How responsive are charitable donors to requests to give?*

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Abstract

People tend to contribute more to a charity when they are asked to. Although this so-called 'power of asking' is well-known among fundraisers, the existing literature does not pay much attention to the role of donation requests in charitable giving. This paper uses a unique data set, which was designed to measure giving behavior in the United States, to estimate the causal effects of charitable solicitations on both the propensity to give and the amount of charitable contributions. In order to address the endogeneity of the donation requests due to non-random solicitation of charitable donors, I link this data set to IRS data on charitable organizations and the 2000 Census and propose identifying instruments. After controlling for the endogeneity, I find that donation requests increase the propensity to give by about twenty percentage points for those who are asked to give. This effect is robust under different specifications and with different sets of instruments, and is much larger than the estimates from univariate models, which assume that charitable solicitations are exogenous. I argue that this result may be associated with *donor fatigue*. Furthermore, I document that some identifiable characteristics of individuals are associated with a higher probability of being solicited. In particular, income, age, education, and race play significant roles in explaining the selection of potential charitable donors.

Keywords: charitable contributions, fundraising, non-profit organizations

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1 Introduction

Among many other fundraising techniques,[1] the iron law of fundraising, as Andreoni (2006) refers to it, is asking. People are not only more likely to give, but they also tend to donate more when they are asked to.[2] Recent studies on charitable activity in the United States show that, on average, charities spend around eighteen cents in fundraising expenditures to receive one dollar worth of donation.[3] If generous people are more likely to give, is it possible that all that fundraising money is really money wasted? Although, it is almost a truism among fundraisers that asking facilitates charitable giving, the relationship between charitable solicitations and giving behavior has rarely been studied, and efforts to understand the determinants of giving have mostly been limited to investigating the impact of numerous demographic variables, income, and the tax price of giving on the amount of charitable contributions. This paper uses a unique data set, which contains a question on whether the respondent is personally asked by a charity to give, to estimate the effect of charitable solicitations on both the propensity to give and the donation amount.

There are several surveys of empirical studies of giving. These include Clotfelter (1985, 1990), Andreoni (2006), and Vesterlund (2006). The established stylized facts in the literature are that better educated individuals with higher incomes are more likely to give and the tax price of giving has a negative effect on the amount of charitable gifts. The results on the other determinants of giving are mixed. For example, Duncan (1999) finds that married people tend to give more, whereas Lankford and Wyckkoff (1991) show that marital status is not a significant determinant of giving. Duncan (1999) and Lankford and Wyckkoff (1991) find no significant effect of age on giving behavior, whereas Andreoni, Brown, and Rischall (2003) find that older people are more likely to give. Similar contradictory results also prevail for the race and other personal characteristics of charitable donors.

[1] Other fundraising techniques include publicizing donor names and donation amounts (Glazer and Konrad, 1996; Harbaugh, 1998; and Romano and Yildirim, 2001), raffles (Duncan, 2002), and using seed money and refunds (Andreoni, 1998; List and Lucking-Reiley, 2002).

[2] Andreoni (2006) states that few people would give in the absence of direct appeals from charitable organizations. The power of asking is also a well-known technique among fundraisers. See, for example, Seymour (1992) and Keegan (1994).

[3] In 1999, public charities spent around \$36 billion on fundraising expenditures and received around \$195 billion from individual donations (Source: The Urban Institute, National Center for Charitable Statistics, Core Files, 1999; see also, Bradley, Jansen, and Silverman, 2003). Some estimates are more conservative. For example, Okten and Weisbrod (2000) report that the ratio between fundraising expenditures and private donations differ between 8% and 21% for different type of charitable organizations.

Only recently has the importance of solicitations in charitable giving and volunteering time been recognized by economists. Using a linear probability analysis, Freeman (1997) investigates whether people who are asked to volunteer their time are more likely to volunteer. He finds that being asked to volunteer has a huge effect on the propensity to volunteer and concludes that being asked by a charity is the single most important reason for why people volunteer their time. He also shows that employed, better educated people with higher incomes are more likely to be asked to volunteer than others and they are also more likely to accede to these requests. Later, Yörük (2007) finds that the effect of personal solicitations on the propensity to volunteer is considerable, yet much less than conventional wisdom once the endogeneity of solicitations is controlled for. Schervish and Havens (1997), estimating an ordinary least squares regression (OLS), show that there is a positive relationship between charitable solicitations and the percentage of income contributed by the household. Using panel data from charitable organizations, Khanna, Posnett, and Sandler (1995) and Okten and Weisbrod (2000) find a positive relationship between total charitable contributions and fundraising expenses. Bryant et al. (2003) take a different approach and investigate the factors that differentiate people who are asked to give from those who are not. They argue that several personal, social, cultural, and income variables explain who is solicited to give.

On the theoretical side, in a recent paper, Andreoni and Payne (2003) develop a model of fundraising that formally incorporates charitable solicitations. Their model assumes that people do not give unless they are solicited. However, their empirical intent is quite different from the current paper. Instead of focusing on the effect of fundraising efforts on giving behavior, they investigate the variation in fundraising efforts when a charity gets a grant from the government and they conclude that fundraising efforts fall due to crowding out.

Why would someone with a desire to give wait until they are asked by a charity? The existing literature offers two distinct answers to this question. On the one hand, Freeman (1993, 1997) and Bryant et al. (2003) suggest that requests for charitable donations carry some social pressure with them. People are more likely to respond to personal requests than to telephone or mail requests, and to requests from relatives and friends than from strangers. This suggests that charitable giving is a conscience activity, one in which people would not like to participate, but feel morally obligated to do so when they are asked to. In contrast, Andreoni and Payne (2003) argue that donors have latent demands to give, but because of prohibitive search costs of finding their favorite charity, their demand stays unexpressed until they are solicited. When solicited, this cost is eliminated and the donation is made. Despite their differences, all these studies share a common underlying hypothesis, that charities randomly select individuals to request donations.[4]

In fact, Schervish and Havens (1997) were the first to recognize that the selection of charitable donors is non-random, yet they fail to incorporate this observation into their empirical methodology. They argue that most of the charitable solicitations arise directly as a result of social interactions among people and that people are less likely to be influenced by impersonal methods, such as solicitations by mail or by phone.[5] Today, almost all charitable organizations hire professional fundraising staff. This fact raises a main concern that one's probability of being solicited is subject to a selection problem. Professional fundraisers are strategic players who carefully identify and keep track of potential donors by relying upon a number of quantifiable information sources, including donor databases.[6] Therefore, I hypothesize that most of the fundraising efforts are well-planned and targeted and hence some people are much more likely to be asked for charitable contributions. The probability of being solicited by a charity is associated with many identifiable personal and demographic characteristics. However, many unidentifiable characteristics that may be correlated with a higher probability of being solicited, such as previous donations, group membership, ideology, and social status, may also affect the probability of giving and the contribution amount.[7] Hence, one must take into account the possible endogeneity problem when estimating the casual effects of being solicited on both the propensity to give and the amount of charitable donations.

If people who are more likely to be solicited are also those who are more likely to give, then simple economic intuition suggests that not controlling for the endogeneity of donation requests would lead one to overstate the true relationship between being solicited and giving behavior.

[4]In their theoretical model, Andreoni and Payne (2003) assume that any individual is equally likely to be solicited by charitable organizations. In his empirical model, Freeman (1997) assumes that the probability of being solicited by a charity is exogeneously determined.

[5]Fundraisers are well aware of this. For example, Warner (1975) indicates that a direct-mailing fundraising campaign costs about two dollars for every new dollar raised. Moreover, impersonal methods generally yield low response rates. Mixer (1993) argues that direct-mailing fundraising campaigns typically yield a response rate of about 1% from a random list of potential donors.

[6]These databases record the information on donors' giving habits as well as the information on personal and demographic characteristics and serve as a primary tool in selecting target donors to solicit. There are dozens of commercial software available for this purpose. DonorPlus and DonorPerfect are widely-used examples.

[7]Notice that these individual characteristics may be available to fundraisers. However, they are not available to the econometrician.

The empirical findings of the current paper are counterintuitive, however. I appeal to a relatively new phenomenon, namely "donor fatigue" to explain this result. This is a widely used term among fundraisers, which is used to describe a state in which donors no longer contribute to a cause because they have become tired of receiving many appeals for donations. In particular, I argue that not controlling for the endogeneity would lead one to underestimate the true effect of being solicited on the propensity to give and the contribution amount because people who are more likely to be asked are also those who are more likely to suffer from donor fatigue. People who are identified as potential givers are more likely to get exhausted from receiving many charitable solicitations and in turn, more likely to decrease their donation amount or give up giving. Considering the expected effect of donor fatigue on giving patterns, a strategic decision of a charity would be to solicit donations from those who are less likely to give and convert non-donors to donors, since these people do not get many donation requests and are less likely to suffer from donor fatigue.

Empirical studies investigating the effect of solicitations on charitable giving, besides their methodological problems,[8] do not control for the endogeneity of being solicited. This is partly due to data limitations. This paper uses the Survey of Giving and Volunteering in United States (2001)[9] to investigate the effect of charitable solicitations on both the propensity to give and the level of contributions. I link this survey to IRS data on charitable organizations, the Religious Congregations and Membership Study (2000),[10] and the 2000 Census at the county level, and develop appropriate instrumental variables to address the endogeneity of charitable solicitations. The initial identifying instrument relies on the fact that public charities' fundraising efforts are generally limited to their local communities. In light of this observation, I hypothesize that as the number of charitable organizations per capita in a county increases, residents of the county are more likely to be solicited, while their giving patterns are affected only through charitable solicitations. Hence, I first use the number of public charities per capita by county as an instrument. Subsequently, as alternative instruments, I consider several measures of charity characteristics by county and some personal characteristics that may be associated with a higher probability of being solicited.

The empirical results confirm the hypothesis that being asked for a donation endogenously

[8] Freeman (1997) uses linear probability analysis and Schervish and Havens (1997) use OLS. Problems associated with using these methods in binary response models are well-known. See, for example, Greene (2003).

[9] Hereafter, SGV.

[10] Hereafter, RCMS.

affects both the probability of giving and the amount of money contributed. Using several techniques borrowed from the program evaluation literature, I find that charitable solicitations increase the propensity to give by about twenty percentage points for those who are asked to give. This effect is robust under different specifications and with different sets of instruments, and is also substantially larger than the effect estimated by conventional methods, which take the probability of being solicited as exogenous. The similar result also prevails for the relationship between being solicited and the contribution amount. I also examine gender differences in giving behavior. Yet in this case, due to data limitations, the results should be taken as informative rather than implying causal relationships. I show that the probability of being asked for a charitable contribution does not differ significantly by gender, but that the propensity to give does.

Finally, I argue that some other personal characteristics are associated with the higher probability of being solicited. In particular, I find that better educated, older people with higher household incomes are more likely to be asked for charitable donations. Furthermore, I find substantial evidence that race plays a key role in the selection of potential charitable donors. Hispanics are far less likely to be solicited compared with whites or blacks.

The rest of this paper is organized as follows. The next section presents a simple model to describe the selection of potential charitable donors. Section three presents the data and discusses various motives for charitable giving. Section four sets out the specifications for different empirical models. Section five presents the results for single equation models as a benchmark. Section six addresses the endogeneity problem of being solicited and discusses the results of bivariate probit and endogenous tobit models. Section seven discusses the validity of alternative identifying instruments. Section eight interprets the results. Section nine provides a conclusion and a discussion of policy implications.

2 How do charities select potential donors to solicit donations?

In selecting a target population to solicit donations, charities face a dilemma. On the one hand, it always seems to be a good idea to solicit donors who are known to have shown interest to the work of charity or those who are known to have given to a particular cause before.[11] Keeping

[11] For this purpose, searchable databases of charitable gifts are available online. For example, using such a database, a charity that works in the area of higher education can easily access the list of donors who have given to higher education before. See for example, www.nozasearch.com, a popular website which holds more than twenty two million searchable records of charitable gifts.

everything else constant, it is plausible to think that these people are more likely to give. On the other hand, there are mainly two reasons to expect that these people would donate less than expected or nothing at all. First, these people are more likely to be identified as potential donors by other charities and hence, more likely to receive many solicitations. Second, these people may think that they have given enough for a particular cause. In general, both of these cases can be interpreted as different forms of donor fatigue and are expected to have a negative effect on giving.

To see how targeting of potential donors depends on donor fatigue, assume that a charity has a fixed amount of money $F \geq 0$ to spend on fundraising and let $c > 0$ be the constant cost of soliciting each potential donor. Therefore, the charity chooses $n = F/c$ individuals to solicit donations.[12] Assume that there are two types of people in the population. The high type people are those who are more likely to be solicited by charities, but keeping everything else constant, are more likely to give. The low types, on the other hand, are those who are less likely to be solicited by charities. However, they are also less likely to give, keeping everything else constant. Suppose that there exists a production function Π with $\Pi' > 0$, which governs the transformation of charitable contributions to services. Let $i \in \{L, H\}$, then n_i denotes the number of people in each type such that $n_i \in [0, n]$. The objective of the charity is to select the number of low and high type donors to solicit donations, with $n = n_L + n_H$, in order to maximize the services provided. Formally, the problem of the charity can be written as:

$$\begin{aligned} \max_{n_H, n_L} \; & \Pi(D_L n_L, D_H n_H) \\ & s.t. \; F \geq cn \\ & n_L, n_H \geq 0 \end{aligned} \tag{1}$$

where D_L and D_H are the expected contribution amount of the low and the high types, respectively. I assume that the expected donation of both types negatively depends on the expected number of solicitors s_i due to the donor fatigue, i.e. $\partial D_i / \partial s_i < 0$, and high types are more likely to be solicited such that $s_H > s_L$.

First, suppose that Π simply depends on the total contributions, i.e., $\Pi = \Pi(D_L n_L + D_H n_H)$. Then, in order to maximize Π, it is sufficient to maximize the total contributions received. Since the total contributions is linear in n_i, there exists a corner solution to the maximization problem given in (1). The assumptions above is sufficient to imply that there exists a $\overline{s} > 0$ such that if

[12] Here, for simplicity, I assume that $n \in [0, \infty)$. The implications of the model does not change if the assumptions are modified such that n is assumed to be a non-negative integer, i.e., $n \in \{0, 1, 2, ..., N\}$.

$s_H - s_L < \overline{s}$, then $D_L < D_H$ and the charity solicits donations only from the high types, i.e., $n_H^* = n$. If $s_H - s_L > \overline{s}$, then $D_L > D_H$ and the charity solicits donations only from the low types, i.e., $n_L^* = n$. Finally, if $s_H - s_L = \overline{s}$, then $D_L = D_H$ and the selection of donors is random such that $n_L^* \in [0, n]$ and $n_H^* = n - n_L^*$.

A similar result prevails if a general form for the production function is assumed. Assuming interior solution to (1), the optimal number of each type to be solicited can be expressed as

$$n_i^* = n_i^*(F, c, D_L, D_H) \tag{2}$$

where $n_i^* > 0$, $\partial n_i^*/\partial D_i > 0$, and $\partial n_i^*/\partial D_j < 0$ for $j = \{L, H\}$. The charity solicits more (less) low type individuals as the number of charities which solicit donations from high (low) types increase, and vice versa since $\partial n_i^*/\partial s_i = \partial n_i^*/\partial D_i \times \partial D_i/\partial s_i < 0$ and $\partial n_i^*/\partial s_j = \partial n_i^*/\partial D_j \times \partial D_j/\partial s_j > 0$. Notice that the cost of soliciting both types of donors is the same. Hence, the equilibrium certainly depends on the relative significance of total amount of contributions received from each type in the production function. For the sake of simplicity, assume that the relative significance of both types are the same. Then, there exists a $\widetilde{s} > 0$ such that if $s_H - s_L < \widetilde{s}$, then $n_L^* \in (0, n/2)$ and $n_H^* = n - n_L^*$ which implies that number of low types of to be solicited must be less than the number of high types to be solicited, i.e., $n_L^* < n_H^*$. Similarly, if $s_H - s_L > \widetilde{s}$, then $n_L^* \in (n/2, n)$, $n_H^* = n - n_L^*$, and $n_L^* > n_H^*$. Finally, if $s_H - s_L = \widetilde{s}$, then the expected contribution of both types are the same and $n_L^* = n_H^* = n/2$ is the optimal number of each types to be solicited.

Therefore, the optimal targeting strategy of the charity is ambiguous. Given this ambiguity, the bias in a regression of being solicited on giving behavior is an important empirical question. If the charity believes that the donor fatigue does not exist or high types do not suffer from it much, then it should solicit donations from the high types. In this case, not controlling for the endogeneity of being solicited in individual giving equations should overestimate the true effect of being solicited. If the charity believes that high types suffer from the donor fatigue, then it solicits donations from those who are less likely to give. If this is the case, not controlling for the endogeneity of being solicited in individual giving equations should underestimate the true effect of being solicited. Finally, given the number of solicitors, if the expected donation of both types is the same, then the selection of donors would be random which implies that being solicited is not endogenous and running simple single equation models yield consistent estimate of being solicited.

3 Data and motives for charitable giving

The SGV is a random-digit dial survey conducted for Independent Sector by Westat Inc. with a sample of 4,216 adults, 21 years of age and older. The survey obtains information on household giving and personal volunteering habits, various indicators of relevant motivations, household social characteristics, selected demographic descriptors, and economic factors. Weighting procedures are used to ensure that the final sample of respondents is representative of all non-instutionalized adults, 21 years of age and older. This survey, given its scale, provides the most recent and comprehensive assessment of charitable activity in United States.[13]

The survey records information on giving for thirteen different charity categories.[14] I identify the respondent as a charitable donor if her household has given to at least one of these categories and calculate the amount of charitable contributions as the sum of money that the respondent has reported giving to each of the specific charity groups. Table 1 reports various personal and household characteristics that might be associated with the propensity to give and the mean amount of charitable contributions of the donors. More than 87% of the households contributed money, with an average contribution of $1,684. Most of the donors are people with high potential earnings at their peak earning ages and with a high opportunity cost of time. They tend to be employed, well-educated, married, and have larger families than non-donors. Among the charitable donors, 64% are employed, 50% are married, 33% are college graduates, and they have a mean family size of 2.48. The mean household income of donors is $55,268, compared with $29,792 of non-donors. Religion is also an important aspect of charitable giving. Among donors, 44% regularly attend religious services.[15] Appendix A further describes all the variables used in the empirical analysis

[13] This is the most recent survey in the 'Giving and Volunteering in the United States' series conducted for Independent Sector. The previous versions of this survey were conducted in person by Gallup on about 2,500 households, every two years, starting from 1988. The previous versions are not used for two reasons. First, the design of the survey and the wording of the questions were considerably changed in 2001. Second, the current version of the survey obtains information on the FIPS code, which clearly identifies the county that the household resides in. This information is used to merge the survey with other datasets and in proposing identifying instruments.

[14] These categories are religious organizations, youth development, education, health, human services, environment and animal welfare, adult recreation, arts, culture, and humanities, public or societal benefit, political organizations and campaigns, private and community foundations, international or foreign programs, and other unnamed areas. The survey also obtains information on giving to relatives and giving to friends and neighbors. This information is not used, however.

[15] Almost 52% of households give to both religious and secular charities, with a mean donation of $1,391 to religious charities.

in detail.

Figure 1, panel A plots the propensity to give and the amount of money contributed for different age groups. Both the propensity to give and amount of charitable donations have a decreasing trend in the 60's, but start to increase in the 70's. People are most likely to give in their 40's but tend to give more in their 50's and 80's.

3.1 Gender differences

Are there any significant gender differences among donors? Since the survey is conducted with only one adult member of household, the data report only household level giving data, not male and female giving separately for married couples and couples living with a partner. Hence, due to data limitations, it is hard to answer this question precisely. Yet, following Andreoni, Brown, and Rischall (2003), I try to provide at least a rough explanation by focusing on a question on the survey on who within the household is the primary decision maker in allocating money to charities. The question is worded as follows:

(Asked to all respondents) "Even though members of a household give as a unit, individual members may select certain charities or non-profit organizations to support. Who in your household is considered most involved in deciding which organizations you give to?"

Excluding the joint decision makers and the respondents who say their spouse, partner or another household member is the primary decision maker results a subsample of 2,397 respondents, 36% of which are male. I report the donor and non-donor characteristics by gender in Table 1. Male and female characteristics are virtually the same as for the whole sample, but differ in magnitude. In particular, a higher percentage of male donors are Hispanic, employed, and college graduates. Female donors are older and much more likely to attend religious services. Relative to their incomes, females contribute more to charities than males do. On average, they give 4.4% of their incomes to charities compared with 3.1% for males.

I further investigate male and female giving patterns in Figure 1, panels B and C. Panel B presents the relationship between age and the probability of giving, by gender. Female and male giving patterns are similar for different age groups, but with some differences. Females are more likely to donate than males up to the age of 59. They are also more likely to donate in their peak earning ages, from 40 to 59. Males are more likely to donate in their 70's. However, males and females considerably differ in the amount of donations. Panel C shows that males donate more money in absolute terms in all age groups except those from 20 to 39, which is also consistent with the earning and giving patterns summarized in Table 1.

As mentioned before, one cannot precisely test the gender differences with the existing data set. Moreover, the sampling of males and females may create a selection bias if any unobservables that affect the selection of the decision maker in an household are also correlated with the giving behavior of that household. Hence, for the rest of this paper, I will mostly focus on the full sample results. For comparison purposes, I will also present empirical results for males and females separately. These results should be interpreted with caution, however.

3.2 The tax price of giving

Since households are allowed to itemize charitable deductions on their federal and most state personal income taxes, each dollar given away costs less than a dollar if the household itemizes deductions. I compute the price of giving as $1 - t$ for those who itemize deductions and 1 for those who do not, where t is the marginal tax rate that the donor faces.[16] Since the SGV does not report marginal tax rates, I calculate this variable for each household using information on itemization status, number of household members, gross income, probable filing status, and the federal and state tax schedules for the relevant year. The calculation depends on two assumptions, both of which are consistent with the common practice in the literature.[17] First, I assume that those who itemize deductions in their federal income tax also itemize deductions in their state income tax, and second those who are married declare joint filing status. The resulting variable depends on the household's contribution amount and is referred to as the "last-dollar price" in the literature. Appendix A further discusses the calculation of this variable in detail.

3.3 The power of asking

The SGV has various questions about the ways in which people make charitable contributions. In particular, I focus on the effect of personal requests on giving behavior. The data on the variable of primary interest, being asked to give, are drawn from the following question:

[16] The marginal tax rate is calculated as the sum of the state and federal marginal tax rates, corrected for the fact that charitable deductions were not allowed in the state income tax in some states as of 2000. These states were Indiana, Massachussets, Ohio, Connecticut, Michigan, New Jersey, Illinois, Pennsylvania, and West Virginia.

[17] See, for example, Duncan (1999), and Andreoni, Brown, and Rischall (2003).

(Asked to all respondents) "Were you or members of your household personally asked to give money or other property to charitable organizations, including religious organizations, in 2000?"

Table 2 summarizes the answers to this question.[18] Even the raw numbers show the power of asking in charitable contributions. During the year prior to the survey, 58% of the respondents were asked to give at least once and more than 95% of those asked contributed money. In contrast, 42% of the respondents were not asked to give and among them, 80% contributed money. In addition, the mean amount given by the people who were asked to give is substantially more than the contribution of the people who were not asked to give. On average, people who were asked to give by a charity donated $1,882 compared with $950 for the people who were not solicited. Alternatively, people who were solicited donated 3.9% of their incomes on average compared with 2.6% for the people who were not solicited. In Table 2, I also report the responses of males and females separately. Females are more likely to be asked and more likely to accede to donation requests. Females also give more when they were asked to. When solicited, females donated 4.4% of their income on average compared with 3% for males.

The data also provide some evidence in support of the underlying hypothesis that most of the fundraising activity is well-planned and hence, the selection of donors for charitable solicitations is non-random. For example, although not reported here, only 8.7% of the respondents said that they or a member of their household contributed money by responding to a TV or radio request, maybe the only fundraising technique for which solicitations are random. More strikingly, among those people, 65% reported that being asked to give is the primary reason for why they or a member of their household made a charitable contribution. fundraising through street collections can also be thought of as an example of random solicitations. However, in contrast to radio or TV solicitations, a fundraiser can choose the location, and hence may target a specific population. Simple tabulations from the data show that 34% of the respondents made a charitable contribution through street collection but among them, 68% reported that being asked to give was the primary reason for their contribution. These tabulations are also in line with those of Freeman (1997), who argues that the same pattern is observed in the previous versions of this survey, in a telephone survey of volunteering and charitable giving among Boston residents (Freeman, 1993), and in a Rockefeller

[18] Although the request to give could have been made by mail, by phone, or face-to-face, there are at least two reasons to believe that most of the requests have been made face-to-face. First, face-to-face solicitations are known to be a more effective way of fund-raising than mail or phone solicitations. Second, people are more likely to remember and therefore report face-to-face requests than mail or phone solicitations.

Brothers study of charitable contributions (Rockefeller Brothers Fund, 1986).

4 The effect of donation requests on charitable giving

Recent formal models on fundraising rarely consider the problem of how charitable solicitations may affect the giving behavior of potential donors. In this section, I consider several limited dependent variable models in which the dependent variables are the propensity to give and the amount of charitable donations. Let θ_i^* be the probability that individual i is solicited by a charity. I hypothesize that fundraisers do not randomly solicit donations but they rely on quantifiable information sources in the selection of charitable donors. Hence, θ_i^* is a function of both the personal and demographic characteristics of donor i, which are observable to the econometrician, and unobservable characteristics, such as previous donations or the ideology of the donor.[19] Let X_i denote the observable characteristics of the donor i, and u_i represent the unobservable characteristics. Then, the probability of being solicited can be defined as $\theta_i^* = \theta_i^*(X_i, u_i)$. Given the solicitations received, individual i donates to charity only if the net benefit from giving is positive.

4.1 Empirical Models

First, consider a probit model with an endogenous binary independent variable of being solicited θ_i. For donor i, let d_i^* describe the net benefit from giving given by the following underlying model:

$$d_i^* = \beta_1' X_{1i} + \gamma\theta_i + u_{1i} \tag{3}$$

where X_{1i} is a covariate vector of income, the tax price of giving, and other observable characteristics of the donor and u_{1i} is a normally distributed random error with zero mean and unit variance. The net benefit from giving is not observed, but one observes whether individual i donated money or not, which is given as

$$d_i = \mathbf{1}\{\beta_1' X_{1i} + \gamma\theta_i + u_{1i} \geq 0\} \tag{4}$$

where $\mathbf{1}(.)$ denotes the indicator function. If fundraisers randomly select individuals to solicit, then, being solicited is exogenous and the parameters of equation (4) can be estimated directly by

[19] By 'ideology', I refer to the different varieties of services that the charity can provide and different charitable tastes of donors. In this context, Rose-Ackerman (1982) uses the word 'ideology', Economides and Rose-Ackerman use (1993) 'type', and Andreoni and Payne (2003) use 'quality'. I follow Rose-Ackerman (1982).

specifying a distribution for u_{1i}. However, if being solicited is endogenous, failing to take this into account results in biased parameter estimates.

In order to address the endogeneity problem, consider the following reduced form behavioral model:

$$\theta_i^* = \beta_2' X_{2i} + u_{2i} \tag{5}$$

where X_{2i} is a vector of covariates and u_{2i} is a normally distributed random error with zero mean unit variance. Again, one does not observe the probability of being solicited θ_i^* but rather a binary variable θ_i, which is given as

$$\theta_i = \mathbf{1}\{\beta_2' X_{2i} + u_{2i} \geq 0\}. \tag{6}$$

Since, both dependent variables are dichotomous, there are four possible states of the world ($\theta_i = 1$ or $\theta_i = 0$ and $d_i = 1$ or $d_i = 0$). Assume that the error terms are independently and identically distributed as bivariate normal with $E[u_{1i}] = E[u_{2i}] = 0$, $var[u_{1i}] = var[u_{2i}] = 1$, and $cov[u_{1i}, u_{2i}] = \rho$. Then, following Evans and Schwab (1995) and Wooldridge (2002), the likelihood function corresponding to this set of events can be estimated as a bivariate probit. If $\rho \neq 0$, then u_{1i} and u_{2i} are correlated and running separate probit regressions for the equations (4) and (6) yields inconsistent estimates for the parameter vectors. I further discuss the derivation of the log-likelihood function for this model in Appendix B.

Following Maddala (1983), it is widely believed in the literature that in the joint estimation of (4) and (6), parameter vectors are not identified in the absence of exclusionary restrictions, that is, if X_{1i} includes all the variables in X_{2i}. However, Wilde (2000) argues that Maddala's statement is valid only if X_{1i} and X_{2i} are both constants and shows that the model is identified as soon as both equations have a varying exogenous regressor. Monfardini and Radice (2006) also state that identification of this model does not require any additional instruments in X_{2i}, but note that in the absence of exclusionary restrictions, identification relies heavily on the functional form. Therefore, estimation with additional instruments yields parameter estimates that are more robust to distributional misspecification. Hence, I rely on identifying instruments in the analysis, but for comparison purposes, I also report the parameter estimates of a model which is identified thorough the functional form assumptions.

The second empirical model investigates the relationship between the probability of being asked and the amount of charitable donations. This analysis is motivated by a well-known fundraising technique, that is, fundraisers often ask for a certain amount when soliciting donations. In general, in order to receive the highest possible donation, the fundraiser proposes an amount, which is higher than what he expects to receive, and slightly reduces it until the donor accepts the proposed amount and makes the donation. Therefore, I hypothesize that being asked by a charity not only increases the probability of giving but also the amount of charitable donations. Let D_i^* be the amount of contribution given by donor i. Since some people do not donate any amount, the contribution amount is censored at 0. Hence, in order to test the above hypothesis, I estimate a tobit model with an endogenous binary variable of being solicited.[20] The joint system is defined as:

$$\begin{aligned} D_i^* &= \alpha_1' X_{1i} + \eta\theta_i + \varepsilon_{1i} \\ \theta_i^* &= \alpha_2' X_{2i} + \varepsilon_{2i} \end{aligned} \tag{7}$$

where D_i^* and θ_i^* are observed according to the following rule:

$$\begin{aligned} D_i &= \max\{(\alpha_1' X_{1i} + \eta\theta_i + \varepsilon_{1i}), 0\} \\ \theta_i &= \mathbf{1}\{\alpha_2' X_{2i} + \varepsilon_{2i} \geq 0\} \end{aligned} \tag{8}$$

where D_i is the amount of contributions censored at 0. The error terms are assumed to be independently and identically distributed as bivariate normal with $E[\varepsilon_{1i}] = E[\varepsilon_{2i}] = 0$, $var[\varepsilon_{1i}] = \sigma^2$ and $var[\varepsilon_{2i}] = 1$, and $cov[\varepsilon_{1i}, \varepsilon_{2i}] = \varphi\sigma$. If $\varphi \neq 0$, then ε_{1i} and ε_{2i} are correlated and separate probit and tobit estimation of the equations in (8) yields inconsistent estimates for the parameter vectors. Similar to the probit model with binary endogenous variable, I use the maximum likelihood (ML) methodology to estimate this model. The log-likelihood functions corresponding to this model is presented in Appendix B.

5 Univariate models

In this section, I first assume that the probability of being solicited is exogenous, i.e., $\rho = 0$ and $\varphi = 0$, and estimate single equation probit and tobit models as a benchmark.

5.1 Univariate probit models

The first three columns of Table 3 reports the univariate probit estimates for equation (4) for both the full sample and for males and females separately. In the first column, the highly significant and positive coefficient of the *asked-to-give* dummy implies that people who are asked to give are much

[20] This type of model is classified as corner solution outcome in Wooldridge (2002).

more likely to donate than those who are not asked to. The estimated coefficients of the other variables are consistent with the literature in this area. Race does not have a significant effect on the propensity to give. Churchgoing, better educated individuals with higher household incomes and larger families are more likely to donate. Furthermore, the coefficient on the tax price of giving is significantly negative.

Table 3 also reports the average treatment effect (ATE) and average treatment effect on the treated (ATT) of the *asked-to-give* dummy on the propensity to give. Let d_{i1} be the propensity to give if an individual is asked to give and d_{i0} be the outcome if she is not asked to. The ATE is defined as

$$ATE = E[d_{i1} - d_{i0}].$$

For a random individual, this corresponds to the average difference between the probability that an individual would donate if she is asked to give and the probability that she would donate if she is not asked to. Let n be the sample size and $\Phi(.)$ be the standard normal cumulative distribution. Then the ATE can be computed for the probit model as

$$\widehat{ATE}_{(p)} \equiv \frac{1}{n}\sum_{i=1}^{n}[\Phi(\widehat{\beta}_1' X_{1i} + \widehat{\gamma}) - \Phi(\widehat{\beta}_1' X_{1i})]. \tag{9}$$

Similarly, the ATT can be defined as

$$ATT = E[d_{i1} - d_{i0}|\theta_i = 1].$$

This is the average effect of being asked on those who actually are asked to give and can be computed as

$$\widehat{ATT}_{(p)} \equiv \left(\sum_{i=1}^{n}\theta_i\right)^{-1}\sum_{i=1}^{n}\theta_i[\Phi(\widehat{\beta}_1' X_{1i} + \widehat{\gamma}) - \Phi(\widehat{\beta}_1' X_{1i})]. \tag{10}$$

The estimated coefficient of the ATE implies that being asked by a charity increases the propensity to give by 9.2% for a random individual. For those who are actually asked to give, this effect is slightly lower. The estimated ATT suggests that solicitations increase the probability of giving by almost 7.8% for those who are solicited. The standard errors computed by the delta method suggest that these effects are highly significant.[21]

In the second and third columns of Table 3, I examine the same empirical model separately for males and females. Comparing male and female models, I find that giving behavior of males and

[21] Appendix C provides the details on the calculation of standard errors for the ATE and ATT.

females are significantly different. The hypothesis that their behavior is identical can be rejected at the 5% level of significance ($\chi^2_{(17)} = 28.65$, $p - value = 0.038$).[22] Both males and females are more likely to donate when they are asked to. Although females seem to be more likely to respond to charitable requests, this difference is insignificant. The equality of coefficients on the *asked-to-give* dummy across male and female equations cannot be rejected at conventional significance levels ($\chi^2_{(1)} = 1.64$, $p - value = 0.201$). As expected, the tax price of giving has a negative effect in both male and female probit models. The coefficient on the income variable is positive in both male and female equations, but is statistically significant only for females. For both males and females, education and attending religious services are positively associated with the propensity to give. The estimated ATE coefficients imply that being asked by a charity increases the probability of giving by 7% for a randomly selected male and 8.4% for randomly selected female. Finally, ATT coefficients imply that for those who are asked to give, being asked by a charity increases the probability of giving by 6% for males and 7% for females.

5.2 Univariate tobit models

In order to investigate the effect of charitable solicitations on the contribution amount, I first estimate a univariate tobit model as a benchmark. In this model, given the censoring of the amount of charitable donations at zero, the dependent variable is the natural logarithm of 1+ *total charitable contributions*. The tobit model with the natural logarithm transformation of the charitable contributions as the dependent variable is widely used in the literature, but I also add the constant 1 so that the transformed variable still takes the value zero if the original amount of donation is zero. I report the parameter estimates of this model in the last three columns of Table 3. The coefficient of the *asked-to-give* dummy is highly significant and positive, which implies that being asked for charitable donations not only increases the probability of giving but also increases the amount of charitable donations. As in the probit models, household income and educational attainment are positively associated with the amount of donations. Furthermore, white people with larger families tend to donate more, and the coefficient on the tax price of giving is significantly negative.

Following Greene (1999) and Angrist (2001), I also approximate the ATE and ATT of being

[22] This is the joint test of the equality of the coefficients in the male and female probability of giving equations.

solicited on the amount of charitable contributions. The ATE and ATT for the tobit model can be expressed as

$$\widehat{ATE}_{(t)} \equiv \frac{1}{n}\widehat{\eta}\sum_{i=1}^{n}[\Phi(\widehat{\alpha}_1' X_{1i} + \widehat{\eta}\theta_i)]. \tag{11}$$

and

$$\widehat{ATT}_{(t)} \equiv \left(\sum_{i=1}^{n}\theta_i\right)^{-1}\widehat{\eta}\sum_{i=1}^{n}\theta_i[\Phi(\widehat{\alpha}_1' X_{1i} + \widehat{\eta}\theta_i)]. \tag{12}$$

The estimated ATE implies that for a random person being asked increases the the donation amount by 1.09 in natural logarithm points, whereas for those who are asked to give this effect is slightly larger.[23]

Running separate tobit models for male and female donors yields similar results to the full sample estimates. Both male and female donors are highly responsive to requests to give. The estimated ATE and ATT coefficients imply that males donate more in response to a donation request. However, comparing the male and female tobit models, I cannot reject the hypothesis that the amount of charitable donations does not differ by sex ($\chi^2_{(17)} = 13.49$, $p - value = 0.703$) and that the coefficients on the *asked-to-give* dummy are equal across male and female equations ($\chi^2_{(1)} = 1.78$, $p - value = 0.182$). The effects of the other independent variables on male and female equations follow the same pattern compared with the full sample. For both males and females, education, household income, family size, and religion are positively associated with and the tax price of giving is negatively associated with charitable contributions.

5.3 Determinants of being solicited

Given the importance of being asked, it is natural to ask what observable characteristics of charitable donors influence fundraisers in selecting their target population to solicit. In Table 4, I consider probability of being asked as a binary outcome and investigate the factors that differentiate between those who are asked to give and those who are not.

Estimating a probit model for equation (6), I find that better educated, older individuals with higher household earnings are more likely to be asked for charitable donations. The probability of being solicited increases by almost 9% in response to a one percentage point increase in household income. College graduates are 12% more likely to be solicited compared with high school graduates.

[23] In order to interpret these estimates more easily, one can run a tobit model where the dependent variable is the total amount of charitable contributions. The estimated ATE coefficient for this model suggests that being asked increases the donation amount by around $596 for a randomly selected individual.

Furthermore, white people and people who regularly attend religious services are more likely to be asked for charitable contributions, whereas Hispanics are far less likely to be asked. The marginal effects of the race dummies on the probability of being solicited suggest that, keeping other variables constant, Hispanics are almost 10% less likely to be solicited, whereas white people are almost 11% more likely to be asked. This shows that race plays an important role in the selection of charitable donors.

Comparing male and female equations, I cannot reject the hypothesis that the probability of being solicited does not differ by gender ($\chi^2_{(16)} = 22.79$, $p-value = 0.120$).[24] As in the full sample estimates, higher household income is associated with a higher probability of being solicited, both for male and female donors. A one percentage point increase in household income increases the probability of being solicited by more than 9% for male donors and 8% for female donors. For both males and females, being white and employed considerably increases the probability of being solicited. Finally, better educated females are more likely to be solicited. For example, a female college graduate is 11% more likely to be solicited than a female high school graduate and moreover, an additional level of education increases the probability of being solicited by about 6%. A similar effect of education on the probability of receiving a donation request is also observed for male donors. For males however, the marginal effects on the education dummies are insignificant except for the coefficient of the *graduate school* dummy.

6 Models with an endogenous probability of being solicited

Up to now, all the single equation probit and tobit models treat the probability of being solicited as exogenous. This section addresses the possible endogeneity of the *asked-to-give* dummy in equations (4) and (8). For this purpose, I estimate several bivariate probit and tobit models with an endogenous probability of being solicited (hereafter, endogenous tobit models) under different specifications. The identification of these models rely on instrumental variables that are correlated with the probability of being solicited, but not with the propensity to give and the contribution amount. For comparison purposes, I also estimate benchmark bivariate probit and endogenous tobit models without considering any additional instruments by relying on functional form assumptions.

Initially, I use the number of public charities in each county adjusted for population (PCP) as

[24] This is the joint test of the equality of the coefficients in the male and female probability of being solicited equations.

an instrument. Using the Federal Information Processing Standard (FIPS) code assigned to each household in the data, I link the SGV to IRS data on charitable organizations, which is available through the National Center for Charitable Statistics compiled by the Urban Institute, and the 2000 Census, which is available through the U.S. Census Bureau. Both of the data sources contain information at the county level. The IRS data record information on both public and private charities, both of which are required to file a tax return unless they report gross receipts of less than $\$25,000$ or they are a religious organization.[25] In the analysis however, I use the data on the public charities for two reasons. First, public charities generally derive their funding primarily from the general public by receiving donations from individuals and grants from governments and private foundations. A private charity, on the other hand, usually derives its principal funding from a single source, such as an individual, family, or corporation, and does not solicit funds from the public. Second, public charities constitute 75% of all charitable organizations and include most of the non-profit organizations involved in the arts, health care, education, human services, and community service, as well as many others. Instead of fundraising at the national level, these charities generally focus on their local communities and solicit donors who reside within that community. Using IRS data, I calculate the total number of public charities for each county in the survey year 2000. The 2000 Census contains the population of each county for the survey year. Hence, for each household, I compute PCP as the total number of public charities located in the county of the household divided by the population of that county. I expect that as the number of charitable organizations per capita in a county increases, people who live in that particular county would be more likely to be solicited for charitable contributions, but their giving behavior is affected only through charitable solicitations.

Subsequently, I consider alternative instruments such as fundraising expenditures per capita by county, number of religious organizations per capita by county, and whether the respondent belongs to an organization or not. I will discuss the validity of PCP and these variables as appropriate instruments in the next section.

[25] This data come from the tax returns filed by IRS section 501(c)(3) organizations for year 2000 and are available at the Urban Institute's website at http://www.urban.org/.

6.1 Bivariate probit models

Table 5 reports the ML estimates of the base bivariate probit models using PCP as an instrument.[26] The estimate of the correlation coefficient ρ is negative, statistically significant, and the null hypothesis that $\rho = 0$ is rejected at 1% level using a simple Wald test.[27] The coefficient on PCP is highly significant and positive as expected. Therefore, one can confidently say that the error terms of the equations (4) and (6) are correlated and being solicited endogenously affects the propensity to give. Since the estimate of ρ is negative, I expect that single equation probit models underestimate the true effect of being solicited. This is precisely the case. Table 5 reports that the ATE and ATT of being asked by a charity on the propensity to give are 30% and 19.6%, respectively, both of which are substantially larger than the effect estimated by the single equation models.[28] Household income and education still have a positive effect on the probability of giving but their impact is much smaller once the endogeneity is controlled for. As in the simple probit model, those who are employed, white, and regularly attend religious services are much more likely to give, but the impact of these variables is smaller in the bivariate probit model. The effect of family size on the probability of giving is significantly positive and almost the same in the univariate probit and bivariate probit models. Finally, the tax price of giving has a significant and negative effect on the propensity to give, but its effect is smaller than in the single equation probit model. As in the probit model, those who are better educated, older, have higher household incomes, and regularly attend religious services are more likely to be solicited. Race remains an important determinant of the probability of being solicited. Whites are more likely to be asked for charitable donations, whereas Hispanics are less likely to be asked.

[26] It is widely argued in the literature that contributions to religious organizations should be studied separately from contributions to nonreligious organizations. Since the survey question on being asked includes both the secular and religious organizations, it is hard to estimate the effect of charitable solicitations on the religious giving separately. However, I also estimate a trivariate probit model in which the binary variables of giving to a secular organization, giving to a religious organization, and being asked are dependent variables. In this model, for those who are asked to give, I find that being asked increases the probability of secular giving by 15% and the probability of religious giving by 12%. These results are available from the author upon request.

[27] Alternatively, one can use a likelihood ratio (LR) test, which is computed as $-2(L_d + L_\theta - L_B)$, where $L_d + L_\theta$ is the sum of the log-likelihood function values of separately estimated probits of the probability of giving and the probability of being solicited equations and L_B is the log-likelihood function value of the bivariate probit model. The LR test, which is asymptotically distributed as $\chi^2_{(1)}$ under the null hypothesis, also rejects the null hypothesis at 1% level ($\chi^2_{(1)} = 71.77$, $p - value = 0.000$).

[28] Equations (7) and (8) are used to compute the ATE and ATT in bivariate probit models.

Table 5 also reports the estimates of the male and females bivariate probit models. The estimated coefficients of the female bivariate probit model are similar to the full sample model. The null hypothesis that $\rho = 0$ is rejected at conventional significance levels and the coefficient on PCP is significantly positive. The estimated ATE and ATT of being solicited on the propensity to give are 34.6% and 16.6%, respectively. For males, however, the results of the bivariate probit model are imprecise. In addition to the estimated ρ, the coefficients on *asked-to-give* and PCP are insignificant, suggesting that the proposed instrument fails to provide enough variation across households probably due to the small sample size of this group.[29]

6.2 Endogenous tobit models

As in the bivariate probit models, the identification strategy in endogenous tobit models relies on an instrument that is correlated with the probability of being solicited, but not with the error term of the contribution amount equation. Initially, I employ PCP as the identifying instrument and consider alternative instruments subsequently.

Table 6 records the ML estimates of the base endogenous tobit models for the full sample and separately for males and females. For the full sample, the estimate of the correlation coefficient φ is negative and statistically significant. Using a simple Wald test, I reject the null hypothesis that $\varphi = 0$ at 1% level. Moreover, the coefficient on PCP is significantly positive. Therefore, estimating a single equation tobit model yields inconsistent coefficients for the parameter vectors. Since the estimate of φ is negative, single equation tobit models underestimate the true effect of being solicited on the amount of charitable donations. As expected, the estimated coefficient on the *asked-to-give* dummy is substantially larger than the single equation estimates. After controlling for the endogeneity, the estimated ATE and ATT coefficients imply that being asked by a charity increases the donation amount by 2.9 in natural logarithm points for a randomly selected individual and 3.6 points for those who are asked to give. This effect is almost three times larger than the estimates of the base univariate tobit model.

The effect of the other control variables on the contribution amount is as expected. Household income, education, and attending to religious services are positively associated with, and the tax price of giving is negatively associated with the amount of charitable contributions. Similarly,

[29] It is also possible that the sampling of males and females is subject to selection bias as I have previously discussed.

people who are better educated, older, and have higher household incomes are more likely to be solicited, and race remains to be an important factor in the selection of potential charitable donors. The last four columns of Table 6 report the coefficient estimates for the male and female endogenous tobit models. As in the bivariate probit model, the endogenous tobit model yields imprecise results for males. The coefficient on the *asked-to-give* dummy is positive but highly insignificant. Moreover, although the coefficient of PCP is positive as expected, it is insignificant at conventional significance levels. In contrast, the estimates of female endogenous tobit model are in line with the full sample estimates. For a randomly selected female, the log donation amount increases by 2.8 points in response to being solicited by a charity. For females who are actually solicited, the log donation amount increases by 3.4 points.

6.3 Robustness Checks

Table 7 shows the results of the sensitivity tests performed to determine whether the estimates of the bivariate probit and endogenous tobit models are robust to exclusion of some covariates, inclusion of alternative control variables, and identification strategies relying on functional form assumptions. For all specifications, the null hypothesis that $\rho = 0$ or $\varphi = 0$ is rejected at the 1% significance level and the coefficient and ATE, and ATT estimates are significantly positive and substantially larger than the estimates of univariate models. The first specification replicates the results of the base bivariate probit model which is estimated using PCP as the instrument. The second specification relies on the functional form assumptions and records the estimates of a bivariate probit model without any additional instruments. In this model, the ATE and ATT of being asked on the propensity give are 26% and 18%, which are slightly lower than the estimates of the base bivariate probit model.

Since the survey does not report the marginal tax rates for the respondents, I calculated this variable for each household under certain assumptions. Hence, this variable may suffer from measurement error. Furthermore, although the tax price of the last dollar contributed is the most economically meaningful, it is also dependent upon the donation amount. Thus, one might suspect that the last-dollar tax price is endogenous and using it as an additional regressor may bias the estimates. In order to address these possibilities, I run two alternative robustness checks in specifications three and four. First, I exclude the tax price of giving from both the propensity to give and the probability of being asked equations. Next, I instrument the tax price of giving with the first-dollar price of giving and re-estimate both models.[30] In the third specification, the estimated coefficient, ATE and ATT of being solicited remain almost the same. In the fourth specification, the ATE increases by 0.3% whereas the ATT increases by only 0.2%. Furthermore, although not reported, the effects of income and the other independent variables on the propensity to give also remained the same.

The fifth specification adds three additional dummies to the propensity to give equation. These variables control for whether the respondent owns her residence, was born in USA, and voted in the 2000 presidential election. I hypothesize that people who own their primary residence are more integrated into their communities and hence more likely to give.[31] Similarly, I expect that people who were born in America and vote in the elections are much more likely to give to charities. Not surprisingly, although not reported, the estimated coefficients on these variables were positive and statistically significant except for the *born-in-the-USA* dummy, which was insignificant in all specifications. Including these extra variables increases the ATE by 2.6% but decreases the ATT by 1.4%.

In the analysis of endogenous giving models, I implicitly assume that people do not care how much others donate. In contrast to this 'pure warm glow' model, one can alternatively consider a 'public goods' model and add charitable gifts of others as an independent variable as in Duncan (1999). In order to construct the data for the charitable gifts of others, I use the FIPS code, which is assigned to each household in the data. Using the IRS data, for each household, the gifts of others are measured as the natural logarithm of the total contributions received in a county, excluding the current household. Although not reported, the coefficient of this variable was insignificant in all the models considered. Yet, the estimated coefficient, ATE, and ATT remains significantly positive. Reported coefficients in specification six shows that including this variable to the base bivariate probit model increases the ATE by 0.4% whereas the ATT remains almost the same.

The models using the PCP as an instrument depends on the assumption that charities' location decision is random. If some unobservable determinants of charitable donations are also correlated with the location decision of charities, then the PCP cannot serve as a valid instrument. Although

[30] The first-dollar tax price, which is the marginal tax rate that applies to the first dollar donated to charity, is a widely used instrument in the literature and assumed to be uncorrelated with the amount of charitable contribution deducted. See, Andreoni (2006) and Appendix A for further discussion.

[31] Another reason why homeowners would be more likely to give is that they are more likely to have substantial amounts of mortgage interest, which would make them more likely to be able to take an itemized deduction for their charitable gifts. I thank an anonymous referee for the interpretation.

there is no evidence that charities are non-randomly located by counties, I consider two possible scenarios in specifications seven and eight to investigate this possibility. The first possible scenario is that charities sort based on the donations they are likely to receive. If this is the case, then they are more likely to be located in countries where people are more likely to give. The seventh specification adds several county level controls to address this potential problem. These variables are the median age, Hispanic and Latino population as a percentage of total population, the total number of college graduates as a percentage of the population twenty five years of age and older, and the natural logarithm of median income.[32] Including these extra variables has almost no effect on the estimated coefficients of ATE and ATT.

The second possibility is that charities sort based on the needs of a community. If this is the case, charities are more likely to be located in counties where government does a bad job in providing public goods. In specification eight, I consider several types of personal transfer receipts from government by county to address this possibility. These variables are the natural logarithm per capita levels of retirement and disability insurance benefits, medical benefits, income maintenance benefits, unemployment insurance compensation, federal education and training assistance, and receipts of nonprofit institutions.[33] The bivariate probit model including these control variables yields virtually the same estimates compared with the base model.

The remaining specifications in Table 7 replicate the same sensitivity tests for endogenous tobit models. As in the bivariate probit models, the estimated coefficient, and the ATE and ATT of being solicited on the donation amount remain virtually the same compared with the estimates of the base model. Under different specifications the ATE and ATT of being solicited deviates from the original estimates at most by 0.06 and 0.1 natural logarithm points, respectively. Therefore, the estimated effect of being asked to give on both the propensity to give and the contribution amount is robust to possible endogeneity of the tax price of giving, the inclusion of alternative control variables, and identification strategies relying on functional form assumptions.

7 The validity of instruments

The PCP must satisfy two conditions to be a valid instrument for being solicited. First, it must be a determinant of being solicited. Second, it must not be a determinant of the propensity to give or

[32] These variables are available through the 2000 Census.

[33] These variables are available through Bureau of Economic Analysis (BEA).

the amount of charitable contributions, i.e., it must not be correlated with the error terms u_1 or ε_1. It is easy to show that PCP satisfies the first condition. As noted before, for the full sample, the coefficient of PCP is positive and significant at conventional significance levels in bivariate probit and endogenous tobit models. Furthermore, a probit regression of the *asked to give* dummy on PCP yields a significantly positive coefficient with a z-statistic of 4.18.

Thus, the credibility of parameter estimates depends on whether the second condition is fulfilled. This condition is violated if people who live in a county where the number of public charities per capita is high are more likely to give or donate more than otherwise identical people who live in a county where fewer public charities are located.[34] There is no empirical evidence to suggest that the number of charities in a county is a significant determinant of the giving behavior of the county residents. Using the data, one can also provide some evidence that there is no considerable relationship between PCP and giving behavior. In order to investigate this relationship, I divide the sample into two groups by PCP. People whose PCP value is less than or equal to the mean PCP represent those who live in a county where fewer number of public charities are located. Similarly, people who have higher PCP value than the mean value of PCP represent those who live in a county where more public charities are located. I find that these two groups are almost equally likely to donate (88.25% and 88.41%) and donate virtually the same amount on average ($\$1,473$ and $\$1,477$). Moreover, when I consider different quartiles of PCP, no significant differences exist in the giving behavior. For example, people in the 25th percentile are almost equally likely to donate compared with people who are in the 75th percentile (86% compared with 88%) and also donate almost the same amount ($\$1,450$ compared with $\$1,451$).

A more formal way of testing the relationship between PCP and giving behavior is to include this variable in the single equation probit and tobit models, yet I recognize that this is not a proper test since if the correct econometric specifications are bivariate probit and endogenous tobit models then single equation models are misspecified and produce biased estimates. If PCP is included in the base single equation probit model, its estimated coefficient is positive but statistically insignificant with a p-value of 0.333. If it is included in the base tobit model, its estimated coefficient is negative and statistically insignificant with a p-value of 0.386. Therefore, the results indicate that there is no significant relationship between PCP and giving behavior.

[34] Intuitively, this condition may also be violated if the number of public charities in a county affects the decision to live in that county. I believe this is highly implausible.

While I recognize that it is not possible to test directly the validity of PCP as an instrument, I further conduct two tests to explore this issue. First, I re-estimate the models using alternative sets of instrumental variables and check whether the estimates are dependent on the selection of instruments. Second, following Evans and Schwab (1995), I test the validity of the alternative instruments in 2SLS models using the tests of overidentification.

7.1 Alternative instruments

Although the dispersion of charitable organizations by population is homogenous in the sample, i.e., more charitable organizations are located in densely populated areas,[35] it is plausible to think that a few large charitable organizations with higher fundraising expenditures may be located in the same county. In this case, although the number of charities in this county is less than the average, the probability of being solicited would be higher due to the fundraising efforts of these charities and hence, using PCP as a single instrument may not be valid. I explore this possibility using the IRS data set, which also reports information on the fundraising expenditures of public charities. Using this information, I calculate total fundraising expenditures for each county divided by population. I use the natural logarithm of this amount as an additional instrument. I hypothesize that fundraising expenditures per capita (FEP) are positively associated with the probability of being solicited,[36] but that the propensity to give and amount of charitable contributions depend on fundraising expenditures through charitable solicitations only. In the second specification reported in Table 8, I use both PCP and FEP as instruments in the bivariate probit model. Comparing this model with the base model reported in the first specification shows that including FEP as an additional instrument only slightly affects the estimated coefficient of the *asked-to-give* dummy.

Another concern about using PCP as an instrument would be the imperfect overlap in the definition of a charity in the SGV and the IRS data. The IRS data exclude religious organizations, while the survey question about charitable solicitations includes religious organizations. Although, there is no direct evidence to suggest that religious organizations raise their funds mostly through fundraising practices, Andreoni (2006) reports that religious organizations receive the largest share of charitable contributions. If religious organizations raise most of their funds through charitable

[35] The correlation coefficient between the number of public charities and population is 0.951. Regressing the number of public charities on population yields a t-statistic of 198.56 with $R^2 = 0.905$.

[36] This hypothesis again can easily be verified. A probit regression of the asked to give dummy on this instrument yields a coefficient of 0.059 with a z-statistic of 4.89.

solicitations and they are more likely to be located in counties where the residents are more likely to contribute, then not controlling the number of religious organizations as an additional instrument may yield biased parameter estimates. To address this possibility, I link the matched sample of the SGV and IRS data to the RCMS at the county level. The RCMS contains detailed statistics for 149 religious bodies on the number of congregations within each county of the United States. I use the total number of congregations for all denominations per capita (RCP) as a proxy for the number of religious organizations per capita.[37] Including this variable as an additional instrument yields almost the same estimates as the base bivariate probit model. Finally, I use PCP, FEP, and RCP together as instruments. In this model, the estimated coefficient of the *asked-to-give* dummy is only slightly higher compared with that of the base model and remains highly significant and much higher than the estimates of the univariate models.

In the third specification, following the arguments of Bryant et. al. (2003) and Schervish and Havens (1997) that social interactions are the key determinant of charitable solicitations, I consider another instrument: whether members of the respondent's household belong to any organizations other than a religious organization (*belong*). I expect that as members of a household become socially active, the probability of being solicited increases.[38] Using this variable as a single instrument slightly increases the coefficient estimate of the *asked-to-give* dummy. Finally, the fourth specification reports the results of a model estimated with all proposed instruments. The estimated effect of being solicited on the propensity to give is similar to the base model. It is positive and significant, and much higher compared with that of the single equation probit model.

The remaining specifications in Table 8 report the results of several endogenous tobit models estimated using the alternative instruments. All of these models yield very similar parameter estimates compared with the estimates of the base endogenous tobit model. The hypothesis that $\varphi = 0$ is rejected at the 1% significance level for all models, and the effect of being solicited on the donation amount remains positive and significant, and much higher compared with that of the univariate tobit model. Therefore, the results of the base bivariate probit and endogenous tobit models are not only robust to the different configuration of control variables but also to the selection of alternative identifying instruments.

[37] Although not reported, I also employ the natural logarithm of total number of adherents per capita for all denominations as an additional instrument. The results are virtually the same as in the base models and are available from the author.

[38] A probit regression of the asked to give dummy on this instrument yields a coefficient of 0.594 with a z-statistic of 12.30. Hence, 'belong' is a significant determinant of being solicited.

7.2 Overidentification tests

Although there is no evidence to suggest that the assumptions necessary to perform the test of overidentifying restrictions are satisfied when both the dependent variable and the endogenous variable are binary, Evans and Schwab (1995) suggest that the test of overidentifying restrictions is the best diagnostic available to test the validity of instruments in bivariate probit models. In light of this argument, I also test the validity of the instruments in linear 2SLS models. Although not reported here, in 2SLS models, the estimated coefficient of the *asked-to-give* dummy was similar to its ATE in the bivariate probit model.[39] The F-test of excluded instruments (Bound et al., 1995) in all models is significant at conventional levels, which suggests that the set of identifying instruments from the first stage regression are not 'weak' in the sense of showing enough relationship with being solicited. The test of overidentifying restrictions cannot be constructed in exactly identified models, i.e., models estimated with a single instrument. However, for the remaining models, the null hypothesis that the instruments are valid clearly cannot be rejected except for the models estimated with using all the proposed instruments.

Rivers and Vuong (1988) provide alternative exogeneity tests for probit and tobit models. The shortcoming of these tests however is that they only produce unbiased results when the endogenous variable is continuous. Nevertheless, I conduct these tests for both the probit and tobit models using PCP as the instrument. I reject the exogeneity of being solicited ($\chi^2_{(1)} = 4.59$, $p - value = 0.032$) for the probit model. Similarly, the same hypothesis is rejected in the tobit model ($\chi^2_{(1)} = 4.40$, $p - value = 0.036$).

Finally, in addition to the results of the overidentification tests and F-tests of excluded instruments in 2SLS models, some comfort on the appropriateness of the instruments can be derived from the statement of Angrist, Imbens and Rubin (1996). They argue that the stronger the instrument, the less sensitive the IV estimand to the violations of exclusionary restrictions. As shown in Table 7 and Table 8, the estimated coefficients are robust to functional form specifications, and they are also much the same regardless of the set of instruments employed. This is also the case in the linear 2SLS models estimated for the full sample.

[39] This point is discussed in Angrist (1991). He shows that the coefficient estimate of a binary variable in a 2SLS model should be similar to its estimated ATE in bivariate probit model. For the current analysis, the coefficient of asked-to-give dummy in 2SLS model estimated using PCP as the instrument was 0.261. This is similar to the ATE of asked-to-give in the base bivariate probit model (0.300).

8 Interpretation of the results

The results of bivariate probit and endogenous tobit models show that the estimated effect of being solicited on the propensity to give and the donation amount is much higher once the endogeneity is controlled for. This result is counterintuitive in a sense that if people who are more likely to be solicited are also those who are more likely the give, then not controlling for the endogeneity of donation requests would lead one to overestimate the true relationship between being solicited and giving behavior rather than to underestimate it. How can one justify the fact the error terms of being solicited and giving equations are negatively correlated?

As mentioned before, I argue that donor fatigue can explain this puzzling result. Some unobservable characteristics of donors which are positively associated with the probability of being solicited such as previous donations might be negatively correlated with the propensity to give and the donation amount. This is because people who are more likely to be solicited are also those who are much more likely to suffer from donor fatigue, and therefore, they are more likely to think that they have given enough for a cause and stop giving. Given this hypothesis, two important questions emerge. First, how severe is the donor fatigue problem? Second, to what extent are charities aware of donor fatigue and do they act accordingly?

In a recent paper, van Diepen et al. (2006) present an evidence of donor fatigue. They conduct a survey on charitable direct mailings and donating behavior among 213 respondents and conclude that too many mailings lead to irritation of donors and that such irritation reduces annual donations. Barnes (2006) reports that people suffering from donor fatigue generally concentrate their giving to few charitable areas rather than giving to many charities operating in different areas. The SGV provides some evidence for this phenomenon. Only 12% of respondents donate to more than five categories of charitable activity out of thirteen possible categories.

In order to shed light on the latter question, consider the following recent headlines appeared in popular press:

"Donor fatigue has become major marketing roadblock for charities that need to raise money steadily, year after year...Charities are revamping their marketing efforts in attempt to reach new audiences of potential donors.[40] *"*

"The Greater Twin Cities United Way says it is $1.5 million short of its goal this year. If

[40] "Charities shift marketing tactics in a bid to offset 'donor fatigue'", The Wall Street Journal, July 13, Section 2, Page 1, Column 3, 1989.

the current pace continues, this will be the first time in four years that the United Way misses its goal...There are about a million non-profit organizations in the United States. And that may be part of the problem...[41] "

As these quotes suggest, intense competition among charities makes donor fatigue an important problem. Today, most of the charities hire professional fundraising staff to develop new tactics to prevent this phenomenon. A widely used method is to approach new people who supposedly do not suffer from donor fatigue. That is, instead of competing for a potential donor who is also likely to be solicited by other charities, a strategic decision of a charity might be to solicit donations from those who are less likely to give and try to convert non-donors to donors.

There may also be other explanations for the counterintuitive results of the current paper. For example, suppose that there are two types of donors, one that will give regardless of whether they are being solicited, and another that is less likely to give than the first group, but for whom asking will increase the propensity to give and the contribution amount. If this is the case, then charities would target their solicitations to those who are less likely to give, since soliciting from the first group has no effect. This explanation is also consistent with the sample statistics presented in Table 2, in which 95% of those who were asked gave, but 80% of those who were not asked still donated money.[42]

An alternative explanation is that charities are more likely to request donations from those who have given in the past. This is consistent with the evidence that charities maintain donor databases. Although this type of donors are more likely to suffer from donor fatigue, charities would solicit donations from these donors since the cost of identifying these people is much cheaper than finding new donors who do not suffer from donor fatigue.

Finally, it is also worth to note that another possible reason for the negative correlation between the error terms of the being solicited and giving equations might be the attenuation bias caused by the measurement error in the *asked-to-give* dummy. In particular, the survey literature generally reports that respondents' answers on attitudinal questions are subject to measurement error. However, bivariate probit and endogenous tobit models estimated by appropriate instruments should correct for the measurement error provided that the instruments are correlated with the true value of the probability of being solicited and not with the measurement error.

[41] "Is donor fatigue hitting Minnesota charities?" by Toni Randolph, December 2006. Available at http://minnesota.publicradio.org/display/web/2006/12/15/donationsdrop/.

[42] I thank an anonymous referee for pointing this out.

9 Conclusion

Although theoretical and empirical research on the response of charitable donors to requests to give is very limited, asking has always been one the major fundraising techniques. Do donation requests indeed increase charitable giving? This is one of the fundamental policy questions that fundraisers would like to know the answer to. In this paper, I address this question using a unique survey that includes a question on whether the respondent is asked to give. The non-random selection of charitable donors makes the causal effect of charitable solicitations on the propensity to give and the amount of donations hard to estimate. In order to address the endogeneity of the probability of being solicited, I match the SGV with the IRS data on charitable organizations, the RCMS, and the 2000 Census at the county level, and propose appropriate instrumental variables.

I find that charitable solicitations endogenously and positively affect both the probability of giving and the contribution amount. The results of several empirical models reveal that being solicited by a charity increases the propensity to give around 20% and log donation amount by 3.6 points for those who are actually solicited. This effect is stable over different sets of instruments and in models with different configurations of explanatory variables, and is much larger than the estimates of the univariate models. These results have three broad implications. First, they show that charitable solicitations have a substantial impact on giving behavior and this impact is larger than conventional wisdom. Second, they imply that fundraisers systematically select potential donors to solicit donations. This result also casts doubt on the exogenous donor selection assumption of the recent fundraising models. Third, a negative correlation between the error terms of the probability of being solicited equation and giving equations provides an evidence for the existence of donor fatigue among charitable donors.

Although I recognize that the SGV does not obtain sufficiently detailed information to assess the gender differences in giving behavior, I also estimate separate models for males and females. I document that the giving patterns of males and females are significantly different. Both males and females are more likely to give when they are solicited. Although females seem to be more responsive to donation requests, this difference is not significant in the univariate probit and tobit models. Furthermore, I show that the probability of being solicited does not significantly differ by gender. Income, education, and age are significant determinants of being asked to give. Strikingly, race also plays a key role in explaining the probability of being solicited. Whites are more likely to be asked to give and Hispanics are less likely to be solicited.

The results reveal charitable solicitations as one of the most important reasons for why people contribute to charities. Yet, some important questions remain untouched, primarily because of the limitations of the survey data. First, although most of the professional fundraising efforts rely on the face-to-face solicitations, it is also important to compare the effect of the different modes of charitable solicitations on giving patterns, i.e., face-to-face solicitations versus direct-mailing or phone solicitations. This paper cannot address this problem due to data limitations. Second, the empirical models used in this paper do not include control variables for the characteristics of fundraisers and for the nature of fundraising campaigns. Recent experimental studies show that physical attractiveness of solicitors and various incentives such as announcing names of donors or offering gifts in exchange for charitable contributions can boost the effect of asking.[43] Finally, the question of why are people more likely to give and even tend to give more only when they are asked to remains unanswered. As Freeman (1993, 1997) and Bryant et. al. (2003) suggest, one possible reason might be a social pressure effect. However, this hypothesis is not testable with the existing survey data. Hence, this study should be viewed as an important step in understanding the effect of charitable solicitations on giving patterns. Yet, future research can focus on how the impact of charitable solicitations would change under different incentives or alternative settings of fundraising campaigns. Obviously, these call for more detailed survey data and careful experimental designs on charitable giving.

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A Definition of key variables

A.1 Dependent variables

give Binary giving variable. 1 if the respondent donated any amount to a charitable organization in 2000.

ln (total charitable contributions+1) Natural logarithm of the total amount of money that the respondent has reported giving to charity in 2000, expressed in 2000 dollars. The constant 1 is also added, so that this variable is still censored at 0.

A.2 Independent variables

asked to give Binary variable, equals to 1 if the respondent has reported being personally solicited by some charity during the survey year.

ln (income) Natural logarithm of the total household income.

ln (price) Natural logarithm of the tax price of giving. For each household, filing status (married, single, or household head) is determined by the respondent's marital status and the presence of children, whereas the itemization status of the household is obtained from the following question in the SGV: "For your 2000 federal tax return, did you, or will you, itemize your deductions?". The number of dependents are calculated using the information on family size and number children under 18 in the household. For those who itemize deductions, following Andreoni, Gale, and Scholz (1996), I assigned the average level of itemized deductions from IRS tax return data, conditioning on filing status and income. The relevant IRS data is available at IRS Statistics of Income, Individual Income Tax Returns 2000, Publication 1304. For each household, I calculate the taxable income as the household income less the value of exemptions (standard personal exemption was $2800 in 2000) less the greater of itemized deductions or the standard deduction. I correct for the fact that individuals who are 65 and older can claim additional standard deduction, but cannot correct for the fact that blind people are also eligible for an extra deduction since this information is unavailable. The marginal tax rate for each household is calculated as the sum of the state and federal marginal tax rates using the relevant tax schedules for 2000 and information on taxable income, and also controlling for the fact that charitable deductions were not allowed in the state income tax in some states as of 2000. These states are identified using NBER's TAXIM data, available at http://www.nber.org/~taxsim/charity-state. The tax price of giving equals 1 minus marginal tax rate for itemizers and 1 for non-itemizers and is calculated to be dependent of the household's contribution amount. The resulting variable is referred to as the last-dollar price in the literature. The first-dollar price on the other hand is independent of the level of contribution. Note that the two measures are the same as long as the household's contribution does not push them into a lower tax bracket and hence raising the price of giving.

age Age of the respondent.

family size Total number of people living in the household including the respondent.

married Binary variable, equals to 1 if the respondent is married.

employed Binary variable, equals to 1 if the respondent is employed.

white, black, Hispanic Binary variables for the race of the respondent. The omitted category is those who are Asian, American Indian or Alaskan native, or some other race.

male Binary variable, equals to 1 if the respondent is male.

education dummies Binary variables for the highest level of education obtained. The omitted category is those who did not complete high school.

attends religious services Binary variable, equals 1 if the respondent has reported that she personally attends religious services for every week or nearly every week.

homeowner Binary variable, equals 1 if the respondent owns her primary residence.

voter Binary variable, equals 1 if the respondent voted in the past presidential election.

born in the USA Binary variable, equals 1 if the respondent was born in the USA.

ln (charitable contributions by others) Natural logarithm of the total amount of charitable contributions in the respondent's county. Excludes the contribution of current household. Total amount of contributions in each county is calculated using the IRS data.

ln (median income) Natural logarithm of median income, by county, expressed in 2000 dollars.

median age Median age, by county.

Hispanic and Latino population Hispanic and Latino population as a percentage of total population, by county.

College graduate Total number of college graduates as a percentage of total population, 25 years and older, by county.

Transfer receipts from government Natural logarithm per capita levels of retirement and disability insurance benefits, medical benefits, income maintenance benefits, unemployment insurance compensation, federal education and training assistance, and receipts of nonprofit institutions, by county, expressed in 2000 dollars.

A.3 Instrumental variables

PCP Number of public charities divided by population, by county.

FEP Natural logarithm of the total fundraising expenditures divided by population, by county.

RCP Number of congregations for all denominations divided by population in 2000, by county. These data are compiled by the Association of Religion Data Archives. Detailed information and data are available at http://www.thearda.com/Archive/Files/Descriptions/RCMSCY.asp.

belong Binary variable, equals 1 if members of respondent's household belong to any organization other than a religious organization. The data for this instrument are drawn from the following question in the SGV: "Do members of your household belong to any other (other than a church, synagogue, mosque, or other formal religious organizations) organization? [If asked: For example, a service club such as Kiwanis or Rotary, an alumni organization, neighborhood organization, professional society, labor union or sports or hobby group.]"

B Log-likelihood functions

B.1 Probit model with a binary endogenous variable

The system of interest was

$$\begin{aligned} d_i^* &= \beta_1' X_{1i} + \gamma\theta_i + u_{1i} \\ \theta_i^* &= \beta_2' X_{2i} + u_{2i} \end{aligned} \tag{13}$$

where θ_i^* and d_i^* are latent variables for the probability of being asked and the probability of giving respectively, and θ_i and d_i are dichotomous variables observed according to the rule:

$$\begin{aligned} d_i &= 1 \text{ if } d_i^* > 0 \text{ and } 0 \text{ otherwise,} \\ \theta_i &= 1 \text{ if } \theta_i^* > 0 \text{ and } 0 \text{ otherwise.} \end{aligned} \tag{14}$$

The error terms are assumed to be independently and identically distributed as bivariate normal with $E[u_{1i}] = E[u_{2i}] = 0$, $var[u_{1i}] = var[u_{2i}] = 1$, and $cov[u_{1i}, u_{2i}] = \rho$. For a single observation, one may drop the subscript i for convenience. The joint density of (u_1, u_2) is:

$$\phi(u_1, u_2) = \frac{1}{2\pi(1-\rho)^{1/2}} \exp[-\frac{1}{2}\frac{u_1^2 + u_2^2 - 2\rho u_1 u_2}{(1-\rho^2)}] \tag{15}$$

and the likelihood functions for the joint events are defined as:

$$
\begin{aligned}
P(d=1,\theta=1) &= \textstyle\int_{-(\beta_2' X_2)}^{\infty} \int_{-(\beta_1' X_1+\gamma)}^{\infty} \phi(u_1,u_2)du_1du_2 \\
P(d=1,\theta=0) &= \textstyle\int_{-\infty}^{-(\beta_2' X_2)} \int_{-(\beta_1' X_1)}^{\infty} \phi(u_1,u_2)du_1du_2 \\
P(d=0,\theta=1) &= \textstyle\int_{-(\beta_2' X_2)}^{\infty} \int_{-\infty}^{-(\beta_1' X_1+\gamma)} \phi(u_1,u_2)du_1du_2 \\
P(d=0,\theta=0) &= \textstyle\int_{-\infty}^{-(\beta_2' X_2)} \int_{-\infty}^{-(\beta_1' X_1)} \phi(u_1,u_2)du_1du_2
\end{aligned} \tag{16}
$$

where $\boldsymbol{\phi}(.)$ is the evaluation of normal probability density function.

Combining the four possible outcomes of (d_1, θ_1) and taking the logarithm gives the log-likelihood function. The log-likelihood function corresponding to this set of events is a bivariate probit.

B.2 Endogenous tobit model

The system of interest was

$$
\begin{aligned}
D_i^* &= \alpha_1' X_{1i} + \eta\theta_i + \varepsilon_{1i} \\
\theta_i^* &= \alpha_2' X_{2i} + \varepsilon_{2i}
\end{aligned} \tag{17}
$$

where D_i and θ_i are observed according to the following rule:

$$
\begin{aligned}
D_i &= \max\{(\alpha_1' X_{1i} + \eta\theta_i + \varepsilon_{1i}), 0\}, \\
\theta_i &= 1 \text{ if } \theta_i^* > 0 \text{ and } 0 \text{ otherwise}
\end{aligned} \tag{18}
$$

where the error terms are assumed to be independently and identically distributed as bivariate normal with $E[\varepsilon_{1i}] = E[\varepsilon_{2i}] = 0$, $var[\varepsilon_{1i}] = \sigma^2$ and $var[\varepsilon_{2i}] = 1$, and $cov[\varepsilon_{1i}, \varepsilon_{2i}] = \varphi\sigma$. Following Li and Rettenmaier (1999), I consider four possible outcomes separately. Again, for a single observation, I drop the subscript i for convenience. The likelihood function for the joint probability of $D > 0$ and $\theta = 1$ is

$$
\begin{aligned}
f(D>0,\theta=1) &= \textstyle\int_{-(\alpha_2' X_2)}^{\infty} f(\varepsilon_1,\varepsilon_2)d\varepsilon_2 \\
&= \textstyle\int_{-(\alpha_2' X_2)}^{\infty} f(\varepsilon_2|\varepsilon_1)f(\varepsilon_1)d\varepsilon_2 \\
&= f(\varepsilon_1)\textstyle\int_{-(\alpha_2' X_2)}^{\infty} f(\varepsilon_2|\varepsilon_1)d\varepsilon_2 \\
&= f(\varepsilon_1)[1-\Phi(\tfrac{-(\alpha_2' X_2)-\varphi\sigma\varepsilon_1}{(1-\varphi^2)^{1/2}})] \\
&= f(\varepsilon_1)\Phi(\tfrac{(\alpha_1' X_2)+\varphi\sigma\varepsilon_1}{(1-\varphi^2)^{1/2}})
\end{aligned} \tag{19}
$$

where $\varepsilon_1 = D - \alpha_1' X_1 - \eta$ and $f(\varepsilon_1) = \frac{1}{(2\pi\sigma^2)^{1/2}} \exp[-\frac{1}{2}\frac{\varepsilon_1^2}{\sigma^2}]$.

The likelihood function for the joint probability of $D > 0$ and $\theta = 0$ is

$$\begin{aligned} f(D > 0, \theta = 0) &= \int_{-\infty}^{-(\alpha_2' X_2)} f(\varepsilon_1, \varepsilon_2) d\varepsilon_2 \\ &= f(\varepsilon_1)\Phi(\tfrac{-(\alpha_2' X_2) - \varphi\sigma\varepsilon_1}{(1-\varphi^2)^{1/2}}) \\ &= f(\varepsilon_1)[1 - \Phi(\tfrac{(\alpha_2' X_2) + \varphi\sigma\varepsilon_1}{(1-\varphi^2)^{1/2}})] \end{aligned} \tag{20}$$

where $\varepsilon_1 = D - \alpha_1' X_1$ and $f(\varepsilon_1) = \frac{1}{(2\pi\sigma^2)^{1/2}} \exp[-\frac{1}{2}\frac{\varepsilon_1^2}{\sigma^2}]$.

The likelihood function for the joint probability of ($D = 0$ and $\theta = 0$) and ($D = 0$ and $\theta = 1$) are the same as the likelihood functions of those corresponding events in the probit model with the endogenous binary regressor (bivariate probit model), where $(\varepsilon_1, \varepsilon_2)$ is distributed as a bivariate normal. Combining the four possible outcomes of (D, θ) and taking the logarithm gives the log-likelihood function for this model. Finally, estimation of this model with multiple binary endogenous variables is also possible using the methodology discussed in Li and Rettenmaier (1999).

C Calculation of standard errors for the ATE and ATT

I use the delta method to approximate standard errors for the ATE and ATT. The variance of $\widehat{ATE}_{(j)}$ for $j = \{p, t\}$ can be approximated as:

$$var(\widehat{ATE}_{(j)}) = \begin{cases} \left(\frac{\partial \widehat{ATE}_{(j)}}{\partial \widehat{\gamma}}\right)' var(\widehat{\gamma}) \left(\frac{\partial \widehat{ATE}_{(j)}}{\partial \widehat{\gamma}}\right) & \text{if } j = p \\ \left(\frac{\partial \widehat{ATE}_{(j)}}{\partial \widehat{\eta}}\right)' var(\widehat{\eta}) \left(\frac{\partial \widehat{ATE}_{(j)}}{\partial \widehat{\eta}}\right) & \text{if } j = t \end{cases} \tag{21}$$

where

$$\frac{\partial \widehat{ATE}_{(j)}}{\partial \widehat{\gamma}} = \frac{1}{n}\sum_{i=1}^{n} \phi(\widehat{\beta}_1' X_{1i} + \widehat{\gamma}) \tag{22}$$

and

$$\frac{\partial \widehat{ATE}_{(j)}}{\partial \widehat{\eta}} = \frac{1}{n}\sum_{i=1}^{n} [\Phi(\widehat{\alpha}_1' X_{1i} + \widehat{\eta}\theta_i) + \widehat{\eta}\theta_i \phi(\widehat{\alpha}_1' X_{1i} + \widehat{\eta}\theta_i)]. \tag{23}$$

The variance of $\widehat{ATT}_{(j)}$ can be approximated similarly, where

$$\frac{\partial \widehat{ATT}_{(j)}}{\partial \widehat{\gamma}} = \left(\sum_{i=1}^{n} \theta_i\right)^{-1} \sum_{i=1}^{n} [\theta_i \phi(\widehat{\beta}_1' X_{1i} + \widehat{\gamma})] \tag{24}$$

and

$$\frac{\partial \widehat{ATT}_{(j)}}{\partial \widehat{\eta}} = \left(\sum_{i=1}^{n} \theta_i\right)^{-1} \sum_{i=1}^{n} [\theta_i \Phi(\widehat{\alpha}_1' X_{1i} + \widehat{\eta}\theta_i) + \widehat{\eta}\theta_i^2 \phi(\widehat{\alpha}_1' X_{1i} + \widehat{\eta}\theta_i)]. \tag{25}$$

Tables

Table 1. The Characteristics of Charitable Donors and Nondonors

	Full sample		Males		Females	
	Donor	Nondonor	Donor	Nondonor	Donor	Nondonor
Percentage male	37.49 (48.41)	38.45 (48.70)	-	-	-	-
Percentage white	85.39 (35.31)	72.75 (44.57)	84.17 (36.52)	80.21 (40.00)	84.16 (36.52)	69.11 (46.34)
Percentage black	9.41 (29.20)	15.93 (36.63)	9.62 (29.50)	11.63 (32.18)	11.99 (32.49)	21.07 (40.90)
Percentage Hispanic	6.88 (25.31)	14.87 (35.62)	7.38 (26.17)	11.61 (32.16)	5.95 (23.67)	13.87 (34.66)
Percentage married	49.62 (50.00)	29.82 (45.79)	28.46 (45.16)	16.00 (36.81)	28.64 (45.23)	14.93 (35.75)
Percentage employed	64.39 (47.89)	55.10 (49.79)	70.82 (45.49)	69.64 (46.16)	59.99 (49.00)	48.34 (50.12)
Percentage college graduate	32.55 (46.86)	12.63 (33.25)	36.21 (48.09)	18.61 (39.07)	30.18 (45.92)	9.68 (29.66)
Percentage regularly attend religious services	44.42 (49.69)	18.79 (39.10)	31.26 (46.39)	6.56 (24.85)	46.68 (49.91)	23.85 (42.74)
Mean age	49.10 (16.61)	46.76 (18.20)	47.36 (16.72)	42.99 (17.73)	51.67 (17.22)	51.09 (18.67)
Mean family size	2.48 (1.40)	2.31 (1.51)	2.02 (1.31)	1.81 (1.28)	2.14 (1.31)	1.98 (1.35)
Mean household income	55,268 (45,452)	29,792 (23,244)	54,999 (49,354)	38,709 (27,821)	45,527 (41,733)	22,039 (17,096)
Mean amount of money contributions	1,684 (3,605)	-	1,415 (2,771)	-	1,327 (3,110)	-
Mean amount of money contributions as a percentage of household income	3.80 (19.44)	-	3.12 (6.86)	-	4,35 (29,01)	-

Notes: The maximum sample for the survey is 4,216. The number of observations for each variable varies modestly due to nonrespondents. Sample weighted means are reported. Standard deviations are in parenthesis.

Table 2. The relationship between charitable solicitations and giving decision

	Full Sample				Males				Females			
Were you asked to give?	Yes		No		Yes		No		Yes		No	
	57.70%		42.30%		54.99%		45.01%		58.11%		41.89%	
	(n=2,410)		(n=1,767)		(n=474)		(n=388)		(n=892)		(n=643)	
Donated money?	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	95.56%	4.44%	80.08%	19.92%	91.14%	8.86%	77.84%	22.16%	95.40%	4.60%	79.47%	20.53%
	(n=2,303)	(n=107)	(n=1,415)	(n=352)	(n=432)	(n=42)	(n=302)	(n=86)	(n=851)	(n=41)	(n=511)	(n=132)
Mean amount donated	1,882		950		1,550		764		1,471		738	
	(3,899)		(2,583)		(2,874)		(2,143)		(3,376)		(2,152)	
Mean amount donated as a percentage of income	3.89		2.59		3.00		2.17		4.40		2.97	
	(21.88)		(11.95)		(5.85)		(6.94)		(32.61)		(17.24)	

Notes: Sample weighted means are reported. Standard deviations are in parenthesis.

Table 3. Determinants of the probability of giving and the contribution amount

	Propensity to give (Probit)			Total Contributions (Tobit)		
Explanatory Variables	Full Sample	Males	Females	Full Sample	Males	Females
Asked to give	0.621	0.441	0.621	1.091	1.330	1.010
	(0.064)***	(0.125)***	(0.105)***	(0.092)***	(0.222)***	(0.147)***
ln (price)	-0.533	-0.128	-0.424	-1.004	-0.613	-0.655
	(0.213)**	(0.359)	(0.388)	(0.277)***	(0.609)	(0.455)
ln (household income)	0.248	0.041	0.299	0.808	0.512	0.847
	(0.045)***	(0.094)	(0.075)***	(0.079)***	(0.176)***	(0.129)***
Age	0.009	0.053	-0.002	0.034	0.086	0.030
	(0.011)	(0.021)**	(0.018)	(0.017)**	(0.039)**	(0.026)
Age^2 (×100)	-0.001	-0.041	0.008	-0.018	-0.060	-0.017
	(0.011)	(0.020)**	(0.017)	(0.017)	(0.038)	(0.025)
Family size	0.061	0.107	0.075	0.092	0.174	0.104
	(0.029)**	(0.060)*	(0.047)	(0.041)**	(0.110)	(0.069)
Employed	0.124	0.172	0.064	0.183	0.449	0.042
	(0.076)*	(0.172)	(0.124)	(0.111)*	(0.310)	(0.171)
Married	0.083	-0.035	-0.020	0.243	0.262	0.088
	(0.074)	(0.170)	(0.140)	(0.107)**	(0.287)	(0.174)
White	0.238	-0.114	0.406	0.618	0.435	0.732
	(0.114)**	(0.239)	(0.202)**	(0.201)***	(0.396)	(0.373)**
Black	-0.018	-0.369	0.039	0.186	-0.097	0.243
	(0.137)	(0.298)	(0.225)	(0.243)	(0.513)	(0.418)
Hispanic	-0.152	-0.181	-0.238	-0.357	-0.288	-0.475
	(0.110)	(0.224)	(0.179)	(0.197)*	(0.427)	(0.326)
Male	-0.096	-	-	0.067	-	-
	(0.062)			(0.087)		
High School (=1)	0.392	0.541	0.488	0.957	1.021	1.443
	(0.087)***	(0.183)***	(0.142)***	(0.191)***	(0.476)**	(0.305)***
Some College (=1)	0.655	1.046	0.610	1.585	1.931	1.982
	(0.099)***	(0.196)***	(0.160)***	(0.192)***	(0.472)***	(0.310)***
College (=1)	0.621	0.975	0.597	1.513	1.845	1.902
	(0.118)***	(0.223)***	(0.202)***	(0.204)***	(0.500)***	(0.339)***
Graduate School (=1)	0.922	1.242	1.474	1.916	2.268	2.435
	(0.161)***	(0.274)***	(0.436)***	(0.209)***	(0.523)***	(0.335)***
Attends religious services	0.627	1.061	0.549	1.852	2.166	1.727
	(0.071)***	(0.174)***	(0.108)***	(0.088)***	(0.201)***	(0.141)***
Intercept	-3.147	-2.142	-3.436	-8.225	-7.111	-8.675
	(0.517)***	(1.098)**	(0.868)***	(0.896)***	(2.041)***	(1.463)***
Average treatment effect (Asked to give)	0.092	0.070	0.084	1.085	1.322	1.002
	(0.010)***	(0.020)***	(0.015)***	(0.092)***	(0.221)***	(0.146)***
Average treatment effect on the treated (Asked to give)	0.078	0.060	0.070	1.091	1.330	1.009
	(0.008)***	(0.018)***	(0.013)***	(0.092)***	(0.222)***	(0.147)***
Pseudo R^2	0.217	0.184	0.226	0.089	0.019	0.015
Log-likelihood	-1166.265	-297.935	-426.711	-8351.732	-1661.727	-3450.636
Sigma	-	-	-	2.496	2.775	2.408
				(0.045)	(0.104)	(0.072)
Number of Censored Observations	-	-	-	545	145	202
Number of Observations	4100	848	1504	3854	803	1410

Notes: Sample weights are used in all regressions. Robust standard errors are reported in parenthesis. The sign *** indicates that the variable is significant at 1% significance level. The sign ** indicates that the variable is significant at 5% significance level. The sign * indicates that the variable is significant at 10% significance level.

Table 4. Determinants of being solicited

	Full Sample		Males		Females	
Explanatory Variables	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
ln (price)	-0.193	-0.076	-0.785	-0.311	-0.026	-0.010
	(0.126)	(0.050)	(0.258)***	(0.102)***	(0.217)	(0.085)
ln (household income)	0.219	0.086	0.234	0.093	0.194	0.076
	(0.036)***	(0.014)***	(0.078)***	(0.031)***	(0.058)***	(0.023)***
Age	0.036	0.014	0.024	0.010	0.043	0.017
	(0.008)***	(0.003)***	(0.016)	(0.006)	(0.013)***	(0.005)***
Age^2 (×100)	-0.030	-0.012	-0.023	-0.009	-0.035	-0.014
	(0.008)***	(0.003)***	(0.016)	(0.006)	(0.012)***	(0.005)***
Family size	-0.013	-0.005	-0.051	-0.020	-0.003	-0.001
	(0.018)	(0.007)	(0.043)	(0.017)	(0.032)	(0.013)
Employed	-0.017	-0.007	-0.290	-0.114	0.182	0.071
	(0.054)	(0.021)	(0.136)**	(0.052)**	(0.088)**	(0.034)**
Married	0.086	0.034	0.214	0.084	0.164	0.064
	(0.051)*	(0.020)*	(0.124)*	(0.048)*	(0.090)*	(0.035)*
White	0.271	0.107	0.351	0.140	0.333	0.132
	(0.092)***	(0.037)***	(0.183)*	(0.072)*	(0.166)**	(0.066)**
Black	0.165	0.064	0.036	0.014	0.253	0.096
	(0.111)	-0.042	(0.227)	(0.089)	(0.188)	(0.069)
Hispanic	-0.249	-0.099	-0.184	-0.073	-0.059	-0.023
	(0.087)***	(0.035)***	(0.182)	(0.073)	(0.145)	(0.057)
Male	-0.048	-0.019	-	-	-	-
	(0.043)	(0.017)				
High School (=1)	0.202	0.078	0.081	0.032	0.200	0.077
	(0.074)***	(0.028)***	(0.165)	(0.065)	(0.121)*	(0.047)*
Some College (=1)	0.385	0.147	0.115	0.045	0.348	0.133
	(0.078)***	(0.029)***	(0.169)	(0.067)	(0.129)***	(0.048)***
College (=1)	0.525	0.196	0.234	0.092	0.491	0.182
	(0.086)***	(0.029)***	(0.183)	(0.070)	(0.148)***	(0.051)***
Graduate School (=1)	0.755	0.265	0.449	0.171	0.799	0.274
	(0.098)***	(0.029)***	(0.208)**	(0.074)**	(0.172)***	(0.048)***
Attends religious services	0.104	0.041	0.056	0.022	0.091	0.036
	(0.045)**	(0.018)**	(0.109)	(0.043)	(0.073)	(0.028)
Intercept	-3.708		-3.267		-3.823	
	(0.399)***		(0.856)***		(0.654)***	
Pseudo R^2	0.077		0.081		0.076	
Log-likelihood	-2588.780		-537.308		-948.569	
Number of Observations	4100		848		1504	

Notes: Sample weights are used in all regressions. Robust standard errors are reported in parenthesis. The sign *** indicates that the variable is significant at 1% significance level. The sign ** indicates that the variable is significant at 5% significance level. The sign * indicates that the variable is significant at 10% significance level.

Table 5. ML estimates of the base bivariate probit models

Explanatory Variables	Full Sample: The prob. of giving	Full Sample: The prob. of being solicited	Males: The prob. of giving	Males: The prob. of being solicited	Females: The prob. of giving	Females: The prob. of being solicited
Asked to give	1.557	-	-0.406	-	1.721	-
	(0.253)***		(0.553)		(0.352)***	
ln (price)	-0.398	-0.194	-0.399	-0.788	-0.330	-0.056
	(0.199)**	(0.127)	(0.389)	(0.263)***	(0.334)	(0.216)
ln (household income)	0.144	0.209	0.123	0.248	0.172	0.175
	(0.056)**	(0.036)***	(0.098)	(0.080)***	(0.094)	(0.060)***
Age	-0.006	0.037	0.053	0.024	-0.021	0.044
	(0.011)	(0.008)***	(0.020)***	(0.016)	(0.017)	(0.013)***
Age^2 (×100)	0.011	-0.031	-0.040	-0.022	0.022	-0.037
	(0.010)	(0.008)***	(0.020)**	(0.016)	(0.016)	(0.012)***
Family size	0.064	-0.012	0.090	-0.047	0.066	-0.005
	(0.027)**	(0.018)	(0.060)	(0.043)	(0.044)	(0.032)
Employed	0.122	-0.022	0.078	-0.298	-0.022	0.172
	(0.069)*	(0.054)	(0.189)	(0.136)**	(0.115)	(0.088)**
Married	0.028	0.099	0.006	0.192	-0.119	0.207
	(0.069)	(0.051)**	(0.170)	(0.126)	(0.124)	(0.092)**
White	0.124	0.290	0.005	0.357	0.216	0.359
	(0.112)	(0.092)***	(0.242)	(0.184)*	(0.199)	(0.167)**
Black	-0.059	0.175	-0.330	0.032	-0.054	0.273
	(0.128)	(0.111)	(0.288)	(0.227)	(0.213)	(0.191)
Hispanic	-0.044	-0.240	-0.224	-0.208	-0.195	-0.043
	(0.109)	(0.088)***	(0.214)	(0.185)	(0.172)	(0.145)
Male	-0.066	-0.038	-	-	-	-
	(0.058)	(0.044)				
High School (=1)	0.267	0.218	0.503	0.042	0.302	0.241
	(0.094)***	(0.075)***	(0.180)***	(0.164)	(0.149)**	(0.125)*
Some College (=1)	0.440	0.406	0.969	0.087	0.354	0.365
	(0.125)***	(0.079)***	(0.208)***	(0.170)	(0.190)*	(0.131)***
College (=1)	0.360	0.518	0.976	0.195	0.282	0.500
	(0.141)**	(0.087)***	(0.219)***	(0.182)	(0.216)	(0.151)***
Graduate School (=1)	0.546	0.750	1.254	0.391	0.858	0.787
	(0.182)***	(0.099)***	(0.262)***	(0.207)**	(0.371)**	(0.173)***
Attends religious services	0.504	0.113	0.974	0.050	0.406	0.100
	(0.083)***	(0.045)**	(0.188)***	(0.109)	(0.121)***	(0.074)
No. of charitable org./population (PCP)	-	137.954	-	84.045	-	192.358
		(41.792)***		(83.689)		(63.421)***
Intercept	-1.990	-3.789	-2.661	-3.443	-1.852	-3.861
	(0.652)***	(0.404)***	(1.052)**	(0.875)***	(1.114)	(0.673)***
Average treatment effect (Asked to give)	0.300		-0.069		0.346	
	(0.056)***		(0.092)		(0.080)***	
Average treatment effect on the treated (Asked to give)	0.196		-0.063		0.166	
	(0.053)***		(0.054)		(0.051)***	
ρ	-0.605		0.491		-0.705	
	(0.161)		(0.309)		(0.215)	
Log-likelihood	-3719.160		-776.494		-1561.867	
Number of Observations	4076		844		1494	

Notes: Sample weights are used in all regressions. Robust standard errors are reported in parenthesis. The sign *** indicates that the variable is significant at 1% significance level. The sign ** indicates that the variable is significant at 5% significance level. The sign * indicates that the variable is significant at 10% significance level.

Table 6. ML estimates of the base endogenous tobit models

Explanatory Variables	Full Sample: The contribution amount	Full Sample: The prob. of being solicited	Males: The contribution amount	Males: The prob. of being solicited	Females: The contribution amount	Females: The prob. of being solicited
Asked to give	3.584	-	-0.661	-	3.446	-
	(0.232)***		(1.266)		(0.387)***	
ln (price)	-1.593	-0.035	-0.930	-0.728	0.278	-0.396
	(0.639)**	(0.213)	(0.791)	(0.302)**	(1.070)	(0.377)
ln (household income)	0.705	0.229	0.762	0.306	0.840	0.158
	(0.145)***	(0.052)***	(0.275)***	(0.101)***	(0.249)***	(0.090)*
Age	0.009	0.042	0.116	0.023	-0.001	0.056
	(0.031)	(0.011)***	(0.047)**	(0.019)	(0.049)	(0.018)***
Age^2 (×100)	0.003	-0.035	-0.084	-0.020	0.002	-0.045
	(0.030)	(0.011)***	(0.046)*	(0.019)	(0.047)	(0.018)**
Family size	0.065	-0.001	-0.087	-0.084	0.148	-0.001
	(0.064)	(0.026)	(0.156)	(0.062)	(0.140)	(0.049)
Employed	0.204	-0.000	0.483	-0.259	-0.062	0.214
	(0.229)	(0.081)	(0.470)	(0.159)	(0.346)	(0.129)*
Married	0.328	0.058	0.530	0.208	-0.038	0.209
	(0.217)	(0.075)	(0.431)	(0.149)	(0.428)	(0.152)
White	-0.091	0.526	-0.123	0.319	0.175	0.543
	(0.275)	(0.117)***	(0.606)	(0.218)	(0.457)	(0.221)**
Black	-0.486	0.377	-0.639	-0.056	-0.705	0.544
	(0.378)	(0.146)***	(0.720)	(0.267)	(0.618)	(0.264)**
Hispanic	-0.253	-0.259	-0.422	-0.227	-0.489	-0.087
	(0.291)	(0.113)**	(0.531)	(0.214)	(0.437)	(0.190)
Male	-0.188	0.034	-	-	-	-
	(0.192)	(0.067)				
High School (=1)	0.588	0.341	0.409	-0.103	0.663	0.537
	(0.267)**	(0.103)***	(0.525)	(0.237)	(0.444)	(0.183)***
Some College (=1)	0.913	0.629	1.836	0.077	1.250	0.655
	(0.292)***	(0.118)***	(0.484)***	(0.203)	(0.494)**	(0.198)***
College (=1)	1.175	0.616	1.847	0.121	1.005	0.824
	(0.353)***	(0.128)***	(0.504)***	(0.221)	(0.632)	(0.240)***
Graduate School (=1)	1.485	0.863	2.407	0.375	2.586	0.767
	(0.465)***	(0.161)***	(0.675)***	(0.242)	(0.763)***	(0.277)***
Attends religious services	2.221	0.042	3.326	0.240	2.286	-0.017
	(0.212)***	(0.070)	(0.534)***	(0.174)	(0.335)***	(0.123)
No. of charitable org./population (PCP)	-	97.025	-	91.071	-	185.95
		(48.751)**		(86.209)		(75.915)**
Intercept	-9.465	-3.647	-12.437	-4.631	-10.118	-3.705
	(1.593)***	(0.581)***	(2.768)***	(1.341)***	(2.759)***	(1.017)***
Average treatment effect (Asked to give)	2.881		-0.475		2.880	
	(0.190)***		(0.848)		(0.328)***	
Average treatment effect on the treated (Asked to give)	3.569		-0.501		3.434	
	(0.237)***		(0.853)		(0.393)***	
φ	-0.074		0.032		-0.085	
	(0.011)		(0.017)		(0.022)	
σ	3.919		5.238		3.643	
	(0.151)		(0.458)		(0.280)	
Log-likelihood	-12565.917		-2454.054		-5197.379	
Number of Observations	3831		799		1400	

Notes: Sample weights are used in all regressions. Robust standard errors are reported in parenthesis. The sign *** indicates that the variable is significant at 1% significance level. The sign ** indicates that the variable is significant at 5% significance level. The sign * indicates that the variable is significant at 10% significance level.

Table 7. Robustness checks for the bivariate probit and endogenous tobit models

	MLE estimates of bivariate probit and endogenous tobit models					
Alternative specifications	Number of Obs.	Coefficient on *asked to give*	ATE	ATT	ρ or φ	Wald Test of ρ=0 (p-value)
The prob. of giving						
1. Base model	4076	1.557	0.300	0.196	-0.605	7.619
		(0.253)	(0.056)	(0.053)	(0.161)	(0.006)
2. Base model without instruments	4100	1.426	0.261	0.184	-0.518	2.737
		(0.392)	(0.081)	(0.086)	(0.254)	(0.098)
3. Exclude ln(price)	4076	1.563	0.303	0.198	-0.604	7.424
		(0.257)	(0.057)	(0.055)	(0.163)	(0.006)
4. Instrument ln(price)	4076	1.559	0.300	0.196	-0.605	7.604
		(0.254)	(0.056)	(0.053)	(0.161)	(0.006)
5. Include dummy variables: vote, homeowner, born in USA	4076	1.642	0.326	0.182	-0.686	15.121
		(0.188)	(0.042)	(0.031)	(0.114)	(0.000)
6. Include ln (Donations by others)	4069	1.573	0.304	0.196	-0.617	9.003
		(0.235)	(0.052)	(0.048)	(0.149)	(0.003)
7. Include ln (median income), median age, Hispanic and Latino population, college graduate	4076	1.560	0.300	0.195	-0.607	7.379
		(0.258)	(0.056)	(0.053)	(0.164)	(0.007)
8. Include personal transfer receipts from government	4009	1.556	0.301	0.195	-0.609	7.362
		(0.259)	(0.057)	(0.054)	(0.164)	(0.007)
ln (1+amount of contributions)						
9. Base model	3831	3.584	2.881	3.569	-0.074	49.06
		(0.232)	(0.190)	(0.237)	(0.011)	(0.000)
10. Base model without instruments	3854	3.587	2.880	3.573	-0.074	52.32
		(0.227)	(0.185)	(0.232)	(0.010)	(0.000)
11. Exclude ln(price)	3831	3.585	2.874	3.569	-0.072	56.41
		(0.226)	(0.185)	(0.231)	(0.010	(0.000)
12. Instrument ln(price)	3831	3.582	2.881	3.567	-0.074	48.59
		(0.232)	(0.190)	(0.237)	(0.011)	(0.000)
13. Include dummy variables: vote, homeowner, born in USA	3831	3.470	2.822	3.455	-0.077	53.08
		(0.227)	(0.188)	(0.232)	(0.011)	(0.000)
14. Include ln (Donations by others)	3824	3.585	2.888	3.570	-0.074	64.48
		(0.216)	(0.177)	(0.221)	(0.009)	(0.000)
15. Include ln (median income), median age, Hispanic and Latino population, college graduate	3831	3.628	2.934	3.613	-0.074	60.11
		(0.218)	(0.180)	(0.224)	(0.010)	(0.000)
16. Include personal transfer receipts from government	3771	3.568	2.897	3.552	-0.073	46.00
		(0.238)	(0.197)	(0.244)	(0.011)	(0.000)

Notes: Sample weights are used in all regressions. Robust standard errors are reported in parenthesis.

Table 8. Tests for the validity of the instrumental variables

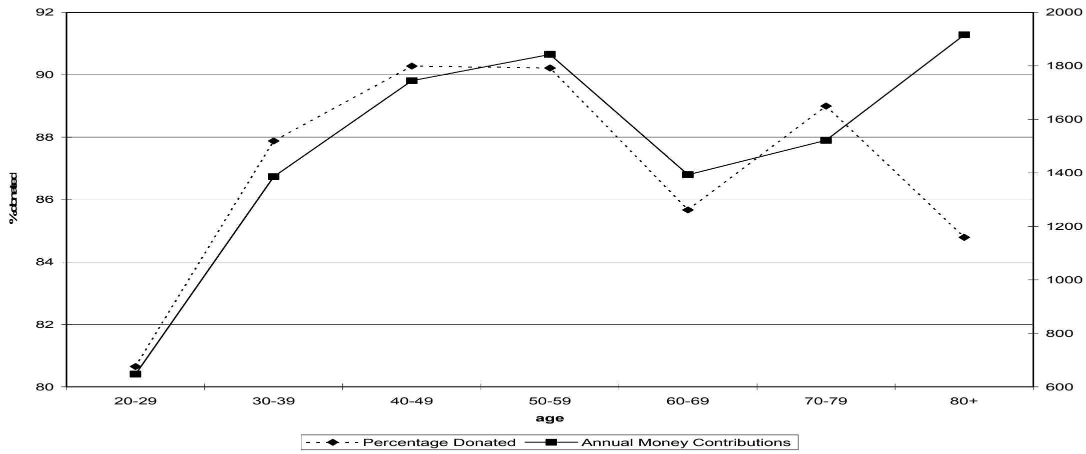
	Models with endogenous probability of being solicited			Tests of instruments in linear 2SLS models	
Alternative Instruments	Coefficient on *asked to give*	ρ or φ	Wald Test of ρ=0 or φ=0 (p-value)	F-test of excluded instruments (p-value)	overidentification test (p-value)
The prob. of giving					
1. PCP (Base model)	1.557	-0.605	7.619	9.28	-
	(0.253)	(0.161)	(0.006)	(0.002)	
2. County level charity characteristics					
PCP, FEP	1.585	-0.623	7.725	6.50	0.838
	(0.254)	(0.161)	(0.005)	(0.002)	(0.361)
PCP, RCP	1.596	-0.628	5.319	9.14	1.94
	(0.302)	(0.194)	(0.021)	(0.000)	(0.163)
PCP, RCP, FEP	1.672	-0.682	10.469	5.70	0.882
	(0.221)	(0.138)	(0.001)	(0.001)	(0.643)
3. Belong	1.711	-0.717	32.736	57.66	-
	(0.132)	(0.077)	(0.000)	(0.000)	
4. All instruments	1.722	-0.717	23.112	8.00	7.515
	(0.153)	(0.091)	(0.000)	(0.000)	(0.059)
ln (1+amount of contributions)					
5. PCP (Base model)	3.584	-0.074	49.06	8.36	-
	(0.232)	(0.011)	(0.000)	(0.004)	
6. County level charity characteristics					
PCP, FEP	3.498	-0.073	50.14	7.34	0.008
	(0.235)	(0.010)	(0.000)	(0.001)	(0.928)
PCP, RCP	3.546	-0.073	36.88	7.66	0.358
	(0.262)	(0.012)	(0.000)	(0.001)	(0.549)
PCP, RCP, FEP	3.435	-0.069	40.64	6.11	0.031
	(0.256)	(0.011)	(0.000)	(0.000)	(0.985)
7. Belong	3.584	-0.075	55.59	50.39	-
	(0.221)	(0.010)	(0.000)	(0.000)	
8. All instruments	3.471	-0.072	42.02	7.58	30.659
	(0.249)	(0.011)	(0.000)	(0.000)	(0.000)

Notes: Sample weights are used in all regressions. Robust standard errors are reported in parenthesis.

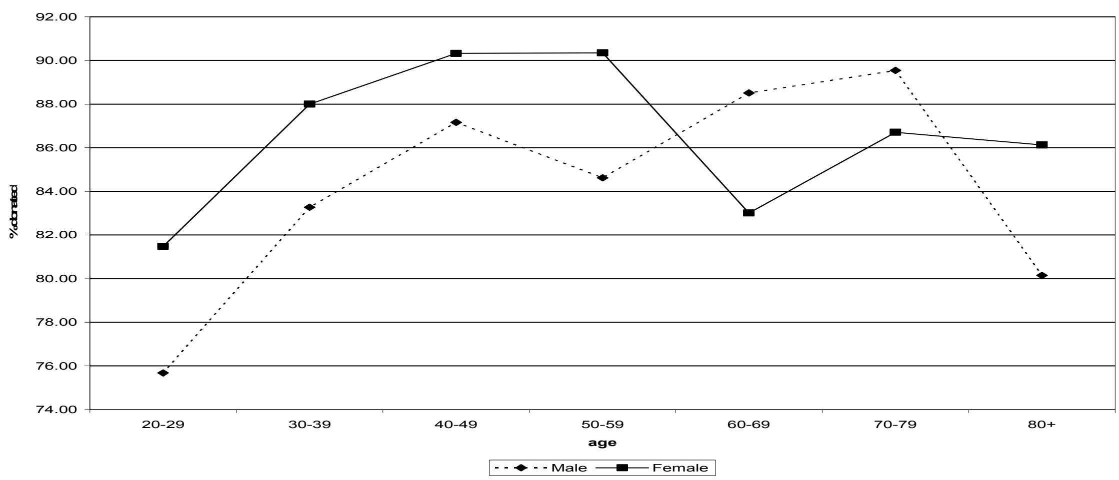
Figures

Figure 1. The propensity to give and amount of charitable contributions by age

A. Full sample



B. The propensity to give by sex



C. The amount of charitable contributions by sex