What Drives Overhead Aversion in Charity? Evidence from Field-Experimental Variation in Fundraising Costs

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Abstract

This paper exploits a randomized field experiment to explore why donors are averse to financing fundraising expenses. Such expenses can signal a charity's efficiency, or affect the donors' perception of the donation's impact on the cause. We demonstrate that donors who are strongly committed to the cause respond positively to improved efficiency, but ignore impact-related information. In contrast, donors who are only weakly committed to the cause do not respond to an efficiency improvement. In accordance with the public-goods crowding-out hypothesis, when learning that the impact of a donation has increased, they become less likely to give.

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1 Introduction

The 25 largest US charities spend between 5% and 25% of total donations on fundraising expenses (Andreoni and Payne, 2011). One reason why high fundraising costs are a matter of concern for charities is an aversion among donors to finance overhead (Tinkelman and Mankaney, 2007; Caviola *et al.*, 2014).[1] Whereas the sensitivity of donors with respect to overhead is well documented, the channels through which overhead-related information affects donors' behavior are not fully understood. Two potential channels have been discussed (Gneezy *et al.*, 2014). First, donors might exploit overhead-related information for inference on the charity's efficiency, or quality more broadly. The motive for doing so would be an aversion against the wasteful spending of donated funds. Second, overhead might affect the donors' perceptions of the a donation's impact on the cause. Here, the motive would be to personally make a difference.

This paper exploits a randomized field experiment to explore the relevance of both channels and to contribute to a better understanding of overhead aversion in charity. We partnered with the Protestant Church in Bavaria, Germany, and communicated a change in fundraising costs in solicitation letters that ask church members to donate to a local church fund. Our treatments allow us to separately identify both the efficiency and the impact channel. First, we measure the church members' response to a signal of improved efficiency while keeping constant the impact a donation has on the cause. Second, we identify the effect of increasing the impact of a donation while keeping constant the charity's efficiency. The church sent out the solicitations to all adult church members, irrespective of their donations in the baseline. This allows us to trace out the heterogeneity of the treatment responses between potential donors who, by their baseline behavior, have revealed their degree of commitment to the cause.

Our analysis delivers three sets of main results. Studying all potential donors, our first main insight is that an overhead reduction that signals an improved efficiency of fundraising positively affects donor behavior. Specifically, improving the charity's efficiency increases the likelihood that donors give more than the amount suggested in

[1] It has long been acknowledged that donors should not, in theory, evaluate charities according to their overhead ratios, but rather focus on charities' cost effectiveness.

the solicitation letter. By contrast, using an overhead reduction to increase the impact a donation has on the cause does not affect donor behavior on average. To study the heterogeneity in treatment responses, we exploit data on donations in the baseline to predict the degree of individuals' commitment to the cause. We differentiate between potential donors who are unlikely to make a donation without an intervention (*weakly committed* donors), and potential donors with a high propensity of a donation absent any treatment (*strongly committed* donors). Our second main finding is that, by reducing its overhead, the fundraiser is unable to positively affect the donation behavior of weakly committed potential donors. Whereas signaling that the overhead reduction has improved the charity's efficiency does not affect donor behavior at all, communicating an increased impact of donations on the cause crowds out the willingness to give of at least some weakly committed donors. The latter finding is counterintuitive, but consistent with economic theory. This is because a lowering of fundraising expenses is equivalent to a third-party transfer to the public good provided by the charity. Hence, our finding on weakly committed donors is in line with the public-goods crowding-out hypothesis (Warr, 1982; Roberts, 1984; Andreoni, 1989), which states that donors with altruistic preferences will reduce their private donations in response to a grant from a third party to the public good. Our third main finding is that donors who are strongly committed to the cause ignore impact-related information, but respond positively to a signal of improved efficiency. The positive efficiency effect on giving among strongly committed donors is economically sizable: Relative to their counterparts in the control group, strongly committed donors give 21.1 percent more on average, and their likelihood to donate more than the suggested amount increases from 28.5 percent to 42.7 percent.

It is surprising that the literature has widely documented overhead aversion in charity (Callen, 1994; Trussell and Parsons, 2007; Tinkelman and Mankaney, 2007; Caviola *et al.*, 2014), but produced little evidence on why changes in overhead costs affect the behavior of real-world donors. Most closely related to our work is Gneezy *et al.* (2014), who run a laboratory experiment where subjects decide which of two charities should receive a $100 donation. Their findings suggest that overhead aversion is driven by individuals' preference for a situation where their personal donation has a positive impact on the cause. In addition, the authors design a field experiment that shows the power of using seed money to cover overhead. Our main contribution relative to the field work of Gneezy *et al.* (2014) is that our treatments directly focus on disentangling the efficiency and the impact effect as the main competing channels. In addition, our design also allows to study the treatment effect heterogeneity with respect to the donors' degree of commitment to the cause.[2] Other previous work on the role of overhead in charity includes, e.g., Okten and Weisbrod (2000), Bowman (2006), and Meer (2014). These studies use administrative data on cross sections of charities to explore how donors respond to changes in the price of giving that are induced by variation in overhead.

As pointed out by, e.g., Vesterlund (2003) and Bekkers and Wiepking (2011), the evidence on leadership donations, seed money, and matching schemes (List and Lucking-Reiley, 2002; Karlan and List, 2007; Landry *et al.*, 2010; Huck and Rasul, 2011; Huck *et al.*, 2015, e.g.) likely reflects that donors use the observable behavior of others to draw inferences about the quality of charities. Our findings on strongly committed donors allow for a similar interpretation: Donors may mainly use overhead-related information to update their believes about the likelihood that the charity will deliver on its promises. Our work thus reinforces the view that a major force shaping the behavior of donors is the preference to give to high-quality charities.

The remainder of the paper is organized as follows. Section 2 presents the setting of the field experiment, Section 3 describes the experimental design and the data, and Section 4 discusses our findings. Section 5 concludes.

2 Setting of the Field Experiment

To implement our research design, we collaborated with the Protestant Church in Bavaria, Germany, and two of its local administrative units, the church districts. In total, the two districts comprise 14 urban parishes with about 35,000 adult church members. In a coordinated fundraising drive, each Bavarian church district sends out

[2] In their laboratory experiment, Gneezy *et al.* (2014) do not have any meaningful variation in donors' commitment. Their field experiment covers only individuals who have given to similar causes before and, hence, are likely rather strongly committed.

a solicitation letter once a year to all resident church members above the age of 18. The letter asks church members to contribute to a district-specific local church fund. The letters furthermore contain a leaflet that provides examples of recent projects the fund supported.

A distinctive feature of our setting is that the solicitation letter displays an income-dependent schedule of suggested donation amounts. The schedule lists suggested amounts ranging from €5 to €100 for a total of six income brackets. This schedule emerges from the fact that the German state allows the churches to raise so-called 'church taxes' from their members.[3] Referring to this provision, the solicitation letter asks the recipients to use the schedule for a self-assessment of income, and to transfer the suggested amount provided in the schedule to the fund's bank account.

Importantly, the church districts have no information on individual incomes and, therefore, no means to enforce that members pay the suggested amounts (or pay anything, for that matter). Moreover, it has been documented that this absence of enforcement is well known among church members (Dwenger *et al.*, 2016). Also, the church districts do not share information on individual payments with the parishes. As a consequence, whether or not church members contribute to the local church fund, and (if they make a payment) whether they pay the suggested amount or not, does neither affect their access to church services nor their social standing with their local congregation. As a result, the setting of our experiment is similar to other charitable giving contexts where potential donors respond to solicitation letters, and individual giving is private information.

While the church districts have no information on individual incomes, the church administration at the state level receives individual income records from the state's tax authorities on all church members who file for the federal income tax. These income records are used to determine the church members' church taxes, the main source of church revenue. A key advantage of our setting is that the church allowed

[3]The Protestant Church in Bavaria finances itself mainly through a state church tax which corresponds to 8 percent of church members' income tax liabilities. Tax collection is organized at the state level, and the state church uses a grant system to channel part of the tax revenue to the local church districts. The church raises about $euro$270 in state church taxes per church member (including non-tax paying members) and year. Church members can avoid paying the state church tax by opting out of their church membership at any time. The church tax is therefore akin to a recurring donor scheme (Bittschi *et al.*, 2021).

us to access the income data and link them to individual donations to the local church funds. This means that, for the sample of church members who file for the federal income tax, we can determine the suggested donation amount implied by the donation schedule highlighted in the solicitation letter, and compare the suggested amount to the actual donation. Hence, despite the fact that the suggested donation amount is differentiated by income, we observe whether individuals follow the suggestion or not. This allows us to control very flexibly for income effects in our estimations, and to construct measures describing how strongly committed to the cause individuals are (see next section for details).

3 Experimental Design, Data, and Methods

3.1 Experimental Design

Letters The solicitation letters were mailed by the church district administrations to all resident church members. All letters were mailed on the same day. In terms of layout and general content, all letters (see the appendix for a sample) were similar to the letters mailed in previous years. The letter highlights that the suggested donation amount depends on the church member's income and asks the recipient to determine the appropriate amount using the schedule of six income brackets. The experimental conditions varied only in a short note referring the recipients to a change in the overhead associated with the fundraising drive.

Our aim is to explore why donors are averse to financing fundraising expenses. Following Gneezy *et al.* (2014), donors respond to information on fundraising expenses because they perceive the information as a signal either about the charity's efficiency, or about the impact a donation has on the cause. Our treatments are meant to disentangle both effects empirically and determine their relative importance for the behavior of donors.

To identify the efficiency effect, we compare donations in an efficiency treatment to a control group. As a signal of improved efficiency, the letter in the respective treatment states that "this year, we were able to reduce the administrative cost associated with the mailing of this letter by 30 percent." For the comparison to identify the efficiency effect, in the control group, we need to hold constant (relative to the efficiency treatment) the impact of a donation. Hence, the control group letter also communicates a 30-percent change in fundraising costs. However, the control group letter communicates the change in fundraising costs in a way that does not signal anything about the efficiency of the church as a charitable organization. Specifically, the control group letter frames the change as a one-time shift of costs from the district to the state church, stating that "this year, we get a refund from the state church that covers 30 percent of the administrative cost associated with the mailing of this letter."

To separately identify the effect of changing the impact of a donation on the cause, we employ a treatment that communicates a 100 percent shift of fundraising costs to the state church, and compare it to the control group with its 30 percent cost shift. The letter in the impact treatment states that "this year, we get a refund from the state church that covers all administrative costs associated with the mailing of this letter." Importantly, between the impact treatment and the control group, the source of the change in fundraising costs is kept constant. Hence, the donors' perception of the efficiency of the church as a charitable organization should not be differentially affected. We would like to highlight that the transfer covering the fundraising cost in the impact treatment can be interpreted like seed money that is used to cover the overhead of a fundraising drive. The impact treatment is thus very similar to the overhead treatment in Gneezy *et al.* (2014).[4] While Gneezy *et al.* (2014) compare their overhead treatment to alternative uses of seed money, we identify the impact effect by varying the fraction of fundraising costs covered by a third party.

Finally, following the same randomization scheme, we also sampled potential donors into a no-intervention group. The respective letter omitted the paragraph on fundraising costs. The purpose of the no-intervention group is to train a model that predicts individual donation behavior in the treatment and control groups absent any treatment (see Subsection 3.3 for details). In our empirical analysis, the predicted

[4]The overhead treatment in Gneezy *et al.* (2014) states that "a private donor who believes in the importance of the project has given this campaign a grant in the amount of $10,000 to cover all the overhead costs associated with raising the needed donations."

donor type is used to test for heterogeneous treatment effects.[5]

Implementation We implemented the changes in fundraising costs borne by districts as follows. In preparing the solicitation letters, the districts rely on in-house service providers operating within the state-level administration of the church. The service providers handle the records of church members, produce mailings on behalf of the district administrations, and deliver them to a mail service company. The service providers bill the districts for their services. In the experiment, those bills represent the fundraising costs borne by the districts. In collaboration with the different tiers of the church administration, we arranged for a partial reimbursement of the districts for the billed cost through state-level church funds. For each district, the overall reimbursement reflected exactly the distribution of treatments and the changes in locally borne fundraising costs communicated in the respective letters. As a result, in the efficiency treatment, the impact treatment, and the control group, each individual letter carried a change in fundraising costs borne by the district in accordance with the respective treatment paragraph. However, as detailed before, only the impact treatment and the control group made it transparent that the change in fundraising costs was implemented through a reimbursement scheme.

3.2 Data and Sampling

Data Sources The church administration provided us with individual characteristics on all adult church members residing in either of the two districts. We also obtained individual-level records of donations for the two years preceding the treatment (baseline) and the treatment year. While the data for the baseline years are used to predict donation behavior absent any treatment, the data for the treatment year is used to derive our outcomes of interest. The third data source consists of individual-level income records, normally used by the state church's tax office to determine the church members' church tax. This data allows us to infer the personalized suggested donation amount for each potential donor, provided that income is observed. It is one of the key

[5] We do not compare outcomes between the no-intervention group and the other groups, because such comparisons would be confounded by differences in the salience of fundraising costs.

features of our study that we can compare personalized suggested donation amounts to actual donations.

Sampling The solicitation letters were sent to all resident adult church members. The sampling for the experiment excluded individuals living in households with more than one adult church member, because household members often combine their individual donations into a single bank transfer, introducing measurement error in outcomes. We also excluded employees of the Protestant Church from the experiment. Using a stratified randomization scheme, we assigned each church member to one of the four letter groups.[6]

We focus on the sample of church members for whom we observe the personalized suggested donation amount (i.e., individual income) in the baseline.[7] This sample comprises 8,617 potential donors in total, out of which 6,433 individuals belong to the estimation sample comprising the efficiency treatment, the impact treatment, and the control group (the remaining 2,184 individuals belong to the no-intervention group). Note that we could not fully determine this sample ex ante, as income tax declarations in Germany are often filed with a considerable time lag. Hence, we could not determine ex ante the sample of church members for whom baseline income information would be available. We therefore sampled all church members (subject to the restrictions discussed before) and restricted the sample ex post to those potential donors with sufficient income information to determine the personalized suggested donation amount in the baseline. A second restriction applies if we condition the sample on income information being available not only in the baseline, but also in the treatment year. The part of the estimation sample which can be used for the respective regressions comprises 3,625 individuals.[8] Table A2 in the appendix shows descriptives

[6] Strata were defined by age, gender, income bracket, baseline donation behavior, and parish.

[7] This essentially limits our sample to church members who file an income tax declaration. For non-filers (comprising most students and retirees), no income data is transmitted to the church tax office. We also lose observations from imperfections in the match between donations and income records (which had to be done based on name, street address, and zip code).

[8] There are two reasons why we observe income for fewer individuals in the treatment year: First, we can predict a donor's type even if income is only observed in one of the baseline years (see the next subsection for details). Second, we had to collect all income data in the year following the intervention, implying that late filing leads to more missing values in the income records for the treatment year relative to the baseline years.

on baseline characteristics and corresponding balancing checks for the sample of potential donors whose type can be determined. Table A3 refers to the sample with a complete set of outcomes.

A possible concern regarding external validity could be that church members might differ from other potential donors in important respects. For instance, it is often claimed that Protestants have a special work ethic, which could translate into higher incomes and specific attitudes towards (some forms of) charitable causes. It could also be that church members are more pro-social in general. Table A4 in the appendix sheds light on these concerns and shows that Protestants are very similar to the overall population in Germany, and also similar to non-church members. If anything, members of the Protestant church earn slightly lower incomes, most likely reflecting a selection effect resulting from a higher likelihood among high-income church members to opt out of their membership and thereby avoid the church tax (Bittschi *et al.*, 2021). The average amount of all charitable donations made in a given tax year is very similar across the different groups, suggesting that Protestants do not, on average, differ from the German population in terms of their general willingness to give to charities.

3.3 Predicting Donor Types

In the charitable giving literature, it is common to distinguish between warm-list and cold-list individuals. Much of the recent experimental work on individual donation decisions covers only warm-list individuals, and when broader samples are considered, it is common to discuss the respective subsamples separately (Landry *et al.*, 2010). The feature of a personalized suggested donation amount, and the fact that we can observe whether donors follow the suggestion or not, allows us to refine the traditional warm-list vs. cold-list distinction. Specifically, we exploit the available information to single out potential donors who are strongly committed to the cause (as opposed to weakly committed donors), and then explore the heterogeneity in treatment responses by the degree of the donors' commitment.

Our approach to identify strongly committed donors is to predict for each potential donor whether the individual would have donated the personalized suggested amount (or more) without an intervention. Hence, our criterion when defining "strong commitment to the cause" is whether the potential donor is predicted to follow the personalized suggestion formulated in the solicitation letter. To make this prediction, we use the observations in the no-intervention group to train a parsimonious model linking the donor's type (strongly vs. weakly committed) in the year of the intervention to information on the donor's characteristics and her payment behavior in the baseline years (donation weakly above personalized suggested amount, or not). After estimating the model, we predict each donor's type (out-of-sample) in the control group and the treatment groups. The predicted type is used to distinguish between strongly and weakly committed donors.

The probit regression[9] used to predict individual i's type (1 for strongly committed donor, 0 otherwise) in the treatment year t reads

$$Prob(TYPE_{i,t}|\cdot) = Prob(\delta_0 + \delta_1 TYPE_{i,t-1} + \delta_2 TYPE_{i,t-2} + X'_{i,t}\pi > u_{i,t}), \qquad (1)$$

where $TYPE_{t-1}$ and $TYPE_{t-2}$ are indicators for the type in the baseline years $t-1$ and $t-2$, respectively, and X_t denotes the vector of strata variables.

The regression results (see Table A5 in the appendix) show that $TYPE_{t-1}$ and $TYPE_{t-2}$ are strong predictors of the type in the treatment year. To evaluate the out-of-sample predictive performance, we randomly split the sample in two equal-sized subsamples. We then use one subsample for the estimation and the other subsample to calculate metrics for predictive accuracy. Using a threshold of 50 percent for the predicted probability to classify an individual as a strongly committed type, our out-of-sample prediction is correct for 91.5 percent of the individuals. Because the successful prediction of types in the majority class ($TYPE = 0$) could mask a possible failure of our model in predicting the minority class ($TYPE = 1$), focusing on true positives provides a more conservative assessment of the model's performance in the zero-inflated data. We find that calculating the number of true positives over all positives still results in a

[9] The no-intervention cross section consists of 1,194 observations. We also evaluated the performance of machine learning (ML) models that can capture more complex relationships between the donor's characteristics and her type, but found that ML methods do not lead to improvements over the probit regression in terms of out-of-sample predictive performance. Moreover, all our results are robust to using a simple heuristic to define donor types (see Subsection 4.3). We also predicted three types (donation strictly above, equal to, and strictly below suggested amount) but we ended up with very small samples for the first two types.

share of correctly predicted types of 80.4 percent. Using as a metric the number of true positives over the number of predicted positives, we get a share of 74.1 percent. We take these metrics as evidence for a favorable out-of-sample predictive performance of our first-stage model.

Not surprisingly, given the small number of donors in the baseline, the distribution of predicted types is heavily skewed towards weak commitment to the cause: 85.0 percent of donors with data on baseline income are classified as weakly committed, and 15.0 percent as strongly committed donors.

4 Evaluating the Field Experiment

4.1 Estimation

We consider three outcome variables: an indicator for individuals whose donation exceeds the personalized suggested amount, an indicator for individuals who make a donation, and the donation amount. When using either the indicator for a donation or the donation amount, we exploit the full sample of 6,433 individuals who are in one of the groups used for estimation (efficiency, impact, and control) and whose type can be predicted. The regression using the indicator for donations exceeding the personalized suggested amount uses only the sample of 3,625 individuals for whom we can also determine the personalized suggested amount in the treatment year.

Using the control group as the omitted reference category, we estimate the efficiency effect and the impact effect by OLS. We consider two specifications: First, we estimate the non-interacted model

$$y_i = \beta_0 + \beta_1 EFF_i + \beta_2 IMP_i + X_i'\gamma + \epsilon_i, \tag{2}$$

where y_i denotes the outcome of interest, EFF_i is an indicator for the efficiency treatment, IMP_i is an indicator for the impact treatment, and X_i denotes the vector of strata variables. Because the strata variables include indicators for income brackets, the estimation flexibly controls for income effects. We use Huber-White robust standard errors for inference. Second, we estimate a model that interacts the treatment indicators with the predicted donor type,

$$\begin{aligned} y_i = &\beta_0 + \beta_1 EFF_i + \beta_2 IMP_i + \\ &\beta_3 EFF_i \times \widehat{TYPE}_i + \beta_4 IMP_i \times \widehat{TYPE}_i + \theta \widehat{TYPE}_i + X_i' \gamma + \epsilon_i, \end{aligned} \tag{3}$$

where the indicator variable $\widehat{TYPE}_i$ is derived from the out-of-sample prediction based on eq. (1). $\widehat{TYPE}_i$ takes on the value one (indicating strongly committed donors) for predicted probabilities greater than 50 percent, and zero otherwise (weakly committed individuals).

For inference on the interacted model, we use a bootstrap. Because predicting donor types involves an estimation, the bootstrap encompasses both, the type prediction and the estimation of treatment effects. This ensures that we take the impact of the sampling variation on the predicted type into account when deriving the standard errors of the treatment effects.

Spillovers across treatments would downward-bias any differences between the treatment and control groups. Arguably, such spillovers would most likely occur within households comprising more than one adult member of the Protestant church. We reiterate that in order to minimize the potential for spillovers, we excluded such households from the experiment (together with church employees and priests).

4.2 Results

Non-Interacted Model Table 1 reports the estimation results. We begin by discussing the findings for the non-interacted model in Panel A described by eq. (2). Column (1) shows how the treatments affect the likelihood that donors give more than the personalized suggested amount. In response to the efficiency treatment, donors are, on average, 2.7 percentage points more likely to donate more than the suggested amount. Given a share of 6.6 percent of donors in the control group whose donation exceeds the suggested amount, this is a sizable effect. We also find that, relative to the 18.5 percent share in the control group, the efficiency treatment does not affect the likelihood for making a donation, and that despite the higher tendency to donate more than the suggested amount, the effect on the donation amount (€ 6.36 on average in the control group) is not significantly different from zero. By contrast, the coefficient of the impact treatment indicator is close to zero and insignificant in all three regressions. Moreover, we can reject the hypothesis that the effects of both treatments in column (1) are equal (p-value 0.053). The non-interacted model thus delivers our first main result: on average, if the charity reduces its overhead in a way that signals an improved efficiency, it triggers a positive response among donors who become more likely to donate more than the suggested amount. In contrast, increasing the impact a donation has on the cause does not, on average, affect donor behavior.

Interacted Model Evidence on the heterogeneity of the treatment effects with respect to the degree of commitment to the cause is reported in Table 1, Panel B. To facilitate the interpretation of the effects, Table A6 additionally displays mean outcomes in the control group separately for both donor types (strongly vs. weakly committed). The coefficients of the efficiency treatment indicator (β_1) and the impact treatment indicator (β_2) capture the treatment effects for individuals who are weakly committed to the cause. A first observation is that weakly committed potential donors do not respond at all to the efficiency treatment: in all three columns, the coefficients are small and not significantly different from zero. For the impact treatment, we even find a negative effect on the probability to make a donation. Whereas 9.1 percent of the weakly committed individuals in the control group make a donation (see Table A6), this share is reduced by 1.9 percentage points in the impact treatment.

Our second main insight is, thus, as follows: By reducing its overhead, the fundraiser is unable to positively affect the donation behavior of weakly committed potential donors. Whereas signaling that the overhead reduction has improved the charity's efficiency does not affect donor behavior at all, communicating an increased impact of donations on the cause actually crowds out the willingness to give of at least some donors. In the light of the evidence in Gneezy *et al.* (2014), this is a novel and surprising result. It should be noted, however, that a negative effect of the impact treatment is perfectly in line with economic theory. A large literature initiated, e.g., by Warr (1982), Roberts (1984), and Andreoni (1989) has shown theoretically that, if preferences are altruistic and a charity receives a grant from a third party, this grant fully crowds out private donations. Although this theoretical literature speaks directly to the empirically important case of charities using seed money to attract private donations, the possibility that the availability of seed money as such actually crowds out private donations has, to our knowledge, rarely been discussed in the empirical fundraising literature. A notable exception is the literature on matching schemes financed by seed money. For instance, Eckel and Grossman (2003), Karlan and List (2007), and Huck and Rasul (2011) show that using seed money to finance a linear matching scheme crowds out actual donations given, and Adena and Huck (2017) present a possible remedy. As highlighted earlier, the intervention in the impact condition can be interpreted as an infusion of seed money that is used, as in Gneezy *et al.* (2014), to cover the overhead of a fundraising drive. According to the public-goods crowding-out hypothesis, the provision of seed money should crowd out donations, irrespective of how the charity uses the seed money. Interestingly, our experimental design, which nets out other potential channels through which a seed money-induced reduction in overhead could positively affect donor behavior,[10] finds at least some support for the public-goods crowding-out hypothesis for weakly committed individuals.

Next, we turn to the evidence on strongly committed donors. The coefficients of the interactions (β_3 and β_4, respectively) capture the extent to which the treatment effects of strongly committed individuals differ from the treatment effects for weakly committed potential donors. For strongly committed donors, the efficiency treatment triggers a significant shift (relative to the weakly committed) towards giving more than the suggested amount ($\beta_3 = 0.134$). The sum of β_1 and β_3 indicates that, relative to the control-group, the likelihood of strongly committed potential donors to donate more than the suggested amount increases from 28.5 percent (see Table A6) to 42.7 percent, an economically sizable effect. The shift towards more generous gifts among strongly committed donors that is visible in column (1) naturally translates into a significant increase in the donation amount. Relative to weakly committed potential donors, the efficiency treatment triggers an increase in the average donation of € 5.86. Again, the sum of β_1 and β_3 shows that the overall increase in the donation

[10] Most prominently, seed money could reveal the charity's quality (Vesterlund, 2003). We would argue that in our design, a possible quality signal transmitted by the impact treatment is netted out. After all, the letter in the control group also communicates a seed money-induced reduction in overhead.

amount among strongly committed individuals is economically significant: relative to the control group mean of €25.71 (see Table A6), donations increase by 21.1 percent. Regarding the strongly committed donors' response to the impact treatment, we note from Table 1 that the respective interaction effects are not significantly different from zero. To evaluate the strongly committed donors' overall response to the impact treatment, we consider the sum of $\hat{\beta}_2$ and $\hat{\beta}_4$. For all three regressions, the sum is not significantly different from zero.

To summarize, our third main insight is that by reducing their overhead, charities can significantly increase the average donation received from strongly committed donors. Importantly, provided that the overhead reduction is framed as an improvement in the charity's efficiency, strongly committed donors respond positively even if the impact a donation has on the cause is held constant. By contrast, an overhead reduction that increases the impact a donation has on the cause but does not change the charity's efficiency leaves the behavior of strongly committed donors unaffected. It is worth noting that, for a donor motivated by altruism, a seed money-induced reduction in overhead is a perfect substitute for her own private contribution, and would thus crowd out rather than increase donations.[11] Hence, the absence of a response to the impact treatment implies that at the margin, strongly committed donors are motivated by joy-of-giving, or warm glow, rather than altruism. Finally, it has long been recognized that the behavior of donors is strongly affected by a preference to single out and give to high-quality charities (Vesterlund, 2003; Bekkers and Wiepking, 2011). Our findings on strongly committed donors are in line with this notion: the power of the efficiency treatment suggests that strongly committed donors respond to overhead-related information due to an aversion against the wasteful spending of donated funds.

[11] Again we make the assumption here that the provision of seed money (i.e., the transfer from the state church to the church districts) does not signal the districts' quality as fundraisers. As argued before, our experimental design supports this assumption.

4.3 Robustness

In the following, we briefly summarize the results of some further analyses and robustness checks.

Income Heterogeneity Although the treatment groups are balanced in observables (see Tables A2 and A3 in the appendix), the diverging responses by strongly vs. weakly committed potential donors could (partly) reflect income differences. For instance, high-income individuals could be more likely to give, and at the same time be more responsive to efficiency-related information. By contrast, low-income individuals could be less likely to give, and at the same time be more likely to have purely altruistic preferences for giving.

To explore this possibility, we run entropy-reweighted estimations of our treatment effects, following the methodology of Hainmueller (2012). The idea is to construct weights for donors classified as strongly committed ensuring that their weighted pre-treatment income distribution follows the income distribution of weakly committed potential donors. We implement the reweighting using a series of six indicators for the different income brackets used by the church to derive the personalized suggested donation amount. The weights thus adjust the income distribution of strongly committed donors in a very flexible way.

Table A7 in the appendix documents that all our findings are robust to the reweighting. This bolsters our confidence that the treatment effect heterogeneity between the different donor types is not an artifact driven by between-type income heterogeneity.

Estimation Sample Table 1 uses different samples. As a further robustness check, we repeat the estimations using the same (smaller) sample for all estimations (all donors with income information both in the baseline and in the treatment year). Table A8 shows that all our findings are confirmed.

Alternative Definition of Donor Types The analysis of heterogeneous treatment effects rests on a prediction of donor types. Table A9 shows that we obtain similar results if we use a simple heuristic instead of a model-based prediction. The heuristic defines strongly committed donors as individuals who have either donated the suggested amount in all baseline years or overpaid at least once, and weakly committed donors as individuals who gave less than the personalized suggested amount at least once and did not overpay in any year.

Estimations Without Controls The estimations in Table 1 control for strata variables. Table A10 in the appendix demonstrates that without controls, we obtain very similar results.

5 Conclusion

This paper asks how charities can use overhead reductions to induce giving. In a field experiment, we randomly varied the information that potential donors received about fundraising costs. The experimental design allows us to separately identify two channels through which overhead reductions could affect behavior: an efficiency channel (donors give more if the charity's fundraising becomes more efficient), and an impact channel (donors give more if the charity manages to increase the impact a donation has on the cause).

We obtain the following main results. Studying all potential donors, an improved efficiency increases the likelihood that donors give more than the suggested amount. By contrast, using an overhead reduction to increase the impact a donation has on the cause does not affect donor behavior on average. Exploring the treatment responses by the donors' degree of commitment to the cause, we find strong heterogeneous effects. Specifically, donors who are strongly committed to the cause ignore impact-related information but respond positively to a signal of improved efficiency. They give 21.1 percent more on average, and their likelihood to donate more than the suggested amount increases from 28.5 percent to 42.7 percent. Donors who are only weakly committed to the cause do not react positively to any of the treatments. They do not respond at all to a signal of improved efficiency, and when learning that the impact of a donation has increased, they become less likely to give. The latter finding is consistent with the public-goods crowding-out hypothesis (Andreoni, 1989). Regarding strongly committed donors, our findings support the view that overhead aversion in charity is mainly driven by a preference among donors to give to high-quality charities.

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Table 1: Responses to Changes in Fundraising Efficiency and Impact

	Donation Exceeds Suggested Amount (1)	Makes Donation (2)	Donated Amount (3)
A: Non-Interacted Model			
Efficiency	0.027***	−0.012	0.188
	(0.010)	(0.011)	(0.546)
Impact	0.007	−0.010	0.071
	(0.010)	(0.011)	(0.539)
Efficiency = Impact	0.053	0.906	0.834
B: Interacted Model			
Efficiency	0.008	−0.010	−0.498
	(0.007)	(0.010)	(0.422)
Impact	−0.001	−0.019**	−0.443
	(0.007)	(0.009)	(0.433)
Efficiency×Strongly Committed	0.134***	0.013	5.864**
	(0.049)	(0.039)	(2.570)
Impact×Strongly Committed	0.018	0.015	1.779
	(0.047)	(0.039)	(2.427)
Strongly Committed	0.221***	0.594***	22.306***
	(0.034)	(0.030)	(1.820)
Number of Observations	3,625	6,433	6,433
Mean Outcome in Control Group	0.066	0.185	€6.36
Controls for Strata Variables	YES	YES	YES
Efficiency + Efficiency×Strongly Committed = 0	0.003	0.930	0.032
Impact + Impact×Strongly Committed = 0	0.706	0.923	0.571

Notes: The table reports the results of OLS regressions to evaluate the effects of the efficiency and the impact treatments relative to the control group. For each outcome considered, the table separately reports a regression of the non-interacted model (Panel A) and the interacted model (Panel B). Column (1) uses a smaller sample as compared to columns (2) and (3), because the dependent variables can only be constructed for church members for whom we can determine the suggested donation amount that is implied by the income-dependent donation scheme in the treatment year. All regressions include a full set of controls for strata variables (based on age, gender, the suggested donation amount in the baseline including an indicator for missing values, and parish fixed effects). Standard errors (SEs) in parentheses. Panel A: SEs are Huber-White robust. Panel B: SEs are bootstrapped. ***, **, * denote significance level at 1, 5, 10 percent level, respectively. The lines with hypothesis tests (Panel A and Panel B) report p-values.

Online Appendix (Not For Publication)

Table A1: Schedule of Personalized Suggested Donation Amounts

Annual Income	Annual Suggested Amount	% of Sample in Income Bracket (Conditional on Income Being Oberved)
€ 8,005 to € 9,999	€ 5	2.9
€ 10,000 to € 24,999	€ 10	37.4
€ 25,000 to € 39,999	€ 25	34.4
€ 40,000 to € 54,999	€ 45 / € 50	13.5
€ 55,000 to € 69,999	€ 70	5.6
€ 70,000 and above	€ 100	6.3

Notes: This table shows the schedule of the suggested donation amount in the two districts where the field experiment was implemented. In one of the districts, potential donors falling into the bracket between € 40,000 and € 54,999 face a suggested amount of € 45, while in the other district the respective suggested donation amount is € 50.

Table A2: Baseline Characteristics

	T0: Control	T1: Efficiency	T2: Impact	Difference T1 - T0	Difference T2 - T0
A: Full Sample					
Female	0.496	0.493	0.487	-0.003	-0.010
				(0.015)	(0.015)
Age	48.8	48.6	48.8	-0.154	0.012
				(0.494)	(0.493)
Suggested Amount ≤ € 10	0.469	0.460	0.473	-0.009	0.004
				(0.015)	(0.015)
€ 25 ≤ Suggested Amount ≤ € 50	0.411	0.421	0.407	0.009	-0.005
				(0.015)	(0.015)
Suggested Amount ≥ € 70	0.120	0.120	0.120	0.000	0.001
				(0.010)	(0.010)
Number of Observations	2,156	2,130	2,147	4,286	4,303
B: Weakly Committed					
Female	0.481	0.478	0.477	-0.004	-0.004
				(0.017)	(0.017)
Age	46.5	46.4	46.5	-0.065	0.062
				(0.488)	(0.489)
Suggested Amount ≤ € 10	0.455	0.450	0.464	-0.005	0.009
				(0.016)	(0.017)
€ 25 ≤ Suggested Amount ≤ € 50	0.422	0.430	0.413	0.008	-0.009
				(0.016)	(0.016)
Suggested Amount ≥ € 70	0.123	0.120	0.123	-0.003	-0.001
				(0.011)	(0.011)
Number of Observations	1,839	1,828	1,808	3,667	3,647
C: Strongly Committed					
Female	0.584	0.589	0.540	0.006	-0.044
				(0.040)	(0.039)
Age	62.2	62.0	60.8	-0.111	-1.335
				(1.410)	(1.386)
Suggested Amount ≤ € 10	0.552	0.520	0.522	-0.032	-0.030
				(0.040)	(0.039)
€ 25 ≤ Suggested Amount ≤ € 50	0.350	0.364	0.372	0.014	0.022
				(0.039)	(0.038)
Suggested Amount ≥ € 70	0.098	0.116	0.106	0.018	0.008
				(0.025)	(0.024)
Number of Observations	317	302	339	619	656

Notes: The table displays means of potential donors' baseline characteristics, together with estimated differences in means and corresponding standard errors in parentheses. The sample consists of all potential donors for whom baseline income is observed. Using this information, the suggested donation amount in the baseline can be determined at the level of the individual donor. The prediction of the donors' type (strongly vs. weakly committed) exploits information on suggested donation amounts and actual donations in the baseline. The sample of potential donors is the same as in Columns (2) and (3) of Table 1.

Table A3: Baseline Characteristics (Suggested Amount Observed in Treatment Year)

	T0: Control	T1: Efficiency	T2: Impact	Difference T1 - T0	Difference T2 - T0
A: Full Sample					
Female	0.489	0.471	0.478	-0.019	-0.011
				(0.020)	(0.020)
Age	49.9	49.3	49.5	-0.566	-0.419
				(0.666)	(0.665)
Suggested Amount $\leq$ € 10	0.441	0.438	0.439	-0.003	-0.002
				(0.020)	(0.020)
€ 25 $\leq$ Suggested Amount $\leq$ € 50	0.449	0.455	0.452	0.007	0.003
				(0.020)	(0.020)
Suggested Amount $\geq$ € 70	0.110	0.107	0.109	-0.004	-0.001
				(0.013)	(0.013)
Number of Observations	1,204	1,228	1,193	2,432	2,397
B: Weakly Committed					
Female	0.479	0.456	0.472	-0.023	-0.007
				(0.022)	(0.022)
Age	47.3	46.9	46.7	-0.337	-0.549
				(0.664)	(0.661)
Suggested Amount $\leq$ € 10	0.434	0.428	0.430	-0.006	-0.005
				(0.022)	(0.022)
€ 25 $\leq$ Suggested Amount $\leq$ € 50	0.450	0.465	0.458	0.015	0.008
				(0.022)	(0.022)
Suggested Amount $\geq$ € 70	0.116	0.106	0.112	-0.009	-0.004
				(0.014)	(0.014)
Number of Observations	1,004	1,034	973	2,038	1,977
C: Strongly Committed					
Female	0.540	0.546	0.505	0.006	-0.035
				(0.050)	(0.049)
Age	62.9	61.9	61.5	-0.982	-1.393
				(1.767)	(1.716)
Suggested Amount $\leq$ € 10	0.475	0.490	0.482	0.015	0.007
				(0.050)	(0.049)
€ 25 $\leq$ Suggested Amount $\leq$ € 50	0.440	0.402	0.423	-0.038	-0.017
				(0.050)	(0.048)
Suggested Amount $\geq$ € 70	0.085	0.108	0.095	0.023	0.010
				(0.030)	(0.028)
Number of Observations	200	194	220	394	420

Notes: The table displays means of potential donors' baseline characteristics, together with estimated differences in means and corresponding standard errors in parentheses. The sample consists of all potential donors for whom income is observed both in the baseline and the treatment year. The sample of potential donors is thus the same as in Column (1) of Table 1. The donors' type (strongly vs. weakly committed) is predicted using information on income and actual donations in the baseline.

Table A4: Comparability of Protestants to General Population

	Single Filers			Joint Filers		
	All Filers	Protestant Filers	Non-Church Members	All Filers	Protestant filers	Non-Church Members
Female	0.474	0.526	0.428	0.500	0.500	0.500
Age	42.8	44.0	42.4	48.2	48.8	47.4
# Child Allowances	0.3	0.3	0.4	1.1	1.1	0.9
Taxable Income (€)	30,425	28,153	33,482	54,795	54,527	55,064
Has Wage Income	0.859	0.858	0.850	0.931	0.928	0.945
Has Capital Income	0.190	0.219	0.153	0.192	0.211	0.149
Has Business Income	0.039	0.033	0.046	0.066	0.066	0.059
Amount Donated (€)	140.0	136.5	144.0	286.8	289.8	305.7

Notes: This table shows the mean characteristics for three groups of income tax filers in Germany, separately for single and joint filing: All filers, Protestants, and non-church members. The source of data are personal income statistics for 2007.

Table A5: Probit Regression for Prediction of Donor Type

Dependent Variable:	Donor Strongly Committed in Treatment Year t
Donor Strongly Committed in $t-1$	0.306***
	(0.041)
Donor Strongly Committed in $t-2$	0.312***
	(0.042)
Female	0.058***
	(0.015)
Second Age Quartile	0.000
	(0.026)
Third Age Quartile	0.024
	(0.027)
Fourth Age Quartile	0.071***
	(0.031)
Parish Dummies	YES
Suggested Amount Dummies	YES
Further Controls	YES
Number of Observations	1,194

Notes: The table reports average individual marginal effects from the Probit regression that predicts individual types in the treatment year. As further controls, we include dummy variables for individuals (separately for both baseline years) for whom income is not observed. We run the regression only on individuals in the no-intervention group. Standard errors in parentheses. ***, **, * denote significance level at 1, 5, 10 percent level, respectively.

Table A6: Donation Behavior by Predicted Donor Type in Control Group

	Donation Exceeds Suggested Amount (1)	Makes Donation (2)	Donated Amount (3)
A: Weakly Committed			
	0.022	0.091	3.029
	(0.005)	(0.007)	(0.299)
Number of Observations	1,004	1,839	1,839
B: Strongly Committed			
	0.285	0.729	25.710
	(0.032)	(0.025)	(1.669)
Number of Observations	200	317	317

Notes: The table documents means and standard deviations of outcomes by predicted donor type in the control group. Panel A reports the figures for individuals who, based on their behavior in the baseline, are predicted to pay less than the suggested amount in the treatment year. We label those individuals as being weakly committed to the cause. Panel B reports the figures for individuals who, based on their behavior in the baseline, are predicted to pay the suggested amount (or more) in the treatment year. We label those individuals as being strongly committed to the cause. Column (3) shows donated amounts in Euro.

Table A7: Entropy-Reweighted Estimations of Treatment Effects

	Donation Exceeds Suggested Amount (1)	Makes Donation (2)	Donated Amount (3)
A: Non-Interacted Model			
Efficiency	0.065**	−0.013	1.711
	(0.026)	(0.022)	(1.194)
Impact	0.010	0.005	0.956
	(0.025)	(0.022)	(1.170)
Efficiency = Impact	0.030	0.421	0.543
B: Interacted Model			
Efficiency	0.009	−0.010	−0.502
	(0.008)	(0.010)	(0.510)
Impact	−0.001	−0.020**	−0.392
	(0.008)	(0.010)	(0.505)
Efficiency×Strongly Committed	0.133***	0.012	5.281**
	(0.051)	(0.041)	(2.446)
Impact×Strongly Committed	0.012	0.016	1.328
	(0.048)	(0.042)	(2.418)
Strongly Committed	0.206***	0.603***	23.221***
	(0.036)	(0.033)	(1.851)
Number of Observations	3,625	6,433	6,433
Mean Outcome in Control Group	0.066	0.185	€6.36
Controls for Strata Variables	YES	YES	YES
Efficiency + Efficiency×Strongly Committed = 0	0.004	0.956	0.044
Impact + Impact×Strongly Committed = 0	0.810	0.925	0.689

Notes: The table reports a robustness test of the findings for the interacted model in Table 1. Results for the non-interacted model are only reported for completeness. Using entropy weights, we adjust the income distribution in the subsample of strongly committed types to the income distribution of weakly committed types. Column (1) uses a smaller sample as compared to columns (2) and (3), because the dependent variables can only be constructed for church members for whom we can determine the suggested donation amount that is implied by the income-dependent donation scheme in the treatment year. All regressions include a full set of controls for strata variables. Standard errors (SEs) in parentheses. Panel A: SEs are Huber-White robust. Panel B: SEs are bootstrapped. ***, **, * denote significance level at 1, 5, 10 percent level, respectively. The lines with hypothesis tests (Panel A and Panel B) report p-values.

Table A8: Treatment Effects Using Identical Sample for All Regressions

	Donation Exceeds Suggested Amount (1)	Makes Donation (2)	Donated Amount (3)
A: Non-Interacted Model			
Efficiency	0.027***	−0.007	0.017
	(0.010)	(0.015)	(0.743)
Impact	0.007	−0.010	−0.214
	(0.010)	(0.015)	(0.749)
Efficiency = Impact	0.048	0.842	0.756
B: Interacted Model			
Efficiency	0.008	−0.011	−0.634
	(0.008)	(0.014)	(0.575)
Impact	−0.001	−0.036***	−1.083*
	(0.007)	(0.013)	(0.582)
Efficiency×Strongly Committed	0.134***	0.059	5.278*
	(0.049)	(0.047)	(3.046)
Impact×Strongly Committed	0.018	0.077	2.205
	(0.047)	(0.047)	(2.932)
Strongly Committed	0.221***	0.578***	23.044***
	(0.034)	(0.037)	(2.234)
Number of Observations	3,625	3,625	3,625
Mean Outcome in Control Group	0.066	0.185	€6.36
Controls for Strata Variables	YES	YES	YES
Efficiency + Efficiency×Strongly Committed = 0	0.003	0.287	0.116
Impact + Impact×Strongly Committed = 0	0.708	0.359	0.691

Notes: The table reports the results of OLS regressions to evaluate the effects of the efficiency and the impact treatments relative to the control group. For each outcome considered, the table separately reports a regression of the non-interacted model (Panel A) and the interacted model (Panel B). For all regression, we restrict the sample to the subpopulation for whom we observe the suggested donation amount in the baseline and in the treatment year. The estimations in Columns (1) is identical to the estimations reported in Table 1 and is reported only for completeness. All regressions include a full set of controls for strata variables. Standard errors (SEs) in parentheses. Panel A: SEs are Huber-White robust. Panel B: SEs are bootstrapped. ***, **, * denote significance level at 1, 5, 10 percent level, respectively. The lines with hypothesis tests (Panel A and Panel B) report *p*-values.

Table A9: Interacted Model Using Heuristic Definition of Donor Types

	Donation Exceeds Suggested Amount (1)	Makes Donation (2)	Donated Amount (3)
Efficiency	0.002	−0.013	−0.653*
	(0.005)	(0.009)	(0.360)
Impact	0.000	−0.022***	−0.629*
	(0.005)	(0.008)	(0.363)
Efficiency×Strongly Committed	0.132***	0.023	5.490**
	(0.043)	(0.035)	(2.201)
Impact×Strongly Committed	0.021	0.048	3.147
	(0.041)	(0.034)	(2.096)
Strongly Committed	0.239***	0.558***	21.522***
	(0.029)	(0.026)	(1.526)
Number of Observations	3,625	6,433	6,433
Mean Outcome in Control Group	0.066	0.185	€ 6.36
Controls for Strata Variables	YES	YES	YES
Efficiency + Efficiency×Strongly Committed = 0	0.002	0.759	0.026
Impact + Impact×Strongly Committed = 0	0.612	0.441	0.223

Notes: The table reports the results of OLS regressions of the interacted model. In contrast to Table 1, donor types are not predicted by a probit regression, but determined by a simple heuristic (see text for details). Column (1) uses a smaller sample as compared to columns (2) and (3), because the dependent variables can only be constructed for church members for whom we can determine the suggested donation amount that is implied by the income-dependent donation scheme in the treatment year. All regressions include a full set of controls for strata variables. Bootstrapped standard errors in parentheses. ***, **, * denote significance level at 1, 5, 10 percent level, respectively. The lines with hypothesis tests report p-values.

Table A10: Treatment Effect Estimations without Strata Controls

	Donation Exceeds Suggested Amount	Makes Donation	Donated Amount
	(1)	(2)	(3)
A: Non-Interacted Model			
Efficiency	0.027**	−0.009	0.347
	(0.011)	(0.012)	(0.580)
Impact	0.006	−0.009	0.098
	(0.010)	(0.012)	(0.569)
Efficiency = Impact	0.063	0.999	0.675
B: Interacted Model			
Efficiency	0.008	−0.009	−0.469
	(0.008)	(0.010)	(0.424)
Impact	−0.001	−0.019**	−0.493
	(0.007)	(0.010)	(0.430)
Efficiency×Strongly Committed	0.135***	0.018	6.414**
	(0.051)	(0.040)	(2.812)
Impact×Strongly Committed	0.016	0.016	2.084
	(0.048)	(0.040)	(2.651)
Strongly Committed	0.263***	0.638***	22.681***
	(0.035)	(0.031)	(1.979)
Number of Observations	3,625	6,433	6,433
Mean Outcome in Control Group	0.066	0.185	€6.36
Controls for Strata Variables	NO	NO	NO
Efficiency + Efficiency×Strongly Committed = 0	0.004	0.801	0.030
Impact + Impact×Strongly Committed = 0	0.749	0.937	0.536

Notes: The table reports the results of OLS regressions to evaluate the effects of the efficiency and the impact treatments relative to the control group. For each outcome considered, the table separately reports a regression of the non-interacted model (Panel A) and the interacted model (Panel B). Column (1) uses a smaller sample as compared to columns (2) and (3), because the dependent variables can only be constructed for church members for whom we can determine the suggested donation amount that is implied by the income-dependent donation scheme in the treatment year. No controls for strata variables included. Standard errors (SEs) in parentheses. Panel A: SEs are Huber-White robust. Panel B: SEs are bootstrapped. ***, **, * denote significance level at 1, 5, 10 percent level, respectively. The lines with hypothesis tests (Panel A and Panel B) report p-values.

Evangelical-Lutheran Church District of < Place >

Evangelical-Lutheran Church District of < Place >, Address

Mr/Mrs
First Name and Family Name
Street
Zip Code and City

< Place >, Date

NOTICE ON CHURCH CONTRIBUTION <YEAR>

Dear Mr/Mrs [addressee's family name],

Based on the state law regulating the church tax, the Evangelical-Lutheran Church District of < Place > raises a local church contribution for the year <YEAR>. The local church contribution forms part of the general church tax and is therefore a compulsory payment. It serves as a local levy to finance parish expenditures.

< Additional paragraph on reduction of overhead >

The local church contribution is staggered according to income. Please self-assess your income using the adjoining schedule and transfer your contribution within a month's time. Please use the attached bank transfer form when making your payment. This helps us to identify your payment.

Yearly Income or Benefits in Euro	Local Church Contribution in Euro
Up to Exemption Level (8,652)	-
8,653 to 9.999	5
10,000 to 24,999	10
25,000 to 39,999	25
40,000 to 54,999	45
55,000 to 69,999	70
70,000 and above	100

In the accompanying leaflet, you will find further information on how the local church contributions are spent. We very much appreciate your cooperation.

With kind regards,
Your Church District Administration in < Place >

See back of this page for legal advice. In case of questions, please contact < phone number >.

< Bank transfer form, pre-filled with church's bank account number, the church member's name, and donor ID >