Does One Contribution Come at the Expense of Another? Empirical Evidence on Substitution Between Charitable Donations*

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Abstract

This paper estimates and describes how a shock that increases an individual's donation to one cause tends to displace her gifts to other charitable causes, an effect I call "expenditure substitution." I use the 2001-2005 waves of the PSID/COPPS, the first data set of its kind. Households that give more to one type of charity tend to give more to others. However, many of the correlations between the residuals after fixed-effects regressions are negative and significant, particularly for larger donors and for certain categories of charitable giving. Given plausible econometric assumptions, the negative correlations are strong evidence of expenditure substitution.

Keywords: Altruism, Public Goods, Charitable Giving, Philanthropy, Expenditure Substitution, Conditional Demand, Panel Data, Stochastic Assumptions.

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1 Introduction and Motivation

On average Americans give about 2% of their income to charity, with about 60% of this going to religious organizations. In a typical year about 70% of households make contributions and fundraising expenses are around $2 billion (Andreoni, 2006). Empirical economists have typically focused on two major issues: the "crowding out" of government grants and the impact of different tax regimes on overall giving. Little academic work has been written about the extent to which an individual's contribution to one cause comes at the expense of her other philanthropy. This issue has come to the attention of policymakers and journalists in the wake of the September 11, 2001 terrorist attacks,[1] and again after the 2004 Indian Ocean tsunami[2] and 2005's Hurricane Katrina[3] – in each case there was a concern that the flood of donations to the well-publicized cause would dampen giving to other charities. However, some have dismissed this concern, claiming that "donor fatigue" is a myth.[4] I address this issue here, examining within-household conditional correlations to measure and describe the extent to which one charitable donation displaces another.

What do I mean by "substitution between charitable donations"? Since I do not observe independent price variation,[5] I cannot measure cross-price elasticities. I model donation decisions (modeling details in appendix) as sequential but occurring in a random order and assume that there is temporary "shock" to utility at the time some decisions are made. For example, a household may experience a powerful appeal from a charitable organization, or a prominent natural disaster may raise the perceived efficacy of some donations. I consider the effect of these shocks to be "preallocations"(as in the terminology of Pollak (1969)) away from the donation that maximizes the un-shocked utility. I aim to measure the "expendi-

[1] *http://www.sptimes.com/2002/09/04/911/Sept_11_donations_swa.shtml*

[2] http://www.cnn.com/2005/WORLD/africa/07/30/africa.hungry.ap/index.html

[3] "Katrina Giving Cuts Donations To Other Groups; As Relief Contributions Pour In, Unrelated Charities Retool Plans To Get Back on Donors' Minds" – *The Wall Street Journal*, September 20, 2005.

In response, the government increased the maximum allowable tax deduction for charitable giving to 100 percent of income on donations made during the last part of 2005. – "Katrina Emergency Tax Relief Act...," by Candace Clark, UNC-Chapel Hill. *http://www.johnbrownlimited.com/newsletter/1005/index.cfm*

[4] "Many Dismissing 'Donor Fatigue' as Myth"– *New York Times,* April 30, 2006

[5] Generally all charities are treated equally for US federal and state taxes.

ture substitution" (or "expenditure complementarity"): the response, in dollars given to one category of charity, to the preallocated expenditure on another category of charitable gift.

Given the rich panel nature of my data, I can control both for the household's long-term propensity to donate to each category of charity and for observables that vary over time. The remaining variation is assumed to have two components. The first is assumed to be an exogenous "true shock" that is orthogonal to all other stochastic variables. The second includes both the effect of omitted or mismeasured variables (in particular, income) and the effect of *permanent* changes in the utility function (in particular, changes in generosity and altruism). Taken collectively, this second component of variation is assumed to be positively correlated across charities.

Since I do not observe the order of the donation decisions, I do not estimate a regression model. Instead, I focus on the correlation coefficients between the residuals (from separate regressions with household-dummies and controls) of giving to each category of charity. Given my stochastic assumptions, although a positive correlation coefficient does not necessarily imply complementarity, a negative coefficient *does* imply "expenditure substitution" (defined in section 2). Even without these modeling assumptions, the results are descriptively useful: they represent the first empirical evidence on an individual's substitution between charitable causes in a panel setting.[6]

The various theoretical models of charitable giving imply different substitution patterns. According to a "pure public goods" model (Becker, 1974) there should be virtually no expenditure substitution between unrelated charities. On the other hand, in the "warm-glow model" (Andreoni, 1990), if charity is a homogeneous good, when an individual increases her gift to one charity she will reduce giving to all other charities by the same amount. A "tithing model" (e.g., Laffont and Martimort (2002)) also predicts "perfect" (100%)

[6]While an instrumental variables approach might be preferable, no strongly significant and plausibly exogenous instrument could be found, although I tried all of the obvious and recommended possibilities (as well as some wild stabs). In a previous version of this paper I used the year of a college reunion as an instrument for giving to education, but on a careful reexamination this instrument proved not highly significant, possibly because of data limitations that made precise identification of the year of bachelor's degree impossible in some cases.

crowding-out. A warm-glow model in which different charities are distinct components of the utility function can yield virtually any result, as can an impact model (Duncan, 2004). The "Kantian" model predicts a moderate amount of expenditure substitution, but little substitution between distinct categories of charity.

My results are also relevant to the empirical issues that have been a focus of the literature. If there is expenditure substitution and a government grant crowds out giving to one cause, donors may increase their giving to other charities, as noted by Feldstein and Taylor (1976). Furthermore, substitution among charities will complicate estimation (as in Reece (1979) and Feldstein and Clotfelter (1976)) of the price and income elasticities of each charity.

A precise measure of expenditure substitution will be useful to policymakers, charities, volunteers, and philanthropists. Tax incentives may have unintended consequences: if the government offers favorable treatment to one charity, this may decrease contributions to other charities. Substitution is also important to fiscal planning: policymakers need to gauge how much an unexpected disaster or predictable change in giving patterns will impact other charities and create a need for greater public funding.[7] They also may want to know the net effect of such a disaster on tax revenues, as more charitable giving means more tax deductions; substitution will dampen this effect. An altruistic nonprofit executive (or individual soliciting donations) might be concerned that increases in giving to his cause may displace contributions to other charities; failure to recognize this could lead to overinvestment in fundraising as discussed by Chua and Ming Wong (2003) and Straub (2003). Finally, if a community institution that offers services to its members (such as a church, library, or opera house) seeks donations rather than relying on membership fees, this may reduce giving to other charities that the institution's leaders care about.

The key results of this paper come from a micro-econometric analysis of individual substitution patterns in the 2001, 2003, and 2005 waves of the Panel Study of Income Dynamics (PSID), in conjunction with the Center on Philanthropy Panel Survey (COPPS). This is the

[7] It is widely accepted that, particularly in the US, private philanthropy often substitutes for public sector provision of goods and services. See, e.g., Hungerman (2005).

first large-scale US data set that includes reliable repeated observations of individuals' giving to several major categories of charities.[8] Thus, I can control for individual-fixed attributes as well as time-varying financial variables, and I limit the sample to households with constant demographic characteristics.

Examining correlations between residuals from fixed-effect regressions (or from simple differences from household-level means), I find a strongly significant negative relationship between contributions to health and contributions to basic needs (henceforth, "Needy") charities, but a positive relationship between Needy and combined-cause charities. While these are robust to various checks, the patterns for other charity pairings are more mixed. Aggregating across categories, I find several other negative relationships; e.g., between religious and non-religious gifts. Overall, there is a greater level of substitution for the larger givers than for those who give smaller amounts. The substitution *does not* tend to occur at the extensive margin: a household that stops (starts) giving to one category tends to stop (start) giving to another category more often then the reverse. Insofar as my results show substitution they are broadly consistent with the results of my laboratory experiments (Reinstein, 2008).

The paper is structured as follows. In section 2, I define and discuss this paper's goal: estimating "expenditure substitution." In section 3 I survey the economic literature on giving and related topics. I first discuss what previous models would predict for expenditure substitution. Next I review key findings on variables that influence giving, and then discuss empirical work on substitution among endogenous choices. I found no papers that tackle substitution in charitable giving at the individual level. Section 4 describes the PSID/COPPS data and presents summary statistics. Section 5 presents and interprets the overall econometric results. I conclude in section 6.

[8]Other data sources include the Consumer Expenditure Survey, which does not have a robust panel dimension, and income-tax data, which does not differentiate by charitable cause.

2 Conceptual model

> Americans have donated more than $1 billion to the [Katrina/ flooding] relief ... But the largess is starting to come at the expense of charities with other missions. ...The challenge is people like Betty and Larry Sullivan .... the couple has given $4,000 for the tsunami relief effort and some $35,000 to help Hurricane Katrina survivors ... As for donations to other charities this year, "That's history," says Mrs. Sullivan.[9]

Economists typically frame demand, including demand for making charitable gifts, as a simultaneous decision to purchase a bundle of goods and services to maximize a utility function subject to a budget constraint. In this framework, parameters that affect the utility function (e.g., good weather) and the budget constraint (income and prices) are said to impact *all* of the consumption choices – these exogenous parameters are not seen as specific to any good. Economists will estimate price elasticities, but to ask "how does consumption of A affect consumption of B?" is not meaningful. We cannot assert causality for such simultaneous decisions, and the ratios of changes in these choices will depend on what is causing the changes.[10] However, as in the quote above, non-economists often pose this question, frequently see their decisions as sequential, and conceive of one purchase coming at the expense of another. Furthermore, in the standard economic framework it is not meaningful to claim that an event such as a tsunami has a direct impact only on gifts to one cause. A shock "μ_{it}^K" can be specific in the sense that it only changes the *marginal utility* of gifts to one cause, but if decisions are simultaneous, the shock will affect all choices.

To reconcile these distinct views and give a conceptual and econometric framework for my analysis, I offer a model of sequential decision-making with temporary shocks. As this model does not yield any crucial theoretical results, I present it in more detail, along with

[9] The Wall Street Journal, September 20, 2005.

[10] Still, our standard economic examples suggest a more direct causation: coffee "substitutes for" tea, while cream "complements" both beverages.

its implications for my econometric identification, in the appendix. In brief, I define "expenditure substitution" (essentially, the change in the expenditure on one good when the consumption of another good is exogenously moved from its long-term optimum) in terms of the cross-derivative of Pollak's (1969) conditional demand. The key restriction on the shock term essentially rules out the possibility that variations that cause *increased* giving to one category of charity inherently tend to coincide with variations that cause *decreased* giving to another category. Under the conditions given I show that where I estimate a negative and significant Pearson correlation coefficient (between residuals from fixed-effects regressions of giving to two distinct charitable causes), I can infer that there is a high probability that these charities are expenditure substitutes.

3 Previous Work

There are several competing theoretical models of giving. Since these predict different patterns of expenditure substitution, as described below, my empirical results can be used to evaluate these theories.[11]

Table 4 about here

Assume people do not have diminishing returns to giving to a single cause, and only care about the total amount that a specific cause receives. Under this model small to medium-sized donors should only give to a single large charity – an individual's small contribution will not significantly help a large charity, and thus should not change the ordering (between charities) of the marginal utility to marginal cost ratio in the individual's decision problem.[12] Similarly, any small shock to (own or others') giving to a charity should leave this ordering unchanged. Thus, for typical small givers to big charities, there should be no expenditure

[11] See appendix list 1 for a formalization of the models discussed below as well as other possibilities. Note that I do not attempt to separate income and substitution effects in my empirical analysis: I leave this for later research. For more complete surveys of the literature, see Andreoni (2006) and Bekkers and Wiepking (2008).

[12] A similar argument is made by Sugden (1983), among others.

substitution between dissimilar charities (net of income effects, which could cause a small amount of substitution).

Warm glow model (Andreoni, 1990)

If there is only a warm glow motivation (the individual gets a positive feeling from donating) and the charitable causes are perfect substitutes (i.e., contribute equally to marginal utility for all levels of giving) as sources of warm glow, then her warm glow will be a function of the total amount donated. This implies complete crowding-out: if she is induced to give a dollar more to charity A then she will reduce contributions to all other charities by one dollar. In a more sophisticated warm glow model (perhaps motivated in part by public recognition), the individual's warm glow may be a concave function of her gifts to a set of charities, with diminishing returns to the gift to each charity, implying a certain degree of substitution. In this model virtually any level of substitution or complementarity is possible, depending on the extent to which these charities are complements or substitutes in providing warm glow.

Impact Philanthropy (Duncan, 2004)

Duncan's model of "impact philanthropy" can be seen as a refinement of Andreoni's model, where the warm glow comes from the donor's perception of her gifts' impact on the recipients. Duncan assumes marginal utility diminishes in this impact-driven warm glow. As in the public goods case, small to moderate gifts should not affect the perceived marginal impact of other gifts. Thus, under this model expenditure substitution should depend on how the much impact the donor thinks the "shocked" gift had. This model should yield an intermediate prediction for expenditure crowd-out. If the shock is perceived to have had no impact at all, it will have no crowding-out effect (net of income effects). If the shock is seen to have as much impact as the gifts the donor otherwise would have given, crowding out will be complete.

Kantian/ individual-group misperception

In this model (mentioned in (Sugden, 1983), formalized in list 1 in the appendix here) the individual makes decisions such that if all others mirrored her, her utility (perhaps altruistic/enlightened) would be maximized. Such an individual will allocate her own charity as a fraction of what she would see as optimal if she were the social planner. Here, net substitution should be large between charities that accomplish the same or similar goals, but small to nonexistent if two causes are vastly different; the pattern depends on the extent to which these charities (considered as public goods) are complements or substitutes in the individual's utility function.

Empirical literature

Previous authors offer evidence on the major determinants of charitable giving, some of which could be seen as "shocks" that specifically shift an individual's gift to one type of charity. An obvious example of a shock is a natural disaster. The Center on Philanthropy at Indiana University (CPIU) noted that for 10 of 13 "major events of terrorism, war (or war-like) acts, and political or economic crises" giving grew at a faster rate in the calendar year after these events than it did in the year of, or the year before the event.[13] In a separate paper, the CPIU surveyed 1,304 adults about their household's philanthropic behavior after the events of September 11, 2001, finding high rates of giving and participation (around 74%). However, surveys of charities do not seem to show a large overall "crowding out" effect of this giving.[14] An individuals' exposure to campaigns and events such as the Aids Ride, the Jerry Lewis Telethon, and Save the Children television spots, as well as the timing and attractiveness of those making face-to-face solicitations will vary from year to year.[15] Many authors find that "peer group" effects and other social influences are significant.[16]

[13]AAFRC Trust for Philanthropy Press Release, Sept 20, 2001 "Update; What do Crises Mean for Giving?"

[14]"Most charities say the September 11 terrorist attacks were not a major damper on year-end fundraising, according to a survey by the Association of Fundraising Professionals" (Chronicle of Philanthropy, Feb 21, 2002, p. 25). However, these reports do not carefully consider the counterfactual: giving to certain causes might have been even *higher* if not for the 9/11 giving.

[15]Landry, Lange, List, Price, and Rupp (2005) report that an "increase in female solicitor physical attractiveness" had a large positive effect on contributions. However, Van Diepen, Donkers, and Franses (2006) show that excessive promotion may lead to irritation and actually reduce giving.

[16]E.g., Long (1976), Keating, Pitts, and Appel (1981), Feldstein and Clotfelter (1976), Schervish and Havens (1998), Carman (2003), and Martin and Randall (2008).

Government policy may also be an important influence on giving. If the government were to offer a special tax concession for gifts to one cause, or were to take away charitable status to certain groups (e.g., to charities suspected of funding terrorism), this could yield a specific shock. In fact, some nations, including Germany, Italy, France, Australia, and Japan do have different deduction rules for different categories of charity,[17] and at least one member of the U.S. Congress has questioned whether all charities deserve equal tax breaks.[18]

Many economists have attempted to estimate the (after-tax) price elasticity of charitable giving.[19] Depicting charity as a composite good, nearly all studies found a significant and negative effect, but these studies disagree as to whether elasticity exceeds one.[20] Some authors have differentiated these estimates by category of charitable cause: Reece (1979) found a wide variation in price elasticities between charities, ranging from -0.077 for educational giving to -1.598 for religious giving, while Feldstein and Taylor (1976) found price elasticities greater than one for all categories except religious contributions. Economists have also examined whether government spending crowds out private giving. While this "crowding-out" is distinct from the one I discuss, if giving is motivated by the public goods model, the two types of crowding out will be equivalent, since such an individual has preferences only over the *total* amount a cause receives. Most empirical accounts show reverse or no crowding-out (Khanna, Posnett, and Sandler (1995); Okten and Weisbrod (2000); and Straub (2003)), while Payne (1998) finds a 50% rate of crowding out.[21]

The most common empirical models regress the log of contributions against the log of income, the log of the price of gifts (defined as one minus the household's marginal tax rate on contributions), and demographic variables such as age, marital status, education,

[17] Source: The Economist Intelligence Unit.

[18] "What Is Charity?," by Stephanie Strom, *The New York Times*, November 14, 2005. *http://www.nytimes.com/2005/11/14/giving/14strom.html*

[19] E.g., Feldstein and Clotfelter (1976); Feldstein and Taylor (1976); Lankford and Wyckoff (1991); Randolph (1995); Auten, Sieg, and Clotfelter (2002)); Reece (1979); Feldstein (1975).

[20] A price elasticity above one is typically seen as a necessary condition to justify the treasury-efficiency of the tax deduction.

[21] In contrast, several laboratory experiments ((Andreoni, 1993); (Bolton and Katok, 1998); and (Eckel, Grossman, and Johnston, 2005)) find significant crowding-out.

and religion or church attendance. Giving tends to be U-shaped as a percent of income (Andreoni, 2006), and the less wealthy give a much larger share to religious institutions (Katzev, 1995).

Economists have not directly addressed the issue of expenditure substitution in charitable giving. Andreoni, Gale, and Scholz (1996) examined substitution between giving and volunteering, a closely related problem,[22] although with more observably distinct prices. Their structural model allows them to estimate differences driven by the (observed and imputed) prices of giving and volunteering, and (if their assumptions hold) consistently estimate own and cross-price elasticities between these two activities. They find that gifts of time and money are gross complements but net (Hicksian) substitutes, although the cross-price effects are small. They also find a significant positive correlation between unobservables that increase the marginal utility of giving time and money, revealing an "unobserved taste for altruism" that would yield a bias towards complementarity in a naive estimation.

Finally, a few papers have analyzed substitution patterns among "endogenous" choices that are part of the same optimization problem without independently varying prices (or other shifters). For example, Montmarquette and Monty (1987) examine household choices of labor market participation, leisure, and volunteerism, offering a nonstructural analysis of the relationship between these variables.[23] Biddle and Hamermesh (1990) estimate a system of decisions that Wooldridge (2003) refers to as not "autonomous," describing "how one endogenous choice variable trades off against another." The authors regress hours of sleep on hours of work, both in cross-sectional, cross-country, and panel fixed effect regressions. These regressions suffer from the same potential endogeneity and bidirectional causation as my estimates: sleep, work, and leisure are jointly chosen, and of these only work has a distinct observable price. They argue that, although they have not strictly established causality, their results are useful, showing at least some substitution between work and

[22]This is particularly relevant if these activities yield distinct "warm glow" payoffs in the utility function, and are thus equivalent to separate charities.

[23]Still, they *do* offer an analysis using price in the latter part of their paper.

sleep. They also claim that their fixed effect methodology controls for one kind of bias from an individual-specific "need for sleep." A similar case can be made for the usefullness of the empirical analysis below, even if the previously mentioned stochastic assumptions do not hold.[24]

4 Data Description, Data Issues, Created Variables

While many studies collect information on charitable giving, the PSID/COPPS is the only U.S. survey that reliably observes giving in a repeated, multi-year (biennial) panel setting. Starting in 2001 the PSID/COPPS survey asks each household a series of question about how much they gave to specific categories of charity in the previous year. They collect the most detailed data (whether contributed, amount contributed, including gifts of money, assets, or property) for the following six categories: Religion – "towards religious purposes"; Combination –"towards combined purpose funds"; Needy –to "organizations that help people in need of basic necessities"; Health – "towards health care or medical research organizations"; Education – "towards educational purposes... colleges, grade schools, PTA's, libraries, or scholarship funds"; and Other.[25]

As discussed above, the after-tax price of giving is seen as a key factor in the giving decision. However, the decision to itemize deductions is not fully exogenous, as it is partially determined by an individual's giving. Because of this, most studies "employ a sample of taxpayers who itemize their returns and would do so even without the deduction for charitable contributions" (Lankford and Wyckoff, 1991). To deal with this, I compute the expected itemization status and the expected (average) after-tax price of giving, both using a

[24]For completeness, I note that the past year has brought some unpublished and preliminary work dealing with similar issues as the present paper. Diepen et al (2009) offer some field experimental evidence on the crowding-out effects of direct mail solicitations. Borgloh (2009) is investigating the impact of the German church tax on households other charitable giving.

[25]These categories are presented in the same order in every survey; I give more information on the precise questions asked in the appendix. Since 2002 "other," is further broken down into: "Youth and family services," "Arts, culture, and ethnic awareness," "Improving neighborhoods or communities," "Preserving the environment," "International aid or world peace", and "Any other charitable purpose or organization we did not mention." I do not focus on the "other" category, and I ignore the subdivisions within this category.

regression-predicted level of giving. I use NBER's Taxsim module to compute the marginal cost of charitable giving – which is one for non-itemizers and one minus the marginal tax rate for itemizers.[26]

Regression analyses of charitable giving often remove several types of observations seen as outliers, unreliable, or irrelevant. Auten, Sieg, and Clotfelter (2002) remove those who change marital status, those with low incomes, dependent filers, and those who itemize but would not have done so without charitable giving – they claim that these are "standard practices" in the literature. Several studies remove individuals with low and/or high incomes (e.g., Lankford and Wyckoff (1991)).[27] Reece (1979) removes giving outliers, as do other authors.

I make similar restrictions. I begin with the "cross-section sample", the segment of the PSID that was designed to be nationally representative in 1968. Except where specified, I remove families with major household composition changes, large changes in total giving in any year (a change in either direction exceeding 30% of total income), and the largest givers (over $80,000 or over 30% of income if income above $10,000). Overall, I drop roughly one third of the households that are present in each of the three years, leaving approximately 3466 household observations per year. I make these removals because I suspect these households are misreporting. In any case, they do not significantly change the estimates, and at worst they imply that my estimator is focused on households with more conventional behavior. Regressions using the log of net income naturally drop the 19 remaining observations where net income is negative or zero. I give details of these calculations in the appendix, as well as other data cleaning details. Some key summary statistics are given below.[28]

Table 5 about here

Table 6 about here

[26]This is described in the appendix. This endogeneity is not a serious problem here anyway: I am not trying specifically to estimate the price elasticity of giving.

[27]The former restriction is mainly relevant to tax data, where only itemizers' deductions are observed, but exemptions change over time (see Auten et al., 2002).

[28]Other summary statistics available by request

Table 7 about here

The rates of giving in table 6 are close to those reported elsewhere and seems to be fairly stable in recent years.[29] For example, Andreoni (2006) reported a 68.5% rate of giving back in 1995 using Independent Sector data, and a 48% rate of giving to religious organizations. Since most households do not give at all to a particular category in a particular year, the medians (table 7) are mostly zero.[30] Average gift conditional on giving are fairly similar across the categories of giving other than religion, although health-related gifts tend to be smaller. These figures are also reasonably close to those from other sources; for example, the Independent Sector reported that the average contributing household gave $1620 in the year 2000 (my comparable figure for this year is $1877).

5 Results

Table 8 about here

No simple pattern fits all, or even most households. Virtually no households behave in a manner consistent with perfect crowding-out. As shown in table 8, most households donate to more than one category of charity, and many donate to several categories (especially among large givers [31]). Both large and small givers tend to vary their giving levels from year to year. Among the 6066 households who gave to charities in all years, the median year-to-year change in total giving was approximately one third of a household's average donation, fewer than 10% of such households changed their giving by less than 10% in a given year, and only 36 households reported giving the exact same amount in each year.

[29] These figures come from the binary question, "did you ... make donations"; not all of these respondents ever reported an amount (nor a range) given, so the conditional-on-positive figures cannot be exactly imputed from these.

[30] On the other hand, the median 2000-2004 yearly non-religious donation for the 1999 "large givers", a focus of later analysis, is $500; details available by request.

[31] Further details available by request.

Median percentage deviations were comparable for larger givers, and higher for nonreligious giving. [31]

Table 9 reports raw correlations among the categories of giving.[32] Unsurprisingly, the amounts a household gives to each of the various categories of charity in a given year are positively and significantly correlated. The residuals from Poisson regressions of each category of charity on income, imputed price, and other standard controls are also nearly all positively and significantly correlated, although less strongly so – this is shown in table 10. The results of this regression are given in the appendix, in table 1; errors are clustered by household. The use of a Poisson regression with a strictly positive non-count dependent variable with corner solutions is motivated by Silva and Tenreyro (2006). For all of the correlation results given in this paper, the residuals from analogous linear (rather than Poisson) regressions show the same or similar patterns. [31]

Tables 9, 10, 11, and 12 about here (or at end) *Ideally, if typesetting considerations permit, all four tables should be aligned in a 2 by 2 matrix on facing pages, allowing easy visual comparison.*

I next examine variation *within* households, i.e., controlling for a household-specific effect. Table 11 gives the matrix of correlations between the "de-meaned" (differenced from household means) gifts to each category.[33]

To control for time-varying observables such as income and imputed price, I run a Poisson (psuedo-maximum-likelihood) regression with fixed effects (Hausman et al., 1984; Wooldridge, 1999), using the command xtpqml in Stata (Simcoe, 2007). Regression results, given in table 2 in the appendix, suggest price elasticities that are heterogeneous by category but below unit elasticity for all categories except education. Net income shows the correct sign, but all categories of giving appear to be income inelastic. The regression also

[32]Unless otherwise noted, all correlations are pairwise. Independent p-values are given for all tables; Bonferroni or Sidak corrected values available by request.

[33]These are equivalent to the residuals from fixed-effects regressions with no control variables.

allows trend and year-specific effects through the year variables; these effects are mixed, but positive where they are significant.

The correlations between the residuals from these regressions (table 12) are similar to the correlations in de-meaned contributions (table 11)the control variables have little impact on the within-household results. The signs of these correlations depend on the pairing of the charity categories. However, comparing these tables to tables 9 and 10 the correlations are, without exception, lower (more negative) when we control for household-specific effects, in line with claim 1 (given in the appendix).

Controlling for other charitable gifts (full partial correlation results available by request) also has virtually no effect on the bivariate coefficients of correlation. Standard ols regressions on the de-meaned variables also lead to similar results; the correlation coefficients are (naturally) bounded between the coefficients of the forward and reverse regressions, and in general are roughly halfway between the two.

Table 13 about here

Two results are consistently significant across a wide variety of alternative specifications: Education and Combined-Cause have a strong positive correlation, while Health and Needy have a significant negative correlation. This is depicted in table 13. Rows a to g present the bivariate correlations in the residuals after various fixed-effects regressions, focusing on various subsets. Rows a and b repeat the results mentioned above. Row c is from regression with an addition "support for others not in household" control variable (which may be interpretable as a proxy for generosity). Row d re-includes households that were classified as giving outliers. Row e drops households that never gave to either charity in the pair examined.[34] Row f focuses on the intensive margin, keeping residuals only for those households that always gave something to both charities in the pair. Row g examines households that were "large givers", declaring over $1000 in total contributions on their

[34]Even where the household *never* gave to one of the charities, the regression residuals may be nonzero because of the predicted effects of time-varying observables. Other correlations are also not sensitive to omitting these. [31]

1998 tax forms).[35] Row h presents partial correlations between the residuals, additionally controlling for the other categories of charitable giving. All of these results are the same in sign and are statistically significant. Coefficients are significantly larger in magnitude when we focus on the intensive margin, and substitution is greater when we focus on the large givers.

Comparing the overall correlations, the correlations in pooled residuals, and the correlations in within-household residuals, we see that both the household-fixed variables and the latent household-fixed effects are important, and both appear to have similar effects across categories of charitable giving. Hence, a pooled cross-sectional analysis is biased towards finding complementarity; both observable and unobservable components of income, and factors such as generosity and altruism, tend to push charitable gifts in the same direction.

Table 14 about here

In table 14 I report correlations from the residuals from fixed effects Poisson regressions with controls between a few key unambiguous categories (and sums of categories) and the sum of giving to all other charities. [36] e see stronger and more negative correlations (in first differences) among gifts for large givers (those who gave $1000 or more to some category in 1998). The "large giver" correlations are more negative for most pairings of charities, as seen in table 3 in the appendix.

This suggests a heterogenous motivation for giving. For example, those who give a large amount may have sophisticated warm glow preferences, in which charitable contributions are imperfect substitutes.[37] Thus, when these individuals increase their contribution to one cause they decrease contributions to other causes. In contrast, small givers may act impulsively or be largely or entirely motivated by shocks such as specific appeals, perhaps gaining little

[35] The $1000 cutoff is arbitrary, but other values yield similar results (as seen in table 17). I use the 1998 data here to avoid a potential problem of "regression to the mean." Pre-2000, the PSID only asks people the total charitable giving they declared for tax purposes, if they itemized their deductions.

[36] W

[37] The data does *not* suggest that these large givers have a pure "public goods" motivation: for these large givers, on average (over years 2000-2004), only about 15% of gave to only one major category in a year, and almost 60% gave to three or more categories.

warm glow and attributing little intrinsic value to any charity.[38] Here, positive correlations may stem from a variable that impacts shocks to multiple charities (as implied by assumption 4 in the appendix), e.g., vulnerability to charitable appeals. For example, someone in the family be staying at home more often or may have taken a job in an office with a culture of fundraising.

Finally, it is important to differentiate the effect of shocks at the extensive and intensive margin. According to at least one fundraising insider, "giving is a learned behavior."[39] This should lead to an expenditure complementarity in giving that should occur at the *extensive* margin, leading households to make positive gifts to other charities for the first time. Table 15 focuses on two pairings of charities and tabulates cases where both charities experienced a "state change" (from zero to positive or positive to zero). Whether we look at the pair that appear to be substitutes (Needy and Health) or the pair that appear to be complements (Combined and Education), these state changes are significantly more likely to go in the *same* direction then in *opposite* directions:

Table 15 about here

As further test of the assumptions and as a reference point I examine another major component of "discretionary" spending: eating out in restaurants.[40] Appendix table 16 reports correlations between (residuals of) such expenditure and the various categories of donations.[41] These correlations are almost entirely positive and often significant, in contrast to the negative relationships in key cells of tables 11 and 12. This lends further support

[38] As the Mad Hatter might point out, those who were giving nothing to A can give no *less* to A when a shock causes them to give more to B. The *reason* these small givers were giving nothing to A is because they put a low value on altruism towards A. The reason they respond to the shock and give to B is not because it gives them warm-glow nor because they care for the public good, but because after the appeal they might feel cruel or be stigmatized if they do not give.

[39] According to Steve Thomas, chair and creative director of Canada's largest direct-response fundraising firm, "... people giving money to the tsunami appeals who haven't given to charities before [will] find that they kind of like the experience, and ... end up giving money to other things...." (TVB, Charities Industry Report).

[40] For households in the sample the average yearly expense on restaurants is $2022.

[41] The first column controls for household-fixed effects as in table 11; the second column also controls for observables as in tables 2 and 12; details by request.

to the assumption that unobserved components of disposable income lead to a bias towards finding expenditure complementarity.

As table 17 demonstrates, the main findings presented are fairly robust; they are not merely an artifact of a few outlying observations.[42] The correlations between (residuals and demeaned values of) health and needy giving, between health plus educational giving and needy giving, and between religious and non-religious giving are negative for all the subsets presented, and the bootstrapped (clustered) standard errors are fairly small. Most of the correlations are significantly negative in a one-tailed test based on the empirically generated ("bootstrapped") distribution, particularly for larger givers and for those with characteristics of large givers (a college degree and a high income).

Table 17 about here

6 Conclusion

My results show that expenditure substitution exists between certain sets of charities, but that a cross-sectional approach will mask this; researchers need to focus on *within*-household variation. The greater (more negative) substitution for large givers, particularly for health versus basic needs giving has a plausible explanation. Small givers may be mainly driven by temporary shocks and personal appeals; if they do not inherently value charitable giving, their sensitivity to one shock may be unaffected by the receipt of another shock. On the other hand, larger givers may be more committed to charitable giving, as they may have multi-charity warm-glow preferences (or follow a Kantian model) and thus giving to a cause such as medical research may partially fill this need for other-directed giving, leading to less giving to causes like soup kitchens. My results do not contradict the notion that giving is a learned behavior; the substitution does not occur at the *extensive* margin.

[42]The bootstrapped residuals presented in columns "with controls" are from similar fixed-effects *linear* regressions (details by request); bootstrapping the Poisson regressions required too much computing time.

There are numerous ways this research can be extended. More data will continue to become available, allowing more precise tests and models with more sophisticated time patterns. Macroeconomic data has the advantages of accuracy, salience, and lack of corner-solution variables ; time-series analysis of such data may prove fruitful. It would also be useful to get richer data that looks within the categories discussed here, to see, for example, whether giving to one cause that supports the needy displaces giving to another similar cause. Finally, experimental evidence (e.g., [citation hidden]) should supplement econometric work by offering truly exogenous shocks and precise measurement. A field experiment (in the mold of (Frey and Meier, 2004)) taking advantage of employer-provided matching for specific charities would also be an excellent way to combine the strengths of the laboratory and happenstance data.

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7 Appendix: Background

7.1 Model of sequential decisions

Imagine the consumer has three choices: own consumption x and her gifts (g^A and g^B) to charities A and B. The giving decisions are made sequentially with any possible ordering, and the consumption decision is made last.[43] Consider the utility function $U(x, g^A, g^B; \mu_{it}^A, \mu_{it}^B)$, where μ_{it}^A and μ_{it}^B are temporary shocks that may occur *only* when the choices of gifts to charities A and B (respectively) are made. If there are no shocks, she will choose the values x^*, g^{A*}, and g^{B*} that solve the program:

$$\max_{x,g^A,g^B} U(x, g^A, g^B; 0, 0) \; s.t. \; y = px + g^A + g^B \tag{1}$$

where y is the household income and p is the normalized price of the consumption good (the prices of the charitable goods are assumed to be identical). Let the consumer face a utility-shock μ_{it}^B (e.g., a fundraising appeal) when she is choosing g^B, leading to a temporary utility function $U(x, g^A, g^B; 0, \mu_{it}^B)$. Hence, the choice $g^B(\mu_{it}^B)$ may differ from g^{B*}: she may give more than she had planned to. I call this difference the "shock" ξ_{it}^B:

$$\xi_{it}^B = \xi_{it}^B(\mu_{it}^B) = g^B(\mu_{it}^B) - g^{B*}. \tag{2}$$

This choice imposes a constraint on later choices, as in the "preallocation" of the Pollak (1969) model of conditional demand.[44] With no other shocks she will maximize conditional utility, solving :

[43] This assumption is made for simple exposition; I could allow a case where consumption is allocated first and the charitable decisions necessarily trade off one-for-one; the general results would be preserved.

[44] For a more recent empirical application of this theory, see, e.g., PITT (1977.) on inter-household allocation. Note that I focus on the effect of ξ^Bon g^A rather than on the effect of μ^B on g^B. This is relevant to the real world: a policymaker has no objective measure of μ^B; instead he wants to predict the expenditure substitution effect (on various categories of giving) as a function of the impact of the shock (e.g., a tsunami) on *giving to the shocked charity.*

$$
\begin{aligned}
& \max_{x, g^A} U(x, g^A, g^B(\mu_{it}^B); 0, 0) \qquad (3) \\
s.t.\ \tilde{Y} &= y - g^B(\mu_{it}^B) = px + g^A
\end{aligned}
$$

I label the difference between the choice after this shock and the long-term choice, $g^A(\xi_{it}^B) - g^{A*}$, the "expenditure crowding-out" effect of B on A, and the derivative of the function $g^A(\xi_{it}^B)$ the "expenditure substitution [complementarity]" if negative [positive]. Since I do not hold $\tilde{Y}$ (remaining income after the choice of g^B) constant the effect includes both a substitution effect and an income effect; similar to Pollak's "pure substitution" and "money expenditure" effects, respectively. In the rest of the paper I model the response as linear; this will hold, for example, if utility is quadratic (derivation available by request). In any case, the linear estimate can be interpreted as a first-order approximation. This specification allows any of the crowding-out predictions (zero, partial, or complete) from the theoretical models described in section 3.

Let Y_{it} represent (a projection into one dimension of) the variables that enter into the budget constraint; I will later drop this variable to ease notation. Utility functions are heterogeneous: households may have different preferences over charities and different levels of generosity. The net effect of these factors is given by the parameters C_i^A and C_i^B. There may also be unobservable wealth and unobservable variables that affect utility: ε_{it}^A and ε_{it}^B represent the effect of these. Let "$\succ$" denote time precedence. If g^A is chosen before g^B, a shock to g^A can affect the choice of gift to B but not vice versa; if $g^B \succ g^A$ this is reversed. When $g_{it}^A \succ g_{it}^B$ (the t subscript refers to the period in which *both* decisions are made), we have the equations:

$$g_{it}^A = C_i^A + \beta_Y^A Y_{it} + \xi_{it}^A + \varepsilon_{it}^A \tag{4}$$
$$g_{it}^B = C_i^B + \beta_Y^B Y_{it} + \beta^B \xi_{it}^A + \xi_{it}^B + \varepsilon_{it}^B$$

and of course, where $g_{it}^B \succ g_{it}^A$, we have the symmetric result (switching A and B).

Assumption 1 $sign(\beta^A) = sign(\beta^B)$

We expect expenditure substitution (complementarity) to be the same in both directions; whether $g_{it}^B \succ g_{it}^A$ or the reverse. In the next subsection I show that this property holds, at least at the margin, using the properties of conditional demand.

Claim 1 $E[(C_i^A - E(C_i^A)(C_i^B - E({C_i}^B)] > 0$

Claim 2 $E[(C_i^A - E(C_i^A|Y_{it})(C_i^B - E({C_i}^B|Y_{it}))] > 0$

I claim (1 and 2) that the effect of the household's observable and unobservable time-invariant variables (e.g., generosity, trust, and unobserved wealth) on gifts to each category of charity are positively correlated. This will be seen empirically: the correlations in residuals are more negative after controlling for a household-effect, whether or not we also control for time-varying observables.

I assume (assumptions 2-4) that the shocks and error terms are mean-zero, the impact of changes in the permanent utility function (especially changes in overall generosity) and in the latent variables (especially changes in unobserved income) are positively correlated, and the shocks to the *temporary* utility function are uncorrelated to each other, and uncorrelated to the effects of unobservables:

Assumption 2 $E[\xi_{it}^A] = E[\xi_{it}^B] = E[\varepsilon_{it}^A] = E[\varepsilon_{it}^B] = 0$

Assumption 3 $E[\xi_{it}^A \xi_{it}^B] = E[\varepsilon_{it}^A \xi_{it}^B] = E[\varepsilon_{it}^A \xi_{it}^A] = E[\varepsilon_{it}^B \xi_{it}^B] = E[\varepsilon_{it}^B \xi_{it}^A] = 0$

Assumption 4 $E[\varepsilon_{it}^A \varepsilon_{it}^B] > 0$

Result 1 *(From assumptions 2 - 4)* $E[(\varepsilon_{it}^A + \xi_{it}^A)(\varepsilon_{it}^B + \xi_{it}^B)] > 0.$

Thus, in net, *if there were no expenditure substitution effect,* there is a positive correlation between the deviations from the predicted values of g^A and g^B, the composite disturbances; result 1 is the fundamental econometric assumption.[45]

Assumption 5 *The decisions are never simultaneous. The decision over* g_{it}^A *precedes the decision over* g_{it}^B *some* ω *proportion of the time, and the determination of the decision-making order is independent of any of the other stochastic variables:*

$\Pr(g_{it}^A \succ g_{it}^B) = \omega$ *and* $\Pr(g_{it}^B \succ g_{it}^A) = (1 - \omega)$ *where* $0 < \omega < 1$.

$E[\mathbf{1}(g_{it}^A \succ g_{it}^B)|\xi_{it}^A, \xi_{it}^B, \varepsilon_{it}^A, \varepsilon_{it}^B] = E[\mathbf{1}(g_{it}^A \succ g_{it}^B)] = \omega$

where $\mathbf{1}()$ *is the indicator function.*

This implies, dropping the Y_{it} variables for clarity, letting $\ddot{X}_t = X_{it} - \frac{1}{T}\sum_{t=1}^{T} X_{ti}$ the demeaned value, for any variable X, and letting $\mathbf{1}_{A\succ B} \equiv \mathbf{1}(g_{it}^A \succ g_{it}^B)$:

$$\begin{aligned}
\ddot{g}_{it}^A &= \mathbf{1}_{A\succ B}(\ddot{\xi}_{it}^A + \ddot{\varepsilon}_{it}^A) + (1 - \mathbf{1}_{A\succ B})(\beta^A \ddot{\xi}_{it}^B + \ddot{\xi}_{it}^A + \ddot{\varepsilon}_{it}^A) \qquad (5)\\
&= \ddot{\xi}_{it}^A + \ddot{\varepsilon}_{it}^A + (1 - \mathbf{1}_{A\succ B})\beta^A \ddot{\xi}_{it}^B\\
\ddot{g}_{it}^B &= \ddot{\xi}_{it}^B + \ddot{\varepsilon}_{it}^B + \mathbf{1}_{A\succ B}\beta^B \ddot{\xi}_{it}^A. \qquad (6)
\end{aligned}$$

Since the ordering of decisions is ambiguous and unknown, either a regression of $\ddot{g}_{it}^A$ on $\ddot{g}_{it}^B$ or the reverse regression will pick up effects in both directions. As a compromise,[46] I estimate the Pearson correlation coefficient between the estimated residuals from fixed-effects linear regressions of each category of giving, which I label $\ddot{\rho}_{A,B}$. Below, I decompose $\ddot{\rho}_{A,B}$ in terms of the coefficients β^A and β^B, the variances $(\sigma^2_{\ddot{\xi}^A}, \sigma^2_{\ddot{\xi}^B}, \sigma^2_{\ddot{\varepsilon}^A}, \sigma^2_{\ddot{\varepsilon}^B})$ and covariances $(\sigma^2_{\varepsilon^A\varepsilon^B})$ of

[45] Essentially, I rule out the possibility that variations that cause *increased* giving to A inherently tend to coincide with variations that cause *decreased* giving to B.

[46] Note that the *estimated* correlation coefficient, $\ddot{r}_{A,B}$, is necessarily bounded between $\hat{\beta}^B$ and $\hat{\beta}^A$, the estimated coefficients from forward and reverse regressions.

the errors and shocks, and the probability ω.

$$\begin{aligned}
\ddot{\rho}_{A,B} &= \frac{Cov(\ddot{g}_{it}^A, \ddot{g}_{it}^B)}{SD(\ddot{g}_{it}^A) \times SD(\ddot{g}_{it}^B)} \qquad (7)\\
&= \frac{E[\left(\ddot{\xi}_{it}^A + \ddot{\varepsilon}_{it}^A + (1-\mathbf{1}_{A\succ B})\beta^A \ddot{\xi}_{it}^B\right)(\ddot{\xi}_{it}^B + \ddot{\varepsilon}_{it}^B + \mathbf{1}_{A\succ B}\beta^B \ddot{\xi}_{it}^A)]}{\sqrt{E[(\ddot{\xi}_{it}^A + \ddot{\varepsilon}_{it}^A + (1-\mathbf{1}_{A\succ B})\beta^A \ddot{\xi}_{it}^B)^2]} \times \sqrt{E[\left(\ddot{\xi}_{it}^A + \ddot{\varepsilon}_{it}^A + (1-\mathbf{1}_{A\succ B})\beta^A \ddot{\xi}_{it}^B\right)^2]}}\\
&= \frac{\sigma^2_{\varepsilon^A\varepsilon^B} + \omega\beta^B\sigma^2_{\ddot{\xi}^A} + (1-\omega)\beta^A\sigma^2_{\ddot{\xi}^B}}{(\sigma^2_{\ddot{\xi}^B} + \sigma^2_{\ddot{\varepsilon}^B} + \omega(\beta^B)^2\sigma^2_{\ddot{\xi}^A})^{\frac{1}{2}}(\sigma^2_{\ddot{\xi}^A} + \sigma^2_{\ddot{\varepsilon}^A} + (1-\omega)(\beta^A)^2\sigma^2_{\ddot{\xi}^B})^{\frac{1}{2}}}
\end{aligned}$$

If β^B is positive, implying β^A is positive by assumption 1, then all terms in the last line of equation 7 are positive and hence the correlation coefficient is positive. Thus, a *negative* correlation coefficient implies that β^A and β^B are *negative*:

Result 2 $\ddot{\rho}_{A,B} < 0 \Longrightarrow (\beta^A < 0$ *and* $\beta^B < 0)$.

The empirical analogue:

$$\ddot{r}_{A,B} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{g}_{it}^A\ddot{g}_{it}^B}{\sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T}(\ddot{g}_{it}^A)^2}\sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T}(\ddot{g}_{it}^B)^2}} \qquad (8)$$

–where $i = 1...N$ indexes households and $t = 1...T$ indexes periods (3 years of data) – is a consistent estimator of $\ddot{\rho}_{A,B}$.[47] Thus, if I estimate a negative and significant $\ddot{r}_{A,B}$, I can infer that there is a high probability that charities A and B are expenditure substitutes.

There are several potential alternatives to the sequential-decision interpretation given in this section. The shock could be seen as a temporary change in *effective* price (e.g., a tsunami makes the cost of aiding a single disaster victim lower); this will be equivalent to a proportional boost in marginal utility, hence it is not entirely distinct from the explanation above. Alternately, the shock could be interpreted as the effect of a parameter of the utility function that changes over time when decisions are made simultaneously, but it is difficult

[47]The equation looks simpler than usual because $\ddot{g}_{it}^A$ and $\ddot{g}_{it}^B$ are mean-zero by construction.

to justify the interpretation of any parameter as specific to one choice.

7.2 Shared sign of conditional demand effects

Adapting the Pollak (1969) model of conditional demand to our notation, the "total derivative" of the conditional demand for g^A with respect to a change ξ^B in the preallocated good g^B, allowing for the change in remaining income is:[48]

$$\begin{aligned}\frac{dg^A(\xi^B)}{d\xi^B} &= \frac{dg^{A\cdot B}}{d\bar{g}^B} = \frac{\partial g^{A\cdot B}}{\partial \xi^B} + \frac{\partial g^{A\cdot B}}{\partial \tilde{Y}}\frac{\partial \tilde{Y}}{\partial \xi^B} = \frac{\partial g^{A\cdot B}}{\partial \xi^B} - \frac{\partial g^{A\cdot B}}{\partial \tilde{Y}} p_{g^B} \\ &= \frac{\partial g^{A\cdot B}}{\partial \xi^B} - \frac{\partial g^{A\cdot B}}{\partial \tilde{Y}} \text{ assuming the price of each charitable good is 1} \end{aligned} \tag{9}$$

Using Pollak's result for a rationed good (from Pollak's equation 4.16):

$$\frac{dg^A(\xi^B)}{d\xi^B} = \frac{\frac{\partial f^A}{\partial p_A}}{\frac{\partial f^B}{\partial p_B}} = \frac{S_{AB}}{S_{BB}} \text{ if } (\bar{g}_B = g^*_B) \tag{10}$$

Where f represents the Hicksian demand, S_{ij} the i, j'th element of the Slutsky matrix, and g^*_n the unconditional demand for the n'th good. In Pollak's statement, the derivative of conditional demand for a good with respect to a binding ration constraint on another good, evaluated at (i.e., when the constraint is originally set to) the unconstrained chosen amount, will equal the ratio of the price derivatives of the Hicksian (utility-constant cost-minimizing) demands. Since, if the ration is binding (before and after), the choice of rationed good should change by the full amount of the change in the ration, this should be equivalent to the case I consider, where the good g^B is exogenously shifted or "preallocated" away from the unconstrained optimum. Since $S_{BB} < 0$ (the Slutsky matrix must be negative semi-definite) the direction of the marginal change depends on S_{AB}, i.e., whether the goods are Hicksian (net) price substitutes or complements. Looking at the reverse effect: $\frac{dg^B(\xi^A)}{d\xi^A} = \frac{S_{AB}}{S_{AA}}$ if

[48] This is virtually identical to Pollak's equation (4.10d), the derivative of the consumption of an unrationed good with respect to the quota of a "straight" rationed good.

$(\bar{g}_i = x_i^*)$ we can see it must have the same sign, but may have a different magnitude.

7.3 Appendix: Literature review

Models of Giving

Notation:

i : indexes individuals

x_i : Individual i's non-charity consumption of the numeraire composite commodity (price normalized to 1)

g_i: i's giving to the charitable or public good m_i: i's income

$G = \sum_{i=1}^{N} g_i + t$: total giving or total supply of the public good

$G_{\sim i} = G - g_i$: Giving by individuals other than i

p_i : Price of a unit of giving to the charitable or public good

All models include some form of the following "standard" budget constraint:

$$x_i + p_i g_i - m_i = 0; g_i \geq 0, x_i \geq 0; \tag{11}$$

List I: Theoretical Models **Name,Author, Year**	**Single Charity/ Public Good** **Utility Function**
1. Pure Public Goods, Becker, 1974	$u(x, G)$
2. Pure Warm Glow (e.g., Andreoni, '04)	$u(x, g_i)$
3. Mixed warm glow, Becker, 1974	$u(x, G_{\sim i}, g_i)$
4. Mixed warm glow (e.g., Andreoni, '04)	$u(x, G, g_i)$
5. Tithing	$g_i = \tau m_i$; where $\tau \in (0, 1)$
6. Kantian or individual/group-	i chooses $\arg\max_{x_i, g_i} u_i(x_i, n g_i)$;
-misperception (e.g., Laffont, 1975)	s.t. eqn. 11
	but i gets actual utility $u_i(x_i, G)$

List II: Multi-Charity	Utility forms and Related Models
Name,Author, Year	**Utility/Expenditure Function**
1. Andreoni et al. (‘04)	$U(x, m, wh, l) = U(\mathbf{Q}) = \alpha'\mathbf{Q} - \frac{1}{2}\mathbf{Q}'\beta\mathbf{Q}$
(Quadratic)	m: \$ gifts, w: imputed volunteer wage,
	h : volunteer hours ; l: leisure
In empirical model:	$\mathbf{Q} = (x, m, wh)$ (leisure not observed)
2. Andreoni et al. (’03)	$U_i = U(x_i\ , g, \theta_i(g_1, g_2))$; $i = h, w$
“...by Married Couples...,”	h: husband; wife;
	g: marriage-specific public good
Considers extreme cases:	$\theta_h = \theta_w = d_1$; $\theta_h = d_1, \theta_w = d_2$;
	$\theta_h = -\theta_w = d_1 - d_2$
3. Harbaugh’s (1998b)	$u_i = ln(x_i\ ) + b\ln(\pi(g_i) + k_1) + c\ln(g_i + k_2)$
(Stone-Geary)	where $\pi(g_i)$ = prestige, k’s: constants
4. Cobb-Douglas, mixed	$u_i = \alpha_0 \ln(x_i\ ) + \alpha'\tilde{\mathbf{G}} + \beta'\tilde{\mathbf{g}}_i$
	where: $\alpha_0 = 1 - \sum_{k=1}^{K} \alpha_k - \sum_{k=1}^{K} \beta_k$
5. Leonteif, pure warm glow	$u_i = \min(\alpha x_i\ , \beta_1 g_{i1}, \beta_2 g_{i2}, ..., \beta_K g_{iK})$
6. Multi-Stage Budgeting	$U(q_i...q_j) = u(v_1(q_1...q_{J1}), v_G(q_{J1}...q_J))$

This table offers some related models from the literature (adapted to my notation – discussed in section 2) as well as some proposed multi-charity models of my own. No previous works offer a robust model of giving to multiple causes. Andreoni, Brown, and Rischall (2003), (model 2, above) consider only extreme cases (in the context of couples' decision-making). Andreoni, Gale, and Scholz (1996), offer the most useful example, estimating a model of giving and volunteering based on a quadratic utility form.[49]

[49] Their utility function could be extended to a model with a second charity (rather than volunteering). However, it is easier for them to observe distinct prices of giving and volunteering then it is for me to observe distinct prices for different charities. The quadratic form can be justified as a second-order approximation of any utility. It includes linear and squared terms and interactions between the choice variables.

7.4 Appendix: Data and summary statistics

Details on PSID data and its use

The COPPS web site offers the following description:

> The Center on Philanthropy Panel Study (COPPS) is the only study that surveys giving and volunteering by the same households over time as families mature, face differing economic circumstances and encounter changes in their family size, health and other factors. It also is the only data available that asks families extensively about their wealth and philanthropy as well as income and other relevant factors ... This is conducted in conjunction with the ISR's long-running Panel Study of Income Dynamics, which has surveyed the same 5,000 households since 1966. As children of these respondents have matured, they have been added to the sample which now exceeds 7,400 households. In 2001, researchers added the philanthropy component, designed and sponsored by the Center on Philanthropy. These first-round results represent the largest one-time study of philanthropy in the United States that will be beneficial to donors, funders, fundraisers and the nonprofit sector as the households' behaviors are tracked over time in the coming years.

My original data has 7662 household observations that appear in the 2000, 2002, and 2004 samples. I remove 2321 families that split or otherwise undergo a major change in composition between the two years, leaving 5321 households, each of which has the same head for all three years. To help ensure my result's robustness (and remove possible miscodes), for most analysis, I leave out (194, 193, and 195 for years 2000, 2000, and 2003 respectively) "outliers" who either reported giving over $80,000 or over 30% of their income (if income above $10,000), or reported a change in total giving between two years exceeding 30% of their total income. This leaves me with 15,381 household/years. Of the 5127 non-outlier households in 2000, 3479 are from the 1968 SRC cross-section sample, 1286 are from the

1968 "Census" poor oversample, and 362 are from the 1997-98 immigrant sample. 3466 households in the 1968 SRC cross-section sample are not outliers in any of the three years.

For each category of charity, the respondent is first asked *whether* they donated to the category and next asked the *amount* donated. If they do not give an exact value, they are asked categorical questions (e.g., "was it $200 or more?") in a prescribed order. For example, questions on religious giving are presented first, and next they are asked "(Not counting the donations you just told me about (during 2004),/During 2004) did you (or anyone in your family) donate to any organization that served a combination of purposes? For example, the United Way, the United Jewish Appeal, the Catholic Charities, or your local community foundation?" Following a "yes" answer, the respondent is asked " (Altogether,) what was the total dollar value of all donations you (and your family) made in 2004 towards combined purpose funds?" If a respondent is asked about a category and realizes that she should have classified a previously mentioned gift in this category, the respondent is allowed to revise her answer. The order and structure of the donation questions (about te categores I focus on) are stable from year to year. Research by Wilhelm (2006) confirms the quality and comparability of this data set.

All nominal variables are adjusted for inflation using the CPI-urban and reported in 2000 dollars.

Weights Although the PSID has introduced new data to deal with the changing composition of the US population, and provides sampling and weights intended to preserve balance in the presence of attrition, the validity of these weights depends on several assumptions, and the use of such weights in statistical analysis, particularly with an individual-level error term, is both difficult and controversial. I thus ignore these weights and accept that my analysis is limited to a population that is not exactly representative of the current US population.

Imputed Variables and Values

When I encounter missing values or refusals, I leave these as missing. I avoid doing any imputation because substitution results might be sensitive to the details of such a procedure. In any case, these represent only a small portion of the data. A small subset of respondents give only a range-coded value for contributions; I leave these out of my analysis as well.

Constructing an exogenous measure of the cost of giving and net income

In line with much of the recent literature, I use NBER's Taxsim module to compute the marginal cost of charitable giving – which is 1 for non-itemizers and 1 minus the marginal tax rate for itemizers. Taxsim imputes both the marginal tax rate and itemization status based on the rich variety of variables (some imputed) that I "feed" it.[50] Taxsim's imputation is highly sophisticated, even differentiating states that allow and do not allow a charitable deduction.

Following Auten et al. (2002) I compare the estimated tax bill with zero charitable contributions and with a predicted (regressing on a standard set of presumed exogenous covariates) level of giving and divide this difference by the predicted (rather than actual) level of charitable giving in this computation.[51] This (one minus the computation described) yields a more precise estimate of an individual's average tax-price of giving (than if I assumed zero contributions and looked for first-dollar price), but it removes the endogeneity of the tax rate and charitable contributions (as charitable contributions can shift the tax bracket and decision to itemize). This simulation seems to slightly underestimate (even when using actual giving rather than predicted zero giving) the number of people who itemize (comparing the "but-for" itemization to their *known* itemization status). This suggests that unobserved income and taxes may be important.

[50] For example, marital status and children are used to determine filing status (single, joint, head of household), while "married filing separate", a fairly rare category, is unidentified and thus ignored. I incorporate dividends, various types of capital gains, itemizable deductions (health care, etc) other than charitable giving, and many other variables. I solve for the the mortgage interest payment, a popular deduction, although I ignore second and third mortgages, and approximate by assuming one payment a year.

[51] In looking for the impact of giving to charity A on giving to B we may or may not want to include the extent to which increased giving to A reduces the price of giving to B – this depends on the policy question. If we want to include this effect we should impute a tax price based on *actual* giving to A and only imputed giving to B. I defer this issue for later study.

7.5 Appendix: Further results

Table 1: **Pooled cross-section Poisson regressions for generating residuals**

	(1) Total	(2) Religion	(3) Non-relig.	(4) Combo	(5) Needy	(6) Educ.	(7) Health	(8) Other
Log net incm	0.54**	0.46**	0.67**	0.77**	0.63**	0.75**	0.62**	0.55**
	(0.073)	(0.092)	(0.071)	(0.12)	(0.079)	(0.14)	(0.082)	(0.10)
Log price	-1.137**	-0.947*	-1.527**	-1.620**	-1.594**	-1.388+	-2.255**	-1.100*
	(0.323)	(0.382)	(0.332)	(0.359)	(0.407)	(0.771)	(0.563)	(0.452)
Nonres wealth	0.000**	0.000	0.000*	0.000*	-0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Resl. wealth	-0.000	-0.000*	0.000	-0.000	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Head is married	0.537**	0.894**	-0.021	0.169	-0.150	-0.035	-0.340+	0.036
	(0.069)	(0.095)	(0.083)	(0.117)	(0.148)	(0.207)	(0.182)	(0.149)
Age of head	0.053**	0.055**	0.055**	0.057**	0.058**	0.078*	0.037+	0.057*
	(0.011)	(0.014)	(0.014)	(0.020)	(0.020)	(0.032)	(0.020)	(0.024)
... age squared	-0.000**	-0.000*	-0.000**	-0.000*	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kids	0.083**	0.119**	0.022	0.004	0.090*	0.031	-0.084	-0.005
	(0.027)	(0.035)	(0.035)	(0.071)	(0.044)	(0.070)	(0.067)	(0.058)
Year 2002	0.028	0.041	0.008	-0.090	0.123	0.074	-0.100	0.026
	(0.026)	(0.026)	(0.053)	(0.084)	(0.079)	(0.138)	(0.155)	(0.136)
Year 2004	0.067*	0.052	0.094+	-0.092	0.252**	0.180	-0.152	0.223
	(0.028)	(0.032)	(0.053)	(0.098)	(0.087)	(0.139)	(0.143)	(0.150)
Head col. deg.	0.282**	0.203*	0.457**	0.564**	0.260**	0.685**	0.386**	0.458**
	(0.057)	(0.082)	(0.069)	(0.102)	(0.100)	(0.213)	(0.130)	(0.122)
Wife col. deg.	0.195**	0.126	0.354**	-0.026	0.327**	0.862**	0.483**	0.576**
	(0.070)	(0.094)	(0.091)	(0.178)	(0.114)	(0.205)	(0.163)	(0.147)
Constant	-1.102	-0.812	-3.453**	-5.724**	-4.045**	-7.524**	-4.630**	-4.272**
	(0.777)	(0.975)	(0.774)	(1.291)	(0.863)	(1.626)	(1.000)	(1.266)
Observations	10417	10417	10417	10417	10417	10417	10417	10417

Robust (clustered by household) standard errors in parentheses

+ $p<0.10$, * $p<0.05$, ** $p<0.01$

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

Giving outliers and households with changing composition removed; details in section 4.

Hidden controls: Religion, race.

Table 2: **Poisson fixed-effects (pseudo-ML) regressions for constructing residuals**

	(1) Total	(2) Religion	(3) Non-relig.	(4) Combo	(5) Needy	(6) Educ.	(7) Health	(8) Other
Log net incm	0.19**	0.13*	0.24**	0.32**	0.23*	0.44**	0.21	-0.028
	(0.048)	(0.053)	(0.079)	(0.11)	(0.10)	(0.14)	(0.13)	(0.18)
Log price	-0.555**	-0.477**	-0.668**	-0.463	-0.693+	-1.294**	-0.951+	-0.315
	(0.124)	(0.135)	(0.213)	(0.344)	(0.364)	(0.447)	(0.547)	(0.535)
Nonres. wealth	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Resl. wealth	-0.000*	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kids	-0.007	0.031	-0.072	-0.233**	0.078	-0.115	-0.016	0.067
	(0.029)	(0.029)	(0.058)	(0.084)	(0.101)	(0.150)	(0.118)	(0.139)
Year 2002	0.058*	0.070**	0.039	-0.077	0.122	0.075	-0.044	0.104
	(0.023)	(0.026)	(0.045)	(0.083)	(0.080)	(0.120)	(0.130)	(0.103)
Year 2004	0.164**	0.141**	0.201**	-0.051	0.266**	0.245+	0.054	0.489**
	(0.024)	(0.025)	(0.049)	(0.103)	(0.094)	(0.131)	(0.107)	(0.106)
Observations	8840	6515	8158	5498	5648	3227	4491	5303

Robust standard errors in parentheses

+ p<0.10, * p<0.05, ** p<0.01

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

Giving outliers and households with changing composition removed; details in section 4.

Groups with all zero outcomes dropped by estimation procedure; 10,420 obs in total.

Table 3: **Correlations: residuals from Poisson FE regressions, large givers**

Variables	Religion	Combination	Needy	Education	Health
Combination	-0.048				
	(0.034)				
Needy	-0.060	0.053			
	(0.009)	(0.020)			
Education	0.071	0.014	-0.078		
	(0.002)	(0.535)	(0.001)		
Health	-0.048	-0.084	-0.065	-0.045	
	(0.037)	(0.000)	(0.004)	(0.050)	
Other	-0.077	-0.025	0.008	0.008	0.033
	(0.001)	(0.269)	(0.733)	(0.725)	(0.153)

P-values (for standard 2-tailed tests of significance) in parentheses.

Giving outliers and households with changing composition removed: see section 4 for details.

Residuals derived from separate Poisson FE for each category, details in table 1.

Subset: household declared over $1000 in total contributions in 1998

8 Tables for main text

Table 4: **Models – predictions for net expenditure substitution**

Model	**Net Substitution?**
Shock/Appeal driven	None
Public Goods (strict)	Only within same category
'Kantian' model	Only between similar categories
Warm Glow (sophisticated)	'Anything goes'
Impact Philanthropy (concave)	Depends on 'impact' of shocked gift
Tithing/Fixed Purse/Homogenous Good	Complete (perfect crowding-out)

Table 5: **Summary statistics: continuous control variables**

	Mean	S.D.	P10	Median	P90	Min.	Max.
Net income	52,267	76,317	14,001	40,241	91,052	47	4,445,506
Bonus income	1,339	14,664	0	0	83	0	549,737
Tax-price of giving.89	.14	.68	1	1	.51	1	
Wealth w/o house	207,407	1,034,313	-2,781	32,817	445,000	-429,361	42,208,000
Wealth w/ house	296,095	1,102,528	0	94,317	639,674	-278,948	43,008,000
Head's Age	49	16	29	47	72	17	99
Wife's Age	45	14	28	45	64	18	92
Number of Children (in household)	.73	1	0	0	2	0	6

10420 observations, 3485 households.

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

Households with changing composition or giving outliers removed

All monetary figures adjusted to year-2000 dollars based on the urban CPI.

See section 4 for details.

P10 and P90 refer to quantiles.

Table 6: **Dummy: gave to (category of) charity**

Variable	Mean
Anything over $25	0.73
Other than Religion	0.61
Religion	0.51
Combination	0.33
Needy	0.33
Health	0.25
Education	0.18
Other	0.29

Notes: Pooled data (2000-2004), SRC sample, 10420 obs., unweighted.
Giving outliers & households with changing composition removed:
details in section 4.

Table 7: **Summary statistics: Charitable giving**

	Mean	Mean positive	Sd	Med	p75	p90	Max
Total	1,387	1,937	2,958	400	1,500	3,889	76,800
Religion	865	1,765	2,103	0	729	2,735	65,000
Non-relig.	522	854	1,616	96	469	1,200	45,762
Combination	152	471	709	0	89	365	38,824
Needy	134	431	538	0	50	306	15,000
Education	70	395	523	0	0	96	27,348
Health	57	233	384	0	0	100	20,000
Other	109	375	585	0	29	212	26,500

Pooled data (2000-2004), SRC sample, 10420 obs., unweighted.
All figures adjusted to year-2000 dollars based on the urban CPI.
Giving outliers & households with changing composition removed; details in sec. 4.
P75 and P90 refer to quantiles, Mean positive refers to mean of positive gifts.

Table 8: **Number of major categories given to in a year**

Item	Number	Per cent
0	2,864	27
1	1,992	19
2	2,067	20
3	1,597	15
4	1,063	10
5	606	6
6	231	2
Total	10,420	100

Pooled data (2000-2004), SRC sample, unweighted.
Giving outliers & households with changing composition removed:
see section 4 for details.

Table 9: **Correlations between charitable gifts in cross-section**

Variables	Religion	Combination	Needy	Education	Health	Other
Combination	0.111					
	(0.000)					
Needy	0.151	0.154				
	(0.000)	(0.000)				
Education	0.186	0.259	0.118			
	(0.000)	(0.000)	(0.000)			
Health	0.172	0.117	0.186	0.195		
	(0.000)	(0.000)	(0.000)	(0.000)		
Other	0.143	0.143	0.179	0.167	0.279	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

P-values (for standard 2-tailed tests of significance) in parentheses.

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

Giving outliers and households with changing composition removed: see section 4 for details.

Table 10: **Correlations: residuals from Poisson regressions**

Variables	Religion	Combination	Needy	Education	Health
Combination	0.046				
	(0.000)				
Needy	0.092	0.103			
	(0.000)	(0.000)			
Education	0.151	0.135	0.075		
	(0.000)	(0.000)	(0.000)		
Health	0.128	0.025	0.131	0.143	
	(0.000)	(0.011)	(0.000)	(0.000)	
Other	0.091	0.075	0.125	0.155	0.202
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

P-values (for standard 2-tailed tests of significance) in parentheses.

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

Giving outliers and households with changing composition removed: see section 4 for details.

Residuals derived from separate Poisson regressions for each category, details in table 1.

Table 11: **Correlations: de-meaned giving variables**

Variables Other	Religion	Combination	Needy	Education	Health
Combination	-0.034				
	(0.000)				
Needy	-0.022	0.017			
	(0.026)	(0.079)			
Education	0.029	0.125	-0.004		
	(0.003)	(0.000)	(0.685)		
Health	-0.022	-0.046	-0.035	-0.010	
	(0.024)	(0.000)	(0.000)	(0.309)	
Other	-0.042	-0.013	0.011	0.023	0.066
	(0.000)	(0.180)	(0.280)	(0.021)	(0.000)

P-values (for standard 2-tailed tests of significance) in parentheses.
Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.
Giving outliers & households with changing composition removed:
... see section 4 for details.

Table 12: **Correlations: residuals from Poisson FE regressions**

Variables	Religion	Combination	Needy	Education	Health
Combination	-0.024				
	(0.013)				
Needy	-0.008	0.001			
	(0.424)	(0.890)			
Education	0.052	0.025	-0.023		
	(0.000)	(0.010)	(0.022)		
Health	-0.043	-0.068	-0.039	-0.025	
	(0.000)	(0.000)	(0.000)	(0.012)	
Other	-0.059	-0.027	-0.012	0.021	0.049
	(0.000)	(0.006)	(0.227)	(0.034)	(0.000)

Residuals derived from separate Poisson FE regressions for each category, details in table 2.
P-values (for standard 2-tailed tests of significance) in parentheses.
Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.
Giving outliers and households with changing composition removed: details in section 4.

Table 13: **Correlations between residuals: robustness**

	Description	Obs.	Educ. × Combo.	Health × Needy
a.	Within correlations without controls	10,420	0.125	-0.035
			(0.00)	(0.00)
b.	Within correlations with controls	10,420	0.025	-0.039
			(0.010)	(0.00)
c.	As in b, with Support Others control	10,420	0.031	-0.037
			(0.00)	(0.00)
d.	As in b, re-including giving outliers.	10,764	0.078	-0.113
			(0.00)	(0.00)
e.	As in b, household gave to at least one	2433; 3344	0.032	-0.056
	category in the pair in some year.		(0.11)	(0.001)
f.	As in b, household gave to both	240; 299	0.204	-0.145
	categories in the pair in all years.		(0.00)	(0.01)
g.	As in b, ”large givers”;	2185	0.039	-0.070
	(declared over $1k total in 1998)		(0.07)	(0.00)
h.	As in b, controlling for all gifts,	10,420	0.026	-0.040
	(i.e., partial correlations)		(0.01)	(0.00)

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

P-values (for standard 2-tailed tests of significance) in parentheses.

Giving outliers and households with changing composition removed except where mentioned.

Residuals for rows b, e-h derived from Poisson-FE regression in table 2.

Separate Poisson-FE regressions for rows c and d; details by request.

Table 14: **Bivariate Correlations in “Within” Residuals: Sums of Categories**

	All (non-outliers)	Small givers	Large givers
Religion versus All Else	-0.048	0.079	-0.102
	(0.000)	(0.000)	(0.000)
Needy versus [Education + Health]	-0.042	0.053	-0.086
	(0.000)	(0.000)	(0.000)
Health versus [Education + Needy]	-0.048	0.032	-0.077
	(0.000)	(0.004)	(0.000)
Education versus [Health + Needy]	-0.037	0.051	-0.070
	(0.000)	(0.000)	(0.001)

Bivariate correlation coefficients between residuals from separate fixed-effects Poisson regressions.

P-values in parentheses.

Pooled data (2000-2004), SRC sample, unweighted.

Giving outliers and households with changing composition removed: see section 4 for details.

Table 15: **Extensive margin results; tabulating state changes**

Stopped or started giving to the category:

	Health			Education	
Needy	Stopped	Started	Combined	Stopped	Started
Stopped	207	135	Stopped	158	115
Expected	*162*	*180*	*Expected*	*125*	*148*
Started	128	237	Started	83	172
Expected	*173*	*192*	*Expected*	*116*	*139*

Nonparametric measures of positive association

Health × Needy		Education × Needy	
Γ	K's τ-b	Γ	K's τ-b
0.48	0.25	0.48	0.25
(0.06)	(0.04)	0.07	0.04

Zeroes removed, asymptotic standard errors in parentheses.

Γ refers to Goodman and Kruskal's measure (1979).

K's τ-b refers to Kendall's (1938) measure of rank correlation.

Giving outliers & households with changing composition removed: details in section 4.

Table 16: **Correlations: Eating out expense and charity; de-meaned with and without controls**

	De-meaned	Residuals from Poisson FE regressions [*]
	Eating out	Eating out
Giving to:		
Religion	0.042	0.029
	(0.000)	(0.004)
Combination	0.011	0.003
	(0.281)	(0.743)
Needy	0.022	0.003
	(0.024)	(0.758)
Education	0.028	0.038
	(0.004)	(0.000)
Health	0.051	0.031
	(0.000)	(0.002)
Other	0.003	-0.016
	(0.799)	(0.099)

P-values in parentheses.

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

Giving outliers & households with changing composition removed:

see section 4 for details.

[*] Residuals from separate regressions for each category (including eating out) as in table 2.

Table 17: **Correlation between de-meaned (and residuals of) gifts, bootstrap standard errors**

Subset	Correlations in de-meaned contributions					
Obs.	Health × Needy	... with controls	Educ+Health × Needy	...w. ctrls.	Relig. × Non-rel.	... w. ctrls.
All givers						
10,420	-.044	-.062+	-.035	-.046	-.039	-.043
	(.052)	(.047)	(.048)	(.039)	(.047)	(.050)
Gave over 500 in 1999						
2904	-.068	-.097*	-.069*	-.084**	-.076	-.086
	(.045)	(.060)	(.038)	(.048)	(.059)	(.063)
Gave over 1000 in 1999						
2166	-.073+	-.105*	-.080*	-.095*	-.113*	-.124*
	(.058)	(.069)	(.049)	(.055)	(.062)	(.060)
Gave over 1500 in 1999						
1878	-.075	-.110*	-.086*	-.105**	-.117*	-.125*
	(.064)	(.071)	(.046)	(.056)	(.064)	(.060)
Gave over 1000 in 1999 and gross income above 50k and hd. coll. degree						
943	-.109+	-.138*	-.110*	-.129**	-.181*	-.187**
	(.094)	(.081)	(.070)	(.065)	(.080)	(.062)

+ $p<0.10$, * $p<0.05$, ** $p<0.01$ from empirical bootstrapped distributions, one-tailed tests

Bootstrapped std errors (100 replications, clustering by household) in parentheses.

Regression residuals generated separately for each bootstrap replication.

Pooled data (2000-2004), 1968 cross-scn sample (SRC), unweighted.

Households with changing composition or giving outliers removed.