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ABSTRACT

Optimal Incentives to Give*

We examine optimal incentives for charitable giving with a large-scale field experiment involving 26 charities and over 112,000 unique individuals. The price of giving is varied by offering a fixed match if the donation meets a threshold amount (e.g. "give at least $25 and the charity receives a $25 match"). Responses are used to structurally estimate a model of charitable giving. The model estimates are employed to evaluate the effectiveness of various counterfactual match incentive schemes, taking into account the goals of the charity and donor preferences. Two of these optimal incentives were subsequently implemented in a follow-up field study. They were found to be effective at implementing the desired goals, as predicted by theory and our simulations. Our findings highlight the pitfalls of relying on a particular parameterization of a policy to evaluate effectiveness. The best-guess incentives in our initial field experiment turned out to be ineffective at increasing donations because optimal incentives should have been set higher.

JEL Classification: D64, H41, C93, D91
Keywords: charitable giving, mechanism design, field experiment

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1 Introduction

Organizations try to design and implement the best policies possible, but this can be challenging. Often, only a narrow set of options is examined, based on best guesses of what might work. This may be driven by limited financial resources and a lack of the necessary information to design optimal schemes. In the end, viable alternatives may never be discovered or tested, even when these could be more effective than the adopted policy.[1] We explore these issues in the context of charities offering incentives to potential donors that lower the price of giving. Typically, this is implemented with a linear match offer for a donation. While popular, there is no evidence to suggest this is the most effective method to lower the price of giving. To advance understanding of optimal incentives, we combine a theoretical foundation of the motives for charitable giving, a large field experiment with partner charities using threshold match incentives and structural estimation of the decision to give.[2] The structural estimation allows an evaluation of match incentives typically not considered by charities, and therefore out of sample. These estimates are applied to the design of optimal incentives under various objectives of the charity. Subsequently, we implement two of these incentives in a follow-up field implementation and assess performance. We find that typical fundraising incentive schemes are far from optimal. Alternative pricing schemes can be very effective at increasing donations, if properly designed.

Charities rely on financial support from a variety of sources, including government grants, foundations and donations. This support is crucial, as many charities exist in a fragile financial state, with 7-8% technically insolvent and roughly half with less than one month of operating revenues (Morris et al., 2018). With diminishing support from state and local grants, stagnant donation levels (at around 2% of U.S. GDP for the past several years) and new charities entering the market every day, the longevity of many charities relies heavily on the effectiveness of their fundraising efforts. Indeed, only 64% of the nonprofits that obtained tax-exempt status from the IRS in 2005 are still considered active 10 years later (National Center for Charitable Statistics, 2015). Other elements also play a role in fundraising outcomes, such as the preferences and constraints of potential donors, the willingness to donate, the timing of a fundraising drive and general economic conditions.

While there are a variety of ways in which charities can and do encourage giving from potential supporters, a common approach is to reduce the price of giving by offering a linear one-to-one match incentive (e.g. "for each $1 given, the charity will receive an additional $1

[1]A discussion of behavioral structural estimation and its use in experimental and policy design is in DellaVigna (2018).

[2]A threshold match incentive is a fixed amount of money that would be given to the charity only if a donation reaches a threshold.

from a generous supporter") that reduces the effective price of giving to one-half.[3] These match incentives have been found to increase the probability of making a donation and the amount received by the charity (Eckel and Grossman, 2003; Karlan and List, 2007; Huck and Rasul, 2011; Hungerman and Ottoni-Wilhelm, 2018).[4] It is a simple approach to reduce the price of giving, and easy to articulate to potential donors, but it may not be the best structure for this type of incentive (see examples in Huck et al., 2015). Importantly, there is little guidance on how to design match incentives to best meet the goals of the charity, especially when a charity has limited information on the willingness to give of new donors.

An alternative approach is to offer a fixed match if the donation meets a certain threshold level, i.e. a threshold match. For example, "Give between $25 - $99, and the charity receives a $25 match, give $100 or more and the charity receives a $100 match." This creates "notches" (e.g. Kleven and Waseem, 2013; Kleven, 2016) in a potential donor's choice set, rather than changing the slope. This alternative was first suggested theoretically by Blinder and Rosen (1985) who showed that notches can increase out-of-pocket donations even when alternative fundraising schemes might decrease donations.[5]

To assess whether notches can be useful in optimal policy design, we implement a large field experiment on charitable giving with non-convex choice sets. This permits us to recover policy-relevant behavioral parameters and evaluate the potential benefits of using notches to affect charitable donations. In our design, thresholds are placed on salient and non-salient numbers to create the kind of out-of-sample bunching predicted by theory. Thus, our study provides empirical evidence of the desirability of notches in policy design for charitable giving and assesses their effectiveness.

The field experiment was conducted in partnership with a private foundation and 26 charities in Chicago. We randomly assigned one of nine threshold incentive match offers, or a control of no match, to over 112,000 unique individuals and observed donation rates and amounts donated. Contrary to a one-to-one match that reduces the effective price of giving

[3] Among alternative approaches, charities may announce a lead donor as a way of signaling charity quality or effectively moving a donor's contribution closer to a target fundraising goal (List and Lucking-Reiley, 2002; Potters et al., 2007; Rondeau and List, 2008; Bracha et al., 2011). Auctions and raffles are also used effectively to raise funds (Carpenter et al., 2008; Onderstal et al., 2013). Donors are offered premium gifts for making a donation, and these gifts may vary by donation level (Eckel et al., 2016). Suggested donation amounts, reporting donations in categories and contingent matches are additional ways to affect donor behavior (Harbaugh, 1998; Reiley and Samek, 2019; Croson and Shang, 2008; Altmann et al., 2019; Anik et al., 2014). Some of these latter approaches create a type of notch in the budget set to get the gift or be reported in the donation category.

[4] Rebates are another way to reduce the price of giving, and there is evidence that donors do not respond equivalently to a match and a rebate (Hungerman and Ottoni-Wilhelm, 2018; Eckel and Grossman, 2003, 2008, 2017; Bekkers, 2015).

[5] The case analyzed by Blinder and Rosen (1985) is a notch subsidy, i.e. the donor is not required to donate the match incentive. We show that their result extends if the match has to be donated to the charity.

to one-half for any donation, threshold match incentives may increase or decrease out-of-pocket donations. A donor may raise the donation to meet a threshold or may decrease it to a lower threshold since the additional dollars given above one threshold, but below another, are priced at one. With the additional dollars from the match, the total amount of money received by the charity could still increase, even when out-of-pocket donations have gone down. Importantly, donation behavior around the notches allows for identification of the structural model parameters.

We derive the theoretically optimal incentives for a charity, assuming quasi-linear preferences over donations and consumption, and estimate a structural model informed by the theoretical framework. The optimal incentive suggested by theory is not a linear match – charities should only offer a price reduction for donations above a threshold and this should be an increasing marginal subsidy. This means that the price of giving is only reduced for donors with a higher willingness to give. Donors below the threshold do not receive a price reduction. Also, absent discontinuities in the underlying distribution of the propensity to donate, incentives should be continuous in the amount donated. The effectiveness of these incentives, however, is diminished if donors pay attention to average instead of marginal prices (as in Rees-Jones and Taubinsky, 2020; Ito, 2014; Liebman and Zeckhauser, 2004). In this case, threshold matches (notches) are more effective than marginal incentives above a threshold.

We then structurally estimate a model of giving using the donation behavior observed in the field experiment. The estimates are used to determine where a charity would want to set the match incentive thresholds, noting that the optimal threshold will depend crucially on what the charity would like to achieve.

The field experiment with the charities raised over $519,000 in donations, and an additional $250,000 was spent on matches paid to the charities. The average donation, conditional on making a gift, was $295, and the donation rate was 1.6%. We found no statistically significant difference in average donations or donation rates across the treatment or control groups, however, there is significant bunching at the treatment-assigned donation thresholds for a match. That is, individuals shifted their donation amounts to just meet the threshold so the charity would receive a match. This is empirically similar to donation behavior in the presence of reporting categories and suggestions.[6]

Estimates from the structural model yield a price elasticity of giving of -0.9. This is similar to estimates from other field experiments on charitable giving when considering the

[6]Charities often recognize donors based on donation categories, and donors tend to bunch at the low end of the range (Harbaugh, 1998). Suggested amounts to donate or default donations also sway donors to give the specified amount presented to them (Croson and Shang, 2008; Reiley and Samek, 2019; Altmann et al., 2019)

total donation received by the charity (Eckel and Grossman, 2008; Huck and Rasul, 2011; Castillo et al., 2020), although Karlan and List (2007) find lower elasticities when considering price effects on out-of-pocket donations. Non-experimental administrative data yield price elasticities of giving in the range of -1.0-1.2 (Hungerman and Ottoni-Wilhelm, 2018; Andreoni and Payne, 2013; Peloza and Steel, 2005; Auten et al., 1992). Definitions and methods to estimate price elasticity differ across these studies. The results using administrative data examine the total amount of money the charity receives, as we do, and are closer to our estimates.

One of our main findings is that one-to-one matching is not the best option for a charity. Other matching schemes, such as a threshold match, do as well, if not better than one-to-one matches. We also explore the optimal threshold match incentive under various potential goals of a charity. For instance, if the goal is to maximize out-of-pocket donations, a charity should set a very high threshold match (e.g. "give $2,000 or above and the charity receives a $2,000 match"), thus lowering the price of giving only for large donors. However, if the goal is to increase the strength of donor participation, and not necessarily out-of-pocket donations, the match threshold should be set lower, e.g. at $175. There are many matching schemes the charity can use, and the best one depends largely on what it is trying to achieve, as well as individuals' willingness to donate in the target population.

In a side-by-side comparison of the model predictions for various matching schemes, assuming a charity's goal is to maximize out-of-pocket donations, the optimal threshold match yields an average out-of-pocket donation that is 11% higher than the average donation absent a match, holding constant fundraising efforts. That is, a threshold match raises donations relative to offering no incentives. In an apples-to-apples comparison of a linear match to the optimal threshold match, we find, for the same fundraising cost, the average out-of-pocket donation is 15% higher using the threshold match compared to the linear match. This means that, if the objective of the charity is to maximize out-of-pocket donations, the charity should use a threshold, not a linear, match, and this is better than no match at all.

The side-by-side comparison also shows that the thresholds we used in the field experiment yield an average out-of-pocket donation that is about 11% lower than offering no match at all.[7] These thresholds were determined in consultation with experts in the charitable giving sector and thought, a priori, to be the most effective. This highlights the perils of determining what works from isolated experiments. Indeed, on the face of it, the results from the field experiment would suggest that threshold matches are an ineffective incen-

[7] As a comparison, donations in the field experiment were 15% lower in the combined six treatments that all charities experienced compared to the control group. We do not find differences across treatments or during the month of November.

tive because average out-of-pocket donations are no different in the control and treatment groups.[8] However, that conclusion is not correct. When coupled with theory and structural estimation, mis-calibrated experiments can be informative of the optimal policy.[9] In our case, the field experiment thresholds were set much lower than would have been best for a charity, in our setting, seeking to maximize out-of-pocket donations.

As a demonstration of the effectiveness of the optimally-designed thresholds predicted from our structural estimations, we apply two of these optimal thresholds in a field implementation with 66 charities the following year. We confirm that the optimal incentives we derive outperform standard fundraising practices and results are in line with the theory. This provides evidence of the benefits of combining field experiments and structural estimation to improve the design of incentives in the field (as noted by DellaVigna, 2018).

Our paper contributes to several literatures. In addition to linear price reductions for giving (e.g., Eckel and Grossman, 2008; Huck and Rasul, 2011; Karlan and List, 2007; List and Lucking-Reiley, 2002; Hungerman and Ottoni-Wilhelm, 2018), non-linear reductions also have been investigated. Huck et al. (2015) compare a variety of matching schemes to assess effectiveness relative to the announcement of a lead donor. As Huck et al. (2015), we find that price incentives may not be the most efficacious for donors, however, we note that this does not imply that price incentives cannot be effective in general.[10] Our paper shows that the most effective incentives can lie far from the parameter space explored in many field experiments and the schemes currently used by charities. Adena and Huck (2019) investigate the use of individualized thresholds to increase donations. They exploit rich information on past and potential donors to predict donations and then tailor thresholds and matches. For a designer with minimal information on potential donors, our approach optimizes incentives at the market level.[11]

There is a growing literature on notches (Kleven and Waseem, 2013; Kleven, 2016), and our findings contribute to this. An important open question is whether or not notches are desirable as a policy tool (e.g. Blinder and Rosen, 1985; Slemrod, 2013). Our derivation of

[8] As discussed in Hungerman and Ottoni-Wilhelm (2018), a lack of response to match incentives could be consistent with a model of pure warm glow giving.

[9] As an example, Duflo et al. (2018)'s field experiment on regulatory enforcement of environmental rules found randomly-assigned extra inspections had little effect on compliance. However, counterfactual simulations uncovered that discretionary targeting by the regulator, not randomly-assigned audits, is more effective.

[10] Most field experiments on fundraising rely on small donors, as we partially do here, and this might explain the difference in results between using experimental data and administrative data. Levin et al. (2016) conduct a field experiment with a population of large donors and find results close to those using administrative data.

[11] This might also appeal to charities who would like an untargeted approach to donors and to reduce possible misalignment of dynamic incentives.

the optimal incentive to maximize out-of-pocket donations requires a price scheme that is non-linear but close to a linear marginal subsidy after a certain donation level. Such a scheme might not be salient enough for potential donors to notice (e.g. Ito, 2014), and notches can be a viable alternative as shown in our estimations and field implementation of two optimal threshold match incentives.[12]

The paper is organized as follows. Section 2 outlines the decision framework for the field experiment. Section 3 explains the experimental design and implementation, and Section 4 discusses results from the field experiment. Section 5 presents the theoretical framework for the optimal incentives to give, the structural estimation, the estimated optimal incentives to give, and the field implementation of the optimal incentives. Section 6 concludes.

2 Decision framework

When faced with a threshold match, how might a potential donor behave? Figure 1 illustrates this decision. A donor faces a budget constraint between private consumption and the donation received by the charity. Absent any match incentive, the constraint is linear (solid black line) where one dollar less of private consumption is one dollar more received by the charity. Suppose the donor is offered a threshold match incentive where any donation of \$25-\$99 gives a match of \$25 to the charity and any donation of \$100 or more gives a match of \$100 to the charity. This new budget constraint is in blue. It is the same as the previous constraint for any donation to the charity of \$0-\$24, and at \$25, it increases to the right discontinuously and creates a "notch" at \$50 received by the charity (\$25 donation + \$25 match). The new budget constraint has the same slope and is parallel to the old budget constraint. There is another "notch" at \$100.

Without a match incentive, the donor will choose to donate the amount where the indifference curve is tangent to the (black) budget constraint. When the threshold match is offered, how donations change depends on preferences. There are two types of donors illustrated in Figure 1. The first donor makes a small donation (<\$25) to the charity in the absence of the match (this is the indifference curve on the upper left-hand side of the budget constraint). When offered the match, this donor increases the out-of-pocket donation to \$25 to reach the threshold and receive the match. In this case, the out-of-pocket donation increases, and the charity receives \$50. The second donor is already making a large donation to the charity in the absence of a match (>\$100, this is the indifference curve on the lower

[12]There are trade-offs between these incentive schemes. Notches are inefficient in that they do not completely discriminate among donors with different willingness to donate. Linear marginal subsidies are closer to the optimal price scheme, but they require donors to pay attention to less salient incentives.

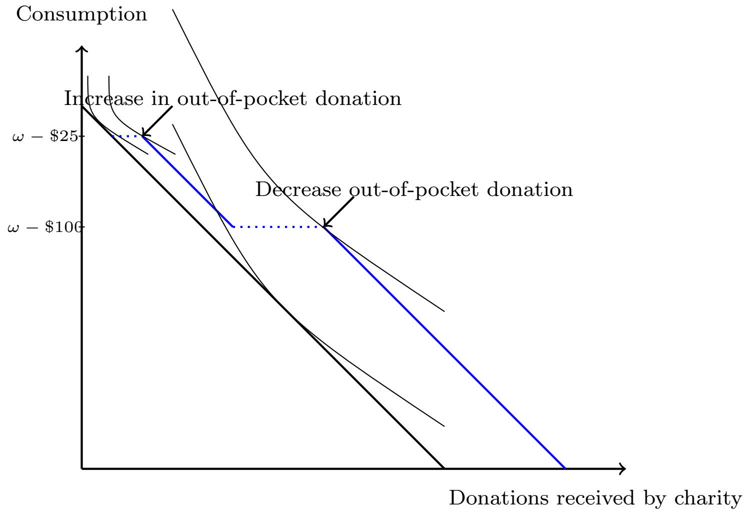


Figure 1: Effect of matches on choice sets

right-hand side of the budget constraint). When offered the match, this donor reduces the out-of-pocket donation to the threshold donation of \$100, and the total amount received by the charity is \$200. In this case, while the total donation received by the charity has increased, the donor reduced out-of-pocket giving.

This example illustrates how a threshold match incentive might increase or decrease out-of-pocket donations. The net effect on the amount of money received by the charity depends on the underlying distribution of donations absent a match and donor preferences. Therefore, where a charity sets its match thresholds will be crucial to the amount of donations it receives. If these thresholds are not set optimally relative to preferences and the population's willingness to give, out-of-pocket giving might decrease or remain constant.

3 Field Experiment

3.1 Design

The aim of the field design is to collect data that will allow us to causally identify how an individual responds to a threshold match offer. The responses at various thresholds can then be used to estimate a structural model of giving and derive optimal policy design. There are nine possible threshold match offers used by the charities, and we randomly offer one to a potential donor. The threshold match offers are chosen based on prior knowledge of the distribution of donations typically received by the charities partnering in the study and a best guess, based on consultation with fundraising experts, of where the thresholds should be placed to affect giving behavior.[13] By varying the threshold levels and matches across the nine possible offers, we alter incentives to donate across individuals. This gives the exogenous variation needed to identify how donations respond to prices and provides the data used to estimate the structural model of giving.

To test these threshold matches in the charitable giving market, we partnered with a private foundation and 26 charities in Chicago. Since we would like to know how individuals react to a threshold match offer from a charity in a natural setting, it is important that the match offers are delivered by the charity during a normal fundraising campaign. To this end, we worked with the charities to embed the threshold match offers in a personalized email fundraising campaign designed and sent by the charity to its respective supporters. The offer was sent via personalized email on November 1, 2017. If the supporter makes a donation above the lowest threshold anytime between November 1-3, the charity receives the specified match. In addition, in the same email, the supporter is informed of another match offer available on November 28 (Giving Tuesday). The November 28 match offer is identical for everyone. The supporter could give November 1-3 and get a match for the charity and also give on November 28 and get a match.

The match incentive treatments are shown in Table 1. All match incentives included three donation tiers, the two listed and a third tier that offered a \$500 match for any donation of \$500 or more. So, for example, the third row of the table shows the 50-100 treatment: the match offer is "a donation of \$50-\$99 receives a \$50 match, a donation of \$100-\$499 receives a \$100 match, and a donation of \$500 or above receive a \$500 match." The treatment name for each match incentive is listed in the first column, and the number of observations for each treatment is listed in the last column. In addition to the match incentive conditions, every charity included a control group that received a personalized email that did not include a match offer for donations made Nov 1-3 but informed the donor of the Nov 28 match.[14]

The text for the match incentive is identical for all 26 charities and is as follows (the

[13] We use data from a 2016 fundraising campaign in Chicago, with 42 charities and over 5,000 individual donations, to assess the underlying distribution of donations. Unfortunately, we did not have any source of price variation as to estimate the underlying price elasticity of donations. A model of impact giving with constant price elasticity is used to assess possible behavioral responses to incentives, assuming that observed donations were the *true* distribution of donations, for different price elasticities. We searched over various thresholds, up to \$500. The estimates showed that a match at \$500 would have a small effect on out-of-pocket donations if demand was inelastic and a 1-to-1 match would have a negative effect. Thus, the highest threshold in all treatments in the field experiment is at \$500. The estimates also showed that including additional lower thresholds would decrease average out-of-pocket donations. Given model uncertainty and the interest by the private foundation funding the study to attract new small donors, we included smaller thresholds as well.

[14] Matching funds for the November campaigns were capped at \$10,000 per charity, and a donor could only receive one match during the Nov 1-3 window and one match during the Nov 28 window. This information was included in the email text. See Appendix A.

Table 1: Match Incentive Treatments

Treatment		Tier 1		Tier 2		
Number	Name	Donation	Match	Donation	Match	Obs
1	25-100	$25-$99	$25	$100-$499	$100	12,625
2	35-100	$35-$99	$35	$100-$499	$100	12,615
3	50-100	$50-$99	$50	$100-$499	$100	12,619
4	25-75	$25-$74	$25	$75-$499	$75	12,612
5	25-150	$25-$149	$25	$150-$499	$150	12,604
6	50-150	$50-$149	$50	$150-$499	$150	12,623
7[a]	25*-100	$25-$99	$35	$100-$499	$100	8,024
8[a]	35*-100	$35-$99	$45	$100-$499	$100	8,020
9[a]	50*-100	$50-$99	$60	$100-$499	$100	8,022
Control		No Nov 1-3 match, informed of GT match				12,588
Total						112,352

[a] These treatments were only used by four large charities.

numbers in brackets change depending on the match offer), "*We have two great match offers in November - one that starts today and one on Giving Tuesday (Nov 28). Thanks to a generous supporter, any donation of at least [$50] between now and November 3 will be matched. [charity name] will receive a [$50] match if your donation is between [$50] - [$149], [$150] match if your donation is between [$150] - [$499], $500 match if your donation is $500 or above. On Giving Tuesday, a donation between $25-$99 will receive a $25 match, a donation between $100-$499 will receive a $100 match, and a donation of $500 or above will receive a $500 match. If you are able to give [$50] or more today, your gift will be matched, and any donation of $25 or more on Giving Tuesday will still be matched.*" The subject line for the email is "*Your donation Nov 1-3 will be matched*".

3.2 Implementation

The fundraising campaign was conducted by sending personalized emails to each charity's supporters. To do this, each charity supplied us with a list of their supporters, including an email address and first and last name. We removed duplicate email addresses or names within a charity, and if there were duplicate email addresses or names across charities, we randomly assigned one charity to that email address or name and removed the email address or name from the remaining charities. These measures assure that each email address and individual

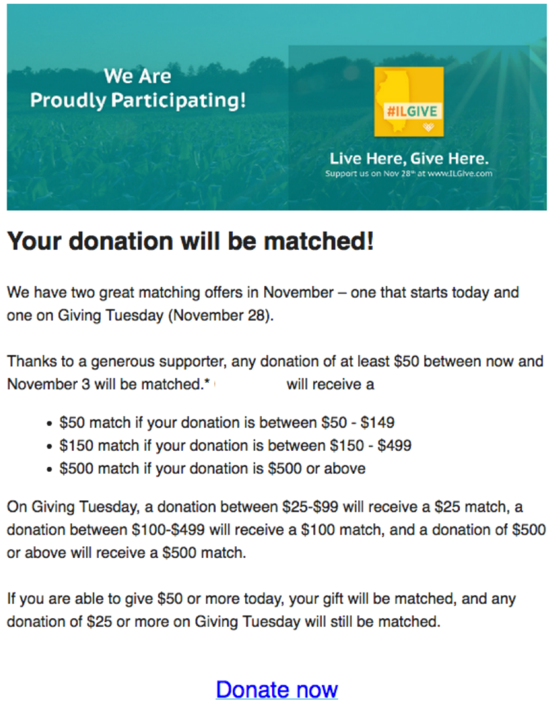


Figure 2: Example email sent for Treatment 50-150

in our experiment only received one match incentive offer from a charity on November 1.[15]

After we removed duplicates, for each charity, we randomly assigned their supporter list to either one of the treatments or the control condition, so that a supporter never received more than one of the match offers. The first six treatments in Table 1 were used with all 26 charities, and the final three treatments were also included for four large charities.[16] This means each charity's supporters experienced all of the first six treatments and the control condition.[17] This approach allows us to identify price effects in our analysis separately from any existing heterogeneity across charities.

[15]AEA RCT Registry number is AEARCTR-0005918. Human subjects approval was completed at Texas A&M University (IRB2016-0721M). In addition, the researchers provided each charity with an MOU detailing the steps that would be taken to preserve confidentiality of data from the charities and their supporters.

[16]These last three treatments are identical to the first three but with a match for the lowest threshold that is equal to the threshold + $10. (e.g. 25*-100 has a match of $35 for a donation between $25-$99, a match of $100 for a donation between $100-$499 and a match of $500 for a donation of $500 or above). We did not include these three treatments for all charities because the charities varied in size (i.e. number of supporters), and we did not have enough power for some charities to assign all 9 treatments and be able to detect effects across treatments. The number of supporters for a charity ranged from 500 to 57,000 across the 26 charities, with most charities having around 2,500 supporters. The large charities had $> 3{,}500$ supporters.

[17]The only background data we have on supporters to check balance across treatment assignment are previous donations. Roughly 55% of supporters donated at some point in the previous three years, and this is not statistically significant different across the first six treatments and control.

The charities developed a fundraising email that was consistent with their image and mission, and we inserted the wording of the incentive offer so that the match offer text was consistent across charities. The wording and layout of the appeal sent in the email for the treatment groups and the control group are listed in Appendix A. An example email sent by one of the charities for treatment 50-150 is in Figure 2. We sent the emails to supporters, on behalf of the charity, using a mail management program (e.g. MailChimp or Constant Contact). All the email delivery and random assignment to treatment was managed by us, however, the email received by the supporter looked like it came from the charity.[18] The charities were blind to treatment assignment, so they did not know which match offer any particular supporter received.

Over 112,000 emails were sent to that many unique individuals on November 1, and over $250,000 was spent on matches during the month of November. Each charity provided us the data for all donations made to the charity for the month of November 2017, including the donor's name, email address (if available), donation date and donation amount. They also provided us donation data for the previous three years. We use this to classify individuals in the study as previous or new donors. Our final data set includes all individuals treated in the field study (i.e. received an email on November 1), whether or not they donated during the month of November, the date and amount of the donation and whether or not they donated in the past and the amount.

4 Giving Behavior in the Field Experiment

We examine giving behavior in the early window (Nov 1-3) when the different threshold matches were offered and on Giving Tuesday (Nov 28) when everyone faced the same price reduction for giving.

Table 2 combines data for both time periods and shows the number of donations, donation rate, total amount donated and average donation for the nine treatments, the control group and the average across the first six treatments, as all charities received these. Over $519,000 were raised in these two periods in November, and 1.6% of all supporters donated. The average unconditional donation was $4.61, and the average donation conditional on having made a donation was $265. The donation rate is similar for the control group and the first six treatment groups, and the average unconditional donation in the control group tends to be higher than the treatment groups. This is due to some large donations in the control group.

[18] The "From:" field in the email had the charity's name and email address, and there was no mention that this was a field study. From the point of view of the supporter, this was a fundraising email sent by the charity.

Table 2: Donations - Nov 1-3 and Nov 28

Treatment	Num Donations	Donation rate	Total Donations	Avg uncond	Avg cond	Avg cond (trim)
25-100	249	1.8	$87,752	$6.94	$352	$273
35-100	268	1.9	$56,892	$4.50	$212	$212
50-100	270	1.8	$69,981	$5.53	$259	$223
25-75	267	1.9	$75,861	$6.01	$284	$248
25-150	253	1.8	$49,337	$3.91	$195	$195
50-150	277	1.9	$70,017	$5.53	$253	$253
25*-100	32	0.4	$3,899	$0.49	$122	$122
35*-100	44	0.5	$7,053	$0.88	$160	$160
50*-100	38	0.4	$7,308	$0.91	$192	$192
Control	259	2.0	$91,061	$7.23	$352	$275
Treatments (1-6, avg)	1,584	1.8	$409,840	$5.40	$259	$233
Total	1,957	1.6	$519,161	$4.61	$265	$235

Note: Last column reports average conditional donation trimmed at donations less than $10,000.

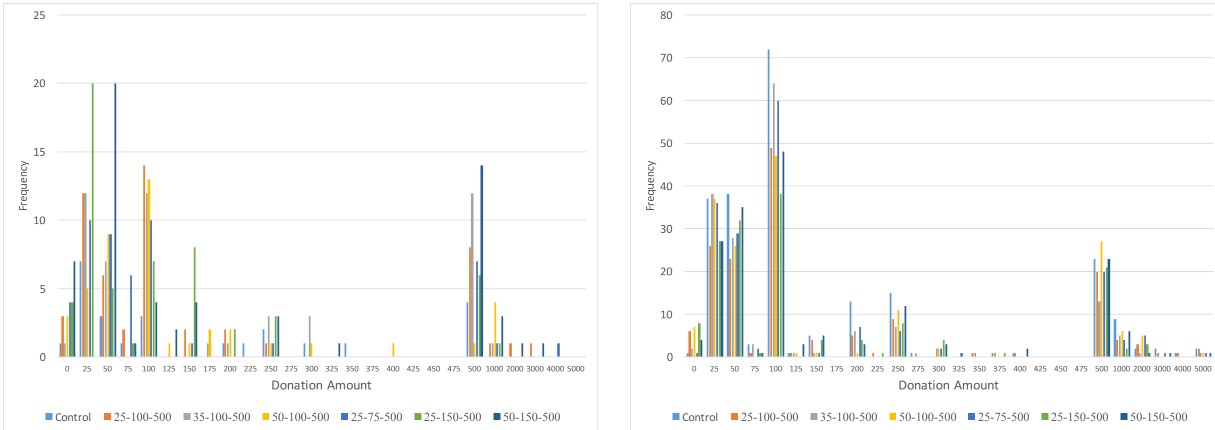
The last column lists the average trimmed conditional donation (i.e. donations <$10,000) and shows donations were more similar (e.g. $275 in the control and $233 in the first six treatments). There are no statistically significant treatment effects on donations, with the exception of the 25-150 treatment compared to the control.[19]

Most donations (74%) were made on Giving Tuesday (Nov 28). There were 1,761 unique donors across the two periods, and despite there being two opportunities to donate with a match, most donors only gave once. Of all donors, 124 (7%) gave in both periods, and 1,637 individuals gave either during Nov 1-3 or on Nov 28.[20] The distribution of donations for the two periods, for those who only gave once, are shown in Figure 3. The figure shows that, on Giving Tuesday (Nov 28), the distribution of donations is similar across all treatment groups and the control group. That is, those who chose to donate on Giving Tuesday behaved similarly and independent of the personalized email received on Nov 1. In contrast, during the Nov 1-3 period, donations are responsive to the treatment match incentives.

We do see evidence of bunching at the threshold donation level to receive a match. To illustrate this, Figure 4 shows the distribution of donations for the first three treatment

[19] The p-values associated with pairwise tests of equality of means are: p-value(25-100 v control) = 0.9658, p-value(35-100 v control) = 0.1685, p-value(50-100 v control) = 0.2365, p-value(25-75 v control) = 0.5718, p-value(25-150 v control) = 0.0579, p-value(50-150 v control) = 0.6340.

[20] Castillo et al. (2020) found a similar pattern of giving.



Nov 1-3 Nov 28

Figure 3: Distribution of donations for those who only gave once

groups (i.e, 25-100, 35-100, 50-100) and the control group for donations made Nov 1-3. There is bunching at \$25, \$35 and \$50. For example, donors in the 25-100 group are at least 4.6 times more likely to make a donation at \$25 than those in the control, 35-100 or 50-100 groups. A similar pattern emerges for donations at \$35 for those in the 35-100 group and at \$50 for those in the 50-100 group. Also, at the second threshold of \$100, there are at least 3 times more donations in the treatment groups relative to the control group.

In sum, the field experiment yields evidence of bunching at the thresholds of the match incentives, but we find no significant treatment effects on average out-of-pocket donations. These findings show that donors do shift their donations to meet thresholds and impact the total amount received by the charity (i.e. their donation plus the match). Using these data, we turn to characterization and estimation of the incentive structure that would maximize donations for a charity.

5 Optimal Incentives to Give

We briefly discuss the nature of optimal incentives to give from the perspective of incentive theory and derive results to inform our estimations. We then structurally estimate preference parameters, assuming donation focal points, using the exogenous variation in the price of giving generated by our field experiment and observed donation behavior. Those estimates are then applied in simulations to determine the set of thresholds that would yield the charity the most fundraising dollars.

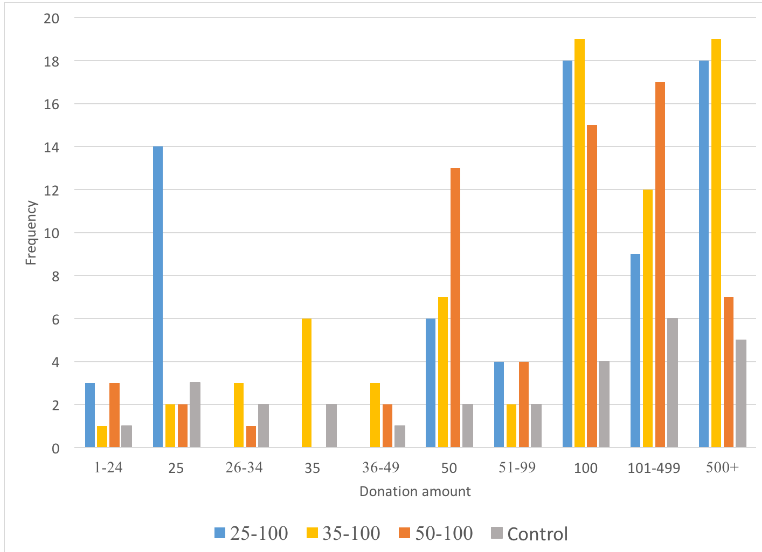


Figure 4: Evidence of bunching

5.1 Theory

The optimal incentives to increase out-of-pocket donations are derived from theory and used to inform our structural estimations. Below, we discuss the derivation, leaving complete details to Appendix B. We do this for brevity and because the results are not novel.

We assume individuals have quasi-linear preferences over consumption and the total donation received by the charity and that they vary in their propensity to donate.[21] The problem faced by a charity is to find the match incentive, tied to an individual's donation amount, that maximizes expected out-of-pocket donations given the propensity to donate in the population. This mechanism design problem has an incentive compatibility constraint and a participation constraint for the potential donor and a budget constraint for the charity. Contrary to the classic monopoly pricing problem (Goldman et al., 1984), a charity cannot prevent individuals from donating directly and bypassing the incentive. Charities, therefore, have to offer incentives in the presence of competitive options available to donors (i.e., donating directly). The problem faced by the charity can then be rewritten as a standard nonlinear pricing problem in which an individual offers a donation $\hat{g}$ in exchange for a payment of $\hat{m}$ with the additional constraint that $\hat{g} \geq g^*(\theta)$, where θ is the propensity to

[21] This characterization of preferences focuses on the impact of the donor's gift (Duncan, 2004; Atkinson, 2009), not on pure warm-glow giving, impure altruism (Andreoni, 1989) or impure impact giving (Hungerman and Ottoni-Wilhelm, 2018). Average donations are similar in the control and treatment groups in the field experiment, however, the significant bunching observed at the thresholds in the field experiment support that donors care about the impact of their gift. They are willing to shift their donation to meet the threshold for a match.

donate and $g^*(\theta)$ is the amount the individual would donate in the absence of an incentive.

The optimal incentive for the charity to offer has two characteristics. First, because charities cannot exclude donors from donating directly and bypassing the incentive, the exclusion principle of nonlinear pricing manifests as the exclusion of small donors from receiving a match for their donation. Thus, the optimal incentive would only offer a match for donations above a certain threshold. Second, the optimal incentive is nonlinear – larger donors are offered more generous matches. Figure B.1 in Appendix B illustrates the optimal match incentive.

Because the optimal incentive, with a minimum donation threshold and nonlinear match, might be too complicated and difficult to explain to potential donors, we also consider simpler incentive schemes suggested by theory. The first class of incentives is a linear marginal subsidy for any donation above a threshold. The second class of incentives is a fixed match for any donation above a threshold. Both schemes are also well suited to maximize out-of-pocket donations. By contrast, the common one-to-one schemes used by charities (e.g. "each \$1 donated is match with \$1") would reduce out-of-pocket donations if preferences are inelastic. This is because a one-to-one match crowds out an individual's underlying willingness to donate and reduces the amount of money raised by the charity.

We note that the field experiment did not include a treatment with a threshold donation plus a linear match. This is for two reasons. First, our partner foundation had implemented a one-to-one match on the excess donation compared to the previous year with little success. Second, research shows that individuals react to average prices and less so to marginal prices (e.g. Rees-Jones and Taubinsky, 2020; Ito, 2014; Liebman and Zeckhauser, 2004). This type of behavior is called "schmeduling." We show in simulations (in Appendix B) that in the presence of schmeduling marginal subsidies do not increase out-of-pocket donations. Intuitively, donors will underestimate price changes and act as if they were more price inelastic than they are. In this case, when there are donors who distort price incentives, notches can be optimal (e.g. Kleven, 2016).

5.2 Structural estimation

The derived optimal incentives illustrate that knowledge of a charity's objective and the distribution of individuals underlying willingness to give are essential to design optimal incentives. Without this information, a charity might inadvertently offer incentives that crowd out, rather than increase, giving. We present structural estimates of such primitives. The estimates presented here refer to a simple model of behavior. Estimates using more complicated models are relegated to Appendix C and allow for heterogeneity in price responsiveness, inattention, dynamic considerations, status as previous donor and nuisance costs.[22] Importantly, we find that the main estimates of the simple model are robust to these additional variations, thus we present the simple model below. We estimate the model using only responses to the Nov 1-3 match and then use behavior on Nov 28 to assess the fit of the model.

We assume that with probability κ an individual donates 0 and with probability $1-\kappa$ an individual donates a positive amount. Further, we assume that with probability ω the individual pays attention to incentives and with probability $1-\omega$ the incentives are ignored. In this case, donors act as warm-glow givers (Andreoni, 1990).[23] In other words, $Pr(0) = \kappa$ and $Pr(g) = (1-\kappa)(Pr(g|g>0, \text{pays attention})\omega + Pr(g|g>0, \text{pays no attention})(1-\omega))$. Conditional on making a donation and paying attention, an individual solves the following problem:

$$max_g \frac{\theta_i}{1+1/e}\left[\left(\frac{g_i + T(g_{i1})}{\theta_i}\right)^{(1+1/e)} - 1\right] + \sum_{k=25,50,100,150,200,250,500,1000} \gamma_k 1[g_i = k] + M - g_i \quad (2)$$

where the utility function is quasilinear in consumption and donations received by the charity, e ($e < 0$) is the price elasticity of giving, g_i is the out-of-pocket donation on Nov 1-3, θ_i is the underlying willingness to donate, and γ_k is the preference for donations of amount k. This latter parameter is included to capture the empirical observation that donations are often made in certain focal amounts (i.e. \$25, \$50, etc.).[24] In our experimental design, because we vary the donation thresholds and match amounts across treatments, and include non-focal thresholds, our estimations can distinguish between the preference for a focal donation amount (γ_k) and the reaction to the match incentives. $T(g)$ is the matching function used in different treatments. The budget constraint is substituted into equation (2).

[22]This alternative specification allows for some sensitivity analysis of model specification (as discussed in DellaVigna, 2018; Andrews et al., 2017). Andrews et al. (2017) suggest providing estimates of their matrix Λ which measures the sensitivity of estimates to small deviations from sustained assumptions. Calculating matrix Λ in our case requires estimating the Jacobian of the first-order conditions of the likelihood maximization problem. We estimate this numerically due to the non-smoothness of our model using the method proposed by (Newey and McFadden, 1994, p. 2190) (see Appendix D). Not surprisingly, the matrix shows a dependency between the estimates of the price elasticity and the strength of donation focal points, in particular donations of \$500.

[23]Our model is similar in spirit to that of Hungerman and Ottoni-Wilhelm (2018) in that donors may care about the impact of their donation, and respond to incentives, and care about their gift. In their model, warm-glow and impact giving are competing motives for a donor. Our model has two latent types, a warm-glow giver and an impact giver, with certain probabilities.

[24]See Andrews et al. (2017), and previous to last footnote, for the importance of accounting for focal points in the context of charitable giving.

This is the decision rule for individuals who pay attention to the offered incentives. To model the possibility of inattention, with probability $1-\omega$, individuals solve the problem below. That is, the donor maximizes utility ignoring the match incentives $T(g)$.

$$max_g \frac{\theta_i}{1+1/e}\left[\left(\frac{g_i}{\theta_i}\right)^{(1+1/e)} - 1\right] + M - g_i \quad (3)$$

In this formulation, the parameter ω provides a measure of how much attention donors pay to incentives. The model is estimated using maximum likelihood, and we make the assumption that θ is distributed log-normal with parameters μ and σ. Further we assume that the probability to donate a positive amount (κ) changes with the size of the charity. κ_S is the probability of donating zero to a small charity and κ_L is the probability for a large charity. Let $g_1(\theta)$ be the optimal donation for a donor with propensity to donate θ who pays attention to incentives and let $g_2(\theta)$ be the optimal donation for a donor with propensity to donate θ who does not pay attention. Let $h(\theta|\mu,\sigma)$ be the density function of θ. The probability of observing g is:

$$\omega \int_{\theta:g=g_1(\theta)} h(\theta|\mu,\sigma)d\theta + (1-\omega)\int_{\theta:g=g_2(\theta)} h(\theta|\mu,\sigma)d\theta \quad (4)$$

Table 3 presents the structural estimates of the model and 90% confidence intervals.[25] The model is estimated with the data from the Nov 1-3 campaign. The estimated price elasticity of giving is less than 1, implying that 1-to-1 matches would be counterproductive, as matches would crowd out out-of-pocket donations. The estimates show that donors have preferences for certain donation amounts (i.e., $25, 50, .., 1000$), apart from their reaction to incentives. The propensity to donate to small charities is larger than to larger charities. The table also shows that not all donors pay attention to incentives. We estimate that 56.5% of donors react to match incentives. In other words, almost half of donors are not paying attention to the change in the price of giving. The estimated average donation is \$209.6 ($= exp(\mu + 0.5\sigma^2)$).

To assess the fit of the estimates, Figure 5 presents graphs comparing the empirical cumulative distribution of donations to predicted donations by treatment. To predict donations, we use 100 draws of a lognormal distribution with parameters as in Table 3 and apply the model estimates to predict what these fictitious donors would have done. This requires randomly assigning them to donate straightforwardly or according to incentives, as the model estimates in Table 3 suggest they would do. The panels in Figure 5 show that the model estimates do a reasonably good job in predicting behavior in the sample across the Control

[25]Standard errors are calculated by implementing 200 bootstrap replications.

Table 3: Parameter estimates

	Estimate	Standard error
Price elasticity		
e	-0.9031	0.0027
Propensity to give		
μ_θ	4.712	0.0602
σ_θ	1.125	0.0413
Preference for certain donation amounts		
γ_{25}	0.895	0.0218
γ_{50}	0.504	0.0363
γ_{100}	0.997	0.0007
γ_{150}	1.070	0.0150
γ_{200}	0.300	0.6492
γ_{250}	1.001	0.0007
γ_{500}	1.112	0.0409
γ_{1000}	1.554	2.1136
Propensity to donate		
$1 - \kappa_{small\,charity}$	0.01166	0.0006
$1 - \kappa_{large\,charity}$	0.00148	0.0001
Attention		
ω	0.565	0.0213
Observations	111,071	

Note: Standard errors are calculated using 200 bootstrap replications.

group and the 9 treatment groups. To test the quality of this fit, we compare 1,000 simulated distributions of donations with the empirical distribution of donations. For 28% of the simulations, a Kolmogorov-Smirnov test of differences in distribution is significant at the 5 percent level, and in 42% of the simulations, the test is significant at the 10 percent level. That is, in most of the simulations, we find no significant difference between the predicted and empirical distributions, providing support that our model fits the data well.

We offer two out-of-sample predictions. The figure in the middle of the bottom panel, titled "Giving Tuesday (25, 100, 500)" predicts donations on Nov 28 from the model estimates based on the Nov 1-3 donations. For this, we pool the data across the treatment and control groups.[26] The figure illustrates that the model estimates fit the donation behavior on Nov 28. In a second prediction, the rightmost figure in the bottom panel, titled "Giving Tuesday (25, 100)" predicts donations on Nov 28 for 38 charities that decided not to participate in the field experiment at all. Contrary to the charities that did participate, these charities did not have matches available on Nov 1-3 and only had two tiers of matches (i.e. a threshold at $25 and at $100) on Nov 28. None of these charities had a match at $500. While the model estimates correctly predict that there will be far less bunching at $500, the predictions miss some other features of the distribution. This is perhaps not surprising since we estimated the model in the subsample of participating charities only. We discuss disparities in the underlying distribution of donations across participating and non-participating charities in the final section of the paper.

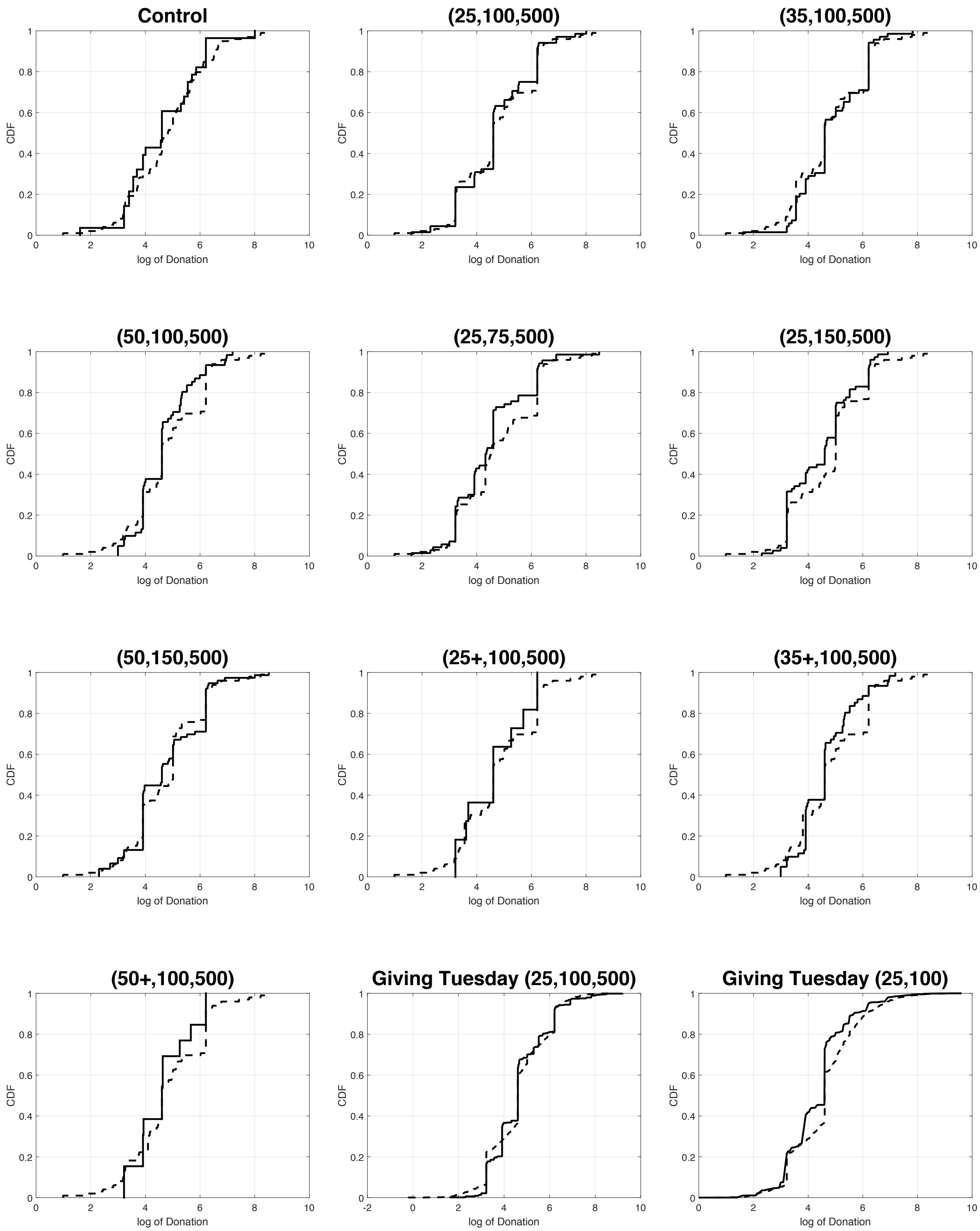
5.3 Optimal incentives based on estimates

We now use the structural estimates from Table 3 to determine the optimal threshold match incentive under scenarios that differ by the objective of the charity. In these simulations, we examine a one-time match incentive. We consider two objectives: a charity seeks to raise as much money as possible from donors or a charity seeks to increase the strength of donor participation. In the first scenario, we determine the optimal incentive that maximizes out-of-pocket donations. In the second, we determine the incentive that maximizes the percent of donors who increase their donation relative to not receiving an incentive at all.

Figure 6 presents simulations of the optimal threshold match for these two scenarios, under the assumption that there is one threshold and the match is $X if the individual donates at least $X.[27] The first simulation (in blue) shows what the average out-of-pocket donation would be for various thresholds if a charity's objective is to maximize out-of-pocket

[26] To predict this distribution we randomly draw 1,500 observations from the estimated lognormal distribution. We do this to mimic the fact that the number of donations on Giving Tuesday was much larger.

[27] These simulations are based on 50,000 draws from a log normal distribution.



Note: Cumulative density functions (CDF) of donations (in log) for expected donations (solid line) and predicted donations (dashed lines)

Figure 5: Model Fit - Control group, 9 treatments, participating charities on Nov 28 and non-participating charities on Nov 28

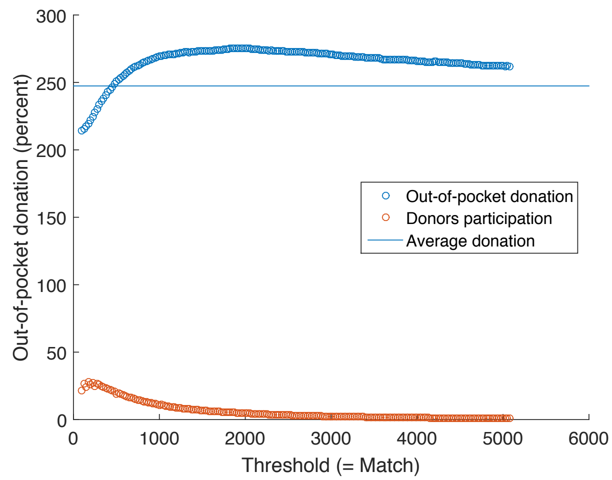


Figure 6: Optimal incentives under two scenarios - maximize out-of-pocket donations, maximize strength of donor participation

donations. As a benchmark, the predicted average donation without a match ($247) is presented as well.[28] The simulation shows that the average donation increases steeply as the threshold rises from $10 to $750 and then continues to rise more slowly to a maximum at a $2,000 threshold, where the average out-of-pocket donation would be $275. We note that the average out-of-pocket donation across thresholds becomes relatively flat. The range of thresholds that are within 1.5 percent of the maximum out-of-pocket donation is from $1,200 to $2,950.

The optimal one-threshold match incentive requires that donations be above $2,000 to receive a match. This is much higher than any thresholds used in our field experiment. We also ran simulations with two thresholds, instead of one. Instead of producing a lower threshold, the optimal thresholds are $2,000 and $8,050. Thus, the optimal incentives should target large, not small, donors.

The second simulation in the figure (in orange) illustrates the optimal incentive when a charity wishes to increase the strength of donor participation. This is the percent of donors who would increase their donation relative to not receiving an incentive at all. The results show that, as the threshold increases, the percent of donors rises but then declines. The threshold at which the strength of donor participation is at its highest is $175. Here, 30% of donors increase their donation. Larger thresholds will increase out-of-pocket donations

[28]To maximize clarity, the predicted average donation without a match ($247) is different from the mean of the lognormal distribution of willingness to donate ($209) due to the fact that in our model we assume that there are donation focal points, or discontinuities, in the utility function of donors.

but reduce the number of individuals who increase their donations. If a charity wishes to increase the strength of donor participation, they should set a threshold at $175.

To give a side-by-side comparison of alternative fundraising schemes, Figure 7 shows the predicted out-of-pocket donation (dark grey) and match amount (light grey).[29] The first bar is for a scheme where there is one donation threshold set at $2,000 (the optimal 1 threshold) with a corresponding match amount. The second bar is for a scheme with two donation thresholds set at $2,000 and $8,050 (the optimal 2 thresholds). To compare the threshold match schemes to a linear match, we find the linear match rate that would approximately cost the same in the amount of money spent on matches. This is rate is 0.5-to-1, and the third bar shows this. The fourth bar shows the result for the 25-100-500 threshold we used in the field experiment. The last bar shows the predicted average donation without any incentives ($247) together with a direct transfer to the charity in the amount equal to the average match from the 0.5-to-1 scheme.

We observe several patterns. First, both the 0.5-to-1 and the 25-100-500 schemes decrease out-of-pocket donations relative to no incentive at all. These two simulations suggest that neither linear matches nor the threshold incentives we used in our field experiment are efficient fundraising techniques if the goal is to increase out-of-pocket donations.[30] Second, for the same amount of money spent on matches, the average out-of-pocket donation is 15% ($36) higher in the threshold schemes compared to the linear 0.5-to-1 scheme. Third, the one and two optimal thresholds increase out-of-pocket donations relative to no incentives at all by about 11% and cost about the same in matches. Fourth, adding a second threshold increases out-of-pocket donations only marginally and cost slightly more in matches. Almost all of the gains in out-of-pocket donations are attained with only one threshold.[31]

5.4 Field implementation of optimal incentives

The optimal incentives derived from our model estimations were implemented in the field in November 2018, giving an opportunity to assess their effectiveness. As part of its annual grant cycle, the private foundation we partnered with offered two possible threshold match incentives to participating charities: a threshold/match of $175 or a threshold/match of $1,250. These thresholds were chosen because they were not salient or common donation amounts and they were derived from the model estimates based on two alternative goals of a

[29] The calculations use the same parameters as those in Figure 6.

[30] Average donations from the field experiment data for Nov 1-3 are $268 in the control and $250 in the 25-100-500 treatment, 7% lower.

[31] We note that further gains could be obtained if the match is allowed to be different from the threshold.

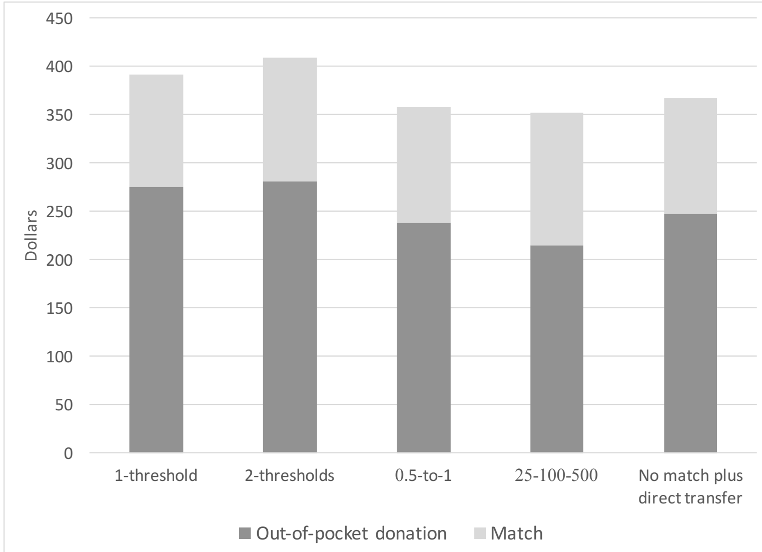


Figure 7: Comparison across alternative fundraising schemes

charity.[32] The \$175 threshold is predicted to maximize the strength of donor participation, albeit not necessarily the average out-of-pocket donation.[33] The \$1,250 threshold is predicted to increase the average out-of-pocket donation. We assess the impact of these thresholds on out-of-pocket donations. Because we do not have historical data on these donors and charities or data without matches, we do not evaluate the impact of these thresholds on the strength of donor participation.

Figure 8 shows the predicted cumulative distribution of donations (in log donations) under these two policies if they had been offered to the charities participating in the 2017 field experiment. That is, we use the model estimates based on the 2017 data to simulate what donors would have done if offered these alternative incentives. The figure shows significant bunching at the threshold donation level in both incentive schemes.

In the 2018 field implementation of these schemes, charities could chose either the \$175 match or the \$1,250 match, total matching funds were restricted to \$10,000 per charity and a donor could only receive one match. To give some perspective on the decision faced by the charity on which scheme to choose, a charity with a base of 100 donors that chose the \$1,250 match would increase out-of-pocket donations by \$2,800 (\$28×100), relative to the baseline donation of \$247, and would require only 10 large donations to exhaust the available

[32]To give perspective, in 2016, from over 5,000 donations made to 42 charities, 7 were for \$175 and 6 were for \$1,250, representing 0.3% of all donations.

[33]For low thresholds, the model predicts that a large number of donors would decrease their donation. By definition, only those willing to donate less than \$175 would increase their donations and the increment in their donations will never exceed \$175. However, anyone willing to donate more than \$175 might decrease their donations. This could lead to a decrease in the average out-of-pocket donation.

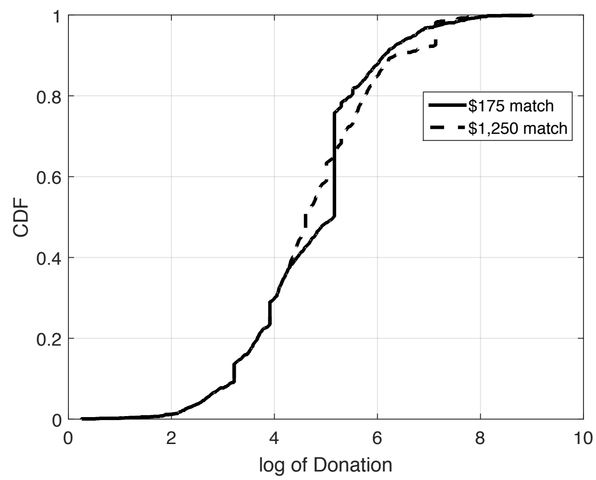


Figure 8: Predicted distribution of donations in 2018 field implementation (using 2017 data)

matching funds.[34] At the \$175 threshold match, the same charity would face a loss in out-of-pocket donations of \$3,000 (-\$30×100), where \$30 is the expected loss in mean out-of-pocket donation under this scheme.[35] Also, it would need 58 donations of at least \$175 to exhaust the matching funds. This exercise suggests that the size of the charity's donor base should affect which policy is adopted. Note that the predictions are based on the estimates from the 2017 field experiment and are not customized to any particular charity.

In total, 66 charities participated in the field implementation, and 36 agreed to share their donation data with us. Twenty-eight out of the 66 participating charities (42%) chose the \$1,250 threshold, and this is comparable to the 17 out of 36 charities (47%) in our sample. Of the charities that chose the \$1,250 threshold, 14 decided to offer the \$175 threshold as well, funded with their own fundraising dollars. While this hybrid threshold match incentive was not one we derived as optimal for the charity, the field implementation was not conducted under the tight experimental conditions we used in November 2017. Charities were free to adjust their messaging and fundraising efforts as they saw fit.[36]

Nonetheless, the hybrid threshold creates an additional counterfactual that allows a further test of the predictions of the model. Figure 9 shows the distribution of donations across the two match incentives and the hybrid incentive in log(donations). First, we observe little

[34] At a threshold of \$1,250, the average donation is predicted to be \$275.

[35] At a threshold of \$175, the average donation is predicted to be \$217.

[36] The only data shared with us by the charities includes donation date and donation amount during November 2018. We do not have background information on the charities or donors or the number of individuals who received the match offer for each charity. Thus, we do not know donation rates and are limited in our ability to assess the balancedness of treatments across charities.

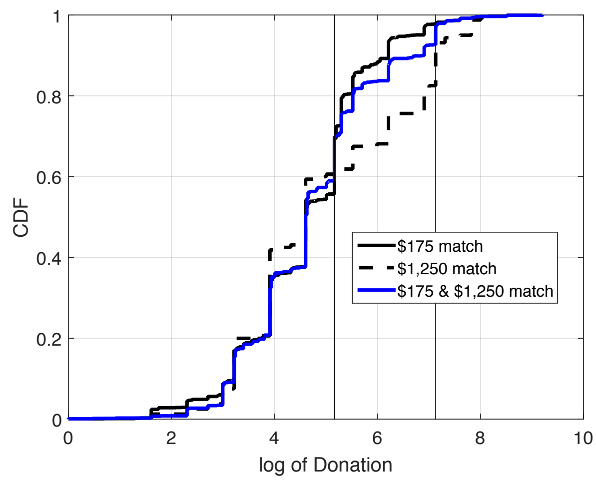


Figure 9: Distribution of donations in 2018

bunching of donations at \$175 ($\sim$ 5.16 in log(donation)) for the charities that chose the \$1,250 threshold only, but significant bunching for charities that chose the \$175 threshold only. There is significant bunching in donations at \$1,250 ($\sim$ 7.13 in log(donations)) for charities that chose the \$1,250 threshold only. Bunching can be observed at both thresholds for those charities that adopted a hybrid match.

Even though the underlying distribution of willingness to donate of donors participating in the 2017 campaign is likely different from those participating in the 2018 campaign, we can perform some comparative statistics exercises to assess the usefulness of the structural estimates. Table 4 reports what our estimates predict would happen if these incentives were used with the 2017 sample and what was observed in practice in 2018. The model predicted that, of those that chose the \$1,250 match incentive, 11.5% of donations would be at this level, and 13.2% actually were. Combining both thresholds, as in the hybrid version, is predicted to decrease the proportion of donations at the high threshold. This is because having a low threshold available reduces the incentive for the marginal donor to increase her out-of-pocket donation. This prediction comes from incentive theory, and we confirm this in our data. In the observed data and the model, the proportion of donations at \$1,250 decline in the hybrid scheme. The model, however, over predicts the proportion of donors giving at the \$175 threshold (57.8% compared to observed 41.0%). The disparities in predicted and observed behavior suggest that charities may change their fundraising efforts, especially among smaller donors.

Another way to assess the effectiveness of the incentive schemes is to look at the overall

Table 4: ACTUAL AND PREDICTED CHOICES

Incentive	Observed in 2018 % at $1,250	% at $175	Avg. Donation	Predictions based on 2017 sample % at $1,250	% at $175	Avg. Donation
$1,250	13.2%		$461	11.5%		$277
$175		44.2%	$222		66.3%	$220
$1,250 & $175	6.4%	41.0%	$285	8.5%	57.8%	$243

performance of the match incentives across all charities. Using the aggregated donations reported to the foundation for all 66 participating charities, the total amount of out-of-pocket donations raised using the thresholds we recommended was $2.1 million, which represents a 3.7% increase from the previous year and the largest in the history of the program. The average out-of-pocket donation in the entire campaign was $309, which is a 48.8% increase from the entire campaign in the previous year.[37] This confirms the drop in fundraising efforts from charities since larger average donations are obtained from fewer donors and can potentially explain the over prediction of $175 donations from the model. The total amount spent in matches was $0.55 million, representing a 6.8% increase over the previous year.

These indicators point to the effectiveness of the incentives derived from our estimations and that there is room to increase donations at the intensive margin even when the demand for giving is inelastic. Importantly, these results illustrate how field experiments coupled with structural estimation can be used to improve incentive designs since they provide a prediction on parameters outside those used in the experiments and by charities themselves.

6 Conclusion

We explore optimal policy design in the context of charitable giving. Charities may wish to encourage giving by offering potential donors match incentive schemes that effectively lower the price of giving. Yet, it is unclear what is the best manner to do so. Important considerations are the willingness of individuals in the target population to donate and the objectives of the charity. A charity might want to encourage giving by new donors, increase the intensity of participation of all donors or aim to maximize out-of-pocket donations. In the latter case, we show that the optimal match a charity should offer is a threshold match. This match creates nonconvex budget sets and excludes individuals with a low willingness to donate (i.e. larger incentives should be offered only to individuals with a higher willingness to donate). This is in stark contrast to the common practice of charities that offer linear one-to-one matches that reduce the price of giving for both low and high willingness to give donors (e.g. “every dollar donated is matched with another dollar given to the charity”).

[37]The 2017 campaign included additional charities that did not participate in our field experiment.

Threshold matches might offer a viable option to designers dealing with *behavioral* agents who distort/ignore marginal incentives (as also noted in, Huck and Rasul, 2011).

Donation behavior is well characterized by a simple model of giving with focal points and inattention, which we structurally estimate using the responses to the threshold match incentives from the field experiment. The parameter estimates are used to evaluate alternative matching schemes under the objective of maximizing out-of-pocket donations. We find that the optimal threshold match should be set high (i.e. $2,000), in line with the theoretical predictions. Small donors should not be offered a match incentive. Comparing various matching schemes, we find that threshold match incentives outperform linear match incentives and no incentives. A linear matching scheme, that costs the same as the threshold scheme in matches paid out to the charity, raises less money than the optimal threshold match scheme. The threshold scheme generates an average out-of-pocket donation that is 15% higher than under the comparable linear scheme.

Importantly, we note that had we stopped our inquiry with the results from our field experiment, we would have concluded that threshold matches were not effective fundraising incentives, since average donations and donation rates did not differ across treatment and control groups. However, we would have been wrong. By combining the exogenous price variation created by the field experiment with structural estimation, we uncovered that a threshold match design can be more effective than a linear match. But, the threshold level needed to receive a match must be set much higher than the levels we set in our field experiment design based on informed best guesses.

Two of the optimal incentive schemes predicted from our structural estimations were subsequently implemented in the field with 66 charities. These new matching schemes illustrate that thresholds properly calibrated to the environment in which these charities operate are effective at increasing out-of-pocket donations. Our findings offer a cautionary warning of the potential pitfalls and costs of relying only on best-guess incentives to evaluate policies. Instead, the results from initially parameterized field experiments, coupled with a structural estimation iteration, can be informative and efficient at discovering optimal policies.

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APPENDICES ARE FOR ONLINE PUBLICATION

A Appendix A

In this Appendix, we show the wording for the treatment and control emails. Amounts in brackets change depending on the treatment.

A.1 Wording of email appeal - $50 - $150 - $500 treatment:

Subject line: Your donation Nov 1-3 will be matched

Message: We have two great matching offers in November – one that starts today and one on Giving Tuesday (November 28).

Thanks to a generous supporter, any donation of at least [$50] between now and November 3 will be matched.* [charity name] will receive a

- [$50] match if your donation is between [$50] - [$149]
- [$150] match if your donation is between [$150] - [$499]
- [$500] match if your donation is [$500] or above

On Giving Tuesday, a donation between $25-$99 will receive a $25 match, a donation between $100-$499 will receive a $100 match, and a donation of $500 or above will receive a $500 match.

If you are able to give [$50] or more today, your gift will be matched, and any donation of $25 or more on Giving Tuesday will still be matched.

[DONATE NOW]

* Today's match offer requirements: (1) Donations must be made using the same email address to which this message was sent, (2) This match offer can only be used by the recipient of this message. It cannot be shared with others, (3) Matches on Giving Tuesday are not subject to these two requirements, (4) Only one donation will be matched per period (Nov 1-3 and Giving Tuesday), (5) November matches subject to a $10,000 cap.

A.2 Wording of Control email:

Subject line: Your donation in November will be matched

Message: We have a great matching offer available on Giving Tuesday (November 28).

Thanks to a generous supporter, any donation of at least $25 will be matched.* [charity name] will receive a

- $25 match if your donation is between $25 - $99

- $100 match if your donation is between $100 - $499
- $500 match if your donation is $500 or above

If you are able to make a donation on Giving Tuesday, remember that your gift of $25 or more will be matched.

[DONATE NOW]

* Match offer requirements: (1) Only one donation will be matched, (2) November matches subject to a $10,000 cap.

B Appendix B: Optimal Incentives to Give

To gain some intuition on the effect of different incentive schemes, we derive the theoretical optimal incentives to increase out-of-pocket donations.[38] Suppose an individual has quasi-linear preferences over donations received by the charity (g) and consumption (c). In particular, assume that $U(g, c : \theta) = v(g : \theta) + \omega - p_g g$, where θ is a propensity to donate, ω is income and p_g is the price of giving.[39] Let $m(g)$ be a match the individual generates for the charity if a donation of amount g is made. Let $F(\theta)$ be the distribution of the propensity to donate in the population, which we assume is know to the charity.

The problem faced by a charity is:

$$\begin{aligned} max_{m(g)} \int g(\theta) dF(\theta) \text{ subject to:} \\ (i)\ g(\theta) \in argmax_g v(g + m(g) : \theta) + \omega - p_g g \\ (ii)\ v(g(\theta) + m(g(\theta)) : \theta) + \omega - p_g g(\theta) \geq max_g v(g : \theta) + \omega - p_g g \\ (iii) \int m(g(\theta)) dF(\theta) \leq M \end{aligned} \tag{4}$$

The charity chooses the incentive to maximize the expected out-of-pocket donation subject to an incentive compatibility constraint (i), a participation constraint (ii) and a budget constraint (iii). Note that the budget constraint is characterized by money already in the charity's possession to incentivize giving. It is common for charities to receive these type of funds from wealthy donors or private foundations. Constraints (i) and (ii) stipulate that an individual will choose the donation amount that maximizes utility and will accept the incentive only if it increases utility with respect to the outside option. Contrary to the classic monopoly pricing problem (Goldman et al., 1984), a charity cannot prevent individuals from donating directly and bypassing the incentive. Charities, therefore, have to offer incentives in the presence of competitive options available to donors (i.e., donating directly). The problem faced by the charity can be rewritten as a standard nonlinear pricing problem in which an indvidual offers a donation $\hat{g}$ in exchange for a payment of $\hat{m}$ with the additional constraint that $\hat{g} \geq g^*(\theta)$, where $g^*(\theta)$ is the amount the individual would donate in the absence of an incentive.[40]

Figure B.1 provides an illustration of the optimal incentive scheme. In this illustration, we assume that $v(g : \theta) = \frac{\theta((\frac{g}{\theta})^{(1-1/e)} - 1)}{1-1/e} + \theta$ and $F(\theta)$ is lognormal with parameters ($\mu =$

[38] We note that a private foundation, granting agency or large donor seeking to support a charity in its fundraising efforts might not have the objective to maximize out-of-pocket donations when offering support. Instead, they might care about creating a habit of giving or enhancing the utility of the donor. Indeed, our conversations with different program and development officers suggest that there might be multiple goals in mind when designing the conditionality of a grant to a charity. Saez (2004) discusses a related issue of optimal taxes in the presence of altruistic agents. Huck et al. (2015) discuss optimal incentives in the presence of a lead donor.

[39] For a discussion of the advantages and disadvantages of this functional form assumption, see Kleven (2016).

[40] Given the assumption discussed in the subsequent footnote, this is a textbook example of an incentive problem.

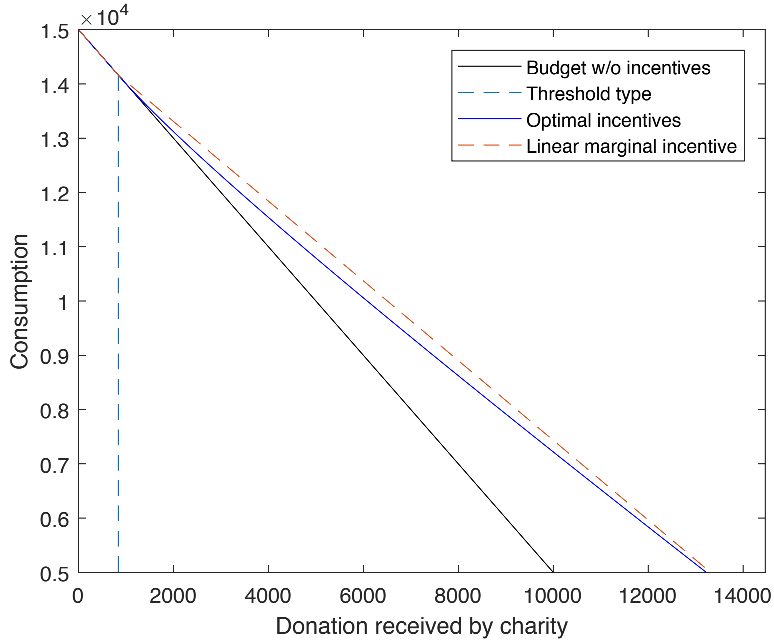


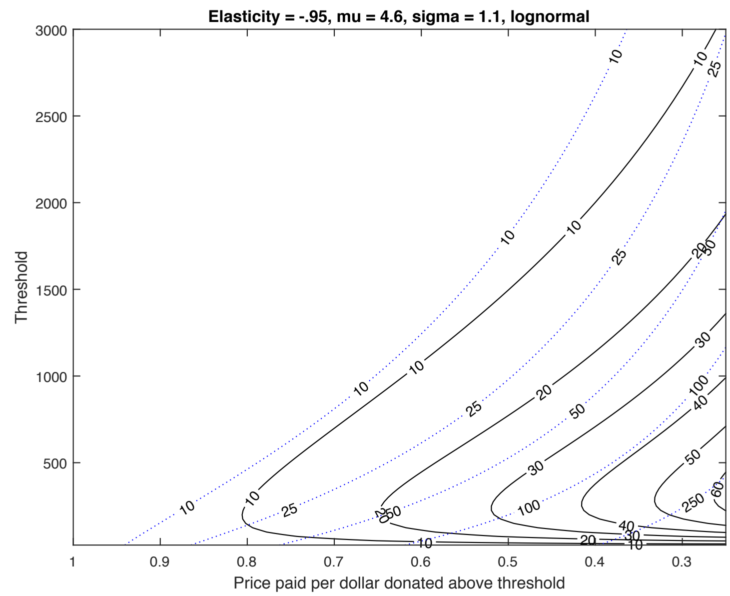
Figure B.1: Theoretical optimal incentives

$4.6, \sigma = 1.1$).[41] The price elasticity, e, is assumed to be 0.95. The chosen parameters reflect the estimates from the full model in Appendix C. The figure shows the budget line an individual would face without a match incentive (black line) and the optimal incentive (blue solid line). There are two characteristics of the optimal incentive. First, because charities cannot exclude donors from donating directly and bypassing the incentive, the exclusion principle of nonlinear pricing manifests as the exclusion of small donors from receiving a match for their donation. Thus, the optimal incentive would only offer a match for donations above a certain threshold. In the figure, that threshold is demarcated at \$950. Second, the optimal incentive is nonlinear – larger donors are offered more generous matches. To highlight this characteristic, Figure B.1 includes a linear marginal incentive (red dashed line) along with the optimal incentive.

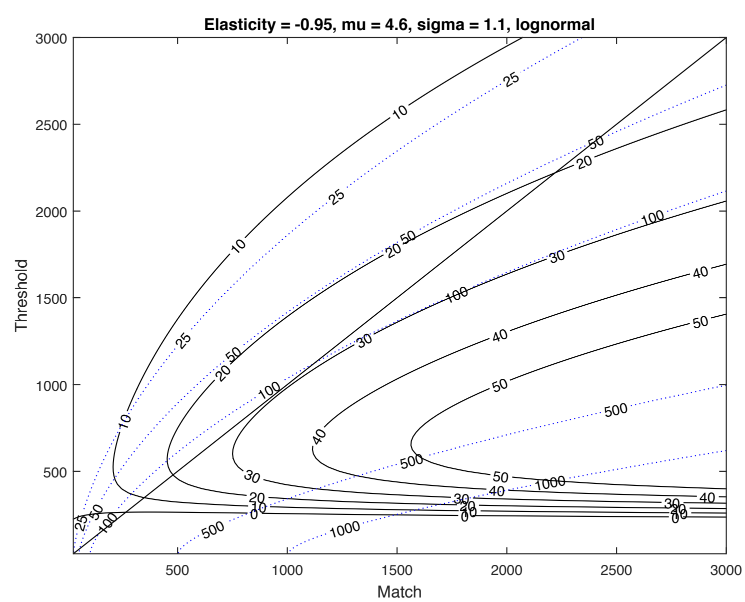
Because the optimal incentive, with a minimum donation threshold and nonlinear match, might be too complicated and difficult to explain to potential donors, we also consider simpler incentive schemes suggested by theory. The first class of incentives is a linear marginal subsidy for any donation above a threshold. The second class of incentives is a fixed match for any donation above a threshold.

We illustrate the optimal incentives under these two alternatives schemes in Figure B.2.

[41] This is an innocuous normalization of the utility function that implies the outside option for all donors is θ if the price of giving is 1. Optimal incentive schemes when outside options are allowed to vary with type are discussed in Jullien (2000) and Noeldeke and Samuelson (2007).



(a) Level curves for linear marginal subsidy



(b) Level curves for fixed match

Figure B.2: Marginal subsidies versus fixed match for a donation above a threshold

The figure presents simulations using the same parameters as before. In both graphs, dark lines represent level curves for a particular increase in mean out-of-pocket donations. The blue-dotted lines represent level curves for a particular average match paid per donor.[42]

The first class of incentives is illustrated in panel (a) in Figure B.2. As an example of how to read the figure, the solid black line labelled 10 traces out all the combinations of a threshold and a marginal linear incentive above that threshold that would increase average out-of-pocket donations by $10. This can be done by setting a threshold around $200 and price per dollar donated above that threshold of $0.80 (this is effectively a rebate of $0.20 per dollar donated). Or, the $10 increase could be achieved by setting a threshold at $1,000 and a price of $0.62 per dollar donated. In another example, if a charity wanted to increase mean out-of-pocket donations by $30, it could do so by offering a 1-to-1 match (a price of $0.50) for any extra dollar in excess of $350. The blue dotted lines represent the expected match to be paid for each threshold-price pair. For this last example, the average match per donor would be about $75.

The second class of incentives is illustrated in panel (b) in Figure B.2. This presents level curves of expected increases in out-of-pocket donations and expected matches to be paid if a charity uses a fixed match above a certain threshold. Note that the fixed match does not have to equal the donation threshold. As the figure shows, it could be higher or lower. As an example from panel (b), a charity trying to increase out-of-pocket donations by $30 could implement this by offering a $1,000 match for any donation of at least $1,000. The average match per donor in this case would be about $100.

The optimal match schemes we have characterized thus far include a combination of a minimum donation threshold to receive a match and the match incentive. Now, we turn to discuss the common 1-to-1 match schemes used by charities (i.e. "each $1 donated is matched with $1"). First, we note that this scheme would actually reduce out-of-pocket donations. To illustrate this and keep consistency with the assumptions made in this section, consider that the donor has an iso-elastic demand for donating equal to $g(p, \theta) = \theta p^{-0.95}$. In this case, a 1-to-1 match is equivalent to a drop in the price of giving to $\frac{1}{2}$ which leads to demand of $\theta \times 1.935$. Since the donor only pays half of the total amount received by the charity, the out-of-pocket donation with a 1-to-1 match decreases by about 4 percent. In this case, a charity would be better off by offering no incentives at all. Offering a 1-to-1 match crowds out an individual's underlying willingness to donate to the charity and reduces the amount of money a charity raises.[43]

Thus far, what the theory and simulations show is that there are a variety of ways that charities can use their funds to promote additional donations. In all examples though, the increase in out-of-pocket donations is less than the match paid out. One might ask, why would a charity offer a match at all? Charities often have other long-run objectives that merit such a strategy (i.e. growing a donor base). Also, some match incentive structures are more effective than others. If the aim is to maximally increase out-of-pocket donations

[42]Note that the level curves bend backwards, reflecting a global optimum. The population of donors are centered around some mean, so thresholds and prices cannot continually be reduced to keep increasing out-of-pocket donations. For some prices/thresholds, the same increase in mean out-of-pocket donations can be achieved by either matches that affect most donors or matches that affect few donors.

[43]This is in line with Huck and Rasul (2011) and Huck et al. (2015) who find that charities would raise more money by announcing a lead donor, rather than offering a linear match.

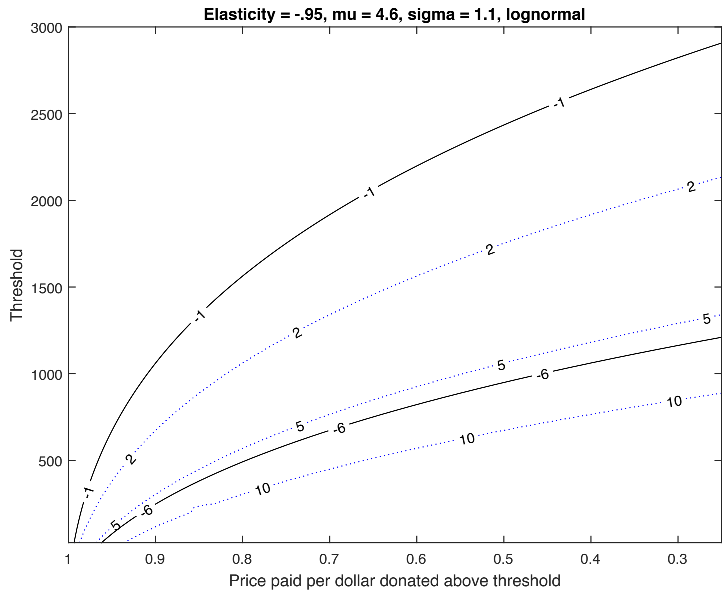


Figure B.3: Linear incentives in the presence of schmeduling

relative to the amount spent on matching, this requires appropriate design of incentives.

We note that the field experiment did not include a treatment with a threshold donation plus a linear match. This is for two reasons. First, our partner foundation had implemented a one-to-one match on the excess donation compared to the previous year with little success. Second, research shows that individuals react weakly to marginal prices (e.g. Ito, 2014).

As an illustration of the second reason, Figure B.3 shows a simulation of linear incentives if donors react to average prices rather than marginal prices as modeled by Liebman and Zeckhauser (2004) and Ito (2014). This type of behavior is called "schmeduling." The simulations show that, in the presence of schmeduling, marginal subsidies do not increase out-of-pocket donations. The intuition is that donors will underestimate price changes and act as if they were more price inelastic than they are.

Importantly, we can see why notches can be optimal in the presence of donors who distort price incentives (e.g. Kleven, 2016). Suppose a donor being offered a \$100 match for a donation above \$100 would like to make a donation as if the price has dropped to $\frac{1}{2}$, i.e. she schmedules. As shown in Figure 1 in Section 2, the optimal choice for a price of $\frac{1}{2}$ is not available to this donor. The donor can only choose between a donation at the notch (or above) or a donation at a price of 1. That is, notches prevent schmedulers from schmeduling. Finally, note that despite the fact that the marginal price above the threshold is equal to 1, schmedulers will think the price is actually below 1. These decision-makers will then crowd out donations less, an additional advantage of notches over marginal subsidies.

C Appendix C: Full structural estimations

We present structural estimations of the full model of giving in order to test the robustness of the assumptions made in the paper. In the estimations, we incorporate several elements: donors can get a price reduction to give in two periods - Nov 1-3 and Nov 28 and donors might also have behavioral biases and nuisance costs. We also allow for heterogeneity across donors. We assume donors solve the following problem:

$$
\begin{aligned}
max_{g_1} max_{g_2|g_1} \frac{\theta_i + \epsilon}{1 + 1/e} \left[\left(\frac{g_{i1} + \lambda_i T_1(g_{i1}) + g_{i2} + T_2(g_{i1}) + \epsilon}{\theta_i + \epsilon} \right)^{(1+1/e)} - 1 \right] \\
+ \gamma_{10} 1[g_{i1}/10 \in \mathbf{N}] + \gamma_{25} 1[g_{i1}/25 \in \mathbf{N}] + \gamma_{100} 1[g_{i1}/100 \in \mathbf{N}] + \\
+ \gamma_{10} 1[g_{i2}/10 \in \mathbf{N}] + \gamma_{25} 1[g_{i2}/25 \in \mathbf{N}] + \gamma_{100} 1[g_{i2}/100 \in \mathbf{N}] + \\
M - g_{i1} - g_{i2} - \\
\mu_i 1[g_{i1} > 0] - \mu_i 1[g_{i2} > 0]
\end{aligned}
$$

where e ($e < 0$) is the price elasticity, $g_{ij}, j \in \{1, 2\}$ is the out-of-pocket donation on Nov 1-3 and Nov 28 respectively, θ_i is the underlying willingness to donate, ϵ is a Stone-Geary parameter reflecting the minimum donation amount,[44] $\gamma_k \in \{10, 25, 100\}$ is a parameter capturing the taste for donations that are multiples of 10, 25 and 100, μ_i is nuisance cost parameter and $\lambda_i \in (0, 1]$ is a parameter capturing limited attention in the first period of a price reduction, Nov 1-3.

In the estimations, we assume that θ_i is distributed lognormal with potential discontinuities at $\{25, 50, 100, 150, 500, 1000\}$, $\lambda_i = \frac{1}{1+exp(-(a+\varepsilon_i))}, \varepsilon \sim N(0, \sigma_\varepsilon)$ and $\mu_i = \alpha + \beta\theta_i + \varepsilon_{\mu_i}, \varepsilon_{\mu_i} \sim N(0, \mu)$. Note that discontinuities in the distribution of the willingness to donate can be identified separately from the taste for round numbers due to the assumption that this taste is independent of the magnitude of the donation. Moreover, treatments 7-9, directly test for the existence of focal points by making matches \$10 larger than the threshold (i.e. \$35 if the donation is at least \$25).

The model above assumes donors care only about the total amount donated in November. While perfect substitutability of donations across time is justified by the results in Castillo et al. (2020), in the estimation, we allow for the possibility that some donors derive utility from each donation separately. We also allow for the elasticity to be correlated with the underlying propensity to donate. In particular, we assume $e = e_0 + e_1\theta + \varepsilon_e$, where $\varepsilon_e \sim N(0, \sigma_e)$.

We estimate this model using the Method of Simulated Moments (MSM). For each set of population and preference parameters (Ω), we simulate a sample of a size similar to that in our experiment (N). Given this simulated sample, we calculate the vector of moments of interest $\widetilde{M}_N(\Omega)$. The characteristics of this simulated sample then depend on all primitive parameters that characterize the model and the actual vector of pseudorandom number draws made in generating the sample. For actual moments M_N, the Simulated Method of

[44] This parameter is necessary to allow for nuisance costs as a reason to donate 0 even if θ, the propensity to donate, is not.

Moments is given by,

$$\hat{\Omega}_{N,W} = argmin_{\Omega}(M_N - \tilde{M}_N(\Omega))' W_N (M_N - \tilde{M}_N(\Omega))$$

where W_N is a symmetric, positive-definite weighting matrix. In our case, we use the inverse of the variance-covariance matrix of the population moments calculated using bootstrap. This process is repeated to minimize the distance between the simulated moments and the moments derived from the experimental data.

Table D.1 presents the parameter estimates of the model using all the data from the experiment. That is, the Nov 1-3 and Nov 28 windows. In the table, new donors are those who did not donate to the charity in the previous three years, and previous donors are those who made at least one donation. Large charities are those with more than 3,500 supporters, and small charities are those with less than 3,500 supporters.

We find that the estimate of the price elasticity is precisely estimated at -0.951. There is little evidence that elasticity is correlated with the underlying propensity to donate (θ) or that there is intrinsic variability in elasticity in the population. The SD of the parameter is very small (0.004). The estimated average donation is \$194.8 ($= exp(\mu_\theta + .5\sigma_\theta^2)$). While we allow for the mean and variance of the distribution of donations to vary across types of donors (previous, new), there is very little evidence that the distribution changes across these populations.[45] However, we do find difference across these populations on the extensive margin. Previous donors from small charities are more likely to donate than new donors.

We, again, find a significant role of attention in donors decisions. The estimates imply that, on average, donors treat matches in early November as half as large as those on November 28. Importantly, the estimates show that there is a lot of dispersion in the estimated level of attention. Given the estimates of the variance in the level of attention (3.659), the model predicts that some donors pay full attention to both matches while some donors ignore them completely. This is consistent with the finding that about 20% of our sample do not behave strategically when making donation decisions.

We can identify the role of inattention separate from the role of inter-temporal substitutability due to the fact that while most donors donate either in early or late November, some donors donate in both periods. We estimate the 3 out of 4 donors perfectly substitute between early and later periods. To our knowledge, our study is the first to report the heterogeneity of preferences for donations across time.

Finally, our field experiment allows us to separately identify the role of discontinuities in the utility function due to a propensity to prefer round numbers from discontinuities in the distribution of donations due to a taste for certain amounts of money. This is because treatments vary the thresholds and matches to differ from focal points found in past donations.

In sum, these alternative estimates show that the simplifying assumptions made in the paper are in line with a more complete model of behavior.

[45] See bottom panel of Table D.1.

Table C.1: Parameter estimates

Price elasticity	Estimate	Std error
e_0	-0.951	0.0002
e_1	1.1E-05	2.3E-8
σ_e	0.004	1.2E-17
Propensity to give		
$exp(\mu_\theta)$	100.9	9.055
σ_θ	1.147	0.0006
ϵ	0.354	0.001
Nuisance costs		
α	1.000	9.7E-8
β	3.750	0.056
σ_{μ_i}	1.214	0.001
Attention		
μ_λ	0.0002	6.7E-7
σ_λ	3.659	0.011
$E[attention]$	0.500	1.6E-7
Proportion of perfect substitutes		
Probability	0.745	0.0005
Taste for round numbers		
γ_{10}	0.026	0.0003
γ_{25}	0.022	0.0003
γ_{100}	0.241	0.0011
Discontinuities in the distribution of θ		
$Pr(g = 0)$: Small, previous	0.9362	0.0036
$Pr(g = 0)$: Large, previous	0.9960	0.0001
$Pr(g = 0)$: Small, new	0.9999	6.E-7
$Pr(g = 0)$: Large, new	0.9999	4.8E-7
Δ_{25}	9.1E-14	4.9E-15
Δ_{50}	1.2E-8	5.4E-10
Δ_{100}	3.5E-5	1.0E-6
Δ_{200}	3.4E-5	1.1E-6
Δ_{500}	3.7E-6	1.2E-7
Δ_{100}	5.1E-5	1.7E-6
Differences in the distribution of willingness to donate		
$exp(\mu_\theta)$: Small, previous	111.6	10.011
$exp(\mu_\theta)$: Large, previous	111.5	9.992
$exp(\mu_\theta)$: Small, new	111.5	9.999
σ_θ: Small, previous	1.267	0.0007
σ_θ: Large, previous	1.268	0.0008
σ_θ: Small, new	1.267	0.0008
N	112,349	

Table D.1: Λ matrix

	e	μ_θ	σ_θ	γ_{25}	γ_{50}	γ_{100}	γ_{150}	γ_{200}	γ_{250}	γ_{500}	γ_{1000}	κ_{small}	κ_{large}	ω
e	-0.0001	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0001	-0.0001	0.0001	-0.0209	0.0000	-0.0017	-0.0001	0.0002
μ_θ	0.0000	0.0035	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0040	0.0000	-0.0272	0.0000	0.0000
σ_θ	0.0000	0.0000	0.0012	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	-0.0322	0.0000	0.0000
γ_{25}	0.0000	0.0000	0.0000	0.0028	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
γ_{50}	0.0000	0.0000	0.0000	0.0000	0.0084	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
γ_{100}	-0.0001	0.0000	0.0000	0.0000	0.0000	0.0004	-0.0001	-0.0001	0.0001	-0.0209	0.0000	-0.0017	-0.0001	0.0002
γ_{150}	-0.0001	0.0000	0.0000	0.0000	0.0000	-0.0001	0.0028	0.0000	0.0000	-0.0116	0.0000	-0.0009	-0.0001	0.0001
γ_{200}	-0.0001	0.0000	0.0000	0.0000	0.0000	-0.0001	0.0000	0.0027	0.0001	-0.0164	0.0000	-0.0013	-0.0001	0.0001
γ_{250}	0.0001	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0167	0.0048	0.0000	0.0004	0.0001	0.0001
γ_{500}	-0.0209	0.0040	0.0002	0.0000	0.0000	-0.0209	-0.0116	-0.0164	0.0048	-0.0437	0.0000	-0.2892	-0.0209	0.0048
γ_{1000}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5295	0.0000	0.0000	0.0000
κ_{small}	-0.0017	-0.0272	-0.0322	0.0000	0.0000	-0.0017	-0.0009	-0.0013	0.0004	-0.2892	0.0000	32.7866	-0.0019	0.0005
κ_{large}	-0.0001	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0001	-0.0001	0.0001	-0.0209	0.0000	-0.0019	0.0346	0.0001
ω	0.0002	0.0000	0.0000	0.0000	0.0000	0.0002	0.0001	0.0001	0.0001	0.0048	0.0000	0.0005	0.0001	0.0093

D Appendix D: Andrews et al. (2017) Λ matrix

Andrews et al. (2017) suggest estimating matrix Λ which measures the sensitivity of estimates to small deviations from sustained assumptions. Calculating matrix Λ in our case requires estimating the Jacobian (matrix G) of the first-order conditions of the likelihood maximization problem. Our problem is not smooth due to the discontinuity of the budget set and discontinuities in the utility function. We estimate matrix G numerically (Newey and McFadden, 1994, p. 2190). In particular, the ε_n's used to approximate the derivates are linear functions of $n^{-\frac{1}{3}}$ to insure that $\varepsilon_n \to 0$ and $\varepsilon_n\sqrt{n} \to \infty$ as required. We customize ε_n for each parameter to deal with boundary and scale issues. The matrix Λ is calculated as $\Lambda = (G'G)^{-1}G'$, and Table D.1 show the results.