Precommitments: Two Field Experiments on Intertemporal Choice in Charitable Giving*

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Abstract

This paper conducts two natural field experiments to explore inter-temporal choices in charitable giving by varying the timing of commitment and payment. Monthly donors were asked to increase their contributions (1) immediately, (2) in one month, (2) in two months, (4) in a free number of months. The results are consistent between the two field experiments; first, mean increases in donations are significantly higher when donors are asked to precommit to future donations. Second, follow-up data show that there is no difference in cancellations rates between the control and treatment groups. Finally, I provide evidence of heterogeneity in the response to different time lags, indicating differences in inter-temporal preferences among donors.

Key words: Field experiment, Intertemporal choice, Charitable giving

JEL classifications: C93, L31; D91

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1 Introduction

Intertemporal choices in which costs and rewards occur at different points in time are of central importance in many economic decisions. People commonly tend towards doing tasks with immediate rewards and delayed costs. Conversely, they procrastinate on tasks with immediate costs and delayed rewards. Retirement savings, credit card borrowing and gym attendance are examples where intertemporal trade-offs have been shown to influence behavior.[1] This paper investigates intertemporal choice in the previously unexplored context of charitable giving.

I design and test a fundraising strategy aimed at increasing donations by varying the timing of commitment and payment. The strategy was implemented in two large-scale natural field experiments. The studies address the following three questions. First, can charities boost donations by allowing donors to precommit to future donations? Second, what is the effect of different time lags between commitment and payment? Third, what are the long-run consequences of precommitments on donations?

The strategy consists of asking existing monthly donors to commit to an increase in their contributions, starting from a period in the future.[2] In a control group, Give More Now (GMN), monthly donors are asked to increase their donations immediately. In two treatment groups, monthly donors are asked to increase their donation (1) in one month time (GMO), or (2) in two months time, (GMT). A third treatment group allows donor to choose when to increase donations, denoted Give More Freely (GMF).

How can intertemporal trade-offs influence charitable donations? To answer this it will be necessary to explore donor time-consistency. Time-consistent donors have a constant discount rate between all future time periods. Time-inconsistent donors

[1] See, e.g., Lowenstein and Thaler, 1989; Laibson, 1997; O'Donoghue and Rabin, 1999; Bernatzi and Thaler, 2004; DellaVigna and Malmendier, 2006.

[2] There is no end date, but the donor is free to opt out at any time. The average donor has contributed on a monthly basis for seven years with Diakonia for 13 years with Save the Children. Drop-out rates tend to be very low. To drop out, the donor must call the charity or alternatively his/her bank and ask them to stop the monthly contributions. No written notification is required.

with present-biased preferences[3] will have a relatively high discount rate over short time horizons and relatively low discount rate over long time horizons. If donors do have present-biased preferences, and the cost associated with contributing to a charity occurs at a different time to the benefit, then it will influence how much a donor contributes to charitable causes.

To understand the intuition behind the fundraising strategy, I sketch a simple framework, combining the warm-glow model of imperfect altruism (Andreoni, 1989, 1990) with a model of quasi-hyperbolic preferences (see, e.g., Laibson, 1997; O'Donoghue and Rabin, 1999). In the warm-glow model, donors derive utility from two sources; the public good to which they are contributing, and the warm-glow from the act of giving. The simplest framework in which quasi-hyperbolic discounting is relevant is a three period model. The warm-glow occurs in the first period when a donor commits to giving, while the public good is realized in the final, third period. We compare the donor's contribution in two cases; (1) when the donor is asked to make an immediate contribution, and (2) when the donor is asked to make a contribution in the following period. The pre-commitment mechanism should help individuals with time-inconsistent preferences to overcome their bias for the present. The model predicts that the difference in contributions between the GMT and the GMN treatments will be larger for donors with quasi-hyperbolic preferences as compared to donors with time-consistent preferences. Furthermore, this prediction holds, notwithstanding if donors are pure altruists, impure altruists or solely motivated by warm-glow. Furthermore, if donors have present-biased preferences, the delay between commitment and payment is important and not the length of the delay. We should then expect to see no quantitative difference in donations between the GMO and GMT treatments.

[3] Throughout this paper, the terms hyperbolic and present-biased preferences will be used interchangeably to characterize donors who have a relatively high discount rate over short horizons and relatively low discount rate over long horizons. The term "quasi-hyperbolic" preferences will be used for the specific functional form used in the theoretical section. The term "quasi-hyperbolic" preferences is used by Laibson (1997), while O'Donoghue and Rabin (1999) use the term "present-biased", Krusell and Smith (2003) "quasi-geometric", and Weibull and Saez-Marti (2005) "quasi-exponential".

Precommitments were advanced by Schelling (1978,1984) as a method to mediate inconsistencies between expected preferences and actual behavior. The seminal paper of Benartzi and Thaler (2004) "Save More Tomorrow" is the first to use the precommitment idea. The authors design and implement the Save More Tomorrow (SMarT) plan, which offers employees to commit in advance to allocating a portion of their future salary increases toward retirement savings. The precommitment helps individuals with time-inconsistent preferences to overcome their self-control problem, while starting at the time of the next salary increase hinges upon the assumption of loss aversion. There are several important differences between the two papers. First, this paper presents the results from two randomized controlled field experiments while the "Save More Tomorrow" implementation was not randomized. Second, while both loss aversion and hyperbolic preferences could drive the result in the SMarT scheme, this paper isolates the pre-commitment effect. Third, the benefits and costs associated with charitable contributions are different from those associated with retirement savings.

To test the precommitment mechanism, I implemented two randomized field experiments at different points in time. The collaborating charities, Diakonia and Save the Children, support long-run sustainable development in poor countries.[4] Thus, donors contribute to a public good that will have positive long-run consequences, but no immediate effect. Moreover, the fact that the recipients are in foreign countries means that donors' motivation to give should stem from altruism or warm-glow rather than from personal consumption or insurance motives.

The field experiments were carried out within the charities' regular fund-raising campaigns. The donors were randomly divided into the control and treatment groups. In each field experiment, a telemarketing company was contracted to make the calls according to pre-written manuscripts. The manuscripts were identical in all respects but the timing of the increase in the donation.

[4] Two projects presented to the monthly donors as examples of the activities they are financing are (1) Working for debt relief for poor countries, and (2) Farming education for poor individuals in Cambodia so as to make them self-reliant.

The results are consistent between the two experiments, showing that charities can boost donations by allowing donors to precommit to future donations. First, the precommitment mechanism significantly increases the average increase in monthly contributions. The treatment effect of the two months lag is economically large; 32 percent in the first field experiment and 11 percent in the second field experiment.

Second, I test and find evidence of heterogeneous treatment effects. The spatial treatment effects are related to gender and length of donation. While men respond to both a one and a two month precommitment period, women respond less to the two month time lag and not to the one month time lag. In additions, as the share of women is considerably higher in the second experiment, these heterogeneous treatment effects explain the quantitative differences in the overall treatment effects between the two field experiments.

Third, in order to investigate the long-term effects, data on donors' monthly contributions were gathered 12 and 6 months after the original study. The follow-up study reveals that donors do not deviate from the increases in contributions that they committed to in the experiment; more than 95 percent of donors participating in the field experiment had chosen to continue their monthly contributions. Importantly, there are no statistically significant differences in cancellation rates or in changes in monthly contributions in the follow-up data.

Overall, these results contribute to our understanding of intertemporal choices and the effect of precommitments. Intertemporal choices have been heavily investigated laboratory experiments (see e.g. Frederick et al. 2002 for an in-depth overview of the experimental literature), but little is known from the field. The data provide evidence on heterogeneity among donors, indicating that some donors have present-biased preferences, and that the precommitment mechanism is more effective on those donors than on others. Further research is needed to increase our understanding of heterogeneity in time-consistency.

In addition, the results have implications for practitioners in the design of fundraising strategies. The follow-up data show that the precommitment strategy is highly profitable for the charity. This study used charities focusing on long-run sustainable development in poor countries. Long-term development projects typically do not receive wide media attention (see Eisensee and Stromberg (2007) for a study on the effect of media coverage on charitable contributions). In the U.S., less than four percent of overall charitable giving targets international relations (Giving USA, 2007). This study shows that precommitments can help increase contributions in this setting.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and section 3 presents the model. Section 4 describes the experimental design, while section 5 presents the results. Section 6 concludes.

2 Review of related literature

To my knowledge, there are no studies investigating precommitments in the context of charitable giving. The study closest to the one in this paper is that by Thaler and Benartzi (2004). A related study is conducted by Ashraf et al. (2006) as a field experiment in the Philippines. The SEED (Save, Earn, Enjoy Deposits) scheme helps individuals increase their savings by offering an enforceable commitment device in collaboration with a local bank. The commitment device is a bank account, which restricts access to the deposits until the individual holding the bank account had reached a targeted savings goal. Both the SMarT and the SEED program have a lasting impact on the participants' savings.[5]

Bazerman and Rogers (2008) run a series of lab experiments, testing whether people are more likely to select choices that they feel that they should do when the choices are implemented in the distant rather than near future. In one setting, they ask participants in the experiment how much would have to be given to a charity to forego $5 cash (i) now and (ii) in one week. They found that significantly more near

[5]Both the SMarT and the SEED plan offer strong evidence that these commitment devices help individuals save more. The SMarT plan was implemented at three independent companies. For instance, in the first company investigated, the average savings rates for SMarT participants increased from 3.5 percent to 13.6 percent in the course of 40 months. Over twelve months, the SEED plan increased average savings balances by 80 percent for the treatment group, relative to the control group.

future cash participants chose to retain the $5 cash than did distant future cash participants. Furthermore, near distant future cash participants required a much higher minimum donations value than did distant future cash participants.

Another related strand of literature is the growing number of studies using randomized field experiments to examine various aspects of charitable giving. This paper employs the same methodology. The experiment is carried out in collaboration with a real charitable organization and donors are randomly allocated into different treatment groups. List and Lucking-Reiley (2002) investigate the effects of seed money[6] on charitable giving, while Falk (2004) studies charitable giving as a gift exchange. Landry et al. (2005) approach nearly 5000 households in a door-to-door fund-raiser. They find that asking donors to participate in a lottery raised approximately 50% more in gross proceeds than the voluntary treatment. Croson and Shang (2006) test social information and its impacts on charitable contribution in a on-air fundraising campaign. They find that social influence increases contribution on average 12% for all donors, and up to 29% for first-time donors. Eckel and Grossman (2005, 2006) conduct two similar field experiments to compare the effects of rebates and matching subsidies for charitable contributions, varying the type of charity. In both cases, they find that the matching subsidy results in larger total contributions relative to their functionally equivalent rebate subsidy. Finally, Karlan and List (2007) also test matching and find that match contributions increases both the revenue per solicitation and the probability that an individual donates, but larger match ratios relative to smaller match ratios had no additional impact.

3 The model

This section presents a simple framework to explain how donors' optimal contribution can be affected by time-inconsistent preferences. The model combines a model

[6] Seed money implies that the charity first raises part of the money required for a project before they solicit money from the general public. The fact that other donors have already contributed sends a signal to the donors that it is an important project and more donors are then likely to follow as shown in the study.

of warm-glow giving (Andreoni, 1989, 1990) with a model of quasi-hyperbolic preferences (see, e.g., Rabin and O'Donoghue, 1999).

Charitable contributions have been modeled as an individual deciding how much to contribute to a public good.[7] Even if the recipients of the charity are individuals who receive a private good, charitable giving, motivated by altruism, creates a public good out of charity. The fact that others feel altruistic toward these individuals means that private consumption of these goods becomes a public good. It is not possible to prevent non-contributors from also benefiting, nor is there a cost associated with others enjoying these benefits. The output of the charity is thus non-exclusive and non-rival in consumption.[8]

In the field experiment, a donor decides how much to contribute to foreign aid. The projects financed by the two charities aim at supporting long-run sustainable development. Thus, there is a delay between the contribution to the charity (the cost) and the realization of the public good (the benefit).

In addition to the benefit the donor receives from the realization of the public good, there is a second benefit from contributing to the charity, which is the warm-glow the donor may derive from giving. The warm-glow will be experienced at the time of committing to giving. This idea was first mentioned by Andreoni and Payne (2003) who write that "a commitment to a charity may yield a warm-glow to the givers before they actually mail the check. Hence, the benefits can flow before the costs are paid". In the experiment, we can expect the warm-glow to be realized at the time of commitment which is (1) at the time of payment in the GMN treatment and (2) before the time of payment in the GMT treatment.

Thus, we have two benefits from giving; the realization of a public good and the warm-glow from giving. In the GMN treatment, the delayed realization from the public good may cause donors to procrastinate and/or give less than the optimal amount. In the GMT treatment, the cost is delayed to help time-inconsistent donors overcome procrastination. Furthermore, the warm-glow now occurs before

[7]See Hochman and Rodgers (1969) and Kolm (1969) for the first papers that argue that charitable giving, motivated by altruism, creates a public good out of giving.

[8]For a more thorough discussion on this topic, see, e.g., Andreoni (2004) or Vesterlund (2006).

the payment. These two effects reinforce each other to increase donations in the GMT treatment as compared to the GMN treatment.

This section first presents donors' intertemporal preferences, and then turns to their instantaneous preferences. Finally, we combine the two models and compare the two cases tested in the field experiment. What is the optimal contribution when individuals are asked to "give more now" and when they are asked to "give more tomorrow"?

3.1 Intertemporal preferences

Assume that there are n individuals in the economy. Let u_{it} be a person i's *instantaneous utility* in period t. A person in period t cares about her present utility, but also about her future instantaneous utilities. Let $U_i^t(u_{it}, u_{it+1}, ..., u_{iT})$ represent person i's *intertemporal preferences* from the perspective of period t, where U_i^t is continuous and increasing in all components. The standard model in economics is exponential discounting. For all $t, U_i^t(u_{it}, u_{it+1}, ..., u_{iT}) \equiv \Sigma_{\tau=t}^{T} \delta^\tau u_{i\tau}$,where $\delta \in (0,1]$ is a "discount factor".

Exponential discount functions capture that individuals are impatient, but assume that they are time consistent, i.e. a person's relative preferences for well-being at an earlier date over a later date are the same notwithstanding when she is asked. But intertemporal preferences might not be time consistent. Instead, people tend to exhibit a special type of time-inconsistent preferences that are called *quasi-hyperbolic* or *present-biased* (Laibson, 1997; O'Donoghue and Rabin, 1999). When considering trade-offs between two future moments, such preferences give a stronger relative weight to the earlier moment as it gets closer. Quasi-hyperbolic preferences can be represented by: for all t,

$$U_i^t(u_{it}, u_{it+1}, ..., u_{iT}) \equiv u_{it} + \beta \Sigma_{\tau=1}^{T-t} \delta^\tau u_{i,t+\tau} \tag{1}$$

where $0 < \beta, \delta \leq 1$. In this model, δ represents long-run, time-consistent discounting while β represents a "bias for the present". If $\beta = 1$, then preferences become exponential, while $\beta < 1$ implies present-bias preferences.

3.2 Charitable behavior

The model employs Andreoni's (1989, 1990) assumption of warm-glow giving to characterize charitable behavior. In this model, individuals do not only care about the overall provision of a public good, but also about the act of giving. This is thus a model of impure altruism from which the cases of pure altruism and pure warm-glow giving can be derived as special cases.[9]

Assume that each individual i in period t consumes a composite private good x_{it} and a public good G. Let an individual's contribution to the public good in period t be g_{it} and define $G_t = \sum_{i=1}^{n} g_{it}$. The feature that the individual does not only care about the provision of the public good, but also about the warm-glow g_{it} from her own donation is captured by directly adding an individual's donation in the utility function: $u_{it} = u_{it}(x_{it}, G_t, g_{it})$. For simplicity, it is standard in the literature to assume that there is a simple linear technology that implies a one-to-one transformation from private good to public good (Andreoni 2004). Furthermore, each individual is endowed with money income, m_{it}. The donor's budget constraint is $x_{it} + g_{it} = m_{it}$. The donor then faces the following optimization problem:

$$\max_{x,g} u_{it} = u_{it}(x_{it}, G_t, g_{it}) \tag{2}$$

$$s.t. \;\; x_{it} + g_{it} = m_{it}$$

$$G_t = \sum_{i=1}^{n} g_{it}$$

$$g_{it} \geq 0$$

The model is solved by assuming a Nash equilibrium, i.e., it is assumed that each person i solves the maximization problem taking the contributions of the others as

[9] A donor is said to be *purely altruistic* if she only cares about the public good while *pure warm-glow giving* implies that the donor is only motivated by warm-glow and does not care about the overall level of the public good.

given. Let $G_{-i} = \sum_{i \neq j} g_i = G - g_i$ equal the total contributions of all individuals except person i. Then, under the Nash assumption, each person i treats G_{-i} as independent of g_i. Add G_{-i} to both sides of the budget constraint and to the fourth constraint. The optimization problem can be written with each individual choosing G_t rather than g_{it}:

$$\max_{x,G} u_{it} = u_{it}(x_{it}, G_t, G_t - G_{-it}) \tag{3}$$

$$s.t.\ x_{it} + G_t = m_{it} + G_{-it}$$
$$G_t = \sum_{i=1}^{n} g_{it}$$
$$G_t \geq G_{-it}$$

To illustrate how warm-glow can affect the level of charitable contributions, assume that the n individuals have identical Cobb-Douglas preferences and identical incomes $m_{it} = m$ that do not change over time. The instantaneous utility function for person i in each period t is then

$$u_{it} = \ln x_{it} + \alpha_1 \ln G_t + \alpha_2 \ln g_{it} \tag{4}$$

where α_1 is the pure altruism weight, i.e. how much the donor cares about the overall level of the public good, and α_2 is the weight the individual assigns to warm-glow.

We analyze the case with three time periods. In each period, the donor has exogenous income m. In the first period, the donor must commit to how much to contribute to the public good. The warm-glow from giving is received at the time of commitment. The actual payment will be made in either the first or the second period, while the public good is realized in the third and final period. It is assumed that the donor can make a credible commitment to giving. This is a strong, but realistic assumption in this setting. The advantage of using existing monthly donors is that the information on their bank accounts is already available to the charity. If the donor agrees to increase his monthly contribution, the charity implements the change in its computer system, and the donor is sent a letter confirming this change. If the donor wants to deviate from his commitment, he has to call the charity (or alternatively the bank) to stop the change from occurring. Thus, there is a cost of deviating, but no cost associated with complying with the commitment.

3.2.1 Behavior with Immediate Payment

This section analyzes the case where donors are asked to increase their payments immediately. In the first period, the donor decides on how much to give, makes the payment and receives the warm-glow from giving. The public good is realized in the third period. Substituting the instantaneous utility into the intertemporal utility function, we get:

$$\max_{x,G} U^t(u_{i1}, u_{i2}, u_{i3}) \equiv \ln x_{i1} + \alpha_2 \ln g_{i1} + \beta\delta[\ln x_{i2}] + \beta\delta^2[\ln x_{i3} + \alpha_1 \ln G] \tag{5}$$

$$s.t.\ x_{it} + G - G_{-i} = m \qquad t = 1$$
$$x_{it} = m \qquad t = 2, 3$$

Inserting the BC into the utility function and solving for the first-order condition give:

$$-\frac{1}{m - G + G_{-i}} + \alpha_2 \frac{1}{G - G_{-i}} + \alpha_1 \frac{\beta\delta^2}{G} = 0 \tag{6}$$

Since individuals are identical, the Nash equilibrium gift will be the same for all i, thus $G = ng^*$. The optimal contribution will then be:

$$g^*_{GMN} = \frac{\alpha_1\beta\delta^2 m/n + \alpha_2 m}{1 + \alpha_1\beta\delta^2/n + \alpha_2} \tag{7}$$

We see that g^*_{GMN} is increasing in $\boldsymbol{\beta}$ indicating that the more patient is the donor in the short run, the more she gives. Equally, it is increasing in δ indicating that the more patient is the donor in the long run, the more she gives.[10]

3.2.2 Behavior with delayed payment

This section analyzes what happens if the charity adopts a Give More Tomorrow Strategy (GMT). In the first period, the donor makes a commitment on how much to give, and receives the warm-glow for giving. In the second period, the donor makes the payment and the public good is realized in the third period. The donor now faces the following optimization problem:

$$\max_{x,G} U^t(u_{i1}, u_{i2}, u_{i3}) \equiv \ln x_{i1} + \alpha_2 \ln g_{i1} + \beta\delta[\ln x_{i2}] + \beta\delta^2[\ln x_{i3} + \alpha_1 \ln G] \tag{8}$$

$$s.t. \quad x_{it} + G - G_{-i} = m \qquad t = 2$$
$$x_{it} = m \qquad t = 1, 3$$

Once more inserting the BC into the utility function and solving for the first-order condition give:

$$\alpha_2 \frac{1}{G - G_{-i}} - \frac{\beta\delta}{m - G + G_{-i}} + \alpha_1 \frac{\beta\delta^2}{G} = 0 \tag{9}$$

The Nash equilibrium contribution is:

$$g^*_{GMT} = \frac{\alpha_1\beta\delta^2 m/n + \alpha_2 m}{\beta\delta + \alpha_1\beta\delta^2/n + \alpha_2} \tag{10}$$

[10] Taking first derivatives, we see that g^*_{GMN} is increasing in m, increasing in α_1 (the parameter of pure altruism), increasing in α_2 (the parameter indicating warm-glow), and decreasing in n (the number of donors).

We see that g^*_{GMT} is now decreasing in $\boldsymbol{\beta}$, indicating that the less patient the donor is in the short run, the more she gives. The effect of δ, the long-run discounting, is ambiguous and depends on the relative strength of the warm-glow parameter α_2 as compared to the pure altruism parameter α_1[11].[12]

Furthermore, the only difference between the optimal contributions in the GMN and GMT treatments is the term $\beta\delta$ in the denominator in (2.10). Thus, we have that $g^*_{GMT} > g^*_{GMN}$. The difference between the GMT and the GMN treatments will be greater if donors have present-biased preferences ($0 < \beta < 1$, and $\beta < \delta$) as compared to the case with time-consistent preferences ($\beta = 1$).[13]

The model thus predicts that there will be a difference between the GMT and the GMN treatments notwithstanding whether donors have time-consistent or preferences or not. But, the difference will be larger for donors with present-biased preferences as compared to time-consistent donors. How large this difference is will depend on the degree of present-bias among donors, i.e. the size of β. The smaller the β, the higher is the difference between the two treatment groups. [14]

The above analysis assumes that individuals are impure altruists motivated by the realization of the public good *and* the warm-glow from giving. However, individuals might be pure altruists only motivated by the public good, or they might be solely motivated by the warm-glow from giving. [15] It is straightforward to show that the prediction of behavior in the experiment holds independent on whether

[11] $\frac{\delta g_{GMT}}{\delta\delta} = \frac{\beta mn(\alpha_1\beta\delta^2 - \alpha_2 n)}{(\alpha_2 n + \beta\delta n + \beta\delta\alpha_1)^2}$.

[12] Once more, taking first derivatives, we see that g^*_{GMT} is increasing in m, increasing in α_1 (the parameter of pure altruism), increasing in α_2 (the parameter indicating warm-glow), and decreasing in n (the number of donors).

[13] $g^*_{GMT} - g^*_{GMN} = \frac{(1-\beta\delta)[\alpha_2 mn^2 + \alpha_1\beta\delta^2 mn]}{(\beta\delta n + \alpha_2 n + \alpha_1\beta\delta^2)(n + \alpha_2 n + \alpha_1\beta\delta^2)}$

[14] A special case, which nicely shows the intuition behind the experiment is when $\delta = 1$, i.e. when we can assume there to be no long-term discounting (cf. Akerlof, 1991; O'Donoghue and Rabin, 1999). In the field experiment, the delay between the commitment and the payment is a matter of months and a reasonable approximation is then that $\delta = 1$. In this case, for individuals with quasi-hyperbolic preferences $0 < \beta < 1$, it follows that $g^*_{GMT} - g^*_{GMN} > 0$. If individuals are time consistent ($\beta = 1$), then $g^*_{GMT} = g^*_{GMN}$.

[15] Note that, in the case of impure altruism, the impact of pure altruism will become small as the number of donors grows large. As $n \to \infty$, donors will only be motivated by warm-glow. This is consistent with the model in Ribar and Wilhelm (2002).

donors are motivated by pure altruism, impure altruism or warm-glow giving does not affect the (see Appendix).

4 Experimental Design

The field experiment was carried out in collaboration with two large charities.[16] This section first describes the overall experimental design common to both field experiments. Then, the two charities and the implementation of the field experiments are presented separately.

4.1 Key design features

There are five key features of the experimental design highlighted in this section; (i) the monthly contribution schemes, (ii) the telemarketing campaign, (iii) the randomization, (iv) the structure of the manuscripts, and (v) the timing of the increase in the donation.

(i) First, both field experiments took place within regular fundraising campaigns aimed at increasing the existing donors' monthly donations. Monthly contributions schemes are common in Sweden, a country where charitable donations are *not* tax deductible. The fiscal year will not influence the timing of donations, and monthly contributions schemes have therefore proven a highly successful fundraising strategy. Monthly donors give a fixed amount, which is automatically withdrawn from the donor's checking account at the end of every month. In this study, the average monthly contributions were SEK 141 and SEK 152 per month, which translates into USD 282 and USD 304 per year, respectively (USD 1$\simeq$ SEK 6).

Using existing donors has the benefit of providing us with information on donor characteristics, such as previous donor behavior, age and gender. This information can be used to test for heterogeneous treatment effects. In addition, it allows us

[16] More detailed information on the two charities is available on www.diakonia.se, and www.rb.se.

to follow donor behavior after the experiment to investigate the long-run impact of the treatments. A third benefit is related to the implementation of the increase in donations. The donors have already signed the consent form, allowing the charity to withdraw the donations from the checking account. Therefore, increases in donation do not require a new consent form and the charity can implement any change in their database and a confirmation letter is sent to the donor. Hence, there is no cost associated with keeping your commitment to increase your contribution.

(ii) Both charities contracted telemarketing companies, specializing in helping charitable organizations, to call the donors and ask them to increase their donations. There are several advantages of employing a telemarketing campaign in this setting. First, the response rate is considerably higher for telemarketing campaigns as compared to mail solicitations. In both field experiments, the response rate was more than 30 percent[17]. In addition, we know the identity of the decision maker. At the beginning of each call, the callers make sure that the person making the decision is the person whose name is on the bank account. As the decisions to increase donations were made over the phone by the person stated on the bank account, it could not be a collective household decision and we get valuable information on donor characteristics.

(iii) The donors were randomly divided into control and treatment groups. In collaboration with the charities, a manuscript for each treatment group was produced and the manuscripts were identical in all respects but the timing of the increase in the donation. Each treatment group had a code in the telemarketing firms' computer system, matching the donor with the correct manuscript.

The telemarketing firm uses a automatic caller system. This implies that the caller press a button on the computer screen and the computer randomly selects the next donor and dials the number. This has two benefits; the donors were called in a random order, and at each point in time the caller is randomly matched with a donor. As a consequence, all callers called on all treatment groups[18]. In additions, this implementation guarantees that there is no experimenter effect due to different

[17] Campaigns using mail solicitations typically yield a response rate of 0.5-5 percent.

[18] This ensures that no caller is matched with high/low quality donors.

abilities among callers.

(iv) The structure of the each phone call was the following; the callers first thanked the donors for contributing to the Charity and then provided examples of projects financed by the donors' contributions.[19] The next step was to ask the donor if they would consider increasing their monthly donation. There callers were instructed to ask for the double amount of the current donation. In the Give More Now treatment, the caller was asked;

"Can you consider increasing your monthly contribution with X kronor?"[20]. In the GMO and GMT treatment groups, the following language was used:

"Can you consider increasing your contribution with X kronor starting in month Y, which means that the first increase will be on the 28th of Month Y?" where Month Y was the month following one or two month ahead in time[21].

If the donor said no, the caller thanked him/her for the current support. If the donor was hesitant, the caller emphasized that any amount, no matter how small, would be valuable and appreciated. If the donor agreed to increase the donation, the caller informed him/her that a letter confirming the change would be sent to the donor, repeating the agreed upon increase in the donation and the date when the first increase would occur. The caller then thanked the donor for her support and wished the donor a pleasant evening/day. Note that the letter was sent only to inform the donor of the change. The donor did not have to send any information back to the charity. Since the donor had already given the charity his/her bank account number, the charity could directly implement the agreed upon change in

[19]For exampl,e with Diakonia, two projects presented to the monthly donors as examples of the activities they are financing are (1) Working for debt relief for poor countries, and (2) Farming education for poor individuals in Cambodia so as to make them self-reliant. Save the Children focused on education for children in poor countries. The full manuscripts are proprietary information.

[20]The amount X was the same in all calls. In the first field experiment, all donors were asked to increase their donations with 100-200 kronor. In the second filed experiment, the donors were asked to give 100 kronor more than their current donation. (USD 1 = SEK 6).

[21]The monthly contribution is always taken on the 28th of every month. If the donor was called on March 7th or March 15, the GMN ask would be March 28th, the GMO ask April 28th and the GMT ask May 28th.

the monthly contribution.

(v) The field experiments vary the time between commitment and payment. In a control group the donors were asked to increase donations immediately, while the treatment groups ask donors to increase donations in (1) One Month (GMO), (2) Two Months (GMT) and (3) Free number of months (GMF). The precommitment period was thus exogenously imposed in all treatments except from the third treatment where donors could choose the date of the increase in donations. Theory predicts that donors with present-biased preferences should increase donations more when asked to precommit to future donations as the cost of giving will be discounted. If donors have present-biased preferences, the existence of a lag, and not the length of the lag should matter. We should therefore see the same quantitative effect of the one month and the two month precommitment period. Time-consistent donors with a constant discount rate, on the other hand, should respond more to a time lag of two months as compared to one month. We added a third treatment group where the donor could choose the time between commitment and payment. This treatment require donors to both choose whether to increase donations and when. The theoretical predictions are less clear. On the one hand, a present-biased donor should want to postpone donation. On the other hand, donors are asked to make two decisions; whether to increase donation *and* when to increase donations. Having to make more several decisions might affect the response rate and/or the level of contributions negatively. Due to the uncertain outcome of the third treatment, we assigned a small sample to the GMF treatment. The paper therefore focuses on the results from the treatments with exogenously imposed time lags[22].

[22] We assigned 389 donors to the GMF treatment group of which 314 were reached. The results from the GMF treatment are presented in the appendix. The results are quite intriguing, but due to the small sample size, should be interpreted with caution.

4.2 Implementation Field Experiment 1

The first field experiment was carried out in collaboration with Diakonia in late October and early November 2005, and followed up in October 2006. Diakonia focuses on international aid. According to its policy document, "Diakonia is a Christian development organization working together with local partners for a sustainable change for the most exposed people of the world" (Diakonia, 2006). The monthly donors are called "Sponsors for Change" to emphasize the charity's goal to influence long-term sustainable development.

Diakonia introduced a monthly contribution scheme ten years ago and at the time of the experiment, the number of monthly donors had reached about 2,000. After excluding the oldest donors (>80 years old) and those who have increased their contributions in the past year, we were left with 1,200 donors. Compared to previous field experiment (see, for example, List and Lucking-Reily 2002, Karlan and List 2007, Falk 2007) this is a small sample size and we therefore decided to use one control (Give More Now) and one treatment group (Give More in Two Months) to strengthen the statistical power of the test. A total of 1134 donors were reached, of which 553 in the GMN treatment and 581 in the GMT treatment.

Furthermore, we gathered data on donor characteristics. The available data is (1) *age*, (2) *gender*, (3) *current monthly contribution,* and (4) *nix*[23]. *Nix* is a binary variable equal to one if the donor is listed in a database restricting the use of telemarketing[24]. A company or a charity should not approach the individuals in the database unless the person is a costumer or a recurrent donor. Hence, the charity is allowed to call "nixed" donors, but we can expect nixed donors to be more negative to telemarketing as compared to non-nixed donors.

[23]Each citizen and permanent resident is assigned a 10 digit unique *person-number*, starting with year/month/day of birth and has four control numbers at the end. The ninth number is even for women and odd for men. The charity can thus derive exact age and gender from the *person-numbers.*

[24]The regulation of the nix-list is such that companies are not allowed to call them if they are not existing costumers. The charities are free to call existing monthly donors, but we can expect these donors to give less than those who are not on the list. If a monthly donor asked to to be contacted by telephone, the charity will not contact them.

Data on donor characteristics is presented in table 1. The average age of the donor participating is 55 years in the GMN treatment and 59 in the GMT treatment. The average (median) contribution before the fund-raising campaign took place was SEK 148 (100) and SEK 133 (100) in the GMN and GMT groups, respectively[25]. The *median* donor contributes SEK 1,200 on a yearly basis, which is approximately USD 200. Women are somewhat overrepresented in the GMT group at 60 percent compared to 52 percent in the GMN treatment, while the share of nixed donors are 27 and 28 percent in the control and treatment group respectively. Despite the randomization, there are some differences in donor characteristics.[26] This could cause the results to be biased if women and men behave differently or if age is of importance for charitable behavior. To test whether this is the case, section 5 presents the results from regressing the increase in donations on a treatment dummy, controlling for donor characteristics.

4.3 Implementation Field Experiment 2

The second field experiment was carried out in March 2007 in collaboration with Save the Children. Save the Children is an international organization founded in the U.K. and Sweden simultaneously in 1919. The goal is to "influence public opinion and support children at risk - in Sweden and the world"[27]. The main focus is to help children in poor countries, but a smaller fraction of contributions is used to strengthen children's' rights domestically.

Save the Children introducing a monthly contribution scheme in the early 1970's. The total number of monthly donors is close to 70,000. Again, we excluded donors over the age of 80 and those donors who increased their donations in the previous

[25] SEK 100 $\simeq$ USD 16.7.

[26] We test whether there are any significant differences in donor characteristics between the two treatment groups. Using t-tests, we cannot reject that the mean donation before the experiment is the same in the two treatment groups (p=.20), but we can reject that the average age (p=.00) and the frequency of women (p=.01) are the same in the two treatment groups.

[27] See *www.rb.se* for a presentation of the Swedish branch of Save the Children. Information is available in English.

year. From the remaining donors, we draw a random sample of 10 000. These donors were randomly assigned into one control group and two treatment groups of equal size: (1) Give More Now (GMN), (2) Give More in One Month (GMO), Give More in Two Months (GMT). In addition, donors were randomly assigned into a smaller treatment group (GMF) where they were asked to choose freely when to increase their donations.

As in the first field experiment, data is available on donor characteristics; including (1) *age*, (2) *gender*, (3) *current monthly donation*. In addition, we have and a range of variables describing previous donor behavior; *intro*, a continuous variable measuring the length of monthly donations in number of months, *spontaneous,* a binary variable equal to one if the donor, in addition to monthly donation, also gives spontaneous donations, *member* which is a binary variable equal to one if the donor is also a paying member of the organization, *spontaneous and member* which is a binary variable equal to one if the donor, in addition to monthly donation, is also both a spontaneous donor and a member. *Rec_ channel* is a binary variable equal to one if the donor was recruited through a face-to-face campaign[28] and zero otherwise. Finally, *cell* is a binary variable equal to one if the equal to one if the donor was reached on a cell phone and zero otherwise.

Donor characteristics are presented in table 2. The average age is 57 years across treatments, the average contribution is SEK 155, 153 and 150 respectively. The share of women is 71% in all treatment groups. The average duration of donations is 167 months (13 years and 9 months) while 25 percent have been monthly donors for less than 4 years, and 25 percent for *more* than 20 years[29]. Slightly more than 50 percent of donors are regular donors, who only contribute on a monthly basis, while the reminder are also members and/or give spontaneous additional donations.

[28]Face-to-face campaigns recruit donors by approaching them in person. The other donors were recruited by mail solicitations or telemarketing.

[29]The most loyal donor has contributed every month for more than 35 years.

Although we do not have the equivalent data for field experiment 1, Diakonia has had monthly donors since 10 years, which put an upper bound of the number of months that a person can have contributed. The charity believes the average time to be about seven years.

A smaller share of donors (11 percent) was recruited face-to-face. Finally, the vast majority (95 percent) were contacted on a fixed land line.[30]

The two experiments differ in the amount of information available about the donors and in cohort distributions. The donors are similar in age distribution and average monthly contributions. The differences are in gender, where the female share is considerably higher with Save the Children than with Diakonia. As Save the Children introduced monthly contributions considerably earlier than Diakonia, the average donor with Save the Children have been giving longer (13 years) than the Diakonia monthly contribution scheme have existed (10 years).

5 Results

This section presents the results from the two field experiments; summary statistics, statistical analysis of the data and heterogeneous treatment effects. Finally, to investigate the long-term effects of the field experiments, I follow up the original studies with data on drop-out rates and contributions 12 and 6 months later for Diakonia and Save the Children, respectively[31].

5.1 Summary statistics

The response rate exceeded 30 percent in both fund-raising campaigns. The median increase in donations was SEK 50 (USD 1 $\simeq$ SEK 6) in both campaigns. The distribution in increases in donations are relatively similar across treatment groups, except from one aspect; Large increases in donations (SEK $\geq$100) were more common in group GMT relative to the control group in both field experiments. The frequency of large donations is 80 percent higher in the GMT treatment as compared to the control treatment in the first experiment, and the equivalent numbers for the second experiment is 30 percent.

[30] I test whether there are any significant differences in donor characteristics between the three groups. Using t-tests, I cannot reject the null hypothesis of equal means for any of the variables.

[31] I asked for the data from Save the Children after 6 months since I wanted to finalize the paper.

Tables 3 and 4 give the summary statistics for the two experiments, focusing on three measures: (i) a continuous variable for the amount given unconditional on upgrading, and (ii) a continuous variable for the amount given conditional on upgrading, and (iii) a binary variable equal to one if the donor agrees to increase the monthly contribution.

In Field Experiment 1, mean increase in donations were 32 percent higher in the GMT group relative to the GMN group. This result is driven by the fact that both average increase in donations and the share of donors upgrading were higher in the GMT treatment. Mean increase in donations conditional on upgrading were 19 percent higher, while the frequency of upgrades was 11 percent higher. The Give More Tomorrow treatment raised SEK 24.6 per solicitation as compared to SEK 18.6 in the Precommitment Treatment.

In Field Experiment 2, the campaign raised SEK 15.03 per solicitation per month in the control group and SEK 15.07 in treatment GMO and SEK 16.61 in GMT respectively. Hence, the aggregated treatment effect is only present for two month and the effect is 11 percent. Again, both mean contributions conditional on giving and the response rate is higher in the GMT treatment as compared to the control treatment. Furthermore, the data from Save the Children allows for an analysis of heterogeneous treatment effects. As we will see later, the aggregated data masks important differences in treatment effects between different cohorts of donors.

Since most donors did not increase their donations, the distribution of increases in donations is skewed towards zero. To test equality of means, double-sided t-tests and the non-parametric bootstrap method are used. Considering the large sample sizes in both field experiments, t-tests should provide unbiased estimates. The bootstrap method is used as a robustness test. Unlike t-tests, bootstrapping does not require that the underlying population mean is normally distributed, only that the observed distribution of the sample is a good estimate of the underlying population distribution (Efron and Tibshirani, 1993). The bootstrapping method consists of drawing with replacement N independent bootstrap samples from the observed sample. Each new sample is of the same size as the observed sample. For each bootstrap replication, a t-test is calculated. The p-value is based on the number of times the bootstrapped t-test is greater or equal to the original t-test calculated from the observed sample.

I test the hypothesis that the average increase in donations μ is higher when donors are allowed to postpone the first payment as compared to the control group. In other words, the average increase should be higher in treatments (GMO and GMT) than in the control group. Hence, we test the following null hypothesis $H_1 : \mu_C = \mu_T$ on the unrestricted sample and the restricted sample (conditional on upgrading). The two hypotheses are tested against the alternative that the mean increase in donation is not equal.

In the first field experiment, the null hypothesis that says that increases in mean donations are equal in the two treatment groups for (1) the unrestricted sample and (2) the sample conditional on upgrading can be rejected. The t-tests reject the null hypothesis of equal means in groups GMN and GMT for the full sample *(p=0.013)* as well as conditional on upgrading *($p = 0.015$).* Bootstrapping confirms this result. Table 3 shows that we can reject the hypothesis of equal means, both for the full sample *($p < .01$)* and for the reduced sample conditional on upgrading *($p = .014$).* Hence, the effect on mean donations of allowing donors to "Give More Tomorrow" is both statistically significant and economically large.

In the second Field Experiment, the two-sided t-tests reject the null hypothesis of equal means in groups GMN and GMT for the full sample *(p=0.061)* as well as conditional on upgrading *($p = 0.072$).* Bootstrapping shows similar results for the full sample *($p = 0.059$)* but somewhat weaker for the restricted sample *($p = 0.20$).* The average increase in donations in the GMO treatment (one month delay), however, is not significantly different from the average increase in donations in the control group.

5.2 Statistical analysis

This section presents the results from the statistical analysis of the experimental results. First, I estimate the specification on the full sample as well as the restricted sample conditional on upgrading. The treatment may alter the type who responds, and can also affect the amount given conditional on upgrading. The unrestricted sample provides an estimate of the aggregate effect of the treatment on charitable giving, combining the effect of the response rate and the increase in the amount given. The restricted sample removes the average effect of the response rate from the estimate, but it cannot longer be taken to be representative of the experimental design; the treatment may attract donors with higher or lower typical giving amounts, at the same time as it might change the size of the increase in donations. In the conditional sample, we therefore risk confounding the treatment effect on the increase in donation with a type of selection effect[32]. The unconditional sample is therefore emphasized for drawing statistical inference.

The following specifications are estimated in the full sample as well as the restricted sample:

1. $I_i = \alpha_0 + \alpha_1 T_i + u_i$

2. $I_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + u_i$

3. $I_i = \gamma_0 + \gamma_1 T_i + \gamma_2 X_i + \gamma_3 T_i X_i + u_i$

where I_i is a continuous variable equal to the increase in monthly donation. T_i equal to one if the donor received the treatment and zero. X_i is a vector of control variables, such as age, gender, previous sum donated, etc.

Next, I estimate the effect of the precommitment treatments on the likelihood of giving. Using probit models, the dependent variable in the first two specifications is a binary variable indicating one if the donor agreed to increase the monthly donation and zero otherwise. The fourth specification is a multinomial probit, testing the probability of receiving a zero, small (SEK 1-49), medium (SEK 50-99) or large (SEK $\geq$ 100) increase in donation. The following four specifications are estimated:

[32] The term selection effect in randomized controlled experiments is somewhat misleading. There is no selection in the traditional meaning as all choices are observed; donors either increase donations or leave them at their previous level. Some conference participants have suggested using a Heckman selection model, but there is no latent, unobserved outcome and no justification for using a selection model here. Instead, as the data is censored at zero, I also run Tobit regressions on the full sample. The results are similar to the OLS results. The regressions are available in the appendix.

1. $Y_i = \alpha_0 + \alpha_1 T_i + u_i$

2. $Y_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + u_i$

3. $Y_i = \gamma_0 + \gamma_1 T_i + \gamma_2 X_i + \gamma_3 T_i X_i + u_i$

4. $Z_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + u_i$

where Y_i is a binary variable equal to one if individual i upgraded his/her donation and zero otherwise. Z_i is the dependent variable in a multinomial probit model and take on the value one if the upgrade is zero, two if the upgrade is positive but smaller than SEK 50, three if the upgrade is SEK 50-99, and four if the upgrade is SEK 100 or more (the omitted baseline is zero).

Table 7 report the results from the first field experiment. The first equation regresses the increase in donations on a treatment dummy (OLS1) and then adds observed donor characteristics (OLS2). A few results are noteworthy. First, the treatment dummy is significant in all specifications. The coefficient on the treatment dummy in OLS2 ($p<0.01$) implies that the mean increase in donation is SEK 7.21 higher on average in the GMT treatment relative to the GMN treatment. The treatment effect is somewhat higher than in the experiment, where the difference is SEK 6.03.

Second, the *female* dummy (which is equal to one for women and zero for men) is negatively correlated with an increase in donations. The effect is large in all specifications, but insignificant. Contrary to previous laboratory experiments, women tend to increase their donations less generously than men. *Age* is negatively correlated with the increase in the sum donated in OLS1 and Tobit, indicating that the older the donor, the lower the increases in donations. The effect is significant, but small.[33] Moreover, the increases in donations do not seem to be determined by the level of contribution before the experiment. The coefficient on the original sum donated is close to zero and insignificant in OLS1 and OLS2. In OLS3 and OLS4, using the restricted sample conditional on upgrading, the coefficient is highly

[33] There is some evidence on younger children, but evidence on other age groups is rare. See Camerer (2003) for an overview of existing literature.

significant (p<0.01) and positive. Finally, the variable "*nix*", indicating reluctance against telephone campaigns is as expected negatively and significantly correlated with the increase of the sum donated.

Table 8 shows the results from the second field experiment. The GMT treatment dummy is statistically significant in all specifications, while the dummy on the GMO treatment remains insignificant. As in the first field experiment, the treatment dummy on female is negative, and with the larger sample size, it is now statistically significant in all specifications. Furthermore, the detailed data on previous donor behavior is shown to be highly associated with increases in donations. The coefficient on *intro* is statistically significant and negative, indicating that long-term donors upgrade their contributions less than newer donors. The various measures on donor activity are all positive and statistically significant, as well as the previous sum donated.

Tables 9 and 10 present the results from the probit regressions. The coefficients on the treatment dummies are positive, but not statistically significant. However, there are differences across the distribution of the treatment effect depend on the size of the increase where large donations (SEK $\geq$100) is more common the precommitment treatments. The multinomial probit regressions confirm this finding. In both field experiment the treatment dummy is highly statistically significant for large increases in donations, but does not affect the likelihood of receiving no increase in donation, a small donation or a medium level increase in donation. Hence, the overall treatment effect seems to be driven by a higher probability of receiving a large increase in monthly contribution.

5.3 Heterogeneous treatment effects

Table 11 and 12 include heterogeneous treatment effects for the first and second field experiments, respectively. Spatial heterogeneity is estimated for gender in both field experiments, and for the duration of donations in the second field experiment.[34]

[34] Interactions with other donor characteristics did not yield any significant results. Regressions are available from the author upon request.

The results stand out. First, in both field experiments, the treatment dummies are all statistically significant. Most importantly, in the second field experiment *both* the GMO and the GMT treatment dummies are now statistically significant. In addition, the GMO and GMT treatment effects are of the same magnitude, indicating the presence of present-biased preferences among donors.

A gender effect explains the significance of the Give More in One Month treatment dummy. The interaction between the GMO treatment and female is negative and statistically significant in the second field experiment, indicating that men, but not women respond to the one month delay in payment. This suggest a strong gender difference in response to the precommitment treatments; men respond both to a one and a two month lag in consistency with hyperbolic preferences, while women do not. Previous literature suggests that there might be a gender difference in relation to time-consistency and discounting (see Ashraf et al., 2004). For several reasons, further research is needed to fully understand this effect. Gender may be correlated with unobserved variables that may also effect donations, such as income and education[35].

In addition, the interaction between duration of donations and the treatment is negative and statistically significant. The fewer number of months a donor has given, the stronger is the treatment effect. The precommit treatment significantly increases the likelihood of receiving a large increase in donation. The longer a donor has contributed, the more times he has been asked to upgrade and the closer to an upper bound on donations he/she will be. Long-term donors do upgrade their monthly contributions, but with smaller sums, making the precommitment mechanism less effective.

Importantly, heterogeneity causes the quantitative differences between the two field experiments. The difference in the composition of donors between the two charities explains the economically larger treatment effect in the first field experiment. Save the Children have a higher representation of women and long-term donors,

[35] Omitted variables will not bias the overall treatment effects as the treatment is exogenous and therefore uncorrelated with any omitted variables.

who respond less to the precommitment treatment. Hence, the higher aggregated treatment effect with Diakonia as compared to Save the Children.

5.4 Follow-up results

Do donors deviate from the increases in contributions that they committed to in the experiment? Are there any differences in changes in donations, including cancellation rates, between the control and treatment groups? To answer these questions, data on monthly contributions were gathered 12 months after the implementation of the first field experiment and 6 months after the second field experiment[36]. This data is important for several reasons. First, the profitability of the GMT strategy hinges upon donors giving for a longer period of time, and that the cancellation rates are not different between the two treatment groups. Second, the GMT strategy was designed to help donors with hyperbolic preferences to overcome their bias for the present, and to induce them to give according to their long-run preferences. If there are more donors cancelling their monthly contributions in the GMT treatment as compared to the GMN treatment, this would imply that the GMT strategy induced donors to give more than what is sustainable in the long-run. On the other hand, the absence of a difference in changes in donations between the control and treatment groups would confirm that the precommitment mechanism is a sustainable strategy to increasing monthly contributions.

Tables 13 and 14 show the changes in monthly contributions divided into (i) increases in donations, (ii) decreases in donations (iii) cancellations, and (iv) the total long-run changes in donations combining the previous three categories[37]. The first noteworthy result from the follow-up data is the low number of cancellations. One year after the first field experiment was implemented, more than 96 percent of donors have chosen to remain as monthly contributors. In the second field experiment, we equally have more than 96 percent of donors remaining after 6 months.

[36] The author was impatient to analyze the results and finalize the paper and therefore asked for the follow-up data from Save the Children after 6 months.

[37] This reflects the difference between mean monthly contribution after the field experiment and the follow-up data. It includes all changes made in donations over the year.

Most importantly, in both experiments, the share of donors cancelling their monthly contributions is almost identical in the control and treatment groups; for example with Diakonia the cancellations rates are 3.6% in the Give More Now treatment, and 3.3% in the Give More in Two Months treatment.

Second, there are few donors lowering or increasing their monthly contributions; only 0.6 percent with Diakonia and 0.3 percent with Save the Children decrease their donations, while further upgrades is somewhat higher at 2.6 percent with Diakonia and 0.6 percent with Save the Children.

What is the total effect of the increases, decreases and cancellations? Tables 15 and 16 presents the results from regressing the total differences in donations on the treatment dummies and other donor characteristics. Differences in cancellation rates are analyzed using probit regressions where the dependent variable is a binary variable equal to one if the donor has cancelled the monthly contribution, and zero otherwise. The treatment dummies are far from significant in all regressions for both field experiments. This provides strong evidence that there are no long-run differences in changes in monthly donations or cancellation rates between control and treatment groups. Hence, the precommitment mechanism is not only effective in increasing donations in the short-run, but also in the long-run. For example, in the first field experiment, after 12 months, the yearly revenue increase was SEK 142,926 for Give More Tomorrow (based on 10 months), while the equivalent number for Give More Now was SEK 123,430 (based on 12 months).

6 Discussion and Conclusions

Can charities boost donations by allowing donors to precommit to future donations? Two large-scale randomized field experiments conducted with separate charities at different points tested the precommitment mechanism. Monthly donors were asked to increase their contributions (1) immediately, (2) in one month time, (2) in two months time, (4) in a free number of months. The results are consistent between the two field experiments; first, mean increases in donations are significantly higher when donors are asked to precommit to future donations. Second, there are differences in the response to treatment between donors cohorts. Newer donors and men increase their contributions significantly more in response to the precommitment treatments as compared to long-term donors and women. As the composition of donors differ between the two field experiments, these heterogeneous treatment effects explain the differences in aggregated treatment effect.

What is the effect of different time lags between commitment and payment? The two month time lag had the largest impact on the aggregated sample and is statistically significant in both studies. The one month time lag, on the other hand, is statistically significant after controlling for heterogeneous treatment effects. Men give significantly more than women in the one month time lag. For men there is no difference in increases in donations between the one and two month time lag, which is consistent with a model of present-biased preferences. Women, on the other hand, respond only to the two months time lag and in both experiment, the treatment effect is smaller than men. Further research is needed to understand whether these differences in intertemporal choices are related to gender or other unobserved factors, such as education or income.

What are the long-run effects on donor behavior? In both studies, the follow up data reveal that more than 96 percent of donors have chosen to stay in the monthly contribution schemes. There are no significant changes between control and treatment groups in cancellation rates or in changes in the level of contributions. Is the treatment effect sufficiently large to make this strategy profitable for the charity? Allowing donors to postpone the increase in donation for two months reduces the short-run revenue of the charity. The long-run outcome clearly demonstrates the effectiveness of the experiment. For example, in the first field experiment, it takes six months of the higher level of donations in group GMT to make up for the two-month delay in payment. After six months, and from then onwards, the GMT strategy will yield 32 percent higher increases in donations each month relative to the GMN group. As monthly contributions scheme are highly effective in retaining donors over many years, the precommitment strategy is highly profitable for the charity.

What do these results suggest for future research? This study focuses on foreign aid with long-term goals. Research on other types of charitable giving will shed further light on intertemporal choice in this setting. Would the results hold for within-country studies where donors could be motivated by private consumption and insurance motives? What happens if the donors are contributing to a cause with immediate rather than long-term effects? In addition, this study shows that individuals respond differently to the treatment. Future research can increase our understanding of heterogeneity in intertemporal preferences. Furthermore, the donors in this study are sophisticated in the sense that they have chosen a commitment device by signing up for monthly contributions. What is the effect of the precommitment strategy if we test a population of donors that have not already committed to giving? This could be done, for example, by testing the strategy in a campaign aiming at recruiting new donors.

Finally, what do our results suggest for policy? A revenue maximizing charity should combine monthly contribution schemes with fund-raising campaigns that implement the precommitment strategy. Monthly donors are highly profitable to a charity. However, simply asking donors to increase their contributions is not the best way to boost monthly donations. This study shows that mean increases in donations are significantly higher when donors are asked to precommit to future increases in donations as compared to when they are asked to increase donations immediately. The follow-up study shows that this result holds, not only in the short-run, but also in the long-run.

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8 Appendix

8.1 Pure Altruists versus Warm-glow Givers

The model presented in section 3 assumes that individuals are impure altruists motivated by the realization of the public good *and* the warm-glow from giving. However, individuals might be pure altruists only motivated by the public good, or they might be solely motivated by the warm-glow from giving. We will call this latter group "warm-glow givers".[38] Does this affect the predicted outcome in the experiment?

The optimal level of contribution if all givers are pure altruists ($\alpha_2 = 0$) is, in the GMN case, $g^*_{GMN} = \frac{\alpha_1\beta\delta^2 m/n}{1+\alpha_1\beta\delta^2/n}$, and in the GMT case, $g^*_{GMT} = \frac{\alpha_1\beta\delta^2 m/n}{\beta\delta+\alpha_1\beta\delta^2/n}$.

If, on the other hand, all givers are warm-glow givers ($\alpha_1 = 0$),the optimal giving is, in the GMN case, $g^*_{GMN} = \frac{\alpha_2 m}{1+\alpha_2}$, and in the GMT case, $g^*_{GMT} = \frac{\alpha_2 m}{\beta\delta+\alpha_2}$. Once more, for individuals with present-bias preferences $0 < \beta < 1$, it follows that $g^*_{GMT} - g^*_{GMN} > 0$, and for time-consistent individuals ($\beta = 1$), $g^*_{GMT} = g^*_{GMN}$.

Once more, the only difference between the optimal contributions in the GMN and GMT treatments, for pure altruists *and* for warm-glow givers, is the term $\beta\delta$ in the denominator in the latter expressions. Thus, we have that $g^*_{GMT} > g^*_{GMN}$ in both cases. The difference between the GMT and the GMN treatments will be greater if donors have present-biased preferences ($0 < \beta < 1$, and $\beta < \delta$) as compared to the case with time-consistent preferences ($\beta = 1$). [39]

Hence, whether donors are motivated by pure altruism, impure altruism or warm-glow giving does not affect the prediction of behavior in the experiment. Due to normal discounting, there will be a difference between the GMT and the GMN treatments notwithstanding whether donors have time-consistent or preferences or

[38]Note that, in the case of impure altriusm, the impact of pure altruism will become small as the number of donors grows large. As $n \to \infty$, donors will only be motivated by warm-glow. This is consistent with the model in Ribar and Wilhelm (2002).

[39]Making the same assumption as above that $\delta = 1$,. i.e. that the long-run discount factor can be approximated by 1, we see that, for individuals with present-bias preferences, $0 < \beta < 1$, it follows that $g^*_{GMT} - g^*_{GMN} > 0$. For time-consistent individuals ($\beta = 1$), $g^*_{GMT} = g^*_{GMN}$.

not. But, the difference will be larger for donors with present-biased preferences as compared to time-consistent donors. How large this difference is will depend on the degree of present-bias among donors, i.e. the size of β. The smaller the β, the higher is the difference between the two treatment groups.[40]

8.2 Give More in Free Number of Months

In the second field experiment, there were three treatment groups: Give More in One Month (GMO), Give More in Two Months (GMT), and Give More in Free Number of Months (GMF). The GMF treatment asked donors to increase their donations from a date of their choice[41]. Donors are asked to make two decisions; whether to increase donation *and* when to increase donations. There are no clear theoretical predictions for the third treatment group. We therefore assigned a smaller sample to this treatment and we should interpret the results with caution. Tables 17 present summary statistics for the control group and the three treatment groups[42], while table 18 present the primary regression results.

The results are quite intriguing. The GMF treatment did not have an impact on the overall increase in donation. The treatment dummy is not statistically significant in the unrestricted sample. However, it does impact the response rate and the increase in donations, condition on upgrading. The response rate is negatively

[40] Once more, if $\delta < 1$, the prediction will be that the difference between the GMT and the GMN treatment will be larger for donors with present-biased preferences compared to time-consistent donors. How large this difference is will depend on the degree of present-bias among donors, i.e. the size of β. The smaller the β, the larger is the difference between the two treatment groups.

[41] In the third treatment where donors were free to choose when to increase donations, the following language was used:

"Can you consider increasing your donations to 2X kronor? If you do, you can choose to increase your donation now or at a later date."

[42] The charity randomly assigned donors to seven groups: (1) GMN, (2) GMO, (3) GMT, (4) GMF, (5) GMN for older donors, (6) GMO for older donors, and (7) GMT for older donors. The last three groups are pooled with the first three groups in the main analysis, but cannot be used in the alanysis of the GMF treatment. (The older groups were designed to test daytime versus evening calls to older donors).

affected by the GMF treatment, while the increase in donation conditional on upgrading is positive. Both effects are statistically significant. This suggests that donors were less likely to increase their donations when allowed to choose the date of the increase. This could be driven by the fact that donors had to make two decisions in this treatment, which complicated the decision-making process. Among the donors that did upgrade their donation, the increase in donation was significantly larger than in the control group (and also larger than the other treatment groups). Again, the treatment effect on the restricted sample can be due to a different type of donor responding.

Finally, we control for heterogeneous treatment effects. The results are identical to previous results with women and newer donors respond less the the Give More Later treatments. In addition we see that women respond less to the GMF treatment as compared to men. The effect is particularly strong for the response rate and the interaction term between female and the GMF treatment dummy is highly significant. This furthers the impression the women respond less to time delays than men.

9 Figures and Tables

Table 1: Field Experiment 1. Donor characteristics

	Control	**Treatment Two months**	**Full sample**
Average age	55	59	57
	(17)	(15)	(16)
Average contribution (SEK)	148	133	141
	(249)	(129)	(197)
Share women	.52	.60	.56
	(.50)	(.49)	(.50)
Nix	.27	.28	.28
	(.45)	(.45)	(.45)
Observations	553	581	1134

Note: Standard deviations within parentheses. USD 1 $\simeq$ SEK 6

Table 2: Field Experiment 2. Donor characteristics

	Control	**Treatment One month**	**Treatment Two Months**	**Full sample**
Average age	57	57	58	57
	(23)	(35)	(36)	(32)
Average contribution (SEK)	155	153	150	152
	(91)	(83)	(82)	(86)
Share women	.71	.71	.71	.71
	(.45)	(.45)	(.45)	(.45)
Average duration in months	167	166	168	167
	(99)	(100)	(99)	(99)
Cell phone	.05	.05	.06	.05
	(.21)	(.21)	(.23)	(.22)
Regular donor	.53	.55	.52	.53
	(.50)	(.50)	(.50)	(.50)
Spontaneous donor	.12	.12	.13	.12
	(.33)	(.33)	(.33)	(.33)
Member	.19	.20	.20	.20
	(.39)	(.40)	(.40)	(.40)
Spontaneous and member	.16	.13	.15	.15
	(.37)	(.34)	(.35)	(.35)
Rec_channel	.10	.11	.11	.11
	(.31)	(.31)	(.31)	(.31)
Observations	2619	2578	2513	7710

Notes: Standard deviations within parantheses. USD 1 $\simeq$ SEK 6.

Table 3: Field Experiment 1. Summary Statistics

	Control	**Treatment Two Months**	**Full sample**
Increase in mean donation (SEK)	18.6	24.64	21.70
Standard Deviation	35.84	45.58	41.22
Number of observations	553	581	1134
Increase in mean donations,			
conditional on upgrading (SEK)	60.53	72.30	66.86
Standard deviation	40.54	51.52	47.08
Number of observations	170	198	368
Share of donors upgrading	30.7%	34.1%	32.5%

Table 4: Field Experiment 2. Summary Statistics

	Control	**Treatment One Month**	**Treatment Two Months**	**Full Sample**
Increase in mean donation (SEK)	15.03	15.07	16.61	15.57
Standard Deviation	28.38	30.70	30.85	29.99
Number of observations	2619	2578	2513	7710
Increase in mean donations,				
conditional on upgrading (SEK)	44.18	44.18	47.10	45.16
Standard deviation	32.77	38.40	35.54	35.65
Number of observations	890	877	886	2653
Share of donors upgrading	34.0%	34.0%	35.3%	34.4%

Table 5: Field Experiment 1: Bootstrapping, T-test

	Bootstrap	**T-test**
Null Hypothesis	$\mu_c = \mu_T$	$\mu_C = \mu_T$
Full sample		
p-value	.0096	.013
Number of observations	1134	1134
Conditional on upgrading		
p-value	.014	.015
Number of observations	368	368

Note: All tests are two-sided

Table 6: Field Experiment 1: Bootstrapping, T-test

	Bootstrap	Bootstrap	T-test	T-test
Null Hypothesis	$\mu_c = \mu_{T1}$	$\mu_c = \mu_{T2}$	$\mu_C = \mu_{T1}$	$\mu_c = \mu_{T2}$
Full sample				
p-value	.978	.059	.978	.061
Number of observations	5197	5132	5197	5132
Conditional on upgrading				
p-value	.980	.20	.997	.072
Number of observations	1767	1776	1767	1776

Note: All tests are two-sided.

Table 7: Field Experiment 1. Primary Regression Results , OLS

Dependent variable: *Increase in donation*	**OLS1** **Full Sample**	**OLS2** **Full sample**	**OLS3** **Conditional on upgrading**	**OLS4** **Conditional on upgrading**
GMT treatment dummy	6.03**	7.21***	11.77**	9.92**
	(2.44)	(2.53)	(4.89)	(4.76)
Age		-.17**		-.17
		(.08)		(.18)
Female		-4.08		-2.44
		(2.55)		(4.76)
Original donation		.008		.18***
		(.008)		(.03)
Nix		-6.51**		-16.23***
		(2.57)		(4.39)
Constant	18.61***	30.77***	60.53***	52.47***
	(1.75)	(5.86)	(3.58)	(13.52)
F-test	6.09	2.85	5.79	11.02
p-value	(.01)	(.01)	(.02)	(.00)
R^2	.0054	.017	.016	.173
Number of observations	1134	1134	368	368

Note: Robust standard errors in parentheses.
***denotes significance at at the p<0.01 level.
**denotes significance at at the p<0.05 level.
*denotes significance at at the p<0.10 level.

Table 8: Field Experiment 2. Primary Regression Results, OLS

Dependent variable *Increase in donation*	**OLS1** **Full Sample**	**OLS2** **Full sample**	**OLS3** **Conditional on upgrading**	**OLS4** **Conditional on upgrading**
GMO Treatment dummy	.022	.155	-.006	-.30
	(.82)	(.80)	(1.66)	(1.62)
GMT Treatment dummy	1.55*	1.77**	2.92*	3.03**
	(.82)	(.81)	(1.62)	(1.52)
Intro		-.019***		-.035***
		(.004)		(.008)
Age		.018		.067**
		(.024)		(.031)
Female		-1.93**		-3.14*
		(.82)		(1.64)
Original donation		.063***		.108***
		(.012)		(.025)
Cell phone		6.02***		4.85**
		(.1.56)		(2.15)
Spontaneous donor		2.29**		.20
		(1.03)		(1.90)
Member donor		2.52***		1.97
		(.90)		(1.61)
Spontaneous and member		2.37**		-.283
		(1.12)		(1.93)
Rec_channel		3.28**		3.92
		(1.54)		(3.16)
Constant	15.05***	7.23***	44.18***	29.52***
	(.55)	(2.39)	(1.09)	(4.75)
F-test	2.18	11.88	2.00	7.34)
p-value	(.11)	(.00)	(.14)	(.00)
R^2	.001	.041	.002	.083
Number of observations	7710	7710	2653	2653

Note: Robust standard errors in parentheses.
***denotes significance at at the p<0.01 level,
**denotes significance at at the p<0.05 level,
*denotes significance at at the p<0.10 level,

Table 9: Field Experiment 1. Probit

Dependent variable:	**Probit1**	**Probit1**	**Multinomial Probit**		
Response rate (binary)	**All**	**All**	**Small**	**Medium**	**Large**
GMT Treatment dummy	.033	.042	.153	-.069	.45***
	(.028)	(.028)	(.16)	(.12)	(.14)
Age		-.0014	-.016***	.004	-.009**
		(.0009)	(.005)	(.004)	(.004)
Female		-.045	-.327**	-.096	-.161
		(.028)	(.16)	(.13)	(.14)
Original donation		-.00013	-.0080***	-.002***	.0005
		(.00008)	(.0015)	(.0006)	(.0003)
Nix		-.020	.150	.094	-.369**
		(.032)	(.180)	(.146)	(.163)
Constant			091	-1.06***	-1.09***
			(.33)	(.29)	(.28)
Pseudo R^2	.0010	.0052			
Number of observations	1134	1134		1134	

Note: Marginal effects in probit 1 and 2. Robust standard errors in parentheses.
Zero increase in donation is the omitted category in the multinomial probit.
***denotes significance at at the p<0.01 level,
**denotes significance at at the p<0.05 level,
*denotes significance at at the p<0.10 level,

Table 10: Field Experiment 2. Probit

Dependent variable	**Probit 1**	**Probit2**	**Multinomial Probit**		
Response rate	**All**	**All**	**Small**	**Medium**	**Large**
GMO Treatment dummy	.0004	.002	.037	-.042	.054
	(.013)	(.013)	(.056)	(.061)	(.093)
GMT Treatment dummy	.013	.014	.012	.031	.256***
	(.013)	(.013)	(.057)	(.061)	(.089)
Age		.-0002	-.0006	-.0095***	.002*
		(.0002)	(.0010)	(.002)	(.0008)
Female		-.186	.005	-.122**	-.17**
		(.012)	(.052)	(.055)	(.078)
Original donation		.0005***	.0005	.0023***	.004***
		(.00007)	(.0003)	(.0003)	(.0004)
Intro		-.00019***	.0001	-.0008**	-.002***
		(.00007)	(.0002)	(.0003)	(.0005)
Cell		.102***	.132	.468***	.316*
		(.027)	(.111)	(.106)	(.164)
Spontaneous donor		.045***	.102	.199***	.322***
		(.017)	(.074)	(.077)	(.109)
Member		.047***	.130**	.176**	.414***
		(.015)	(.064)	(.070)	(.102)
Spontaneous and member		.066***	.258***	.188**	.369***
		(.018)	(.071)	(.079)	(.111)
Rec_channel		.044**	.156*	.046	.329***
		(.020)	(.086)	(.089)	(.122)
Constant			-1.23***	-.979***	-2.670***
			(.099)	(.126)	(.139)
Wald chi2	1.18	118.19		299.85	
p-value	(.55)	(.00)		(.000)	
Pseudo R^2	.0001	.008			
Number of observations	7710	7710		7710	

Note: Marginal effects. Robust standard errors in parentheses.
Zero increase in donation is the omitted category in the multinomial probit.
***denotes significance at at the p<0.01 level,
**denotes significance at at the p<0.05 level,
*denotes significance at at the p<0.10 level,

Table 11: Field Experiment 1. Heterogeneous treatment effects , OLS and Probit

	OLS1 Full sample	**OLS2 Conditional on upgrading**	**Probit Full Sample**
Dependent variable:	*Increase in donation*	*Increase in donation*	*Donated (binary)*
GMT Treatment dummy	8.96**	16.23**	.075
	(4.23)	(7.48)	(.116)
Age	-.17**	-.15	-.004
	(.08)	(.18)	(.002)
Female	-2.48	4.17	-.164
	(3.02)	(5.71)	(.113)
Original donation	.008	.19***	-.0004
	(.009)	(.03)	(.0002)
Nix	-6.64**	-16.48***	-.053
	(2.63)	(4.45)	(.090)
GMT*Female	-3.16	-12.27	.077
	(5.12)	(9.17)	(.157)
Constant	29.84***	48.08***	
	(5.58)	(12.50)	
F-test	2.50	9.42	
p-value	(.02)	(.00)	
R^2	.017	.177	.0053
Number of observations	1134	368	1134

Note: Robust standard errors in parentheses. Marginal effects in probit.
***denotes significance at at the p<0.01 level,
**denotes significance at at the p<0.05 level,
*denotes significance at at the p<0.10 level,

Table 12: Field Experiment 2. Heterogeneous Treatment Effects, OLS and Probit

	OLS2	**OLS4**	**Probit**
	Full sample	**Conditional on upgrading**	**Full sample**
Dependent variable	*Increase in donation*	*Increase in donation*	*Donated (binary)*
GMO Treatment dummy	6.34**	10.18**	065**
	(2.48)	(5.18)	(.029)
GMT Treatment dummy	5.41***	10.47***	..041
	(1.92)	(3.27)	(.161)
Age	.017	.065**	-.0002
	(.024)	(.031)	(.0002)
Female	-.59	-1.08	-.001
	(1.21)	(2.13)	(.021)
Original donation	.062***	.108***	.0005***
	(.012)	(.025)	.00007
Cell phone	6.10***	5.00**	.103***
	(.1.56)	(2.17)	(.027)
Spontaneous donor	2.31**	.55	.045***
	(1.04)	(1.88)	(.017)
Member donor	2.32**	1.95	.043***
	(.91)	(1.63)	(.015)
Spontaneous and member	2.05*	-.655	.061***
	(1.11)	(1.91)	(.017)
Rec_channel	4.00***	4.73	.056***
	(1.46)	(3.00)	(.020)
GMO*female	-4.46**	-6.41*	-.054*
	(2.01)	(3.87)	(.028)
GMT*female	.35	.25	.001
	(1.83)	(3.30)	(.029)
GMO*intro	-.018***	-.038***	-.0001
	(.007)	(.014)	(.0001)
GMT*intro	-.023***	-.047***	-.0001
	(.007)	(.013)	(.0001)
Constant	3.13	22.45***	
	(2.28)	(4.24)	
F-test	9.05	5.43	118.76
p-value	(.000)	(.000)	(.000)
R^2	.042	.086	.013
Number of observations	7710	2653	7710

Note: Marginal effects in probit. Robust standard errors in parentheses.
***denotes significance at at the $p<0.01$ level,
**denotes significance at at the $p<0.05$ level,
*denotes significance at at the $p<0.10$ level,

Table 13: Field Experiment 1. Changes in contributions and cancellation rates

Treatment group	**Control**	**Treatment Two months**	**Total**
Increases in donations			
Number of donors	16	13	29
(percentage)	2.9%	2.2%	2.6%
Mean change in donations (SEK)	128	133	130
Decreases in donations			
Number of donors	5	2	7
(percentage)	0.9%	0.3%	0.6%
Mean change in donations (SEK)	-70	-125	-86
Cancellations			
Number of donors	21	23	44
(percentage)	3.8%	4.0%	3.9%
Mean change in donations (SEK)	-135	-108	-121
Total long-run changes			
Number of donors	42	38	80
Percentage	7.6%	6.5%	7.1%
Total mean change in donations (SEK)	-2.07	-1.76	-1.91
Number of observations	553	581	1134

Table 14: Field Experiment 2. Changes in contributions and cancellation rates

	Control	**Treatment One Month**	**Treatment Two Months**	**Full Sample**
Increases in donations				
Number of donors	14	18	10	42
(percentage)	0.53%	0.70%	0.40%	0.55%
Mean change in donations (SEK)	95	99	127	124
Decreases in donations				
Number of donors	14	7	4	25
(percentage)	0.53%	0.27%	0.16%	0.32%
Mean change in donations (SEK)	-77	-114	-88	-89
Cancellations				
Number of donors	82	90	91	263
(percentage)	3.1%	3.5%	3.6%	3.4%
Mean change in donations (SEK)	-164	-160	165	-160
Total long-run changes				
Number of donors	110	115	105	330
Percentage	4.2%	4.5%	4.2%	4.3%
Total mean change in donations (SEK)	-5.02	-5.21	-5.27	-5.17
Number of observations	2619	2578	2513	7710

Table 15: Field Experiment 1. Donations after 12 months, OLS and Probit

	Probit1	**Probit2**	**OLS1**	**OLS2**
Dependent variable:	*Drop-out rate (binary)*	*Drop-out rate (binary)*	*Difference in donations*	*Difference in donations*
GMT Treatment dummy	-.003	-.0012	.314	1.016
	(.010)	(.009)	(2.67)	(2.60)
Age		-.0008***		-.098
		(.0003)		(.137)
Female		.009		-2.738
		(.009)		(2.68)
Original donation		-.00014**		.005
		(.00005)		(.004)
Nix		-.0115		-1.929
		(.009)		(2.97)
Constant			-2.07	4.463
			(2.03)	(9.53)
F-test			.01	.55
p-value			(.90)	(.73)
R^2	.0003	0.0469	.000	.0028
Number of observations	1134	1134	1134	368

Note: Robust standard errors in parentheses. Mrginal effects and Pseudo R^2 for probit regressions.
***denotes significance at at the p<0.01 level,
**denotes significance at at the p<0.05 level,
*denotes significance at at the p<0.10 level,

Table 16: Field Experiment 2. Donations after 6 months, OLS and Probit

	Probit1	**Probit2**	**OLS1**	**OLS2**
Dependent variable:	*Drop-out rate (binary)*	*Drop-out rate (binary)*	*Difference in donations*	*Difference in donations*
GMO Treatment dummy	.049	.040	-.187	-.229
	. (067)	(.068)	(.989)	(.982)
GMT Treatment dummy	.065	.062	-.248	-.437
	(.067)	(.068)	(1.03)	(1.02)
Age		-.0007		.006
		(.0010)		(.006)
Female		.097		-.496
		(.063)		(.953)
Original donation		.0004		-.044***
		(.0003)		(.011)
Intro		-.0005		.009*
		(.0003)		(.005)
Cell phone		.065		-1.03
		(.114)		(1.62)
Spontaneous		.0036		-.643
		(.084)		(1.43)
Member		-.163**		.083
		(.082)		(1.08)
Spontaneous and member		-.180*		1.24
		(.095)		(1.18)
Rec_channel		.350***		-5.67***
		(.086)		(1.58)
Constant	-1.86***	-1.88***	-5.02***	.771
	(.048)	(.112)	(.695)	(1.80)
F-test			.03	3.75
p-value			(.97)	(.00)
R^2	.0004	0.0235	.000	.0131
Number of observations	7710	7710	7710	7710

Note: Robust standard errors in parentheses. Pseudo R^2 for probit regressions.
***denotes significance at at the p<0.01 level,
**denotes significance at at the p<0.05 level,
*denotes significance at at the p<0.10 level,

Table 17: Field Experiment 2. Summary Statistics with GMF

	Control	**Treatment One month**	**Treatment Two Months**	**Treatment Free**
Average age	52	53	54	53
	(25)	(39)	(40)	(13)
Average contribution (SEK)	153	152	148	145
	(90)	(81)	(79)	(71)
Share women	.71	.71	.71	.73
	(.45)	(.45)	(.45)	(.45)
Average duration in months	158	155	157	156
	(98)	(98)	(99)	(98)
Cell phone	.06	.06	.07	.02
	(.24)	(.24)	(.26)	(.14)
Regular donor	.57	.60	.56	.54
	(.50)	(.49)	(.50)	(.50)
Spontaneous donor	.12	.12	.12	.14
	(.33)	(.33)	(.33)	(.35)
Member	.18	.18	.19	.18
	(.38)	(.38)	(.39)	(.39)
Spontaneous and member	.13	.10	.12	.13
	(.34)	(.31)	(.33)	(.3)
Rec_channel	.12	.12	.13	.12
	(.33)	(.33)	(.34)	(.32)
Observations	2040	1973	1931	314

Notes: Standard deviations within parantheses. USD 1 $\simeq$ SEK 6.

Table 18: Field Experiment 2. OLS and Probit with GMF

	OLS2	**OLS4**	**Probit**
	Full sample	**Conditional on upgrading**	**Full sample**
Dependent variable	*Increase in donation*	*Increase in donation*	*Donated (binary)*
GMO Treatment dummy	.30	-.47	006
	(.95)	(1.96)	(.015)
GMT Treatment dummy	1.57*	1.99	.019
	(.86)	(1.51)	(.015)
GMF Treatment Dummy	-.26	8.43**	-.055*
	(1.70)	(3.41)	(.028)
Age	.015	.061*	-.0002
	(.026)	(.032)	(.0002)
Female	-2.73***	-3.91**	-.029**
	(.92)	(1.81)	(.014)
Original donation	.066***	.107***	.0006***
	(.015)	(.030)	.00008
Intro	-.022***	-.035***	-.0002***
	(.005)	(.01)	(.00007)
Cell phone	6.24***	5.12**	.105***
	(.1.54)	(2.17)	(.027)
Spontaneous donor	1.49	-.87	.036*
	(1.12)	(2.05)	(.019)
Member donor	2.86***	1.74	.055***
	(1.05)	(1.84)	(.018)
Spontaneous and member	1.81	-1.30	.060***
	(1.37)	(2.41)	(.021)
Rec_channel	1.12	1.02	.022
	(1.33)	(2.55)	(.021)
Constant	8.27***	31.52***	
	(2.70)	(5.51)	
F-test	9.24	5.12	116.19
p-value	(.000)	(.000)	(.000)
R^2	.044	.085	.016
Number of observations	6258	2144	6258

Note: Marginal effects in probit. Robust standard errors in parentheses. Pseudo R^2 in probit
***denotes significance at at the p<0.01 level,
**denotes significance at at the p<0.05 level,
*denotes significance at at the p<0.10 level,