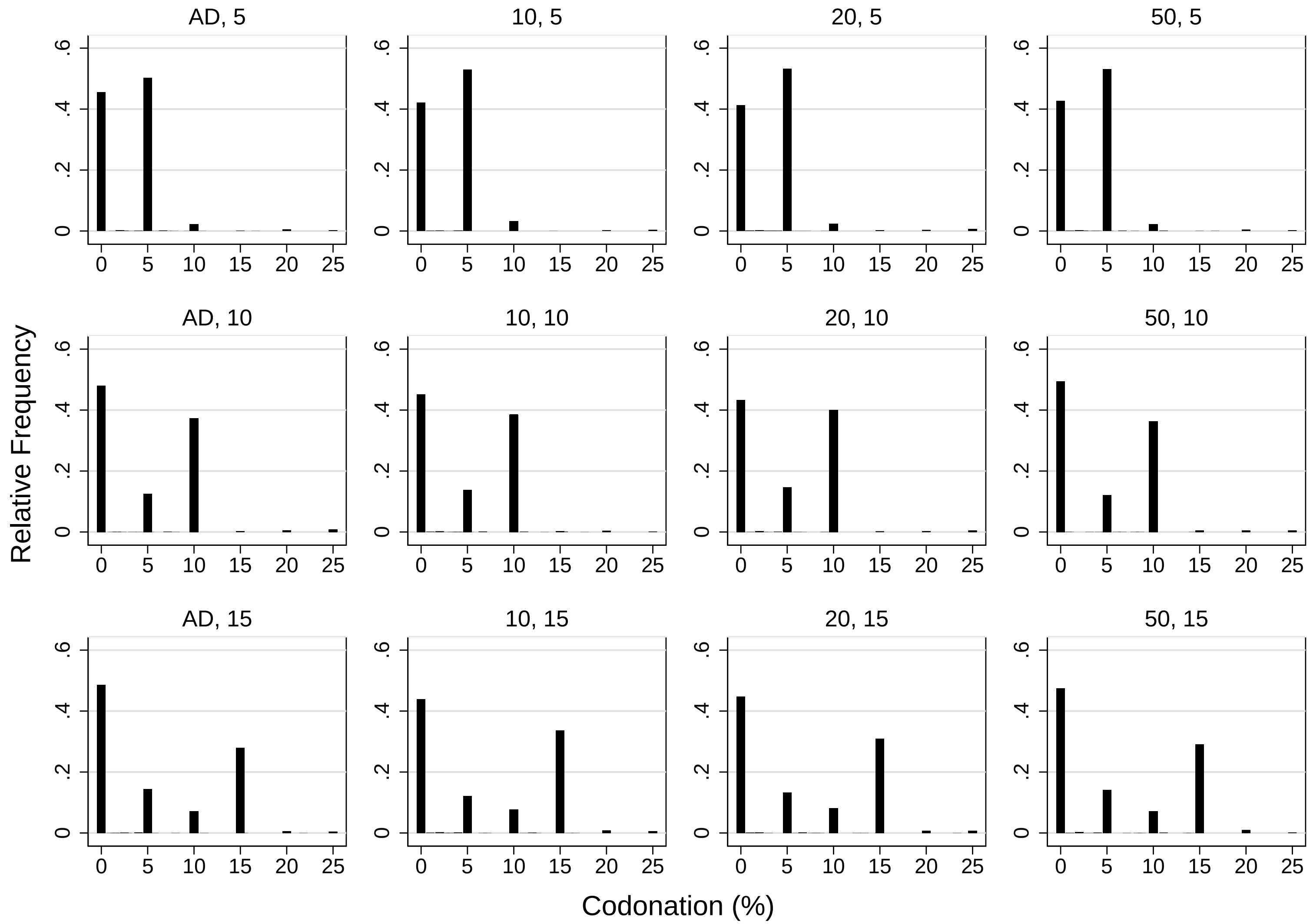

Figure A.5: Codonation distributions by treatment. *Notes:* This figure describes the relative frequencies of codonations in the different treatments, denoted by their respective donation / codonation default.

		Treatment (Donation Default)			
		AD	€10	€20	€50
(1)	Donation rate (%)	3.35	3.39	3.35	3.23
(2)	Av. donation (overall)	1.69	1.70	1.68	1.77
(3)	Av. donation (donors only)	50.29	50.16	50.17	54.59
(4)	Median donation (donors only)	20	20	20	25
(5)	No. Obs.	170,660	170,770	170,977	171,503
(6)	No. donors	5,725	5,795	5,727	5,545

Table A.1: Summary statistics by default donation level. *Notes:* The table gives an overview of donation behavior for different donation defaults (subsamples pooled across codonation treatments)

		Treatment (D€, C%)											
		(AD,5)	(AD,10)	(AD,15)	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		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
		Codonations											
(5)	Conation 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)	Conation 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. codonation (€, 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. codonation (€, 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
(9)	N. Obs.	56,894	56,959	56,807	56,739	57,014	57,017	56,777	57,083	57,117	57,138	56,985	57,335
(10)	N. 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

Table A.2: Summary statistics by treatment. *Notes:* The table gives an overview of key outcome variables in the different treatments.

A.2 Default Adherence in Both Treatment Dimensions

In this section, we illustrate in more detail how the combination of defaults in our two treatment dimensions affects the joint distribution of donations and codonations. Table A.3 depicts the number of donors in the different treatments who choose donation-codonation tuples along a grid that is defined by the different combinations of donation-codonation defaults in our experiment. The table thus combines the evidence depicted in Tables 3 and 4, restricting the "action set" to the grid imposed by the 9 different default combinations from our treatments. The highlighted cells in Table A.3 demonstrate that the modal action in this partial distribution invariably corresponds to the default amounts for each of our treatments, mirroring the observations from the separate choice dimensions (Tables 3 and 4) for the joint distribution.

The mass of observations at the defaults observed in Table A.3 is clearly non-random. To see this, consider the null hypothesis that defaults are not a pole of attraction for people's behavior, and consider the first row of Table A.3. This row looks at the number of donors who choose to donate $(10, 5)$ for each of the 12 treatments. Absent default effects, any cell in this row is equally likely to contain the highest frequency of donors. Hence, the probability that we observe the highest frequency of donors contributing $(10, 5)$ in treatment $(10, 5)$ when there is no default effect is $1/12$. Similarly, in any other row the probability that the highest frequency of donors falls into the cell in which this choice happens to be the default option is $1/12$. One may thus be tempted to conclude that the probability that the highest frequency of donors always choose a given action in the treatment where this action happens to be the default is $(1/12)^9$, which however ignores that these tests are not independent. To see this, suppose that the highest frequency of donors choosing the action $(10, 5), (10, 10), (10, 15), ..., (50, 5), (50, 10)$ would fall into the treatment $(10, 5)$ (and no donor chooses an amount not on the grid). Then, the highest frequency of donors for the action $(50, 15)$ cannot fall into the treatment $(10, 5)$ as the numbers cannot exceed 100%. A very conservative estimate is to assume that in case the highest frequency of donors gives the default amount in the first treatment, this treatment cannot have the highest amount of donors in any other treatment, and similarly for any subsequent treatment. For this conservative estimate, the chance that the default amount has the highest frequency of donors is bounded from above by $1/\,(12 \times 11 \times \ldots \times 4) = 1/79,833,600$.

	Treatment (D€, C%)											
	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)	(AD,5)	(AD,10)	(AD,15)
Action	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(10,5)	**290**	39	33	133	29	24	128	32	30	166	36	36
(10,10)	14	**258**	23	10	102	24	7	108	20	9	146	18
(10,15)	0	1	**211**	1	1	85	0	0	87	2	1	97
(20,5)	132	39	24	**295**	47	59	124	24	44	123	28	44
(20,10)	16	90	19	6	**234**	35	3	87	17	7	92	30
(20,15)	0	0	81	2	0	**210**	0	1	56	0	0	78
(50,5)	122	52	38	100	42	33	**224**	35	35	128	39	40
(50,10)	2	73	17	9	86	14	9	**154**	25	0	74	18
(50,15)	0	0	56	0	0	46	0	1	**117**	0	0	54

Table A.3: Number of donations and codonations at default amounts. *Notes:* The table denotes the number of observations which correspond exactly to the donation and codonation default amounts of the different treatments.