The effect of media on charitable giving and volunteering: Evidence from the "Give Five" campaign*

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Abstract

Fundraising campaigns advertised via mass media are common. To what extent such campaigns affect charitable behavior is mostly unknown, however. Using giving and volunteering surveys conducted biannually from 1988 to 1996, I investigate the effect of a national fundraising campaign, "Give Five", on charitable giving and volunteering patterns. The widely advertised "Give Five" campaign was aimed to encourage people to give five percent of their income and volunteer five hours a week. After controlling for selection into being informed about the "Give Five", I find that people who were informed about the campaign increased their weekly volunteering activity on average by almost half an hour, but their giving behavior was not significantly affected. I discuss the policy implications associated with this result and argue that although the "Give Five" campaign did not achieve its goal, its economic impact was considerable.

Keywords: charitable giving, fundraising, mass media, volunteering

JEL classification: H43, L38, L82

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1 Introduction

Mass media is a widely used tool to promote charitable causes.[1] Although it is almost a truism among fundraisers that media exposure of charitable causes facilitates giving and volunteering,[2] the causal effect of media campaigns on charitable behavior is mostly unknown. This is the first paper which investigates the effect of a national fundraising campaign that was advertised via mass media. Initiated by the Independent Sector (IS)[3], the "Give Five" campaign, hereafter the GFC, began in 1987 to encourage people to volunteer five hours a week and give five percent of their income to charitable organizations of their choice, including religious organizations. The campaign also encouraged people to help a friend or neighbor in need. From 1987 to 1995, the GFC was advertised with the collaboration of the Ad Council through a series of public service announcements on television and radio, billboard displays, bus-side posters, and magazine and newspaper ads. Local charities were also supplied with promotional materials and asked to support the campaign. The thin red "pie piece" used in "Give Five" logo emphasize the amount of time and income that people are encouraged to contribute, with the remaining majority of the circle indicating what people have left over.[4] During the early stages of the campaign, IS officials announced a substantial increase in giving and volunteering.[5] However, after eight years of promoting the GFC, the unchanging pattern in charitable behavior documented by the household surveys of giving and volunteering led IS officials to conclude that American's do not and may never give five percent of their income and volunteer five hours a week. Hence, the IS announced that it was phasing out the GFC in 1995. Burlingame (1997) states that instead of trying to change donor behavior, IS launched a new campaign in 1995, using the slogan: "Thanks for all you've given. Imagine what more could do". Although the IS stopped advertising the GFC via mass

[1] A possible reason that may explain the popularity of media campaigns among charities is that occasionally, some charities are offered free radio airtime, billboard space, or other marketing opportunities. For example, in her Chronicle of Philanthropy article "Why free advertising might not be a bargain?" (February 6, 2009), Brennen Jensen reports that One Laptop Per Child, a charity in Cambridge, MA received as much as $15 million in free media exposure including TV, print, and billboard.

[2] See, for example, Bray (2005).

[3] Founded in 1980, IS is a non-profit organization with a main goal of promoting the development of strategies to strengthen volunteering, voting, giving, and other forms of citizen engagement.

[4] A selection of "Give Five" advertisements are available at www.independentsector.org/give5/through_years.htm.

[5] In her New York Times article "No rise is found in volunteerism" (November 24, 1989), Kathleen Teltsch reports that Virginia A. Hodgkinson, vice president for research for the IS, announced a substantial increase in giving and volunteering due to the GFC. However, the article also mentions that in the Denver area, the first area to report on its progress in the campaign, annual household donations to charitable causes increased from $715 in 1986 to $815 in 1988, but the level of volunteering did not change significantly.

media in 1995, it still continues to promote the campaign in its official web site. The campaign's goal of having people donate five percent of their income and volunteer five hours a week is also widely promoted by various charitable organizations as a guide for contributions.[6]

Recent studies have shown the positive effect of fundraising on charitable giving and volunteering. For example, using panel data from the tax returns of charities, Khanna, Posnett, and Sandler (1995) and Okten and Weisbrod (2000) show the positive effect of fundraising expenses on charitable contributions. Using household level survey data, Schervish and Havens (1997) and Yörük (2009) find a positive relationship between personal charitable solicitations and giving. Meer and Rosen (2009) find a similar result using data on alumni donations. The positive effect of personal solicitations on volunteering is well-documented in the literature as well. Freeman (1997) and Yörük (2008) show that being solicited by a charity is the most important reason for why people volunteer their time. Andreoni and Payne (2003) suggest that these findings are due to the informative effect of fundraising. Media is another important tool for charities to inform potential donors about the activities and services they provide. Recent work documents how the informational effect of media changes the public's knowledge, attitudes, and behavior.[7] However, the existing literature is silent on how media affects charitable behavior.[8]

Part of this deficiency in the literature is due to lack of data on fundraising campaigns advertised via mass media. In this paper, I use biannual household surveys of charitable giving and volunteering conducted from 1988 to 1996, which contain a unique question on whether the respondent is informed about the GFC, to estimate the effect of the GFC on charitable giving and volunteering patterns. During the active campaign period, the number of people who heard about the GFC remained stable but was relatively low. I hypothesize that people who are more charitably inclined may be more likely to hear about the GFC. I use several empirical models based on propensity to score matching estimators to control for the possible selection into being informed about the GFC.

Using conventional regression methods, which do not control for the selection problem, I document that people who heard about the GFC significantly increased their giving as a percentage of their

[6] For example, Just Give organization promotes this goal in its website.

[7] See, for example, DellaVigna and Kaplan (2007), Dyck and Zingales (2002), and Karlan, Gerber, and Bergan (2009).

[8] The exception is Brown and Minty (2008), who investigate the effect of the media coverage of the 2004 tsunami on charitable donations to relief agencies. Furthermore, some recent studies use web based TV, internet, and radio as experimental tools to understand the determinants of charitable behavior. See, for example, Fong and Luttmer (2009) and Jen and Croson (2009).

household income by around 0.4 percentage points and their weekly volunteering hours by half an hour. However, the magnitude of the effect of the GFC on charitable giving decreases and becomes insignificant once the selection into being informed about the GFC is controlled for. Similarly, the magnitude of the effect of the GFC on volunteering decreases once the selection is controlled for but its effect remains mostly significant. After controlling for the selection into being informed about the GFC, I find that people who heard about the campaign increased their weekly volunteering activity on average by slightly less than half an hour. In general, this result is also robust to the selection of regression methods, different matching estimators, and control variables. Although my findings imply that the GFC did not have a significant effect on giving patterns, a rough estimate suggests that the dollar value of an increase in volunteering due to the GFC during the campaign period was at least $48 million a week. This result highlights the importance of media campaigns as a valuable to tool to promote charitable causes and facilitate charitable behavior.

The rest of this paper is organized as follows. The next section describes the econometric framework. Section three presents the data and summary statistics. The results, robustness tests, and the economic impact of the GFC are discussed in section four. Section five concludes with a summary of results and suggestions for future research.

2 Empirical framework

Let $Y_{1i,t}$ and $Y_{0i,t}$ be the outcome for a random person i surveyed in year t in the two counterfactual situations of treatment ($T_{i,t} = 1$) and non-treatment ($T_{i,t} = 0$), where the outcome is the amount of money donated as a percentage of income or volunteering hours per week and the treatment is whether person i is informed about the GFC. Hence, the outcome observed for individual i is $Y_{i,t} = (1 - T_{i,t})Y_{0i,t} + T_{i,t}Y_{1i,t}$. The parameter that is of primary policy interest is the average treatment effect of the GFC on the outcome variables, defined as $ATT = E(Y_{1i,t} - Y_{0i,t}|T_{i,t} = 1)$. This is the effect of the campaign on those who actually heard about the GFC.

The GFC did not target a specific group of people, hence I start with the assumption that exposure to the GFC is random. The outcome variables are censored due to the large number of observations for people who do not donate or do not volunteer. In order to account for the censored outcome, I

estimate the following standard Tobit model:

$$Y_{i,t} = \max(0, \beta^{'} X_{i,t} + \alpha T_{i,t} + \delta^{'} D_t + \varepsilon_{i,t}) \tag{1}$$

where $X_{i,t}$ is the set observable characteristics of the respondent, D_t is a set of survey year dummies, and $\varepsilon_{i,t}$ is the well-behaved error term with zero mean and constant variance σ. Year dummies in this model capture aggregate factors during the campaign period that would cause changes in the outcome variable such as potential variations in charitable behavior due to macroeconomic shocks or possible changes in the content of the GFC advertising from one year to another.[9] However, this model assumes that the effect of the GFC on the outcome variables remains constant over time.[10] Although this model has the advantage of accounting for the censored outcome, it has the disadvantage of imposing linear functional form and restrictions on the values of the treatment effects that are based on the shape of the normal distribution.

People who are more charitably inclined may be more likely to pay attention to the news about charitable organizations and fundraising campaigns, and hence, may be more likely to hear about the GFC. In order to control for this possible selection problem, I use several propensity score matching estimators. The main identifying assumption of matching estimators is that if one can observe enough information on strictly exogenous variables that determine the probability of being informed about the GFC, then giving and volunteering is mean independent of the treatment conditional on observable covariates. In this case, the effect of treatment on the outcome variables can be consistently estimated. Traditional matching estimators match each treatment unit to a fixed number of control units (those who did not hear about the campaign). The application of these methods is impractical to implement when the set of controls gets large and includes continuous variables. Following Rosenbaum and Rubin (1983), I use a propensity score matching estimator to deal with the dimensionality problem. Let $P(X_{i,t})$ be the propensity score, defined as $P(X_{i,t}) = \Pr(T_{i,t} = 1|X_{i,t})$. Then, the ATT is redefined as

$$ATT = E\{E[Y_{1i,t}|T_{i,t} = 1, P(X_{i,t})] - E[Y_{0i,t}|T_{i,t} = 0, P(X_{i,t})]|T_{i,t} = 1\}. \tag{2}$$

Formally, in order to derive equation (2), balancing and unconfoundedness properties should be

[9] Year dummies cannot control the potential changes in the content of the GFC advertising within the same year. However, there is no evidence to suggest this was the case.

[10] In this paper, I focus on the average effect of the GFC on giving and volunteering patterns during the campaign period. One can also estimate the effect of the GFC for different years by interacting year dummies with the treatment variable.

satisfied.[11] The balancing property states that for a given propensity score, exposure to treatment is random, hence treated and control units should be on average identical in terms of observable covariates. On the other hand, the unconfoundedness property guarantees that the treatment is random conditional on the set of observable characteristics, which allows for selection on observables. In principle, since the propensity score is a continuous variable, one cannot observe two units with exactly the same value of $P(X_{i,t})$. Therefore, an estimate of the propensity score is not sufficient to estimate equation (2). Following Dehejia and Wahba (2002), I use several propensity score matching methods in order to overcome this problem, namely nearest neighborhood matching (NM) with and without replacement, nearest four matching (NFM), radius matching (RM) with different calipers, and kernel matching (KM).

Rosenbaum (1995) argues that in NM without replacement, the results can be sensitive to the order in which treatment units and control units are matched. I consider 'low-to-high' matching, in which the treatment units are ranked according to their propensity score in an ascending order. In this method, the highest ranked treatment unit is first matched to a control unit then that particular unit is removed from the matching algorithm.[12] In NM with replacement however, the matching algorithm minimizes the propensity score distance between the matched control units and reduces bias since each treatment unit can be matched to the nearest control unit even if a control unit is used several times. Given the estimated propensity score, NFM matches each treatment unit with the four closest control units. RM sets a neighborhood in terms of a radius around the propensity score of the treated observation and excludes matches that lie outside this predefined neighborhood. In order to test the robustness of results to the selection of neighborhood, I implement the RM estimator with two different calipers, 0.001 and 0.005. In KM, all treated units are matched with a weighted average of all controls with weights that are inversely proportional to the distance between propensity scores of treatment and control groups. In conducting the KM, I use an Epanechnikov kernel with a bandwidth of 0.01.[13] All of these methods are estimated non-parametrically and share the advantage

[11] I also assume that matching assumption is satisfied such that $\Pr\left(T_{i,t}=1|P(X_{i,t})\right) \in (0,1)$. This assumption ensures that for each value of the propensity score, there are both treated and untreated individuals.

[12] Alternatively, in high-to-low matching, the treatment units are ranked according to their propensity score in a descending order. This method yields similar results compared with the low-to-high matching under different specifications. The results are available from the author upon request.

[13] Black and Smith (2004) find that the Epanechnikov kernel estimator performs better than Gaussian kernel independent of the bandwidth selected and the performance of the Kernel estimator is relatively independent of the selection of bandwidth until one gets to very small bandwidths. I also try several bandwidths between 0.001 and 0.1. The results

that they avoid functional form assumptions to estimate equation (2). However, they are reliable to the extent that unobservables correlated with being informed about the GFC do not directly affect the outcome variables.

3 Data

The propensity score matching analysis requires a large set of strictly exogenous control variables. I use a rich data set of biannual household surveys conducted from 1988 to 1996 by the Gallup Organization, and commissioned by the IS. These five independent cross-sectional surveys were conducted in person with one adult member of the household and provide one of the most comprehensive assessments of giving and volunteering activity in the United States. Pooling the biannual data from 1988 to 1996 gives a nationally representative sample of $12,401$ households.[14] However, eliminating observations missing key variables yields a sub-sample of $8,851$ households for the empirical analysis.

The surveys record information on giving and volunteering for 12 different functional categories of charitable activity.[15] For each household, I calculate the amount of charitable contributions as the sum of money that the household has reported giving to each of these categories. Similarly, for each respondent, the total hours of volunteering is calculated as the sum of time that the respondent volunteered for each of the charitable activities. From 1987 to 1995, the average volunteering and giving rates were 48 and 73 percent, respectively. On average, people donate 1.8 percent of their income to charitable organizations, and volunteer 1.7 hours per week.[16] Table 1 presents the summary statistics and the definitions of key variables used in the empirical analysis. Compared with those who did not hear about the GFC, people who were informed about the campaign tend to have higher household incomes. They also tend to be younger, employed, and well educated.

are comparable to my original estimate and available upon request.

[14] Each wave contains data for the prior year. The IS also collected data for 1999 and 2001. However, respondents of these surveys were not asked questions about the GFC. Gallup Organization collected charitable giving data at the household level but volunteering data at the individual level.

[15] These categories are health, education, religious, human services, environment, public benefit, recreation, art, youth development, private community, international, and other unnamed organizations. Compared with the other editions, the wording of the questions on giving and volunteering to different areas of charitable activity is slightly different in the 1988 edition. For this particular survey year, I estimate total giving (volunteering) as the sum of money (time) that the respondent has reported contributing to each of the specific charity groups that she was asked about, excluding her donations (volunteering hours) to political organizations. I also exclude informal and work-related contributions, and contributions to friends, neighbors, relatives, and strangers.

[16] On average, donors donated 2.2 percent of their income and volunteers volunteered 3.5 hours per week.

Since households are allowed to itemize charitable deductions on their 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. Since the survey does not report marginal tax rates, following Andreoni, Brown, and Rischall (2003), I calculate this variable for each household using information on itemization status, number of household members, gross income, probable filing status, and the tax schedules for the relevant year.[17]

The unique feature of the Gallup survey is that it contains a question on whether the respondent is informed about the GFC. The question is worded "Have you heard about the national program, Give Five, the goal being for people to become "fivers" by contributing at least 5 percent of income to charities and religious organizations and volunteering at least 5 hours per week?". Simple tabulations of responses to this question reveals that on average 9 percent of the respondents have heard about the campaign. In Table 2, I report that on average, those who were informed about the campaign donated 2.1 percent of their income and volunteered 2 hours per week, while those who were uninformed donated 1.7 percent of their income and volunteered 1.6 hours per week. Hence, the raw numbers suggest that the GFC increased household giving as a percentage of income by 0.3 percentage points and weekly volunteering by around $60 \times 0.378 = 22.7$ minutes. Furthermore, these effects were statistically significant, There results are also similar within individual years. Figure 1 shows that those who heard about the campaign always reported donating and volunteering more than those who were uninformed about the campaign, except for 1987. In 1987, although the informed respondents volunteered more than the uninformed respondents, they gave slightly less than those who did not hear about the GFC. However, Table 2 also reports that the effect of the GFC on those who were donors and volunteers during the campaign period was insignificant. Hence, simple tabulations show that the GFC was not effective in increasing the contribution amount and volunteering time of existing donors but did a good job in generating new volunteers and converting non-donors to donors.

The 1990, 1992, and 1994 waves of the Gallup survey contain an additional question on how the respondent learned about the GFC. Among those who were aware of the GFC, the most popular answers were TV (61 percent), newspapers (18 percent), other sources (17 percent), radio (12 percent),

[17] Following Andreoni (2006), the price of volunteering can be calculated as $w(1-t)$, where w is the wage rate of the respondent. Since the information on wage rate is available only in 1992 and 1994 editions of the survey, I do not use this information in the analysis.

charitable organizations (12 percent), and magazines (9 percent). Moreover, in the 1992, 1994, and 1996 waves of the survey, respondents who were informed about the GFC were also asked how reasonable they think the GFC's goal is. More than 62 percent of the respondents reported that the goal of the GFC is very reasonable or somewhat reasonable.

4 Results

In this section, I first assume that the selection into the treatment (being informed about the GFC) is random and estimate standard tobit models for comparison purposes. Next, I estimate several models under different specifications to address the possible selection into being informed about the GFC. These models rely on selection on observables, i.e., propensity score matching methods. As a robustness check, I also discuss methods relying on selection on unobservables.

4.1 Baseline Tobit estimates

Under different specifications, I estimate equation (1) and present the marginal effects of control variables conditional on the outcome being uncensored in Table 3. The first specification includes traditional control variables and dummies controlling for the year effects. Since different states may have different treatments for giving and volunteering, I control for the state effects in the second specification. People who are integrated with their community may be more likely to donate and volunteer. In order to address this possibility, the third specification includes community effects. These are the dummies controlling for whether the respondent owns his or her home and the number of years that the respondent lived in her current community. Fourth specification uses full set of controls and includes both state effects and community effects simultaneously.[18] In general, the marginal effects of the control variables have the expected signs under all specifications. Income, educational attainment, and regular attendance to religious services are positively associated with charitable behavior. whereas tax price has a negative affect on both giving and volunteering. The

[18] I also run two robustness tests in order to check the sensitivity of the Tobit models to the possible endogenity of the tax price. First, I exclude the tax price of giving from the Tobit model and check whether the effect of the GFC is sensitive to this alternative specification. Second, I instrument the tax price with the "first dollar price", which is the marginal tax rate that applies to the first dollar donated to charity, and re-estimate the Tobit models. The estimated effect of the GFC remains similar in both models. The results from these alternative models are available from the author upon request.

significant marginal effects of the GFC in giving equations differ between 0.21 and 0.23 percentage points, implying that the GFC increased giving as a percent of household income for those who actually donated money. Being informed about the campaign also positively affects volunteering. Under different specifications, I find that the marginal effect of the GFC on volunteering is around half an hour per week. In order to find the effect of the GFC on those who are actually informed about the campaign, using the simple formula suggested by Angrist (2001), I calculate the ATT of the GFC. The estimated ATT coefficients imply that people who heard about the campaign increased their giving as a percent of their household income by around 0.4 percentage points and their weekly volunteering hours by approximately half an hour. Furthermore, the standard errors calculated by the delta method suggest that these effects are significant at conventional significance levels.

As mentioned before, the 1990, 1992, and 1994 waves of the Gallup survey includes an additional question on how the respondent learned about the GFC. Several respondents report that they were informed about the campaign by multiple media sources. Hence, it is hard to distinguish the effect of a particular media source from the rest. Yet, I estimate several tobit models to investigate whether the source of information on the GFC, namely TV, radio, newspaper, or magazine, has any effect on the giving and volunteering patterns of those who heard about the campaign. [19] Table 4 shows that when it comes to charitable giving, how the respondent learned about the GFC does not matter. For those who heard about the campaign, the effect of being informed about the GFC from a particular media source on giving is not signficantly different from the effect of being informed about the GFC from any other media source. A similar result also applies for the volunteering patterns of those who heard about the GFC, except that the effect of being informed about the GFC from a newspaper or a magazine ad on weekly volunteering hours is significantly different than the effect of being informed about the GFC from a TV commercial.[20]

[19] In these models, the dependent variables are giving as a percent of income and weekly volunteering hours for those who heard about the GFC. Binary treatment variables are whether the respondent was informed about the GFC via TV, radio, newspaper, or magazine. The rest of the control variables are the same as the first specification reported in columns one and five of Table 3 for corresponding dependent variables.

[20] Although not reported, tobit estimates suggest that those who heard about the campaign from a newspaper or a magazine volunteered slightly more compared with those who heard about the campaign via TV.

4.2 Propensity score matching estimates

In order to conduct propensity score matching, I first estimate the propensity score, a probit model of the probability of being informed about the GFC as a function of observable characteristics. Table 5 shows the marginal effects of control variables on the probability of being informed about the GFC under four different specifications.[21] The first specification controls for household income, the tax price of giving, age, family size, gender, educational attainment, race, ethnicity, employment and marital status, regular attendance at religious services, and year effects. In addition to media, the IS also used its local member charities in several states to promote the GFC.[22] Hence, I consider state effects in the second specification. As in the Tobit models, the third specification includes community effects, whereas the fourth specification adds both state effects and the community effects as additional controls.

Figure 2 shows the distribution of the estimated propensity score for treatment and control groups under four different specifications. In all specifications, treatment and control groups have similar propensity scores. There are sufficiently many untreated individuals to be used for matches for the treatment group. Support condition and balancing assumption are also satisfied.

Table 6 reports the ATT of being informed about the GFC on giving as a percent of income and weekly volunteering hours for alternative estimated propensity scores and matching estimators. If people who are more charitably inclined are also more likely to hear about the GFC, then controlling for the selection into being informed about the GFC should decrease the estimated effect of the GFC on giving and volunteering patterns. As expected, controlling for the selection into being informed about the GFC reduces the estimated impact of the campaign. In general, compared with the Tobit models, the ATT of the GFC on giving as a percent of income is much smaller and insignificant under all alternative models. The effect of the GFC on weekly volunteering hours remains mostly significant but again, it is mostly smaller than the estimates of the Tobit models. Under different models, the effect of the GFC on volunteering is always significant when the NFM, KM or RM with different calipers are employed. In model 4, the NM without replacement and in models 3 and 4,

[21] In order to estimate the propensity score for different specifications, I begin with a starting specification which incorporates all observable covariates linearly and include some higher order and interaction terms when necessary to ensure that balancing property is satisfied. I also conduct standard t-tests for equality of means in the treatment and control groups, both before and after matching. These test and full estimates from the first stage probit models are available upon request.

[22] For example, as of the campaign start date, the IS had 32 member charities in New York, but none in several states.

the NM with replacement yields an insignificant estimated effect of the GFC on weekly volunteering hours. However, using Monte Carlo experiments, Frölich (2004) shows that k-nearest neighborhood matching estimators in general perform worse than Kernel estimators. Hence, my analysis relies on the significant ATT coefficients of the GFC. The estimated ATT coefficients in model 1 imply that people who heard about the GFC volunteered 21 to 27 minutes more per week compared with those who did not hear about the campaign. Model 2, which controls for the state effects, yields slightly higher estimated effect of the GFC on volunteering. This model suggests that people who were informed about the GFC increased their weekly volunteering activity by around 24 to 34 minutes. Model 3, which includes community effects as additional controls, yields relatively similar estimates compared with model 1. The estimated ATT coefficients in this model show that people who heard about the GFC volunteered 22 to 27 minutes more per week. Model 4, which includes full set of controls, yields the largest estimated effect of the GFC on volunteering. This model implies that people who heard about the GFC volunteered by around 30 to 33 minutes more per week than those who did not hear about the campaign. Hence, increase in individual weekly volunteering activity in response to the GFC was considerable but in general, slightly less than the effect estimated by the standard tobit models.

4.3 Selection on unobservables

The estimated effect of the GFC reported above depends on the assumption that observable characteristics of individuals determine the selection into being informed about the campaign. If some unobservable factors affect both charitable behavior and probability of being informed about the GFC, then propensity score matching methods do not yield consistent estimates. In order to address this possibility, I estimate several two-step endogenous Tobit models. In these models, following Angrist (2001), I estimate a probit model of being informed about the GFC as a function of observable characteristics in the first stage.[23] Next, I calculate a Mills-ratio type endogeneity correction term $T_i(-\phi_i/\Phi_i) + (1-T_i)\phi_i/(1-\Phi_i)$, where T_i indicates the treatment status and ϕ_i and Φ_i are normal density and cumulative distribution functions evaluated at the probit first-stage fitted values. In the second stage, I run standard Tobit models by including this correction term as an additional control variable. The coefficient of the correction term is $\rho\sigma$, where ρ is the correlation between the latent

[23] The observable characteristics are the same as those reported in section 4.2 above.

error determining treatment assignment and the outcome residual and σ is the standard deviation of the outcome residual. If this coefficient is significantly different from zero, then sample selection correction using the two-step endogenous Tobit model is needed.

The identification of this model requires either functional form assumptions or at least one instrumental variable that is correlated with the probability of being informed about the GFC but not with unobservable determinants of giving or volunteering. I use the respondent's confidence in media as an instrument for being informed about the GFC.[24] Although not reported, the first-stage probit estimates show that this variable is a significant determinant of the probability of being informed about the campaign. However, the coefficient of the correction term is insignificant in the second-stage Tobit models.[25] Similarly, using functional form assumptions that do not require any instrumental variables, I find that the coefficient of the correction term is insignificant and hence, sample selection correction due to selection on unobservables is not needed.[26]

4.4 The economic impact of the GFC

According to the most conservative estimate generated by the NFM estimator in model 1 above, the GFC did not have a significant effect on charitable giving patterns but those who heard about the campaign increased their weekly volunteering activity by slightly over 20 minutes. Although this effect seems to be small, the economic impact of an increase in volunteering activity by this amount is considerable. The IS's annual reports on volunteering contain information on the estimated dollar value of volunteering time, which is based on the average hourly wage of all production and non-supervisory workers on private nonfarm payrolls as reported by Bureau of Labor Statistics. The average estimated dollar value of volunteering calculated by the IS from 1988 to 1996 was $13.5 in 1996 dollars. During the same period, on average 9 percent of the US adult population heard about the GFC and among them 57 percent volunteered. Using the average US adult population during the campaign period, I calculate that the value of the estimated increase in weekly volunteering activity

[24] This a binary variable which is equal to one if the respondent reported that she has a great deal or a lot of confidence in media. This variable is not available for the 1988 wave of the survey.

[25] Here, I naturally assume that the functional form assumptions.for how the GFC and other observable characteristics of the respondents affect giving and volunteering are correct and that the confidence in media is a valid instrument for being informed about the GFC. If these assumptions fail, then the two-step procedure may yield inconsistent parameter estimates.

[26] The usual standard errors from the two-step procedure is incorrect. I use the bootstrap with 500 replications to calculate the correct standard errors. The results are available upon request.

of those who heard about the campaign is slightly more than $48 million per week in 1996 dollars.[27] Hence, although the GFC did not achieve its goal of making people to give five percent of their income and volunteer five hours per week, the economic value of the extra charity created due to the campaign was substantial.

5 Conclusion

In this paper, I investigate the effect of a national fundraising campaign, which was advertised from 1987 to 1995 via mass media, on charitable giving and volunteering patterns. The main objective of the GFC was to encourage people to give five percent of their income and volunteer five hours a week. Since U.S. citizens donate on average two percent of their income and volunteer two hours per week,[28] the GFC was directly aimed at changing donor behavior by setting new standards for giving and volunteering.

Using standard Tobit models, which do not control for selection into being informed about the GFC, I find that people who heard about the GFC increased their giving as a percentage of their household income by around 0.4 percentage points and their weekly volunteering hours by more than half an hour. Moreover, for those who heard about the campaign, the effect of being informed about the GFC from a particular media source on charitable giving is not signficantly different from the effect of being informed about the GFC from any other media source.

However, the effect of the GFC on giving and volunteering is much smaller once selection into being informed about the GFC is controlled for. Using propensity score matching methods and several matching estimators, I find that the aggregate effect of the GFC on monetary giving patterns was insignificant during the campaign period. The effect of the GFC on volunteering remains significant, however. After controlling for selection into being informed about the GFC, I find that people who heard about the campaign increased their weekly volunteering activity on average by almost half an hour. In general, this result is also robust to the choice of regression methods, matching estimators,

[27] The average US adult population druing the campaign period was 200,126,000. I calculate the economic impact of the GFC as 200,126,000×0.09×0.57×$13.5×20.8/60=$48,047,051. For comparison purposes, IS reports that in 2001, 83.9 million Americans volunteered, representing the equivalent of 9 million full-time employees at a value of $239 billion.

[28] This numbers are consistent with the historical trends (Andreoni, 2006). The most recent estimates are slightly higher. For example Giving USA (2007) reports that people on average donate three percent of their income to charitable causes.

and control variables. Although my findings imply that the GFC did not have a significant effect on giving patterns, a rough estimate suggests that the dollar value of the increase in volunteering due to the GFC was at least $48 million a week. Hence, although the GFC did not achieve its goal of setting new standards for giving and volunteering, its economic impact was quite substantial.

Considering the economic impact of the GFC, my results reveal media as an effective tool to inform potential donors and facilitate charitable behavior. Yet, some questions remain untouched, primarily due to the limitations of the survey data. First, mass media advertising for the GFC was more likely to influence people who regard charity as a non-monetary exchange.[29] Why was the GFC more effective in making people donate time rather than money? A possible reason is that mass media campaigns are most likely to be heard by people who have low opportunity cost of time such as retired or unemployed since these people spend most of their time watching TV or listening to radio. It is not surprising that these people may want to respond charitable campaigns by volunteering rather than donating money.

Second, to what extent do my results on the GFC generalize to other national fundraising campaigns of the same nature? Given the lack of comparable studies on national fundraising campaigns, this study should be viewed as a first step in understanding the effect of mass media on charitable giving and volunteering. Future research can focus on how media would affect charitable behavior under different incentives or due to the alternative settings of fundraising campaigns. These questions call for more detailed survey and experimental data on charitable giving and volunteering.

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Tables

Table 1. Definition of key variables and summary statistics

	Definition	Mean (Standard deviation)		
		Full Sample	Informed about the GFC	Uninformed about the GFC
Outcome variables				
Giving as a percent of income	Household's total charitable contributions divided by the household's income and multiplied by hundred.	1.758 (4.804)	2.053 (4.386)	1.719 (4.833)
Weekly volunteering hours	Total number of hours volunteered by the respondent per week. The data report monthly volunteering hours. I divide this amount by four to calculate weekly volunteering hours.	1.681 (4.073)	2.025 (4.216)	1.647 (4.050)
Main control variables				
Informed about the GFC	=1 if the respondent reported that she heard about the GFC.	0.092 (0.290)	-	-
Household income	Total household income in 1996 dollars. Respondents reported income in one of 15 before-tax income ranges. I use the midpoint of the each range as the actual income measure.	42,528 (30,061)	44,832 (30,661)	42,331 (29,990)
Tax price	=1 minus marginal tax rate for itemizers and 1 nonitemizers. Tax rates are calculated from information on probable filing status, income, itemization status, and other key variables.	0.911 (0.112)	0.899 (0.117)	0.912 (0.112)
Age	Age of the respondent.	44.384 (17.589)	40.054 (15.545)	44.797 (17.731)
Family size	Number of people in the household including the respondent.	3.043 (1.521)	2.990 (1.432)	3.048 (1.531)
Female	=1 if the respondent is female.	0.518 (0.500)	0.484 (0.500)	0.523 (0.500)
Black	=1 if the respondent is black.	0.107 (0.310)	0.108 (0.310)	0.107 (0.309)

Hispanic	=1 if the respondent is Hispanic.	0.072	0.043	0.075
		(0.258)	(0.204)	(0.263)
Married	=1 if the respondent is married.	0.644	0.604	0.649
		(0.479)	(0.489)	(0.477)
High school graduate	=1 if the highest level of education obtained by the respondent is a high school degree.	0.322	0.238	0.331
		(0.467)	(0.426)	(0.470)
Attended college	=1 if the respondent attended college but did not receive a four-year degree.	0.167	0.223	0.162
		(0.373)	(0.416)	(0.369)
College graduate	=1 if the respondent obtained a four-year college or higher degree.	0.168	0.226	0.161
		(0.374)	(0.418)	(0.368)
Employed	=1 if the respondent is employed.	0.605	0.695	0.596
		(0.489)	(0.460)	(0.491)
Regularly attends to religious services	=1 if the respondent reported attending religious services for every week or nearly every week.	0.441	0.404	0.445
		(0.497)	(0.491)	(0.497)
Other control variables				
Years lived in current community: 2 to 4	=1 if the respondent reported living in her current community 2 to 4 years.	0.136	0.163	0.135
		(0.343)	(0.369)	(0.341)
Years lived in current community: 5 to 9	=1 if the respondent reported living in her current community 5 to 9 years.	0.150	0.158	0.149
		(0.357)	(0.365)	(0.356)
Years lived in current community: 10+	=1 if the respondent reported living in her current community more than 10 years.	0.567	0.491	0.574
		(0.495)	(0.500)	(0.494)
Homeowner	=1 if the respondent owns her current residence.	0.676	0.631	0.681
		(0.468)	(0.483)	(0.466)

Notes: Sample weighted means are reported. Standard deviations are in parentheses. The maximum sample size is 12,401. The number of observations for each variable varies modestly due to non-respondents. The excluded category in education dummies is those who did not complete high school. The excluded category in community dummies is those who lived in their current community for less than two years.

Table 2. The relationship between giving and volunteering and the GFC

	Informed about the GFC	Uninformed about the GFC	Difference
Full Sample			
Giving as a percent of income	2.053 (0.143)	1.719 (0.047)	0.334 (0.155)
Weekly volunteering hours	2.025 (0.135)	1.647 (0.038)	0.378 (0.127)
Donor and/or volunteer			
Giving as a percent of income	2.725 (0.182)	2.613 (0.070)	0.112 (0.213)
Weekly volunteering hours	4.939 (0.261)	4.906 (0.093)	0.033 (0.280)

Notes: Sample weighted means are reported. Standard errors are in parentheses.

Table 3. Giving as a percent of income and weekly volunteering hours: Tobit model

	Giving as a percent of income				Weekly volunteering hours			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Informed about the GFC	0.230	0.209	0.238	0.215	0.452	0.440	0.464	0.450
	(0.084)***	(0.084)**	(0.084)***	(0.084)***	(0.109)***	(0.109)***	(0.109)***	(0.109)***
ln (Household income)	-	-	-	-	0.298	0.349	0.263	0.312
					(0.053)***	(0.054)***	(0.054)***	(0.055)***
ln (Tax price)	-1.361	-1.467	-1.305	-1.418	-0.999	-0.995	-0.913	-0.914
	(0.190)***	(0.191)***	(0.195)***	(0.197)***	(0.266)***	(0.265)***	(0.269)***	(0.268)***
Age	0.012	0.012	0.009	0.009	0.001	0.001	-0.003	-0.003
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)	(0.002)	(0.002)	(0.002)
Family size	0.000	0.001	-0.004	-0.003	0.103	0.105	0.095	0.097
	(0.017)	(0.017)	(0.017)	(0.017)	(0.021)***	(0.021)***	(0.022)***	(0.021)***
Female	-0.068	-0.065	-0.069	-0.066	0.276	0.267	0.273	0.264
	(0.047)	(0.047)	(0.047)	(0.047)	(0.060)***	(0.059)***	(0.060)***	(0.059)***
Black	-0.393	-0.367	-0.383	-0.360	-0.239	-0.137	-0.215	-0.121
	(0.063)***	(0.066)***	(0.064)***	(0.066)***	(0.086)***	(0.091)	(0.087)**	(0.091)
Hispanic	-0.343	-0.363	-0.330	-0.356	-0.458	-0.406	-0.437	-0.397
	(0.067)***	(0.073)***	(0.067)***	(0.073)***	(0.088)***	(0.096)***	(0.089)***	(0.096)***
Married	0.194	0.188	0.193	0.190	0.162	0.123	0.154	0.123
	(0.054)***	(0.053)***	(0.054)***	(0.054)***	(0.071)**	(0.071)*	(0.072)**	(0.072)*
High school graduate	0.113	0.114	0.103	0.106	0.144	0.132	0.133	0.123
	(0.064)*	(0.064)*	(0.064)	(0.064)	(0.087)*	(0.086)	(0.087)	(0.086)
Attended college	0.452	0.438	0.444	0.429	0.696	0.653	0.692	0.650
	(0.082)***	(0.082)***	(0.082)***	(0.082)***	(0.112)***	(0.111)***	(0.112)***	(0.111)***
College graduate	0.531	0.518	0.532	0.518	1.142	1.116	1.159	1.131
	(0.079)***	(0.080)***	(0.080)***	(0.080)***	(0.113)***	(0.112)***	(0.114)***	(0.113)***
Employed	0.067	0.062	0.058	0.053	0.268	0.228	0.254	0.214
	(0.054)	(0.054)	(0.055)	(0.055)	(0.071)***	(0.070)***	(0.071)***	(0.070)***
Regularly attends to religious services	0.967	0.946	0.954	0.936	1.213	1.197	1.191	1.177
	(0.047)***	(0.049)***	(0.049)***	(0.049)***	(0.063)***	(0.063)***	(0.063)***	(0.064)***
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State effects	No	Yes	No	Yes	No	Yes	No	Yes
Community effects	No	No	Yes	Yes	No	No	Yes	Yes
ATT	0.403	0.365	0.415	0.373	0.494	0.496	0.512	0.510
	(0.165)***	(0.161)**	(0.165)***	(0.161)**	(0.162)***	(0.167)***	(0.165)***	(0.168)***
σ	5.213	5.181	5.213	5.181	8.111	8.024	8.102	8.013
	(0.048)***	(0.048)***	(0.048)***	(0.048)***	(0.110)***	(0.109)***	(0.110)***	(0.109)***
Log-likelihood	-20597.50	-20542.79	-20560.48	-20506.19	-14127.83	-14048.76	-14090.60	-14011.61
Pseudo R^2	0.024	0.027	0.024	0.027	0.041	0.046	0.041	0.047
Number of censored obs.	2730	2730	2727	2727	5575	5575	5569	5569
Number of obs.	8851	8851	8838	8838	8851	8851	8838	8838

Notes: Marginal effects conditional on the outcome being uncensored are reported. Standard errors are in parentheses. All models include a constant term. The signs *, **, and *** indicate 10%, 5%, and 1% significance levels respectively.

Table 4. Tests of equality of the effect of alternative media sources on giving and volunteering

A. Giving as a percent of income

	TV	Radio	Newspaper
Radio	1.50 (0.221)	-	-
Newspaper	0.86 (0.353)	0.05 (0.826)	-
Magazine	1.89 (0.169)	0.15 (0.703)	0.43 (0.516)

B. Weekly volunteering hours

	TV	Radio	Newspaper
Radio	0.78 (0.377)	-	-
Newspaper	3.61 (0.057)*	0.59 (0.443)	-
Magazine	3.03 (0.082)*	0.86 (0.354)	0.02 (0.879)

Notes: Data from survey years 1990, 1992, and 1994 are used. Two-sided chi-squared test statistics with one degree of freedom for the equality of the coefficients on binary control variables for alternative media sources across different tobit models are reported. Standard errors are in parentheses. The null hypothesis is that for those who heard about the GFC, the effect of being informed about GFC from a particular media source is equal to the effect of being informed about the GFC from another media source. The sign * indicates that the null hypothesis is rejected at 10% significance level.

Table 5. The probability of being informed about the GFC: Probit model

	(1)	(2)	(3)	(4)
ln (Household income)	-0.006	-0.007	-0.005	0.009
	(0.005)	(0.005)	(0.005)	(0.113)
ln (Tax price)	-0.079	-0.094	-0.085	-0.105
	(0.027)***	(0.026)***	(0.027)***	(0.027)***
Age	0.001	-0.000	0.001	0.003
	(0.001)	(0.000)	(0.001)	(0.002)
Family size	-0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.017	-0.016	-0.017	-0.009
	(0.006)***	(0.006)***	(0.006)***	(0.017)
Black	-0.002	0.002	-0.004	-0.036
	(0.009)	(0.010)	(0.009)	(0.018)*
Hispanic	-0.029	-0.020	-0.030	-0.020
	(0.008)***	(0.009)**	(0.009)***	(0.009)**
Married	-0.004	-0.001	-0.003	-0.000
	(0.007)	(0.007)	(0.007)	(0.007)
High school graduate	-0.020	-0.020	-0.020	-0.018
	(0.008)**	(0.008)***	(0.008)**	(0.008)**
Attended college	0.008	0.008	0.009	0.011
	(0.010)	(0.010)	(0.010)	(0.010)
College graduate	0.022	0.023	0.022	0.023
	(0.010)**	(0.010)**	(0.010)**	(0.011)**
Employed	-0.010	-0.007	-0.010	-0.008
	(0.008)	(0.007)	(0.007)	(0.007)
Regularly attends to religious services	0.000	0.002	0.001	0.003
	(0.006)	(0.006)	(0.006)	(0.006)
Year effects	Yes	Yes	Yes	Yes
State effects	No	Yes	No	Yes
Community effects	No	No	Yes	Yes
Log-likelihood	-2542.84	-2466.42	-2534.79	-2455.75
Pseudo R^2	0.024	0.052	0.025	0.055
Number of obs.	8851	8823	8838	8810

Notes: Marginal effects are reported. Standard errors are in parentheses. All models include a constant term. All models also include higher order and/or interaction terms in order to satisfy the balancing property. The signs *, **, and *** indicate 10%, 5%, and 1% significance levels respectively.

Table 6. Propensity score matching estimates

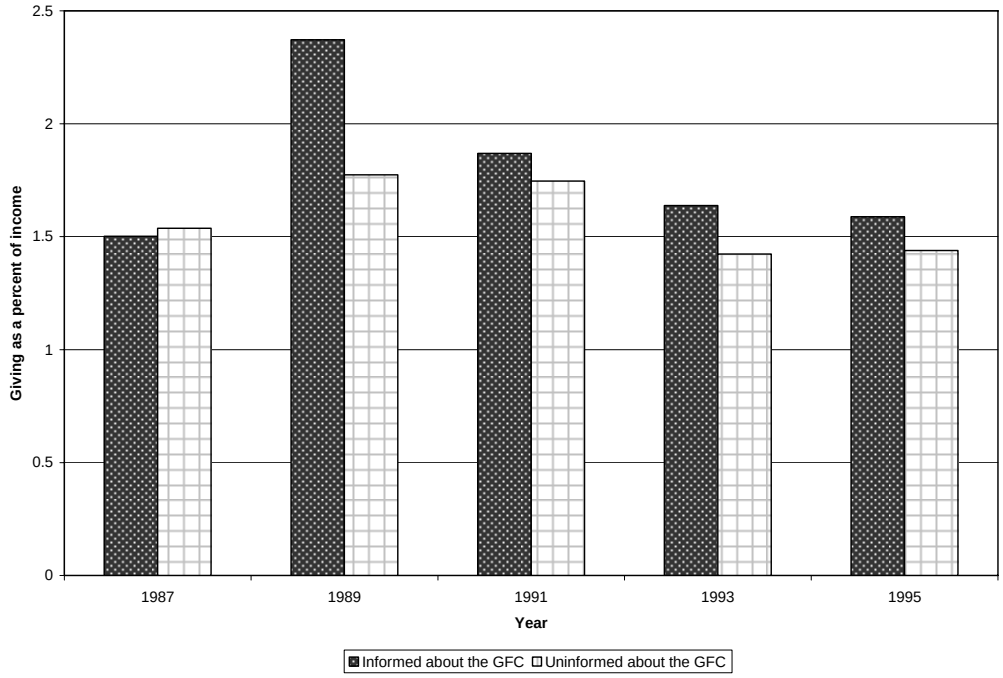
	NM without replacement (low-to-high)	NM with replacement	NFM	RM (caliper = 0.005)	RM (caliper = 0.001)	KM
Model 1						
Number of treated obs.	765	765	765	765	763	765
Number of untreated obs.	765	711	2416	8078	7996	8083
ATT (Giving)	0.180	0.229	0.118	0.157	0.162	0.160
	(0.214)	(0.219)	(0.186)	(0.155)	(0.155)	(0.145)
ATT (Volunteering)	0.393	0.424	0.347	0.434	0.445	0.435
	(0.239)*	(0.262)*	(0.211)*	(0.182)**	(0.190)**	(0.183)**
Model 2						
Number of treated obs.	765	765	765	760	747	765
Number of untreated obs.	765	702	2374	8035	7896	8056
ATT (Giving)	0.154	0.163	0.246	0.202	0.260	0.214
	(0.219)	(0.249)	(0.202)	(0.162)	(0.168)	(0.159)
ATT (Volunteering)	0.392	0.438	0.560	0.500	0.498	0.503
	(0.233)*	(0.262)*	(0.231)**	(0.188)***	(0.188)***	(0.193)***
Model 3						
Number of treated obs.	764	764	764	764	763	764
Number of untreated obs.	764	708	2427	8067	7981	8072
ATT (Giving)	0.113	0.074	0.117	0.172	0.186	0.172
	(0.225)	(0.259)	(0.193)	(0.151)	(0.151)	(0.148)
ATT (Volunteering)	0.376	0.303	0.461	0.466	0.473	0.459
	(0.228)*	(0.241)	(0.217)**	(0.173)***	(0.173)***	(0.182)**
Model 4						
Number of treated obs.	764	764	764	762	748	764
Number of untreated obs.	764	688	2316	8007	7797	8046
ATT (Giving)	0.182	0.171	0.167	0.216	0.203	0.219
	(0.221)	(0.303)	(0.234)	(0.162)	(0.173)	(0.155)
ATT (Volunteering)	0.322	0.344	0.498	0.525	0.543	0.494
	(0.241)	(0.244)	(0.215)**	(0.196)***	(0.187)***	(0.184)***

Notes: Standard errors calculated via 500 bootstrap replications are in parentheses. The signs *, **, and *** indicate 10%, 5%, and 1% significance levels respectively. In estimating the propensity score, Model 1 controls for household income, tax price of giving, age, family size, gender, educational attainment, race, ethnicity, employment and marital status, regular attendance to religious services, and year effects. Model 2 adds state effects. Model 3 excludes state effects but includes community effects. Model 4 adds both state and community effects as additional controls.

Figures

Figure 1. The effect of the GFC on charitable giving and volunteering

A. Giving as a percent of income



B. Weekly volunteering hours

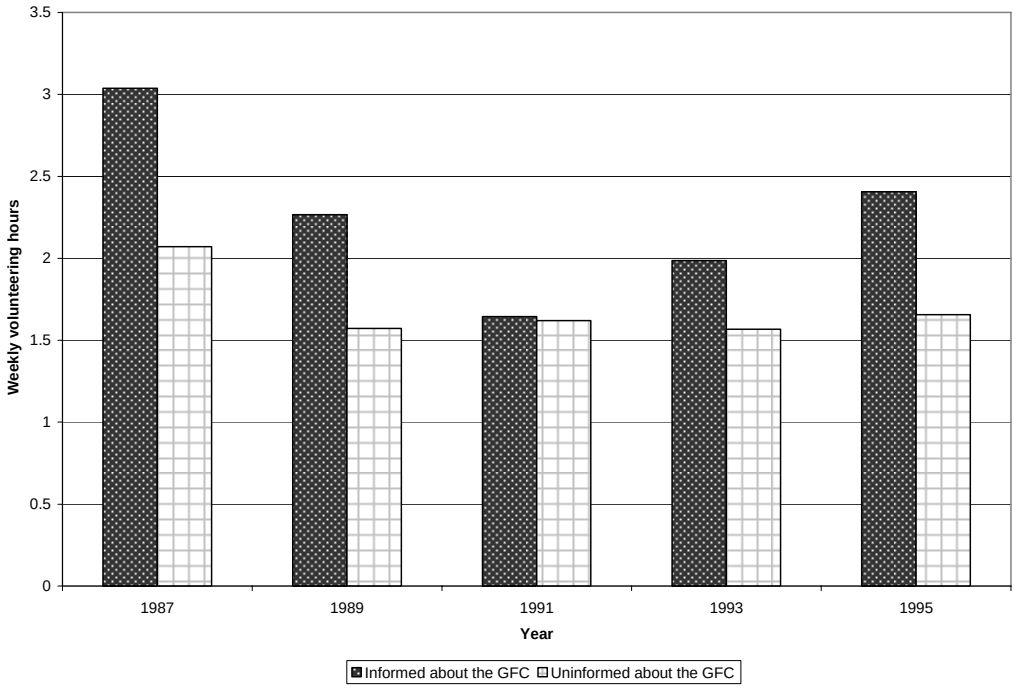
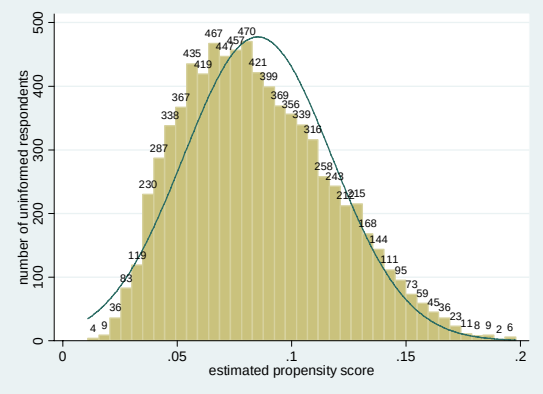
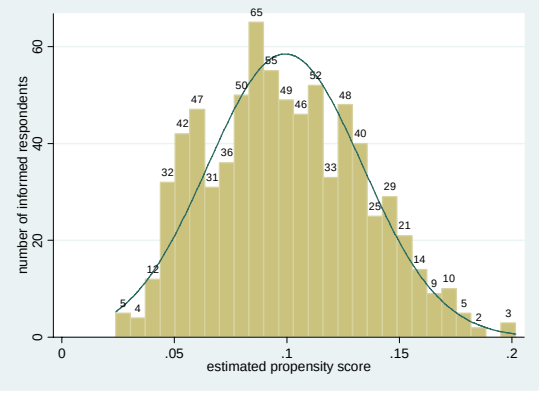


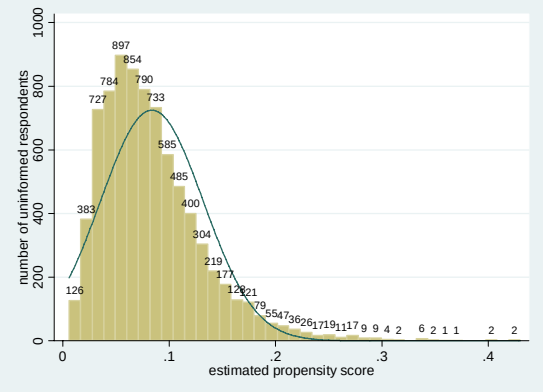
Figure 2. Propensity score matching with different set of controls

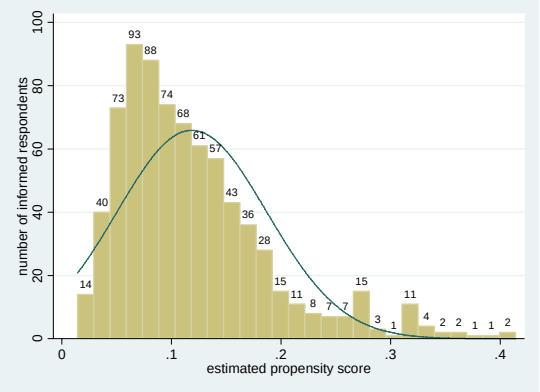
Model 1



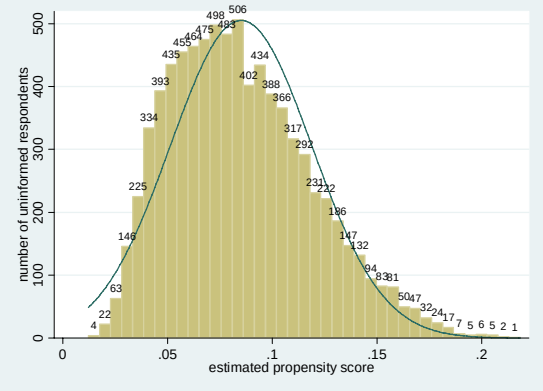


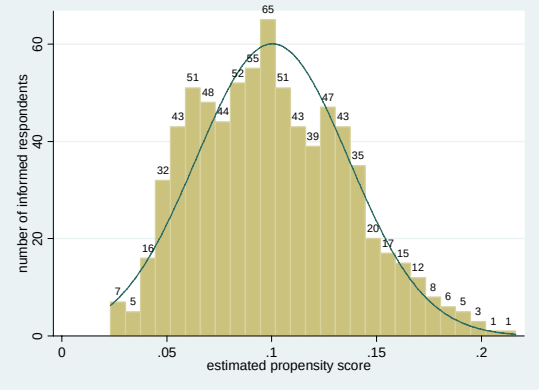
Model 2



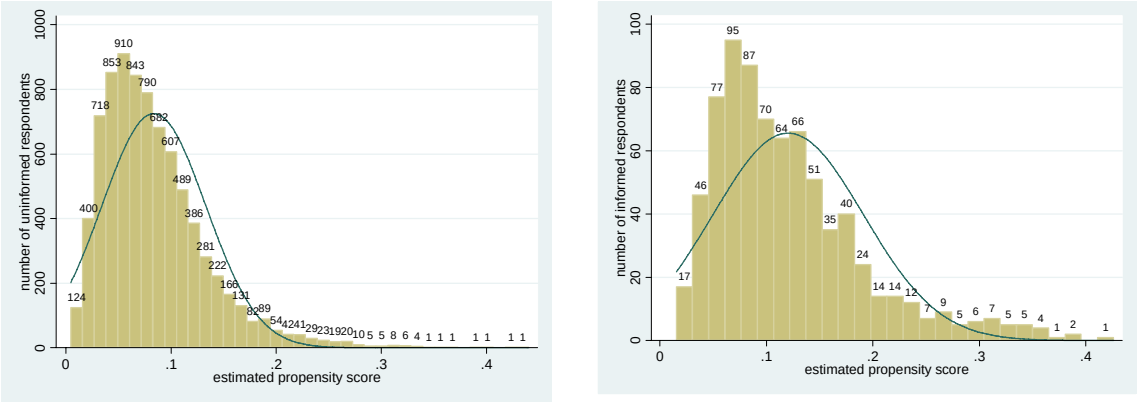


Model 3





Model 4



Notes: Sample sizes differ between 8810 and 8851 due to missing information for some control variables. Model 1 controls for household income, tax price of giving, age, family size, gender, educational attainment, race, ethnicity, employment and marital status, regular attendance at religious services, and year effects. Model 2 includes state effects as additional controls. Model 3 includes community effects as additional controls but excludes state effects. Model 4 includes both state effects and community effects as additional controls.