# *An Exploration of Donor Giving Patterns and Optimal Solicitation Strategies*

Ruicong Yan, Ryan Geczi, Alexander Zaiken, Matthew Puzder
Washington University in St. Louis
Advised by Seethu Seetharaman, Ph.D.
May 2015

## Introduction

There have been many studies on the effectiveness of advertising. Our research, as an extension of that literature, is concerned with whether soliciting for donations to non-profits has similar positive results. We feel that, as non-profits tend to serve the greater social good, researching a way to optimize donor solicitation at non-profits could have positive social consequences. Specifically, we want to look at firm-level data to see if there is a way to predict how likely a given person is to donate, and, if they do donate, the magnitude of that donation. Prior literature exists on giving rates on an industry-wide scale, but less research has been done at the firm level.

In this paper, we will discuss analyzing a dataset of approximately 100,000 donors to an anonymized, national non-profit organization. In this dataset, we were given each donor's giving history, their solicitation history, and as well as their postal code. We pulled the demographics of each donor's postal code to interpret what type of area each donor lives in. Using this information, we hope to build a model to predict the likelihood and magnitude of donations for this anonymous non-profit.

## Literature Review

To understand the donation process and the mindset on the receiving end of donor solicitation, our team analyzed literature on internet marketing, the effects of the growing number of nonprofits, psychological research on helping behavior, and analyses of the effects of morals and calls to moral action on decision making. These past publications allowed us to frame our analysis more effectively, and allowed us to explore existing experimental results to generalize the donor mindset and decision making process prior to designing our own model. Existing research has allowed us to identify the need to take a demographics-based approach to our analysis.

### *Understanding Targeted Marketing*

The donor solicitation process consists primarily of targeted marketing, often conducted through an interpersonal interaction during either the initial solicitation or later follow up attempts. While this type of interaction is fundamentally different than something like click-through advertising online, the main purpose of the marketing is the same in both approaches: to influence behavior and cause the target to undertake an action that he or she would not otherwise have done. Specifically in regards to click-through advertising, a study involving *Yahoo!* and a major retailer segmented the advertising shown to one million internet users to analyze changes in their click-through rates and purchasing behavior. In this study, users in the experimental group were exposed to two ad campaigns over the course of two months, leading to an average of 48 ad impressions per participant by the end of the campaign.

Because of the experimental design, the ad targeting was not influenced by purchasing behavior during the study with the intent of creating a causal link between the intentional display of the retailer's ads and purchasing behavior of recipients. The experimental group had a click-through rate of 0.28% and 7.2% of users clicked on at least one ad once the ads were shown. Among the users who did click on the ads instead of simply viewing them in a webpage, there was a measurable increase in per-user sales. However, the standard industry metrics such as page views and click-through rates could not be directly tied to accurate projections of the magnitude of the increases in customer spending after the campaigns (Lewis and Reilly 2011).

The results indicated that this type of advertising was effective, but could only be analyzed in terms of facilitating a sale rather than the total expenditure on the sale. The restrictions on predictability observed in this paper have implications that may translate directly to donor solicitation. Predicting the amount a new donor gives may be difficult, but as long as solicitation methods are well-targeted, there should be an implied incremental value to each new donor that would allow the organization to measure the effectiveness of a campaign.

With this lens in mind, the incremental analysis of sales and customer acquisition remains important when considering the manner in which advertising is conducted. According to conventional wisdom in advertising, promotional campaigns for a product can be viewed as interchangeable with targeted marketing efforts. When the sales from these two campaign types are measured on an incremental basis, a surprising number of promotions can be viewed as losing money when the comparison between the cost of the promotion and short-term sales is made (Abraham and Lodish 1990). This observation is analogous to the difference in approaches used by nonprofits in a benefit night (promotion) and through direct solicitation (i.e. targeted marketing).

Through applying concepts from business school core coursework on marketing, we think this is an important comparison to be made and may help us comprehend the effect of incentives on donation. At the end of the day, attending a benefit night can be a convenient manner to "give back" in the same manner that one might buy a promotional product in a store simply because it is prominently displayed in the aisle. The switching costs are lowered because pricing is the primary driver of purchase here. In the same manner, attending a benefit night that donates a portion of proceeds to the nonprofit implicitly uses another medium to pull in attendees – the brand awareness of the hosting restaurant – rather than directly appealing to potential donors with solicitation. The transactional nature of both attending a benefit night and buying a promotional product is an important distinction to make when analyzing donor outreach methods and their effects. This mindset helped frame the initial stages of our data analysis and pushed us to focus on individual solicitation types to the extent our anonymized data allowed us to do so.

*Nonprofit donations*

Annual charitable giving the in US now exceeds 2 percent of annual GDP and nearly doubled since 1990 when adjusted for inflation. The interactions between the three players in the space – donors, organizations, and the government – controls the policy implications and tax treatment of charitable activities. As nonprofits continue to become a larger economic force, policymakers have to continually reevaluate the tax implications for both the nonprofits and donors. According to John A. List, a professor of economics at the University of Chicago, real growth in charitable donations has outpaced the growth in the S&P 500 since 1990. Despite several recessions, List posits that social pressure to maintain past giving levels provides an implied sticky level of donations during bad economic conditions. His paper also observes a U-shaped pattern in giving across income levels, with both the high (>$100,000) and low (<$40,000) income brackets showing slightly higher average giving rates than the middle income bracket (~$75,000), with the median percentage of income donated to annually charity in 2005 being 5% (List 2011).

Most nonprofit donations are solicited via targeted fundraising campaigns, which are evaluated for success by metrics such as participation rates and aggregate contribution levels. Both are necessary for a thorough understanding of a campaign because a highly concentrated donor base can become problematic if attrition occurs when economic conditions deteriorate. Fundraising strategies typically involve ranking and segmenting potential donors, involving outreach to both existing donors and non-donors. These outreach efforts are typically classified as “warm-list” and “cold-list,” respectively.

Intuitively, the warm-list donors should be expected to have a higher participation rate in a campaign. A 2004 experiment involving the Center for Natural Hazards Research at Eastern Carolina University tested the effects of the warm/cold list approach and the effects of several solicitation types. A door-to-door marketing campaign was accompanied by a later solicitation mailing, with all donors (both warm and cold list) receiving the same solicitation materials over the course of the campaign. Analysis of donations received during and after the door-to-door campaign showed that warm-list donors had a participation rate nearly double that of the cold-list ones and also typically made larger contributions. In the mail solicitation campaign, participation was negligible from both groups, suggesting a “moral wiggle room” effect that did not occur during a face-to-face interaction (Landry et. al 2008).

The relationship between the nonprofit and warm-list donors suggests that following up in an acceptable manner must be prioritized, but the relationship may not be as simple as the common approach of checking in a few times per year for small donations. The choice and training of a solicitor, especially in face-to-face interactions, has a measureable effect on donor contributions. An experiment again involving the Center for Natural Hazards Research segmented solicitors along race and gender lines explored the effects of latent biases on donor contributions. Once donations were tabulated, the results indicated that minority households had contributed less compared to Caucasian households, regardless of the race of the solicitor, and that minority male solicitors raised the least amount of money overall, regardless of the race demographics of the target household (List and Price 2007). In addition to the implications about the choice of solicitors, these results indicate several potential effects of demographics on donor habits.

The List paper is likely intentionally open-ended in regards to this observation as further research is needed. Its findings suggest that controlling for demographic variables when evaluating pools of potential donors is important when trying to optimize solicitation strategies. Some of these demographic interactions will be explored later in this paper.

### *Helping Behavior*

Morals and morally motivated actions require one to consider the desires and interests of others. Religion, philosophy, and even the general norms of society often encourage helping behavior and the act of imaging yourself in another's place to determine the moral action one should undertake. Prompting someone into the act of perspective taking can make normative societal expectations more likely to trump self-interest during decision making. Essentially, this is the Golden Rule in action in society. One example of this effect can be found in task assignment activities. A two-part experiment involving helping behavior was conducted with psychology students at the University of Kansas to explore this phenomenon. Each member of the first experimental group was asked to assign tasks to himself/herself and a fictional "other", with the option of a coin flip to decide, if necessary. This group was given no guidance or directions regarding perspective taking and was simply asked to evaluate the potential reaction of the other after the task division was complete.

The second experimental group was told that there would be asymmetric consequences upon completion of the task, where the participant would receive two raffle tickets for successful completion of each component of the assigned task and the other would receive none. The participants were then provided with an opportunity to adjust the outcome to be "symmetrical" where each participant would receive one raffle ticket. In this group, an increased number proposed a fair division of tasks in addition to choosing to flip the coin, which was also perceived as fair by many participants. However, even in participants acting in the interest of fairness, task assignment was often still self-biased (Batson et. al 2002).

The belief that when one imagines himself in another's position it can stimulate moral action is common, but has had very little experimental testing outside of this study. The noticeably different outcomes between the two experimental groups in the Batson study indicate that framing and context drive perspective taking even when the baseline situation is nearly identical (as it was in the study). A shift in perceived status or severity of the other's dilemma in the experiment is the variable linked to the change in outcomes. The link between the universality of the results and the framing of the decision, though, was less clear as a potential predictive measure in the experiment. This observation has important implications for donor solicitation – the decision to help another clearly has many components in even the simplest of contexts, suggesting the multiple marketing approaches may be needed to optimize donor solicitation among a target group (Batson et. al 2002).

Understanding the most important components of the decision to help another is vital in determining what types of marketing and solicitation strategies to use. A collaborative study between professors at Texas A&M University, Oklahoma State University, and the University of Kansas explored the process of a helping decision and created several process diagrams to illustrate the multi-faceted influences on the process of the decision. They segmented the decision making process into 4 major components – perception, motivation, behavior, consequences – and identified factors that influence each. Within the subcategories created by these components of the decision making process, they were able to identify variables affecting the delivery of the request, common mood and situational variables affecting the donors, and other outside situational variables that could affect the process. From these identified variables of decision making, a conceptual framework and process map were developed and proposed to show the nonlinear nature of the decision to help another (Bendapudi et. al 1996).

The many junctures a decision must pass to elicit helping behavior indicates the potential severity of the hurdles a solicitor may encounter while trying to recruit a cold-list donor. Even with a warm-list donor, the decision to donate again is almost never a one-step process, which the study's map of helping decisions implies. The final identified component of the process ("consequences") contains the final decision point of whether to donate for the first time (cold-list) or continue to donate (warm-list). Reaching this step is an uphill battle, but suboptimal donor solicitation can still cause efforts to fail during follow up. The indications of this study regarding the multiple possible points of failure for donor recruitment show the importance of understanding as many variables that can affect the decision as possible, something our study aims to do while building upon the view of the decision to help as a nonlinear and sometimes non-economic decision.

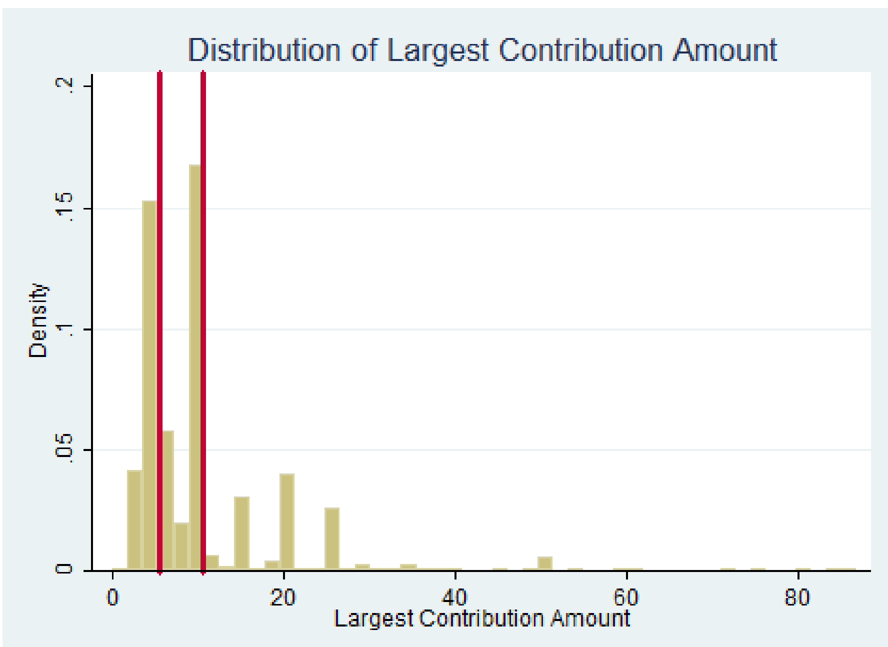
## Description of Dataset

Professor Seethu Seetharaman obtained the dataset used in this study from the Direct Marketing Educational Foundation (DMEF), which provides a variety of datasets to academic researchers and students. Working with Academic Data Set One, we examined data relating to a non-profit organization that uses direct mail to solicit additional contributions from past donors whose information is retained by the organization. The data are given for the period from October 1986 to October 1995 (base period), with a binary indicator of donation for each donor at December 1995 (later period). The data consist of 99,154 usable donor observations across both time periods. This dataset can be used to measure performance of solicitations in the base period and predict likelihood of future donations based on past observations.

Through this, we observe individual donor variables including latest 1-10 donations by date, dollar amount of each donation, type of solicitation prior to each donation, latest 1-11 solicitations by date and type, and zip code data on the donor's current residence. No other demographic information was given about individual characteristics of each donor. In an effort to improve on this gap in the dataset, we used the 2010 US Census to aggregate information on each zip code. Using the given zip codes for each donor, we collected the total population, percentage white, percentage of college graduates or higher, median household income, percentage below the federal poverty line, and median individual age. Given the lack of individualized information, we use this zip code level demographic data to make inferences about individual donors. We use a sample size of 1000 in our models analyzing this zip level demographic data. This size was largely due to the time constraint of Census lookup.

Observing the distribution of largest contribution amount, we note roughly three distinct "levels" of contribution, which we label small (up to $4), medium ($4 to $10), and large ($10 and up). This categorization holds approximately equal number of donors per group and allows some separation of effects based on donation magnitude. In particular, we see a clustering of donations at the $5 and $10 levels, suggesting some relation to the format of the solicitations sent. Though we are provided with no further details about the method of solicitation and how donation forms may be filled out (such as a check box with suggested dollar amounts versus a blank line to be written in), the observed clustering at $5 and $10 suggest that these may be offered as default options for donors. We note that this default setting may be an important driver of cumulative donation dollars, though further examination of its effects is outside the scope of our current research.

*Figure 1:*



Though we are given fields containing 1-10 past donations by date and 1-11 past solicitations by date in the base period, we choose to focus only on the most recent donation and solicitation date. Cleansing and proofing the data yielded significant gaps in historical donation and solicitations which over-complicated our planned analysis - as such, we use primarily the most recent dates of donation and solicitation in predicting outcomes in the later time period.

The mode of solicitation is given as coded categories A, B, C, and M (standing for miscellaneous) corresponding to numerous solicitation date ranges. Data by this organization suggest that different solicitation modes were employed based on the month of the year. Type A solicitations largely were employed in the months of October and March, Type B in January, and Type C in July and August. This was not strictly true, however, as approximately 20% of each solicitation mode was observed outside of its main usage month. As well, Type M captured miscellaneous solicitations that spanned a variety of different month frames over the 10 years. Overall, by matching each solicitation date instance with the given solicitation type, we categorize the latest solicitation as one of the four possible categories.

Finally, gender is given on each donor and listed as a categorical value representing Male, Female, Both, Company, and Unknown. For clarity of analysis and due to the limited number of observations other than male and female, we drop all other observations to only use male and female designations in our analysis.

Summary Statistics of Key Variables

| Variable | Description | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| TARGRESP | Donation Binary | 99154 | 0.27 | 0.45 | 0 | 1 |
| SLDAT1 | Latest Solicitation Date | 99154 | - | - | - | - |
| CNDAT1 | Latest Contribution Date | 99154 | - | - | - | - |
| CNDOL1 | Latest Contribution Dollar | 99154 | 9.13 | 6.73 | 0 | 85 |
| CNTRLIF | Lifetime Dollars Contributed | 99154 | 20.07 | 21.30 | 0 | 99 |
| CNTMLIF | Lifetime Times Contributed | 99154 | 2.22 | 2.14 | 0 | 9 |
| SLTMLIF | Lifetime Times Solicited | 99154 | 8.75 | 10.87 | 1 | 75 |
| SEX | Gender | 99154 | - | - | - | - |
| CONLARG | Largest Contribution | | | | | |
| 5-9 | | 38944 | - | - | - | - |
| 10+ | | 50942 | - | - | - | - |
| SLProgram | Solicitation Program | | | | | |
| B | | 98713 | - | - | - | - |
| C | | 98713 | - | - | - | - |
| M | | 98713 | - | - | - | - |

Interestingly, we see a relatively small mean donation amount (around $9) across the dataset which we would not expect from aggregate information from a national level non-profit. Without more complete context on the scope of our data, we cannot make any concrete conclusions about these observations. However, due to the direct mail method mentioned, we posit that this data contains merely a subset of total solicitations and donations, possibly part of a small scale campaign focused on one particular recurring initiative.

## <u>Analysis</u>

*Simple Choice Framework*

We began our consideration of donor actions through a discrete binary choice framework where we observe certain attributes of the donor in their decision to donate but have no information about the possible alternatives. Thinking about the net utility of a person to donate, some positive utility is achieved depending on the characteristics of that individual, some of which we observe in our dataset. Unobserved effects are captured in an error term assumed to follow a logistic distribution. From this we subtract the “cost” of donating multiplied by some coefficient of utility, or here, the magnitude of donation given, to result in the final net utility. This is compared to the possible alternative utilities of giving to another organization or not giving at all. So long as the net utility of giving to our specific organization is larger than the alternatives, the observed individual will (in theory) choose to donate. We summarize this choice in the equation below, where donor *i* in time *t* chooses to donate given observables *X* and the price utility *p*.

$$d_{it} = 1 \quad iff \quad X_{it}\beta_1 - \gamma p_{it} + \varepsilon_{1it} > Z_{it}\beta_2 + \varepsilon_{2it}$$

*Empirical Model Results (Logit + OLS)*

We begin by estimating the probability of donation across all solicitation types without differentiating out effects by type or largest contribution size. Model A:

$$Donate = \beta_0 + \beta_1(LatestSolDate) + \beta_2(LatestConDate) + \beta_3(LatestConDol) + \beta_4(DolConLife) + \beta_5(TimesConLife) + \beta_6(TimesSol) + \beta_7(LarCon) + \beta_8(Sex) + \varepsilon$$

Table 2
Model A Logit Output

| Variable | Description | Coeff. | Std. Error | Z | P > \|z\| | 95% Conf. | Interval |
|---|---|---|---|---|---|---|---|
| *SLDAT1* | Latest Solicitation Date | -0.00143** | 0.00 | -2.10 | 0.036 | -0.00277 | -0.00009 |
| *CNDAT1* | Latest Contribution Date | 0.00741*** | 0.00 | 66.64 | 0 | 0.00719 | 0.00763 |
| *CNDOL1* | Latest Contribution Dollar | -0.0259*** | 0.00 | -10.76 | 0 | -0.03063 | -0.02119 |
| *CNTRLIF* | Lifetime Dollars Contributed | 0.00472*** | 0.00 | 9.26 | 0 | 0.00372 | 0.00572 |
| *CNTMLIF* | Lifetime Times Contributed | 0.0428*** | 0.00 | 9.98 | 0 | 0.03436 | 0.05116 |
| *SLTMLIF* | Lifetime Times Solicited | 0.0176*** | 0.00 | 17.28 | 0 | 0.01563 | 0.01963 |
| *CONLARG* | Largest Contribution | -0.0025 | 0.00 | -1.15 | 0.252 | -0.00664 | 0.00174 |
| *SEX* | Gender | 0.0105 | 0.02 | 0.67 | 0.501 | -0.01998 | 0.04090 |
| *Constant* | - | -57.49 | 6.52 | -8.81 | 0 | -70.27459 | -44.70689 |
| *Observations* | 99154 | | | | | | |
| *LR Chi Squared* | 7859.03 | | | | | | |

Stars denote significance levels: 99 percent (***), 95 percent (**), 90 percent (*)

In this base model, we observe intuitive directionally of coefficients consistent with our expectations**.** As the total number of times contributed and cumulative dollars increases per donor, the likelihood of donation increases - both these results are significant at the 99% confidence level. As well, as lifetime solicitation instances increases, the log odds of donation also increase by 0.0176. We test for the marginal effects and find declining impact of each marginal solicitation. This is consistent with the intuition that though successive solicitations will likely stimulate more interest, each additional invitation sent will have a declining impact.

As the latest solicitation date increases and approaches the current time of observation, the log odds of donation decrease by 0.00143. This means that as the time between solicitations decreases, the probability of donation also decreases. Interestingly, we find the opposite effect with the latest contribution date, where time between contributions actually increases the likelihood of donation. As well, we find insignificant results between genders (where a value of 1 stands for male donors) and the single largest contribution.

We move on to include effects from each solicitation type. Model B:

$$Donate = \beta_0 + \beta_1(LatestSolDate) + \beta_2(LatestConDate) + \beta_3(LatestConDol) + \beta_4(DolConLife) + \beta_5(TimesConLife) + \beta_6(TimesSol) + \beta_7(LarCon) + \beta_8(Sex) + \beta_{9,10,11}(Solicitation) + \varepsilon$$

Table 3
Model B Logit Output

| Variable | Description | Coeff. | Std. Error | Z | P > \|z\| | 95% Conf. | Interval |
|---|---|---|---|---|---|---|---|
| *SLDAT1* | Latest Solicitation Date | -0.00126* | 0.00 | -1.83 | 0.067 | -0.00263 | 0.00009 |
| *CNDAT1* | Latest Contribution Date | 0.00731*** | 0.00 | 61.37 | 0 | 0.00707 | 0.00754 |
| *CNDOL1* | Latest Contribution Dollar | -0.0262*** | 0.00 | -10.86 | 0 | -0.03090 | -0.02145 |
| *CNTRLIF* | Lifetime Dollars Contributed | 0.0048*** | 0.00 | 9.40 | 0 | 0.00380 | 0.00580 |
| *CNTMLIF* | Lifetime Times Contributed | 0.0442*** | 0.00 | 10.22 | 0 | 0.03569 | 0.05262 |
| *SLTMLIF* | Lifetime Times Solicited | 0.0180*** | 0.00 | 17.49 | 0 | 0.01596 | 0.01999 |
| *CONLARG* | Largest Contribution | -0.00237 | 0.00 | -1.11 | 0.269 | -0.00656 | 0.00182 |
| *SEX* | Gender | 0.0083 | 0.02 | 0.53 | 0.593 | -0.02221 | 0.03885 |
| *SLProgramlvls* | Solicitation Type | | | | | | |
| *B* | | -0.0711 | 0.27 | -0.26 | 0.795 | -0.60765 | 0.46541 |
| *C* | | 0.0332 | 0.02 | 1.45 | 0.147 | -0.01169 | 0.07806 |
| *M* | | 0.110*** | 0.03 | 3.37 | 0.001 | 0.04592 | 0.17399 |
| *Constant* | - | -58.0477 | 6.64 | -8.75 | 0 | -71.05654 | -45.03877 |
| | | | | | | | |
| *Observations* | 98713 | | | | | | |
| *LR Chi Squared* | 7875.56 | | | | | | |

Stars denote significance levels: 99 percent (***), 95 percent (**), 90 percent (*)

We find largely consistent results with the previous model though we observe a significant decline in magnitude and significance of the latest solicitation date variable. Compared to the omitted solicitation type A, we find only M to be meaningfully more effective. Depending on the differences in cost between each program, it may be advised that B or C programs to be discontinued. In particular, since the B coefficient is negative (though not statistically significant), it is shown here to be less effective than A or C to solicit donations.

We move on to ignore differences between solicitation types but include the three different levels of contribution. Model C:

$$Donate = \beta_0 + \beta_1(LatestSolDate) + \beta_2(LatestConDate) + \beta_3(LatestConDol) + \beta_4(DolConLife) + \beta_5(TimesConLife) + \beta_6(TimesSol) + \beta_7(Sex) + \beta_{8,9}(ConSize) + \varepsilon$$

Table 4
Model C Logit Output

| Variable | Description | Coeff. | Std. Error | Z | P > \|z\| | 95% Conf. Interval | |
|---|---|---|---|---|---|---|---|
| *SLDAT1* | Latest Solicitation Date | -0.00146** | 0.00 | -2.14 | 0.033 | -0.00279 | -0.00012 |
| *CNDAT1* | Latest Contribution Date | 0.00735*** | 0.00 | 66.03 | 0 | 0.00713 | 0.00757 |
| *CNDOL1* | Latest Contribution Dollar | -0.0211*** | 0.00 | -13.67 | 0 | -0.02410 | -0.01806 |
| *CNTRLIF* | Lifetime Dollars Contributed | 0.00544*** | 0.00 | 10.58 | 0 | 0.00443 | 0.00645 |
| *CNTMLIF* | Lifetime Times Contributed | 0.0417*** | 0.00 | 9.75 | 0 | 0.03333 | 0.05011 |
| *SLTMLIF* | Lifetime Times Solicited | 0.0175*** | 0.00 | 17.54 | 0 | 0.01555 | 0.01947 |
| *SEX* | Gender | 0.0150 | 0.02 | 0.96 | 0.335 | -0.01547 | 0.04545 |
| *CONLARG* | Largest Contribution | | | | | | |
| *5-9* | | -0.117*** | 0.03 | -4.56 | 0 | -0.16724 | -0.06675 |
| *10+* | | -0.240 | 0.03 | -8.14 | 0 | -0.29802 | -0.18233 |
| *Constant* | - | -56.5733 | 6.52 | -8.67 | 0 | -69.35518 | -43.79145 |
| *Observations* | 99154 | | | | | | |
| *LR Chi Squared* | 7929.47 | | | | | | |

Stars denote significance levels: 99 percent (***), 95 percent (**), 90 percent (*)

We observe a highly significant decrease in the log odds of donation from donors who have donated a “medium” amount, from $5 up to $10, when compared to donors who have donated below $5. Though our findings in the “large” group are not statistically significant, the directionality of effect is similar. From this, we posit that past donors who have donated above a “small” amount are approaching their maximum willingness to donate to this specific initiative. In the sense that each individual has a maximum level of total donation dollars mentally allocated for a specific cause, larger past donation amounts lead these donors closer to this upper bound.

Finally, we include all factors in Model D:

$$Donate = \beta_0 + \beta_1(LatestSolDate) + \beta_2(LatestConDate) + \beta_3(LatestConDol) + \beta_4(DolConLife) +$$
$$\beta_5(TimesConLife) + \beta_6(TimesSol) + \beta_7(Sex) + \beta_{8,9}(ConSize) + \beta_{10,11,12}(Solicitation) + \varepsilon$$

Table 5

Model D Logit Output

| Variable | Description | Coeff. | Std. Error | Z | P > \|z\| | 95% Conf. | Interval |
|---|---|---|---|---|---|---|---|
| *SLDAT1* | Latest Solicitation Date | -0.00129** | 0.000693 | -1.87 | 0.062 | -0.00265 | 6.44E-05 |
| *CNDAT1* | Latest Contribution Date | 0.00725*** | 0.000119 | 60.89 | 0 | 0.007017 | 0.007484 |
| *CNDOL1* | Latest Contribution Dollar | -0.0213*** | 0.001545 | -13.8 | 0 | -0.02432 | -0.01827 |
| *CNTRLIF* | Lifetime Dollars Contributed | 0.00551*** | 0.000515 | 10.7 | 0 | 0.0045 | 0.00652 |
| *CNTMLIF* | Lifetime Times Contributed | 0.0431*** | 0.004314 | 9.99 | 0 | 0.034637 | 0.051547 |
| *SLTMLIF* | Lifetime Times Solicited | 0.0179*** | 0.001007 | 17.74 | 0 | 0.01589 | 0.019837 |
| *SEX* | Gender | 0.0128 | 0.015592 | 0.82 | 0.41 | -0.01771 | 0.043408 |
| *CONLARG* | Largest Contribution | | | | | | |
| *5-9* | | -0.1168** | 0.025726 | -4.54 | 0 | -0.16727 | -0.06643 |
| *10+* | | -0.2394*** | 0.029605 | -8.09 | 0 | -0.29744 | -0.18139 |
| *SLProgramlvls* | Solicitation Type | | | | | | |
| *B* | | -0.056 | 0.273544 | -0.2 | 0.838 | -0.59218 | 0.480094 |
| *C* | | 0.0323 | 0.022908 | 1.41 | 0.158 | -0.01256 | 0.077237 |
| *M* | | 0.108*** | 0.032698 | 3.3 | 0.001 | 0.043689 | 0.171862 |
| *Constant* | - | -57.19906 | 6.636274 | -8.62 | 0 | -70.2059 | -44.1922 |
| | | | | | | | |
| *Observations* | 98713 | | | | | | |
| *LR Chi Squared* | 7945.18 | | | | | | |

Stars denote significance levels: 99 percent (***), 95 percent (**), 90 percent (*)

Inclusive of all variables given, the observed effects are consistent with models A-C. We observe a decline of 0.1168 and 0.2394 in log odds of donation from “medium” and “large” donation groups respectively. As well, solicitation type M is shown to improve log odds of donation by 0.108 over program A, significant at the 99% level. Though not shown, we test for interactions between gender and different solicitation types in each model but find no significant results - there is no evidence to suggest that different types of solicitation methods affect each sex in a statistically different way. As well, interaction effects are also not significant in different contribution buckets (i.e. medium vs. large) by gender.

The lack of these interactions is not particularly surprising since it’s difficult to imagine scenarios where different wording or physical flyer characteristics may lead to different donations between genders. Perhaps most interestingly, we see no interaction between different types of solicitation and the latest contribution amount. Whereas differences in solicitation programs may be made in an attempt to increase donations, we do not see these effects - there is no statistical difference in donation amount across solicitation types. As a result, this nonprofit should seek to pursue the lowest cost and effort solicitation. We present a comparison of these models below (Table 6):

Table 6
Logit Model Comparison

| Variable | Description | ( A ) | ( B ) | ( C ) | ( D ) |
|---|---|---|---|---|---|
| *SLDAT1* | Latest Solicitation Date | -0.00143** | -0.00126* | -0.00146** | -0.00129** |
| | | (0.000682) | (0.000693) | (0.000682) | (0.000693) |
| *CNDAT1* | Latest Contribution Date | 0.00741*** | 0.00731*** | 0.00735*** | 0.00725*** |
| | | (0.000111) | (0.000119) | (0.000111) | (0.0001191) |
| *CNDOL1* | Latest Contribution Dollar | -0.0259*** | -0.0262*** | -0.0211*** | -0.0213*** |
| | | (0.00241) | (0.00241) | 0.00 | (0.00155) |
| *CNTRLIF* | Lifetime Dollars Contributed | 0.00472*** | 0.0048*** | 0.00544*** | 0.00551*** |
| | | (0.000510) | (0.000511) | 0.00 | (0.000515) |
| *CNTMLIF* | Lifetime Times Contributed | 0.0428*** | 0.0442*** | 0.0417*** | 0.0431*** |
| | | (0.00429) | (0.00432) | (0.00428) | (0.00431) |
| *SLTMLIF* | Lifetime Times Solicited | 0.0176*** | 0.0180*** | 0.0175*** | 0.0179*** |
| | | (0.00102) | (0.00103) | (0.000999) | (0.00101) |
| *SEX* | Gender | 0.0105 | 0.0083 | 0.0150 | 0.0128 |
| | | (0.0155) | (0.0156) | (0.0155) | (0.0156) |
| *CONLARG* | Largest Contribution | -0.0025 | - | - | |
| | | (0.00214) | - | - | |
| *5-9* | | - | - | -0.117*** | -0.1168** |
| | | - | - | (0.0256) | (0.0257) |
| *10+* | | - | - | -0.240 | -0.2394*** |
| | | - | - | (0.0295) | (0.0296) |
| *SLProgramlvls* | Solicitation Type | | | | |
| *B* | | - | -0.0711 | - | -0.056 |
| | | - | (0.274) | - | (0.274) |
| *C* | | - | 0.0332 | - | 0.0323 |
| | | - | (0.0229) | - | (0.0229) |
| *M* | | - | 0.110*** | - | 0.108*** |
| | | - | (0.0327) | - | (0.0327) |
| *Constant* | - | -57.49 | -58.0477 | -56.5733 | -57.19906 |
| | | (6.522) | (6.637) | (6.521) | (6.636) |
| *Observations* | | 99154 | 98713 | 99154 | 98713 |
| *LR Chi Squared* | | 7859.03 | 7875.56 | 7929.47 | 7945.18 |

Stars denote significance levels: 99 percent (***), 95 percent (**), 90 percent (*)

*OLS Analysis*

In addition to examining the likelihood of donation, we also explore the magnitude of effects given past behavior. We replicate our logit model formulations with OLS to view impacts of independent variables on donors who decided to donate. Roughly 27% of donor IDs actually donated - we pick out these respondents in our OLS regressions and examine the same variables effects on the dollar amount donated.

*Demographic Analysis - Logit*

Each observation also had the postal (zip) code that the observation was residing in at the time of giving. We used data from the 2010 United States Census and pulled in the following demographic variables based on zip code: the population, percent white, percent with a college degree or higher, median age, and median household income. Using this information, we wanted to see if there was a way to predict donations using the demographic area of where a donor resides -- specifically, the socioeconomic demographics listed. Given that Model D provided the best logit estimate for our data, we decided to use Model D with the demographic variables added in. Model E:

$$Donate = \beta_0 + \beta_1(LatestSolDate) + \beta_2(LatestConDate) + \beta_3(LatestConDol) + \beta_4(DolConLife) + \beta_5(TimesConLife) + \beta_6(TimesSol) + \beta_7(Sex) + \beta_{8,9}(ConSize) + \beta_{10,11,12}(Solicitation) + \beta_{13}(White) + \beta_{14}(BachelorsDegree) + \beta_{15}(Income) + \beta_{16}(Age) + \varepsilon$$

Table 7
Model D Logit Output (Demographics)

| Variable | Description | Coeff. | Std. Error | Z | P > \|z\| | 95% Conf. Interval | |
|---|---|---|---|---|---|---|---|
| *SLDAT1* | Latest Solicitation Date | -0.0041271 | 0.01025 | -0.40000 | 0.68700 | -0.02421 | 0.01596 |
| *CNDAT1* | Latest Contribution Date | 0.0066817*** | 0.00121 | 5.51000 | 0.00000 | 0.00430 | 0.00906 |
| *CNDOL1* | Latest Contribution Dollar | -0.0309843* | 0.01672 | -1.85000 | 0.06400 | -0.06375 | 0.00178 |
| *CNTRLIF* | Lifetime Dollars Contributed | 0.00935* | 0.00495 | 1.89000 | 0.05900 | -0.00035 | 0.01905 |
| *CNTMLIF* | Lifetime Times Contributed | 0.1045561** | 0.04738 | 2.21000 | 0.02700 | 0.01169 | 0.19742 |
| *SLTMLIF* | Lifetime Times Solicited | -0.0021901 | 0.01113 | -0.20000 | 0.84400 | -0.02400 | 0.01962 |
| *SEX* | Gender | -0.0572757 | 0.15770 | -0.36000 | 0.71600 | -0.36636 | 0.25181 |
| *CONLARG* | Largest Contribution | | | | | | |
| *5-9* | | 0.0329305 | 0.26517 | 0.12000 | 0.90100 | -0.48679 | 0.55265 |
| *10+* | | 0.0067211 | 0.30315 | 0.02000 | 0.98200 | -0.58745 | 0.60089 |
| *POPULATION* | Population of zip code | 0.00000607 | 0.00000 | 1.33000 | 0.18400 | 0.00000 | 0.00002 |
| *WHITE* | Percentage white of zip code | -0.0018286 | 0.00395 | -0.46000 | 0.64300 | -0.00957 | 0.00591 |
| *BACHELORSDEGREE* | Percentage with college degree | -0.003419 | 0.00746 | -0.46000 | 0.64700 | -0.01805 | 0.01121 |
| *INCOME* | Median income of zip code | 0.00000519 | 0.00001 | 0.79000 | 0.42800 | -0.00001 | 0.00002 |
| *SLProgramlvls* | Solicitation Type | | | | | | |
| *B* | | 0 | (omitted) | | | | |
| *C* | | 0.12344 | 0.23150 | 0.53000 | 0.59400 | -0.33030 | 0.57718 |
| *M* | | 0.2155586 | 0.30979 | 0.70000 | 0.48700 | -0.39162 | 0.82274 |
| *MEDIANAGE* | Median age of zip code | 0.0279426* | 0.01553 | 1.80000 | 0.07200 | -0.00250 | 0.05839 |
| *Constant* | Constant | -26.15425 | 97.73472 | -0.27000 | 0.78900 | -217.71080 | 165.40230 |
| *Observations* | 942 | | | | | | |
| *LR Chi Squared* | 93.57 | | | | | | |

Stars denote significance levels: 99 percent (***), 95 percent (**), 90 percent (*)

Given our randomized sample of approximately 1000 (58 observations were dropped due to a lack of data), we see a drop off in significance for several variables when compared with model D. Only latest contribution date remains at the same level of significance (at α=0.01). Latest contribution amount and the number of lifetime donations are the only other original variables that retain any significance, albeit a reduced amount -- however, we see significance at α=0.05 for the median age. We theorize that the median age variable is higher because older individuals may be more likely to donate. Adults later in life tend to have higher incomes, and our age variable does not account for the fact that for approximately the first fifteen to twenty years of life an individual has low to no income and could not donate to charity.

*Demographic Analysis – OLS*

We repeat this demographics model using OLS:

Table 8
OLS Model Comparison

| Variable | Description | ( A ) | ( B ) | ( C ) | ( D ) |
|---|---|---|---|---|---|
| *SLDAT1* | Latest Solicitation Date | 0.000154 | -0.000239 | 0.000624 | 0.000215 |
| | | (0.00579) | (0.00590) | (0.00579) | (0.00591) |
| *CNDAT1* | Latest Contribution Date | -0.00313*** | -0.00379*** | -0.00294*** | -0.00356*** |
| | | (0.000942) | (0.000999) | (0.0009446) | (0.00100) |
| *CNDOL1* | Latest Contribution Dollar | 0.656*** | 0.654*** | 0.779*** | 0.778*** |
| | | (0.0198) | (0.0198) | (0.0134) | (0.0134) |
| *CNTRLIF* | Lifetime Dollars Contributed | -0.0026 | -0.00176 | 0.000014 | 0.000846 |
| | | (0.00403) | (0.00405) | (0.00408) | (0.00410) |
| *CNTMLIF* | Lifetime Times Contributed | -0.0087 | 0.00358 | -0.00166 | 0.00971 |
| | | (0.0343) | (0.0349) | (0.0344) | (0.0349) |
| *SLTMLIF* | Lifetime Times Solicited | 0.0057 | 0.00843 | 0.0185** | 0.0211*** |
| | | (0.00801) | (0.00812) | (0.00784) | (0.00796) |
| *SEX* | Gender | 0.530*** | 0.516*** | 0.562*** | 0.549*** |
| | | (0.138) | (0.138) | (0.138) | (0.139) |
| *CONLARG* | Largest Contribution | 0.138*** | - | - | |
| | | (0.0172) | - | - | |
| *5-9* | | - | - | -0.504** | -0.518** |
| | | - | - | (0.222) | (0.223) |
| *10+* | | - | - | -0.140 | -0.165 |
| | | - | - | (0.255) | (0.256) |
| *SLProgramlvls* | Solicitation Type | | | | |
| *B* | | - | -1.569 | - | -1.707 |
| | | - | (2.221) | - | (2.223) |
| *C* | | - | 0.389* | - | 0.357* |
| | | - | (0.205) | - | (0.205) |
| *M* | | - | 0.337 | - | 0.320 |
| | | - | (0.289) | - | (0.289) |
| *Constant* | - | 29.658 | 39.558 | 23.753 | 33.383 |
| | | (55.209) | (56.389) | (55.264) | (56.445) |
| *Observations* | | 27162 | 27032 | 27162 | 27032 |
| *R Squared* | | 0.1763 | 0.1763 | 0.1746 | 0.1746 |

Stars denote significance levels: 99 percent (***), 95 percent (**), 90 percent (*)

Surprisingly, we find insignificance in the latest solicitation, lifetime donations and lifetime solicitation variables across all models. Whereas we find these variables to impact the likelihood of future donations, they do not seem to statistically impact the magnitude of those subsequent donations. This suggests a somewhat rigid range of donations inherent to each individual which remains unchanged by increasing the number of solicitations or repeated donations. Conventional thought on the differences between repeat and first donors may suggest that repeat donors are likely to donate higher dollar amounts. However, we find no evidence to support this claim and show that increased past donations have no significant change in donation amounts in the future.

As well, we observe the same ineffectiveness of solicitation type B and M over the base case A. Similar to our logit findings, type B solicitations directionally actually decrease the dollar amount donated, though this finding is also statistically insignificant in OLS. Overall, only type C solicitations seem to economically and statistically create higher returns than type A. Given mean donations of \$9.13, donors exposed to type C solicitations generate a 4% higher than mean donation amount when compared to type A.

This set of findings leads us to posit that donors are relatively difficult to persuade through the efficacy of solicitation material. Though they may increase the likelihood of donating overall, solicitations from this organization seem to have little effect on how much is actually donated each instance. Without knowing more information on the content of these solicitations, we can merely conclude that more research needs to be done on the efficacy of the messaging included in each solicitation. As well, due to the lack of evidence to show higher donations by repeat donors, we observe a lack of engagement in the organization's initiatives over time. Whereas repeat interactions typically are expected to increase donation dollars, we do not observe this effect with this dataset - this poses important questions about the specific messaging provided.

### *RFM Implications*

RFM (recency, frequency, monetary) analysis is used to classify donors and determine which donors are most likely to make donations again based on how *recently* they donated, how *often* they have donated, and how *much* they have donated in the past.

In terms of recency, our variables indicate that less recent contributions increase the odds of future donation. While this charity does have regular donors, these donors generally wait significant intervals of time before donating again. Despite waiting a long time in between donations, the data indicates that donors who have donated many times in the past are more likely to donate in the future. While solicitations are positively correlated with donations, successive donations have declining impact on frequent donors. Our monetary analysis is restricted to donations below \$80, but we do find that donors of a medium amount (\$5-10) are less likely to donate again than those who donate a small amount (>\$5). As we have stated, it is possible that individuals have a certain mental level of total donations allocated to this cause, and that they taper off donating as they approach this limit.

This charity may be able to increase the likelihood of future donation by targeting warm list donors (F), waiting a significant period of time between solicitations (R), and by only soliciting small amounts of money from such donors (M) in order to increase the odds of future donation. It is reasonable to assume that if people are donating small amounts of money regularly, they are less likely to *feel* that they are spending a large amount of money than if they had spent it all at once - this may help overcome the theoretical mental total donation limit. For example, if someone donates $80 he may feel that he has done his part, and he will remember donating this substantial amount of money, allowing him to rationalize a refusal to respond to solicitations and donate again because he feels that he has already done so much. However, if someone donates the same amount in $3 increments over a long period, he may get into a habit, and lose track of the total amount he has donated (and the mental limit).

It is likely to be more beneficial to the charity to have smaller (per donation) but more stable cash flows than higher one-time lump sum donations, so it should target its marketing and solicitation campaigns accordingly, particularly if the stable cash-flows sum to more total money per donor than the less frequent medium or large donations. This is consistent with Pierre Desmet's findings in his paper "Asking for Less to Obtain More" where he finds through an RFM analysis that asking for smaller amounts increases the likelihood of future donations, while asking for large donations decreases this likelihood (Desmet 1999). This strategy may also mitigate a steep decline in donations during periods of economic difficulty, since each small donation would have less of an economic impact on the donor.

In order to combat the declining marginal effectiveness of each solicitation, the charitable organization could both optimize the period of time between solicitations to maximize the marginal effectiveness of each, and solicit people in novel ways so that they continue to feel engaged even after repeated solicitations.

## **Results and Limitations**

We find that "warm-list" households are both more likely to contribute and tend to donate a higher dollar amount per giving instance. This result is intuitive because if someone has donated in the past, they are at least open to donating to this organization, whereas a random person might not be.

The single largest "small" or "large" donation made in the past increases future donation dollars while "medium" donations tend to decrease future donation dollars, however, these findings are only slightly significant. It is also worth considering that with a maximum of $80, it is hard to draw any conclusions from this result.

All of the demographic variables we tested such as race, income, and education level are statistically insignificant in determining the likelihood of an individual to contribute to this charitable organization. Given the nature of our data set, we are extremely reluctant to extrapolate this surprising result to charitable organizations in general. One explanation for income level not explaining one's willingness to donate is that this dataset only represents small donations (>$80). It is conceivable that for small amounts, average income does not have a substantial effect on likelihood to donate. Intuitively, donations of $1, $5, or $10 should be less sensitive to the donor's income level than donations of $1000 or more for example. Another explanation of this unlikely result, which likely played at least a small role, is that we assume that if residents on average within a certain zip-code make a certain amount of money, that the individual who donated makes that amount of money. Unfortunately, this method was the best possible proxy for an individual donor, and it is a weak one. Situations such as income disparity could have skewed our results. One extreme example of this is the existence of a zip code in which 1000 people report $1,000,000 in annual income, and 10,000 people report $100 in annual income. The average income in this area is $99,109, although no one actually makes that amount of money.

We also find that more solicitations improve the odds of donating up to a certain point, after which, the marginal benefit of each solicitation declines sharply. This also makes intuitive sense, because if a potential donor feels bothered by an organization, that ill-will is unlikely to manifest itself as monetary gifts. This result implies the existence of a cooling period between solicitations, which would maximize the marginal contributions per solicitation. More research would be needed to define the length, and other characteristics, of this period.

## Extensions

We would like to replicate this research with a more complete dataset, and many donation seeking organizations, such as charities, universities, churches, and political groups. While it is difficult to draw any conclusions regarding donation-seeking organizations in general based on the dataset used in this study, it would be possible to draw conclusions with richer data from a wide variety of institutions. The similarities and differences between these organizations would become clear. If we, or other researchers, were able to find the length of an optimal cooling period across organizations for example, this knowledge would be very helpful for such organizations in optimizing the allocation of resources across multiple solicitation campaigns. Additionally, if there is evidence found to support that a feeling of involvement with an organization increased the odds of donation, such organizations could invest more in reward ceremonies, dinners, and social events, while knowing the likelihood and magnitude of a return on their investment.

Overall, our research provides an important baseline in conceptualizing returns on investment for non-profit solicitations. There exists substantial opportunity for researchers armed with more robust datasets to dive deeper into the marginal effects of additional solicitations and the differences in response across multiple solicitation types.

# **Works Cited**


Abraham, Magid and Leonard M. Lodish. “Getting the Most Out of Advertising and Promotion.” *Harvard Business Review* (1990): Web. 6 Apr. 2015.

Batson, C. Daniel, David A. Lishner, Amy Carpenter, Luis Dulin, Sanna Harjusola-Webb, E. L. Stocks, Shawna Gale, Omar Hassan, and Brenda Sampat. "" . . . As You Would Have Them Do Unto You”: Does Imagining Yourself in the Other’s Place Stimulate Moral Action?" *Personality and Social Psychology Bulletin* 29.9 (2003): 1190-201. 2 July 2002. Web. 2 Mar. 2015.

Bendapudi, Neeli, Surendra N. Singh, and Venkat Bendapudi. "Enhancing Helping Behavior: An Integrative Framework for Promotion Planning." *Journal of Marketing* 60.3 (1996): 33-49. Web. 4 Mar. 2015.

Desmet, Pierre. "Asking for Less to Obtain More." *Journal of Interactive Marketing* 13.3 (1999): 55-65. Web. 28 Apr. 2015.

Landry, Craig E., Andreas Lange, John A. List, Michael K. Price, and Nicholas G. Rupp. "Is a Donor in Hand Better than Two in the Bush? Evidence from a Natural Field Experiment." *American Economic Review* 100.3 (2010): 958-83. Web. 3 Apr. 2015.

Lewis, Randall A., and David H. Reiley. *Does Retail Advertising Work? Measuring the Effects of Advertising on Sales via a Controlled Experiment on Yahoo!* Tech. Mountain View: Google, 2008. 21 Aug. 2008. Web. 27 Mar. 2015.

List, John A. "The Market for Charitable Giving." *Journal of Economic Perspectives* 25.2 (2011): 157-80. Web. 28 Mar. 2015.

List, John A., and Michael K. Price. "The Role of Social Connections in Charitable Fundraising: Evidence from a Natural Field Experiment." *Journal of Economic Behavior & Organization* 69.2 (2009): 160-69. Web. 4 Apr. 2015.