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Does One Charitable Contribution Come at the Expense of Another?

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Abstract

This paper defines, discusses, and measures "expenditure substitution" in charitable giving. Motivated by a model of conditional demand, I consider the extent to which a "temporary shock" that increases an individual's donation to one cause by a particular amount displaces her gifts to other charitable causes. I use the 2001-2007 waves of the PSID/COPPS, the first data set of its kind, to identify this. 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. Overall, these results suggest heterogeneous motivations for giving: small givers may be mainly driven by temporary shocks and personal appeals while larger givers may have concave multi-charity warm-glow preferences.

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. While this has been prominently discussed in the wake of recent disasters,[1]the competition between charities and charitable causes has long been an issue of great concern to charities, policymakers, and charitable donors.[2]

I address this issue here for the first time in the literature, examining within-household conditional correlations to measure and describe the extent to which one charitable donation displaces another. I focus on the commonplace "shocks" at the personal level, such as direct appeals from friends and church fundraisers, that may boost an individual's giving to one cause, perhaps at the expense of other charities. These shocks[3] are likely to be more important to overall giving behavior, as much research notes that the majority of donations occur in response to a solicitation (Bryant et al., 2003; Bekkers, 2005).

What do I mean by "substitution between charitable donations"? Since my data does not contain independent price variation,[4] I cannot measure cross-price elasticities. I model donation decisions as sequential but occurring in a random order and assume that there are often temporary "shocks" to utility that induce charitable giving to certain causes. For example, a household may experience a

[1]On September 20, 2005, the *The Wall Street Journal* reported "Katrina Giving Cuts Donations To Other Groups; As Relief Contributions Pour In, Unrelated Charities Retool Plans To Get Back on Donors' Minds." On the other hand, a later *New York Times* (April 30, 2006*)* headline read "Many Dismissing 'Donor Fatigue' as Myth."

[2]For example, in a letter to the NCAA president challenging their tax-exempt status, US House Ways and Means Committee Chairman Bill Thomas notes "if financial contributions to universities increase based on athletic success, contributions to other worthy charities may decline" (Reported in USA Today, <http://www.usatoday.com/sports/college/2006-10-05-congress-ncaa-tax-letter_x.htm>, Posted 10/5/2006 1:57 PM ET.) Another example: in September 1992 the Herald Scotland reported "Britain's charities find themselves in competition with each other as demands on their services grow while donations decline" <http://www.heraldscotland.com/sport/spl/aberdeen/charities-forced-to-compete-for-compassion-and-cash-1.794533>.

[3]Although these appeals are not observable in my data, in section 2 I argue that my estimates provide indirect evidence of their effects, and offer evidence of some expenditure substitution.

[4]Generally all charities are treated equally for US federal and state taxes. Political contributions are not tax-deductible, but these are not measured in the PSID.

powerful appeal from a charitable organization, or a media report on 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 "expenditure 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 within a year, I do not estimate a linear (regression) model here. 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.[5]

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%) 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

[5] 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.

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. 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, this could yield a specific shock.[6] In fact, some nations, including Germany, Italy, France, Australia, and Japan do have different deduction rules for different categories of charity,[7] the UK government has recently introduced a special matched funding scheme for donations to educational institutions,[8] and at least one member of the U.S. Congress has questioned whether all charities deserve equal "tax breaks."[9]

Substitution is also important to fiscal planning: policymakers need to gage how much an unexpected disaster or strong promotional push for one charity will impact other charities and create a need for greater public funding.[10] They also may want to know the net effect of such an event 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 over-investment in fundraising as discussed by Chua

[6]This is in fact a looming threat for many small charities in the US. According to *The New York Times* "At midnight on May 15, an estimated one-fifth to one-quarter of some 1.6 million charities, trade associations and membership groups will lose their tax exemptions, thanks to a provision buried in a 2006 federal bill aimed at pension reform." ("One-Fourth of Nonprofits Are to Lose Tax Breaks", Published: April 22, 2010, <http://www.nytimes.com/2010/04/23/us/23exempt.html>)

[7]Source: The Economist Intelligence Unit.

[8]This scheme was introduced on April 3, 2008, and it will last through 2011 and cost up to £200 million. See <http://www.hefce.ac.uk/pubs/circlets/2008/cl11_08/>

[9]"What Is Charity?," by Stephanie Strom, *The New York Times*, November 14, 2005. <*http://www.nytimes.com/2005/11/14/giving/14strom.html*>. While the present paper does not directly identify cross-price elasticities, as I argue in section 2, these are likely to agree in sign with the effects I identify.

[10]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).

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, 2005, and 2007 waves of the Panel Study of Income Dynamics (PSID), in conjunction with the Center on Philanthropy Panel Survey (COPPS). This is the first large-scale US data set that includes reliable repeated observations of individuals' giving to several major categories of charities.[11] Thus, I can control for individual-fixed attributes as well as time-varying financial variables.

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 charities and contributions to educational charities.[12] Aggregating across categories, I find a negative correlation between giving to health charities and giving to contributions to basic needs (henceforth "Needy") or educational charities that is robust to various checks. Overall, there is more 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 Reinstein (2009).

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. 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.

[11] 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.

[12] There is an equally strong negative correlation between health and "combined purpose" charities, but this latter correlation is more vulnerable to survey response variation, as these categories are less clearly distinct – this is addressed later in the paper.

2 Model

Economists 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 we do not ask "how does the choice of consumption of A affect the choice of consumption of B?"; this question is not meaningful as posed. We cannot assert causality for such simultaneous decisions, and the ratios of changes in these choices will depend on what is causing the changes.[13] However, non-economists 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, e.g., a request by a colleague to sponsor her running a marathon for breast cancer 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 may 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. By "sequential" the model requires only that, for every pairing of categories of charity, there is a positive probability that a specific shock leading to a gift to one category occurs before the reasoned choice of how much to give to the other category. I do not assert nor do my results require that the substitution response to *all* shocks are observed – indeed, many shocks that might affect charitable giving may happen in the latter part of the year, when most giving to other charities has already been determined. Furthermore, the COPPS data only permits observation of broad categories of charitable giving; hence substitution *within* categories is not observable.

While this model does not yield crucial implications, it provides a case for my econometric identification. 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

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

from fixed-effects regressions of giving to two distinct charitable causes), I can infer that these charities are expenditure substitutes (to be statistically correct, it is highly *likely* that these are expenditure substitutes.) In other words, the model predicts that my estimates are biased towards finding complementarity, hence where negative coefficients are observed, the case for expenditure substitution is strong.

2.1 Model of sequential decisions[14]

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.[15] 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, defined as

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

This choice imposes a constraint on later choices, as in the "preallocation" of the Pollak (1969) model of conditional demand.[16]

Note that I focus on the effect of ξ^Bon g^A rather than on the effect of μ^B on g^A. It could be argued that it really is not giving to charity B that affects giving to charity A, but rather the shock that affects giving to both charities. However, if we consider the shock as specific to g^B then the effect on g^A is indirect, and depends critically on the extent to which the marginal utility of g^A changes as g^B is "moved." More

[14]Note: The next two sections can be skipped by the less technically-minded reader without loss of continuity.

[15]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.

[16]For an empirical application of this theory, see, e.g., Pitt (1977) on intra-household allocation. DellaVigna et al. (2009) offer a related model, in which the marginal utility of giving is higher "while the fundraiser is present."

importantly, this framework is both more observable in my data and more relevant to the real world. A policymaker has no objective measure of the magnitude of a shock itself; 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 major fundraising campaign) on *giving to the shocked charity.*

With no shocks other than ξ^B the household will solve:

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

I label the difference between the choice after this shock and the long-term choice, $g^A(\xi^B_{it}) - g^{A*}$, the "expenditure crowding-out" effect of B on A, and the derivative of the function $g^A(\xi^B_{it})$ 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.[17]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^A_i and C^B_i. There may also be unobservable wealth and unobservable variables that affect utility: ε^A_{it} and ε^B_{it} 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 $g^A_{it} \succ g^B_{it}$ (the t subscript refers to the period in which *both* decisions are made), we have the equations:[18]

$$\begin{aligned} g^A_{it} &= C^A_i + \beta^A_Y Y_{it} + \xi^A_{it} + \varepsilon^A_{it} \\ g^B_{it} &= C^B_i + \beta^B_Y Y_{it} + \beta^B \xi^A_{it} + \xi^B_{it} + \varepsilon^B_{it}. \end{aligned} \tag{4}$$

We expect expenditure substitution (complementarity) to have the same sign in both directions; whether $g^B_{it} \succ g^A_{it}$ or the reverse. Formally,

[17]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.

[18]And of course, where $g^B_{it} \succ g^A_{it}$, we have the symmetric result (switching A and B).

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

In the appendix I show that this property holds, at least at the margin, using the properties of conditional demand.

At the household level, factors that increase generosity to one charitable category are likely to be correlated with factors that increase gifts to other categories. The effect of the household's observable and unobservable time-invariant variables (e.g., generosity, trust, unobserved wealth, and propensity to be asked for donations) on gifts to each category of charity is likely to be positively correlated across categories.[19] This will be seen in the data: the correlations in residuals are more negative after controlling for a household-fixed-effect, whether or not we also control for time-varying observables. While this positive correlation is not necessary for my identification strategy, it can be seen as evidence in favor of my assumptions below. If the effects of household-fixed variables are positively correlated across charitable categories, the time-variant unobservables are likely to be positively correlated as well.

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 would be 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. In other words, 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. Again, intuition suggests that such household-specific shocks – such as changes in generosity, trust, unobserved wealth, and the propensity to be asked for donations – should tend to shift giving to each category in the same direction.

Assumption 5. *In general, 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.*[20]

[19] Formally, $E[(C_i^A - E(C_i^A)(C_i^B - E(C_i{}^B)] > 0$ and $E[(C_i^A - E(C_i^A|Y_{it})(C_i^B - E(C_i{}^B|Y_{it}))] > 0$.

[20] Formally, $\Pr(g_{it}^A \succ g_{it}^B) = \omega$ and $\Pr(g_{it}^B \succ g_{it}^A) = (1-\omega)$ where $0 < \omega < 1$.

In the appendix I characterize the de-meaned values of the charity variables ($\ddot{g}_{it}^{A}$ and $\ddot{g}_{it}^{B}$) in terms of the error terms, the fundamental parameters, and the order of the decisions. Where 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,[21] as the decision order is ambiguous, I estimate the Pearson correlation coefficient between the estimated residuals from fixed-effects linear regressions of each category of giving, which I label $\ddot{\rho}_{A,B}$.[22] In the appendix I decompose $\ddot{\rho}_{A,B}$ in terms of the coefficients, β^{A} and β^{B}, the variances and covariances of the errors and shocks, and the probability ω, and show that a negative correlation coefficient implies that β^{A} and β^{B} are negative, i.e.,

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

The empirical analogue $\ddot{r}_{A,B}$ (the empirical correlation coefficient) [23] is a consistent estimator of $\ddot{\rho}_{A,B}$.[24] Thus, if I estimate a negative and significant $\ddot{r}_{A,B}$, I can infer with confidence 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 to justify the interpretation of any parameter as specific to one choice.

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

[22] Formally defined as $\ddot{\rho}_{A,B} = \frac{Cov(\ddot{g}_{it}^{A}, \ddot{g}_{it}^{B})}{SD(\ddot{g}_{it}^{A}) \times SD(\ddot{g}_{it}^{B})}$.

[23]

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

Note that $i = 1...N$ indexes households and $t = 1...T$ indexes periods (years of data).

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

3 Previous Work

3.1 Theoretical models of giving

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.[25]

Table 1: 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)

Pure public goods, linear (e.g., Becker, 1974)

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 major 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.[26] 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 substitution between dissimilar charities (net of income effects, which could cause a small amount of substitution). Hence, for the categories in COPPS, we should expect little substitution between categories that are distinct in function, e.g., health versus religion, but greater substitution if categories have significant overlap (such as "combined cause" versus "basic needs").

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

[25] 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, instead reporting the gross effect. For more complete surveys of the literature, see **?**, Sargeant and Woodliffe (2007), or Bekkers and Wiepking (2008).

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

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 or beneficiaries, with (individual) diminishing returns to this warm glow. 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.[27] 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 shocked gift is perceived to have had no impact at all, it will have no crowding-out effect (net of income effects). If the shocked gift is seen to have as much impact as the gifts the donor otherwise would have made, crowding out will be complete.

Kantian/ individual-group misperception

In this model (mentioned in Sugden, 1983) 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, as in the public goods model, 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. Between some pairings, such as health and education, the substitution should depend on "policy concerns." For example, a Kantian who is shocked into giving towards education and considering how to adjust her "health" donation might ask "Will the increased education lead to better health outcomes directly, lessening the need for further

[27] However unlike the public goods model, an impact model *can* explain giving to multiple causes by typical givers, if we assume that the individual gains utility from her impact in various realms, with diminishing marginal returns to impact within a particular category, as well as diminishing returns to overall impact.

support?"

3.2 Empirical literature

Previous authors offer evidence on the major determinants of charitable giving, some of which could be seen as "shocks" that 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.[28] 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.[29] Advertising campaigns and events such as the Aids Ride, the Jerry Lewis Telethon, and Save the Children television spots are examples of promotions that attempt to shift giving patterns. Many authors find that "peer group" effects and other social influences are significant.[30]

Government policy may also be an important influence on giving, both through the tax-treatment of giving and through government spending on "charity-like" programs. Many economists have attempted to estimate the (after-tax) price elasticity of charitable giving.[31] Only a few 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.[32] This variation suggests that charitable contributions are not homogeneous in an individual's utility function, thus ruling out a simple version of the warm glow model, and suggesting that individual crowding-out (as defined in section 2.1) is likely to be less than complete.

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

[29] "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.

[30] E.g., Long (1976), Keating et al. (1981) , Feldstein and Clotfelter (1976), Schervish and Havens (1998) , Carman (2003), and Martin and Randall (2008).

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

[32] However, these results can be interpreted as reflecting heterogeneity of donors to different causes, rather than heterogeneous elasticities for any particular donor.

Economists have also examined whether government spending crowds out private giving. While this "crowding-out" is distinct from the one I discuss, if giving follows 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 et al., 1995; Okten and Weisbrod, 2000; and Straub, 2003), while Payne (1998) finds a 50% rate of crowding out.

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, and religion or church attendance. Giving tends to be U-shaped as a percent of income , and the less wealthy give a much larger share to religious institutions (Katzev, 1995). To reflect this, I use a flexible representation of income (including a quadratic term) in my statistical analysis.

To the best of my knowledge, no academic publications have directly addressed the issue of expenditure substitution in charitable giving. Andreoni et al. (1996) examined substitution between giving and volunteering, a closely related problem,[33] although with more observably distinct prices. They find that gifts of time and money are gross complements but net (Hicksian) substitutes, although the cross-price effects are small.[34] 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.

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.[35] 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. They argue that, although they have not strictly established causality, their results are useful, describing overall patterns and showing at least some substitution between work and sleep.

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

[34] Their structural model allows them to estimate differences driven by the (observed and imputed) prices of giving and volunteering. Thus, if their assumptions hold, they can accurately estimate own and cross-price elasticities.

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

A similar case can be made for the usefulness of the empirical analysis below, even if the previously mentioned stochastic assumptions do not hold.[36]

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 and 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.[37,38] These categories were designed to be clearly distinct and non-overlapping; interviewers offered specific examples of charities in each category, and for each category, respondents were instructed not to include donations reported in other categories. However, we might not want to rule out the possibility that different respondents might classify the same charities in different categories, or that a respondent might even change her classifications of a particular charity from year to year. As the latter would cause my estimates to be biased in a *negative* direction (going against my previous claims) I focus on the

[36]For completeness, I note that some very recent work has begun to address issues closely related to the present paper. Van Diepen et al. (2009) offer some field experimental evidence on the crowding-out effects of direct mail solicitations. Borgloh investigates the impact of the German church tax on households' other charitable giving.

[37]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.

[38]Although the COPPS/PSID typically interviews respondents about their behavior in the previous complete calendar year only, in 2005 respondents were asked to report their donations to help victims of the December 26, 2004 Indian ocean tsunami, While they were asked to report their year-2004 giving for other categories specifically excluding any "tsunami gifts," they were asked to report their total donations to tsunami relief *up to the point of interview.* Although the Tsunami presents an intuitive example of a temporary "shock" motivating charitable giving to one cause, this data offers little help in identifying typical patterns of expenditure substitution. In the supplementary appendix, I offer a brief analysis of the Tsunami relief giving and its relationship to 2006 giving to other causes, as well as a discussion of the limits of this analysis.

relationship between gifts to categories that are unlikely to be interchanged, such as Health, Education, and Needy.

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 after-tax price of giving, both using a 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.[39]

Regression analyses of charitable giving often remove several types of observations seen as outliers, unreliable, or irrelevant. Auten et al. (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).[40] 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,[41] large changes in total giving in any year (a change in either direction exceeding 15% of total income), and the largest proportional givers (over 30% of income if income is above $10,000). 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. Overall, I drop roughly one third of the households that are present in each of the four years, leaving 2903 household observations per year.[42] I give further details of these calculations in the appendix, as well as other data cleaning

[39]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. Furthermore, my results are not sensitive to the whether I use the "expected" price, the "first dollar" price, the price derived using actual giving (details available by request).

[40]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).

[41]For the few instances where the household splits because a child leaves the household and forms a new family but remaining in the PSID, I keep the original household for the years before the child moves out. These represent only 41 household-year observations.

[42]2903 represents the minimum, i.e., the number in the included data set present in all four years. In each year the included sample size ranges between 2903 and 2907. This small variation (slightly unbalanced panel) is explained by the previous footnote.

details. Some key summary statistics are given below; further details are available by request.

Table 2: Summary statistics: control variables

	N	mean	sd	p10	p50	p90	min	max
Net income	11,560	54,073	55,173	14,054	43,133	98,391	-103,069	1,655,266
Bonus income	11,621	1015	9699	0	0	0	0	450,000
Tax-price of gvg	11,560	0.920	0.119	0.711	1	1	0.518	1
Wealth wo house	11,621	222,690	10,631,158	-2680	36,463	485,166	-429,360	42,516,144
Wealth w. house	11,621	319,700	1,116,911	136.7	104,995	710,000	-278,947	43,114,064
Head's age	11,621	49.47	15.77	30	48	73	18	101
Wife's age	6,079	44.94	13.66	28	44	64	18	91
Nmr. kids	11,621	0.730	1.064	0	0	2	0	7

p10, p50, and p90 indicate quantiles.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.
Households with changing composition or giving outliers (in any year) removed.
All monetary figures adjusted to year-2000 dollars based on the urban CPI.
See section [Data] for further details.

Table 3: Dummy: gave to (category of) charity

Variable	Mean
Anything over $25	0.74
Other than Religion	0.63
Religion	0.51
Combination	0.33
Needy	0.33
Health	0.26
Education	0.18
Other	0.31

Notes: Pooled data (2000-2006, SRC sample, 11,621 observations), unweighted.
Giving outliers & households with changing composition removed:
... details in section 4.

The rates of giving[43] in table 3 are close to those reported elsewhere and seems to be fairly stable in recent years. For example, **?** 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

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

Table 4: Summary statistics: charitable giving

	Mean	Mean positive	Sd	Med	p75	p90	Max
Total	1385	1956	2610	427	1516	4015	46,350
Religion	894	1819	1985	0	820	2872	26,802
Non-relig.	548	836	1555	108	500	1300	50,200
Combination	139	445	530	0	77	365	18,232
Needy	137	434	533	0	80	342	15,000
Education	68	384	623	0	0	96	42,708
Health	54	221	330	0	9	100	20,000
Other	110	353	521	0	43	250	22,208

Pooled data (2000-2006, SRC sample), unweighted.

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

Giving outliers & households with changing composition removed; details in sec. 4.

P50, P75 and P90 refer to quantiles, Mean positive refers to mean of positive gifts.

particular year, the medians (table 4) are mostly zero.[44] 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 that year is \$1835).

5 Results

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 5, a majority of households donate to more than one category of charity, and many donate to several categories (especially among large givers; details in the supplementary appendix.) Both large and small givers tend to vary their giving levels from year to year. Among the 1623 (56% of the analyzed sample) households who gave over \$25 to charities in all years, the median change in total giving over a two-year interval was 40% of a household's average donation, fewer than 10% of such households changed their giving by less than 7% in a given year, and only a single household reported giving the exact same total amount (in nominal dollars) in each year.

[44] On the other hand, the median 2000-2006 yearly non-religious donation for the 1998 "large givers", a focus of later analysis, is \$474.

Table 5: Number of major categories given to in a year

Item	Number	Per cent
0	3054	26
1	2238	19
2	2337	20
3	1806	16
4	1219	10
5 or more	967	8
Total	11,621	100

Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.
Giving outliers & households with changing composition removed:
... see section 4 for details.

Median percentage deviations were comparable for larger givers, and higher for non-religious giving.

Table 6 reports raw correlations among the categories of giving.[45] 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 regressions of each category of charity on income, imputed price, and other standard controls are also nearly all positively and significantly correlated, although (in most cases) less strongly so – this is shown in table 7.[46]

I next examine variation *within* households, i.e., controlling for a household-specific effect. Table 8 gives the matrix of correlations between the "de-meaned" (differenced from household means) gifts to each category.[47] These are much smaller, and in several cases, negative and significant.

To control for time-varying observables such as income and imputed price, I

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

[46] The estimated coefficients of this regression are given in the supplementary appendix, in table 17; errors are clustered by household. In the supplementary appendix I also report evidence from exponential Poisson regressions, as a robustness check for the sensitivity of our results to the linear specification. The use of a Poisson regression with a strictly positive non-count dependent variable with corner solutions is motivated by Santos-Silva and Tenreyro (2006). The correlation results are broadly similar across specifications. This is not surprising, as the predicted values of the charitable gifts are highly correlated across specifications; e.g., the correlation between the predictions for religious giving using zero-inflated Poisson and OLS specifications is 0.9 (see supplementary appendix).

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

Table 6: Correlations between charitable gifts in cross-section

Variables	Religion	Combination	Needy	Education	Health
Combination	0.122				
	(0.000)				
Needy	0.076	0.136			
	(0.000)	(0.000)			
Education	0.095	0.246	0.060		
	(0.000)	(0.000)	(0.000)		
Health	0.114	0.116	0.122	0.145	
	(0.000)	(0.000)	(0.000)	(0.000)	
Other	0.056	0.127	0.109	0.135	0.143
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

P-values (for standard 2-tailed tests of significance) in parentheses.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.
Giving outliers & households with changing composition removed:
details in sec. 4

Table 7: Correlations: residuals from OLS regressions

Variables	Religion	Combination	Needy	Education	Health
Combination	0.046				
	(0.000)				
Needy	0.017	0.069			
	(0.064)	(0.000)			
Education	0.047	0.134	0.011		
	(0.000)	(0.000)	(0.244)		
Health	0.060	0.032	0.064	0.070	
	(0.000)	(0.001)	(0.000)	(0.000)	
Other	-0.005	0.050	0.056	0.071	0.076
	(0.571)	(0.000)	(0.000)	(0.000)	(0.000)

Correlation coeficients btwn. residuals from linear fixed-effects regressions for each category.
P-values (for standard 2-tailed tests of significance) in parentheses.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted, 11,480-11,524 obs.
Giving outliers & households with changing composition removed:
details in sec. 4

Table 8: Correlations: de-meaned giving variables

Variables	Religion	Combination	Needy	Education	Health
Combination	0.01				
	(0.190)				
Needy	**0.037**	**-0.021**			
	(0.000)	(0.028)			
Education	0.004	**-0.031**	0.013		
	(0.661)	(0.001)	(0.159)		
Health	-0.008	**-0.061**	-0.011	**-0.030**	
	(0.383)	(0.000)	(0.221)	(0.001)	
Other	**0.016**	**-0.058**	-0.006	**0.030**	-0.009
	(0.089)	(0.000)	(0.542)	(0.001)	(0.339)

P-values (for standard 2-tailed tests of significance) in parentheses.
Coefficients in bold where p<0.10.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted, 11,536-11,585 obs.
Giving outliers & households with changing composition removed:
see section 4 and Appendix for details.

Table 9: Correlations: residuals from linear FE regressions

Variables	Religion	Combination	Needy	Education	Health
Combination	0.009				
	(0.318)				
Needy	**0.031**	**-0.022**			
	(0.001)	(0.016)			
Education	0.003	**-0.021**	0.009		
	(0.716)	(0.025)	(0.360)		
Health	-0.012	**-0.051**	-0.015	**-0.050**	
	(0.215)	(0.000)	(0.107)	(0.000)	
Other	0.010	**-0.064**	-0.009	**0.036**	-0.012
	(0.308)	(0.000)	(0.345)	(0.000)	(0.208)

Correlation coefficients btwn. residuals from fixed-effects regressions for each category.
P-values (for standard 2-tailed tests of significance) in parentheses, coefficients bold where p<0.10.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted, (11,474-11,524 obs.)
Giving outliers & households with changing composition removed:
see section 4 and Appendix for details.

Table 10: Correlations: residuals from linear FE regressions, large givers

Variables	Religion	Combination	Needy	Education	Health
Combination	-0.009				
	(0.700)				
Needy	0.030	0.021			
	(0.172)	(0.345)			
Education	**-0.070**	0.014	-0.028		
	(0.002)	(0.515)	(0.211)		
Health	**-0.039**	**-0.061**	**-0.069**	**-0.075**	
	(0.079)	(0.006)	(0.002)	(0.001)	
Other	0.019	**-0.120**	0.015	0.035	-0.006
	(0.384)	(0.000)	(0.494)	(0.111)	(0.778)

Corr'n coef's btwn. residuals from fixed-effects regressions for each category for "large giver" subset.
P-values (for standard 2-tailed tests of significance) in parentheses, bold where p<0.10.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted, "large" givers (2059-2073 obs.).
Giving outliers & households with changing composition removed:
see section 4 and Appendix for details.
Subset: household declared (as income tax deduction) over $1000 in total contributions in 1998.

run linear fixed-effects regressions controlling for these variables.[48] Noting that the dependent variable in these regressions is a strictly non-negative variable (with a corner solution at zero for some observations), I also run exponential Poisson regressions with fixed effects. These are included both as a robustness check and to estimate elasticities for comparison with other work as a check on the data and variable construction.[49] These regression results, given in table 16 in the appendix, suggest price elasticities that are heterogeneous by category but below unit elasticity for all categories except Health.[50]Net income shows the "correct" sign, but all categories of giving appear to be income inelastic. Wealth measures have the expected positive sign in most regressions. This control variable raises endogeneity issues: last year's expenditure diminishes this year's wealth. However, none of the key results are sensitive to the the inclusion of wealth in the regression analysis (see supplementary appendix). Both sets of fixed effects regressions allow for trend and year-specific effects through the year dummy variables.

[48]Linear fixed effects regression results are in appendix table 15.

[49]These Poisson regressions directly estimate an exponential function as recommended by Santos-Silva and Tenreyro (2006). I use the Stata command xtpqml (Simcoe, 2007).

[50]However, the coefficients on after-tax prices may be reflecting the effects of omitted variables and nonlinear income effects. Note that neither of the aforementioned studies differentiating the price elasticity of giving by charity used panel data.

The correlations between the residuals from the linear fixed effects regressions (regressions in table 15 in the Appendix, correlations in table 9) are similar to the correlations in de-meaned contributions (table 8).[51] The signs of these correlations depend on the pairing of the charity categories. However, comparing these to tables 6 and 7 the correlations are, almost without exception, lower (more negative) when we control for household-specific effects, supporting my claim in section 2.1 that the effects of time-invariant variables on gifts to each category of charity are positively correlated.

Note that table 8, the correlation in the de-meaned gifts, is fairly similar to table 9, the within-household residual correlation matrix; the control variables have little impact on the within-household results. 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 (see supplementary appendix) also lead to similar results; for any pairing of charities, the correlation coefficients are (naturally) bounded between the coefficients of the forward and reverse regressions, and in general are roughly halfway between the two.

Comparing the overall correlations (table 6), the correlations in pooled residuals (table 7), and the correlations in within-household residuals (tables 8 and 9), we see that both the household-fixed variables and the latent household-fixed effects are important, and both tend 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.

[51] As a robustness check, I also examined correlations (see supplementary appendix, table 19) in the residuals from the Poisson fixed-effects regressions mentioned above. For the most part, where significant, these correlations agree in sign with the correlations in the linear FE regression residuals (table 9). The only exception is Religion $\times$Education, which is positive and marginally significant in for Poisson FE case but negative and insignificant in the linear FE case). Furthermore, correlations in one table tend to be significant where they are significant in the other table.

Table 11: Correlations in "distinct category" residuals from linear FE regressions; by 1998 giving

	All givers	Small givers[A]	Large givers[A]
Religion vs. All Else	**0.023**	**0.085**	-0.035
	(0.014)	(0.000)	(0.104)
Needy vs. [Educ. + Health]	-0.002	**0.067**	**-0.061**
	(0.868)	(0.000)	(0.005)
Health vs. [Educ. + Needy]	**-0.047**	**0.022**	**-0.102**
	(0.000)	(0.033)	(0.000)
Educ. vs. [Health + Needy]	**-0.020**	**0.041**	**-0.071**
	(0.037)	(0.000)	(0.001)
Observations used (min. of rows)	11,474	9412	2062

Bivariate correlation coefficients between residuals from separate linear fixed-effect regressions for each subgroup. P-values in parentheses, coefficients in bold where p<0.10.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.
[A] "Large (small) givers": household (did not) claimed (as tax deduction) over $1000 in total contributions in 1998. Giving outliers and households with changing composition removed: see section 4 and Appendix for details.

In table 11 I report correlations from the residuals from fixed effects regressions with controls between a few key unambiguous categories (and sums of categories) and the sum of giving to all other clearly distinct categories of charity. Religious giving (mainly giving to one's church) is paired with nonreligious giving, as these are not likely to be mixed up, while each of Needy, Health, and Education are paired with the sum of the other two, for the same reason. For each pairing (and for most pairings of individual categories, as seen in table 10), we see more negative correlations among gifts for large givers – those who gave $1000 or more (in 1998 dollars) to some category in 1998 and itemized this on their tax forms.[52] Comparing tables 10 and 9, we see the same pattern – "large givers substitute more" – for most pairings of individual categories.

This suggests heterogeneous motivations for giving. For example, those who give a large amount may have sophisticated warm glow preferences, in which char-

[52] Before the COPPS module was introduced in 2001 only itemized giving was measured in the PSID. These "large givers" thus represent a subset defined not only by their philanthropy but by their decision to itemize their deductions, which will typically depend on income, number of children, home ownership, and many other factors. I use the 1998 data to avoid the obvious bias that would arise from categorizing large givers based on the same years' data that being used in the correlation analysis.

itable contributions are imperfect substitutes.[53] 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 warm glow and attributing little intrinsic value to any charity.[54]For these households, positive correlations may stem from a variable that impacts shocks to multiple charities (as implied by assumption 4), 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.

To more credibly establish the presence of expenditure substitution, I next focus on the strongest result, the negative correlation between Health giving and giving towards Education or the Needy, and investigate the sensitivity of this estimate to the modeling choices and the subset of data used. This is depicted in table 12, which presents correlation coefficients between residuals from fixed-effects regressions of giving to these categories constructed in various ways and for various subsets. The column headings explain the subset of the data used, while the row headings explain the way that the residuals were constructed. For key cells, both analytic and bootstrapped standard errors (as well as bootstrapped confidence intervals) are given.[55] The bootstrapped tests offer a robustness check, demonstrating that the apparent significance of my main results is not driven by the assumption of normal errors, and is not merely an artifact of a few outlying observations.

The first row "(1)" presents correlations between the de-meaned variables. While the correlations are negative and significant overall (first column), this masks heterogeneity: for small givers the correlation is positive, while for large givers the correlations is negative and significant in both standard significance tests and using bootstrapped confidence intervals (in braces). Row (2) depicts the correlations between residuals after linear fixed effects regressions (with controls as in table 15 in the appendix). Again, these are negative and significant overall and for large givers (including in the bootstrapped test), but positive and significant for small givers. However, inclusion of these control variables leads to more negative coef-

[53]Following the logic of section 3, the data do *not* suggest that these large givers have a pure "public goods" motivation: for these large givers, on average (over years 2000-2006) , only 16.5% gave to only one major category in a year, and 39.1% gave to three or more categories.

[54]As Lewis Carroll's 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.

[55]The latter are computed using 100 repetitions. For each repetition a sample of size n is drawn and a separate set of regression residuals generated, and the correlation is computed for the residuals from that repetition.

Table 12: Correlations between residuals of Health and [Education + Needy]: robustness and heterogeneity

Residuals from;	**Subset of data**		
	All	Small givers[A]	Large givers (1000)[A]
(1) De-meaned – i.e., no controls	**-0.030**	**0.028**	**-0.056**
	(0.002) [0.025]	(0.006)	(0.011) [0.038]
	{-0.063, 0.022}		{-0.126,-0.000}
	n=11,534	*n=9468*	*n=2066*
(2) With controls, i.e., Linear FE	**-0.047**	**0.022**	**-0.102**
	(0.000) [0.025]	(0.033)	(0.000) [0.043]
	{-0.074,-0.006}		{-0.143, -0.031}
	n=11,474	*n=9412*	*n=2068*
(3) As in (2), w/ a ctrl for each other char'l category[B]	**-0.049**	**0.019**	**-0.104**
	(0.000)	(0.067)	(0.000)
	n=11,413	*n=9367*	*n=2046*

Residuals from:	**Other subsets of data**		
	Lg. givers (500)	L.g. (1500)	L.g. (1%+ of income)[C]
(4) As in (2)	**-0.094**	**-0.113**	**-0.097**
	(0.000)	(0.000)	(0.000)
	n=2753	*n=1806*	*n=1539*
	Demog 'elite'[D]	Gave E,H, or N[E] in any year.	Gave H & EN[E] in all years
(5) As in (2)	**-0.084**	**-0.048**	**-0.146**
	(0.000)	(0.000)	(0.003)
	n=2601	*n=8599*	*n=408*

Bivariate correlation coef's between resid's from separate linear FE regressions for each subgroup.
P-values of standard significance tests in parentheses, coefficients in bold where p<0.10.
Bootstraps: 100 repetitions, clustered by household, full procedure bootstrapped where necessary:
[Boostrapped standard errors in square brackets], {90% bias-corrected bootstrap CI's in braces}
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.
[A] Defined using 1998 tax-deducted contributions only
[B] Regressions include 3 additional controls: for "Religious," "Combined Cause" & "Other" donations.
[C] 1998 tax deducted contributions > 1% of 1998 gross income, where 1998 income > $20,000
[D] "Elite"': Households with gross incomes above $50,000 and head has a bachelor's degree.
[E] E = Education, H=Health, N=Needy, EN = Education+Needy
Giving outliers & households w/ changing composition removed: see sec. 4 and Appendix.

ficients than in row 1. Row (3) reports correlations between residuals constructed as in (2) but with three additional controls – for "Religious," "Combined Cause", and "Other" donations – these could be interpreted as proxies for further changes in generosity or taste for giving. However, these controls have virtually no impact on the correlations between the residuals.

Rows (4) and (5) present correlations between residuals after controlled fixed effects regressions as in row (2), but constructed from regressions run on different subsets of the data. These are included both as robustness checks and to explore heterogeneity. Row (4) examines different definitions of "large" givers: those who gave over \$500 in 1998, those who gave over \$1500 in 1998, and those who gave over 1% of income in 1998 (and had incomes over \$20,000). While these correlations are all negative and significant, the magnitudes are somewhat larger for the larger threshold 1998 contributions. Row (5) first examines the demographic "elite" – those households with gross incomes above \$50,000 and where the head has a bachelor's degree. This allows me to focus on households that are more likely to be (larger) charitable givers, but without directly using any of their giving choices to define the subset. Again, the correlations in residuals are negative and significant.

The results from the middle column of (5) drops households that never gave to either Needy, Health, or Education in any year. 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. However, this omission is not important; the correlation is nearly the same as when these are included (row 2, left column). Finally, in the right column I examine the correlation in the residuals constructed using the 408 households who gave both to Needy and to Health or Education in each of the four years. The coefficient is strongly negative and significant, suggesting that intensive margin effects are very important, and that regular givers are prone to expenditure substitution.

It is important to differentiate the effect of shocks at the extensive margin. According to at least one fundraising insider, "giving is a learned behavior."[56] 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 13 focuses on two pairings of charities and tabulates cases where both charities experienced a "state change" (from zero to positive or positive to zero). For either of these pairs that appear to be expenditure substitutes in the above analysis (Needy and Health or Needy and Education), these state changes are significantly more likely to go in the *same* direction then in *opposite* directions:

[56] 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).

Table 13: Extensive margin results; tabulating state changes

Stopped or started giving to the category:

	Health			Education	
Needy	Stopped	Started	Needy	Stopped	Started
Stopped	193	144	Stopped	150	91
Expected	*163*	*174*	*Expected*	109	*133*
Started	162	235	Started	94	207
Expected	*192*	*205*	*Expected*	*136*	*166*

Nonparametric measures of positive association

Health × Needy		Education × Needy	
Γ	K's τ-b	Γ	K's τ-b
0.32	0.16	0.57	0.31
(0.07)	(0.04)	(0.06)	(0.04)

Zeroes removed, asymptotic standard errors in parentheses.
"Expected" refers to predicted value assuming row and column independence.
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.

Clearly, if expenditure on one good increases, expenditure on certain other goods, and on other goods in net, must decrease. This is typically is depicted by the the "Cournot aggregation" condition on the Marshallian demand response to a price change. [57] In the context of conditional demand, assuming a unit price for each good, the aggregation condition must follow: $\sum_k \frac{dg^{K \cdot B}}{d\bar{g}^B} = -1$, where $g^{K \cdot B}$ is the conditional demand for good k, and $d\bar{g}^B$ represents an an uncompensated change in the preallocation of good B.

The adjustment might be equally balanced across other expenditures; e.g., an exogenously-driven 1% increase in giving to the needy could lead to a 1% decrease in giving to health, in giving to religion, in restaurant expenditure, travel, etc. However, unless preferences are functionally separable, this need not hold. For any *particular* good, the conditional expenditure response may be negative or positive, depending on whether the increased consumption of the first good causes the marginal utility of this good to increases enough to outweigh the effect of hav-

[57] The response to a change in price p_i must follow $\sum_k p_k \frac{\partial g_k}{\partial p_i} + g_i(x,p) = 0$ for $i = 1, \ldots n$ goods, where k sums across goods and $g_i(x,p)$ is the Marshallian demand function for good i as a function of income and the price vector. This is also commonly expressed in terms of budget shares $w_i$and price elasticities e_{ki} as $\sum_k w_k e_{ki} + w_i = 0$.

ing less remaining income to spend – as noted in appendix 6 the marginal effect depends on the ratio of Slutsky terms. [58]

The plausible bias in expenditure substitution, as argued for the case of charitable contributions example, is towards finding complementarity, and therefore negative coefficients can be seen as strong evidence for expenditure substitution. At least in terms of unobservable permanent income, the argument is parallel for each type of consumption . As increases in giving to one charity will tend to coincide with increases in generosity and in the propensity to be asked to donate, we might expect a greater positive bias to correlation coefficients (relative to the correlation driven by causal responses to shocks) between charitable contributions than between a charitable contribution and a consumption good, or between distinct consumption categories.

As a benchmark, I examine two other other major components of discretionary spending: eating out in restaurants and food eaten at home.[59] There is, at least, no obvious argument for food and charitable giving to be either expenditure complements or substitutes (nor complements or substitutes in the traditional sense); any observed (residual) correlation seems likely to reflect unobservable components of income or "non-frugality" that are positively correlated to each. Table 14 reports correlations between (residuals of) these expenditures and the various categories of donations.[60] These correlations are mainly positive and sometimes significant (where positive), in contrast to the negative relationships in key cells of tables 8 - 12. In the final row I also present results on the correlations between the two components of food expenditure. Although strong intuition suggests that food eaten in restaurants and food at home are substitutes, This lends further support to the assumption that unobserved components of disposable income lead to a bias towards finding expenditure complementarity, and supports the case that the negative correlations between (residuals of) certain categories of charitable giving are indeed "special", reflecting expenditure substitution.

[58] However, as discussed, given the ambiguous ordering of decisions and shocks, and the presumed positive bias, , I do not attempt to measure such a response function.

[59] Food is essentially the only major category of expense that is in the PSID for all of the years 2000-2006. For the households in the sample who gave a numerical response, the average yearly expense on restaurants is \$2579, the average for food at home is \$4131 (not including food stamp recipients).

[60] The first column reports correlations in de-meaned variables, essentially controlling for household-fixed effects as in table 8. The second and third columns report correlations from residuals from controlled linear regressions with fixed effects as in tables 15 and 9. For the third column the regression is implemented on those who reported over \$1000 in giving in 1998 for tax deductions. Details available by request.

Table 14: Correlations in residuals: Food and charity; de-meaned with and without controls.

Resid's from:	De-meaned	Linear FE reg's [*]	...Large givers [**]	De-meaned	Lin. FE reg's [*]	...Lg. gvr's [**]
Expense:	Eating out	Eating out	Eating out	Food at home	Food at home	Food at home
Total giving	**0.042**	0.010	0.022	0.0039	-0.006	0.029
	(0.000)	(0.278)	(0.317)	(0.724)	(0.587)	(0.274)
Needy	**0.029**	0.012	0.036	0.0064	0.002	-0.010
	(0.003)	(0.192)	(0.108)	(0.561)	(0.871)	(0.717)
Education	0.008	-0.004	-0.021	-0.005	-0.006	**0.052**
	(0.375)	(0.664)	(0.357)	(0.681)	(0.578)	(0.052)
Health	**0.024**	**0.027**	**0.045**	0.005	0.005	-0.004
	(0.011)	(0.005)	(0.047)	(0.650)	(0.665)	(0.889)
Educ + Needy	**0.026**	0.006	0.005	0.0016	-0.003	0.030
	(0.006)	(0.527)	(0.823)	(0.883)	(0.785)	(0.263)
Food at home	**0.053**	-0.012	-0.031			
	(0.000)	(0.306)	(0.253)			
Min. obs. in col.	11,042	10,979	1981	8,129	8,094	1,405

P-values in parentheses. Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted (11,037-11,086 obs.).
Giving outliers & households with changing composition removed: ... see section 4 for details.
[*] Residuals from separate FE regressions for each category (including food) as in table 15.
again, residuals derived from separate FE regressions for each category for this subset as in table 10.
[**] "Large givers": household (did not) claimed (as tax deduction) over $1000 in total contributions in 1998.

6 Conclusion

My results show that expenditure substitution exists between certain sets of charities, but a cross-sectional approach will mask this; researchers need to focus on *within*-household variation. This implies that in these cases an exogenous shift in giving to one charity leads to at least some decrease in giving to another charity. The greater (more negative) substitution for large givers, particularly between health-related and basic needs or educational 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 concave multi-charity warm-glow preferences 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. The large givers' behavior is also consistent with Duncan's (2004) impact model. If we allow diminishing returns to overall impact (as well as to impact within each category, to explain donations to several categories), donations to medical research may fill some of the donor's desire to have an overall impact, and thus she may give less to the needy. The evidence for large givers is *inconsistent* with a pure public goods model, as this would predict no expenditure substitution (and, according to a strict interpretation, would also predict giving to only a single cause). Although, as noted, there is a bias towards finding complementarity, the evidence weakly suggests that the expenditure crowding out is not complete – this argues against a *simple* warm glow model, which would predict one-for-one substitution. Still, my results do not contradict the notion that giving is a learned behavior; the substitution does not occur at the *extensive* margin.

As noted in the introduction, these findings have implications for philanthropists, nonprofit organizations, and policy-makers. Fundraisers for hospitals and medical research who are also personally concerned with the plight of the needy and the state of education (and vice-versa) might want to be cautious in targeting households likely to be "regular givers." Politicians may also want to consider that programs designed to encourage giving to (e.g.) educational institutions (such as the UK's recent matched funding scheme) may do so at the expense of health and basic needs charities. Finally, if (e.g.) hospitals announce they are soliciting support from typical donors using state-of-the-art fundraising techniques that are likely to be successful, schools and universities may want to lower their expectations for the years' "development."

There are numerous ways this research can be extended. The analysis of correlations in residuals could be extended to parametrize and directly measure the heterogeneity in correlations; i.e., these could be interacted with demographic variables, the size of 1998 gift, etc**.** Although my comparison with restaurant expenditure suggests that the substitution I observe is more than a mere income effect, future research may strive to separate the "money expenditure" effect from the "pure substitution" effect (as defined in Pollak, 1969), and to also consider the relationship between charitable giving and household savings. More data will continue to become available, allowing more precise tests and models with more sophisticated intertemporal patterns. The extent to which the benefit of giving to donors is a “durable” or perishable good remains an open question, and is critical to understanding philanthropic decisions over the life cycle. Research should continue to search for relevant instruments and exogenous shocks to that differentially affect households’ charitable giving to particular categories – this will allow econometric identification of the *magnitude* of expenditure substitution and complementarity. Macroeconomic data (which has the advantages of accuracy, salience, and lack of corner-solution variables) could also be expanded to include more years (pre-1978) as well as cross-country patterns; 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.

Experimental evidence (e.g., Reinstein, 2009) should supplement observational econometric work by offering truly exogenous shocks and precise measurement. Field experiments may also prove a fruitful way to combine the strengths of the laboratory and happenstance data. For example a design (in the mold of Frey and Meier, 2004) taking advantage of differential employer-provided incentives to donate to specific charities could allow direct estimation of own and cross-price elasticities. Finally, I note a related question that is ripe for investigation: if the overall “warm glow” benefits of other-regarding behavior exhibits diminishing marginal returns, when a shock (or price change) motivates a household head to offer financial support for friends and family members, this may substitute for “regular” charitable giving.[61]

6.1 Appendix: Model

Shared sign of conditional demand effects

Adapting Pollak’s (1969) model of conditional demand to my notation, the “total derivative” of the conditional demand for g^A with respect to a change ξ^B in the

[61] Auten and Joulfaian (1996) offer evidence that “parents give more to charities when their children are economically better off,” offering suggestive support for this hypothesis.

preallocated good g^B, allowing for the change in remaining income is:[62]

$$\frac{dg^A(\xi^B)}{d\xi^B} = \frac{dg^{A\cdot B}}{d\bar{g}^B} = \frac{\partial g^{A\cdot B}}{\partial \xi^B} + \frac{\partial g^{A\cdot B}}{\partial \tilde{Y}}\frac{\partial \tilde{Y}}{\partial \xi^B} = \frac{\partial g^{A\cdot B}}{\partial \xi^B} - \frac{\partial g^{A\cdot B}}{\partial \tilde{Y}} p_{g^B}$$
$$= \frac{\partial g^{A\cdot B}}{\partial \xi^B} - \frac{\partial g^{A\cdot B}}{\partial \tilde{Y}} \text{ assuming the price of each charitable good is 1} \quad (5)$$

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

$$\frac{dg^A(\xi^B)}{d\xi^B} = \frac{\frac{\partial f^A}{\partial p_A}}{\frac{\partial f^B}{\partial p_B}} = \frac{S_{AB}}{S_{BB}} \text{ if } (\bar{g}_B = g_B^*) \quad (6)$$

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

[62] 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.

Proof that a negative correlation coefficient implies that β^A and β^B are *negative*:

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

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, i.e.,
$\ddot{\rho}_{A,B} < 0 \Longrightarrow (\beta^A < 0 \text{ and } \beta^B < 0)$.

De-meaned charitable contributions in sequential model:

I characterize the de-meaned values of the charity variables ($\ddot{g}^A_{it}$ and $\ddot{g}^B_{it}$) in terms of the error terms, the fundamental parameters, and the order of the decisions, dropping the Y_{it} variables for clarity, letting $\ddot{X}_t = X_{it} - \frac{1}{T}\sum_{t=1}^{T} X_{ti}$ the de-meaned value, for any variable X, and letting $\mathbf{1}_{A\succ B} \equiv \mathbf{1}(g^A_{it} \succ g^B_{it})$:

$$\begin{aligned}
\ddot{g}^A_{it} &= \mathbf{1}_{A\succ B}(\ddot{\xi}^A_{it} + \ddot{\varepsilon}^A_{it}) + (1-\mathbf{1}_{A\succ B})(\beta^A\ddot{\xi}^B_{it} + \ddot{\xi}^A_{it} + \ddot{\varepsilon}^A_{it}) \qquad (8)\\
&= \ddot{\xi}^A_{it} + \ddot{\varepsilon}^A_{it} + (1-\mathbf{1}_{A\succ B})\beta^A\ddot{\xi}^B_{it}\\
\ddot{g}^B_{it} &= \ddot{\xi}^B_{it} + \ddot{\varepsilon}^B_{it} + \mathbf{1}_{A\succ B}\beta^B\ddot{\xi}^A_{it}. \qquad (9)
\end{aligned}$$

As mentioned, in the case of the tsunami, we might suppose that 2005 relief giving responded to a temporary utility function, and thus this shock preceded giving decisions for 2006. Allow 2005 and 2006 to be part of the same time period 't' (from the utility and error variance perspective, but as mentioned the 2005 decision precedes the 2006 decisions). Let g_B represent giving to a cause other than the tsunami and g_A be tsunami giving. This yields:

$$\ddot{g}^B_{it} = \ddot{\xi}^B_{it} + \ddot{\varepsilon}^B_{it} + \beta^B\ddot{\xi}^A_{it},$$

$$\ddot{g}^A_{it} = \ddot{\xi}^A_{it} + \ddot{\varepsilon}^A_{it}$$

In light of the variance assumptions (recall $E[\varepsilon_{it}^{A}\varepsilon_{it}^{B}] > 0$ in particular), this implies (the proof is standard and thus omitted) that a fixed-effects regression of giving to B in 2006 on tsunami giving in 2005 will yield a measure of the rate of expenditure substitution β^B that is again biased towards finding complementarity.

6.2 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:

$$x_i + p_i g_i - m_i = 0; g_i \geq 0, x_i \geq 0; \tag{10}$$

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 $\arg\max_{x_i, g_i} u_i(x_i, ng_i)$;
-misperception (e.g., Laffont, 1975)	s.t. eqn. 10
	but $i$gets actual utility $u_i(x_i, G)$

6.3 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.

I begin with the households that appear in the 2000, 2002, 2004, and 2006 samples. I remove families that split or otherwise undergo a major change in composition between these years, leaving households which have the same head for all four years. To help ensure my result's robustness (and remove possible miscodes), I leave out "outliers" who either reported giving over 30% of their income (if income above $10,000), or reported a change in total giving between two years exceeding 15% of their total income. I further limit my analysis to the 1968 SRC cross-section sample.

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 the 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 year-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 (even though the original SRC sample was designed to be nationally representative).

Missing Variables and Values

When I encounter missing values or refusals, I leave these as missing (unless the household indicated having not given to a category at all in a separate binary question, in which case the value is set to zero.). I avoid doing imputation here 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 (less than 1% of my sample) give only a range-coded value for contributions; I set these to the average value of respondents who report *actual* giving in that interval (details by request).. My main results are not sensitive to this (details by request). For the summed charity variables (e.g., Education + Health) if one of the two responses is missing, I assume it is zero and use the other one.

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 ("tax price") 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.[63] 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.[64] This (one minus

[63] 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.

[64] 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*

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). Note that the computed price is not highly sensitive to these choices (details by request).

6.4 Appendix: Further results

A supplementary appendix can be found at <http://davidreinstein.wordpress.com/research-and-publications/supplemental-appendices-and-data/>.

giving to *A* and only imputed giving to *B*. I defer this issue for later study.

Table 15: Linear fixed-effects regressions

	(1) Total	(2) Relig	(3) Nonrelig	(4) Combo	(5) Needy	(6) Health	(7) Educ	(8) Other
Net income	.0064**	.0028**	.0037**	8.1e-04*	7.2e-04*	2.1e-04	.0015	4.6e-04
	(.0013)	(6.6e-04)	(.0011)	(3.8e-04)	(2.8e-04)	(1.9e-04)	(.0011)	(4.5e-04)
Square net income	-3.4e-09*	-2.4e-09**	-9.8e-10	-2.4e-10	-4.9e-10*	-3.3e-11	3.1e-10	-5.8e-10
	(1.4e-09)	(4.8e-10)	(1.5e-09)	(6.9e-10)	(2.0e-10)	(2.3e-10)	(1.0e-09)	(3.8e-10)
Bonus income	.0062	.0013	.0049	-.0021	3.5e-04	.0046	4.3e-04	.0016
	(.0041)	(.0032)	(.0042)	(.0013)	(.0011)	(.004)	(6.4e-04)	(.0016)
Price	-607*	-375*	-192	-45.8	-62	-72**	-37.1	39.9
	(264)	(162)	(196)	(89.5)	(72.6)	(26.7)	(106)	(79.2)
Wealth w.o. house	-3.2e-04	-1.5e-04	-1.8e-04	3.0e-04+	-9.4e-05	-2.4e-05	-2.4e-04	-1.1e-04
	(4.6e-04)	(2.3e-04)	(3.5e-04)	(1.6e-04)	(1.1e-04)	(1.9e-04)	(2.8e-04)	(1.7e-04)
Wealth w. house	2.9e-04	2.0e-04	1.0e-04	-2.3e-04	9.1e-05	-1.0e-05	1.1e-04	1.4e-04
	(4.3e-04)	(2.3e-04)	(3.0e-04)	(1.6e-04)	(1.1e-04)	(1.6e-04)	(1.8e-04)	(1.8e-04)
Nmr. kids in hshld.	39	66.6*	-26.8	-8.07	24.6*	-3.74	-35.5	-3.05
	(46.4)	(26.4)	(41.5)	(9.94)	(12.3)	(4.13)	(31.4)	(16.2)
Year 2002	104**	90.1**	13.9	-11.2	9.92	-2.08	13.6	3.57
	(29.7)	(21.9)	(22.6)	(10.3)	(9.93)	(8.53)	(11.6)	(8.25)
Year 2004	232**	126**	109**	3.46	36.6**	4.9	31.2+	34.3**
	(39.7)	(25)	(31.3)	(12.7)	(13.2)	(5.79)	(17.2)	(12)
Year 2006	219**	117**	106**	-2.26	35.6**	9.81	27.1	36.8**
	(39.2)	(26.3)	(29.6)	(10.2)	(12.3)	(6.18)	(22)	(10.7)
Constant	1463**	959**	467**	162+	116	114**	43.8	15.3
	(243)	(150)	(180)	(88.9)	(73.7)	(28.5)	(82.9)	(78.8)
Observations	11560	11518	11518	11513	11508	11510	11533	11549
R^2	0.026	0.013	0.023	0.015	0.004	0.027	0.047	0.007

Standard errors in parentheses. + p<0.10, * p<0.05, ** p<0.01.

Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.

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

Table 16: Poisson fixed-effects (pseudo-ML) exponential regressions

	(1) Total	(2) Relig	(3) Nonrelig	(4) Combo	(5) Needy	(6) Health	(7) Educ	(8) Other
Log net income	.127**	.0846**	.204**	.205**	.145*	.169+	.369*	.151
	(.0266)	(.0271)	(.0452)	(.0676)	(.0634)	(.0956)	(.164)	(.111)
Log bonus income	.006	7.1e-05	.0143*	.0153	8.0e-04	.0403	-.0095	.0254
	(.0038)	(.0045)	(.0063)	(.0119)	(.014)	(.0303)	(.0174)	(.0172)
Log price	-.341**	-.347**	-.252	-.0579	-.264	-1.07**	-.146	.0688
	(.121)	(.128)	(.197)	(.348)	(.284)	(.338)	(.575)	(.482)
Log wealth w.o. house	.0099+	.004	.0214*	.0064	.0431*	.0143	.0582**	-.0064
	(.0055)	(.0064)	(.0101)	(.0168)	(.017)	(.0237)	(.0208)	(.0253)
Log wealth	.0064	.0107	-7.1e-04	-9.4e-04	.0017	.0071	-.0242	.0105
	(.0082)	(.0095)	(.0148)	(.0241)	(.0262)	(.034)	(.0341)	(.0308)
Nmr. kids in hshld.	.0428+	.0643**	.0101	-.0294	.178*	-.0432	-.21	.0184
	(.0236)	(.0246)	(.0512)	(.058)	(.0806)	(.0832)	(.171)	(.146)
Year 2002	.0729**	.104**	.0194	-.104	.0784	-.0062	.111	.0684
	(.0216)	(.0232)	(.0449)	(.0732)	(.0824)	(.16)	(.145)	(.101)
Year 2004	.167**	.153**	.19**	-.0551	.27**	.117	.263+	.391**
	(.0258)	(.0265)	(.0508)	(.0832)	(.09)	(.133)	(.142)	(.124)
Year 2006	.164**	.146**	.2**	-.0465	.274**	.162	.199	.432**
	(.0267)	(.0276)	(.0525)	(.0858)	(.0927)	(.119)	(.176)	(.14)
Observations	10223	7629	9531	6822	7207	5777	4055	6853

Standard errors in parentheses. + p<0.10, * p<0.05, ** p<0.01.

Note: procedure 'drops' households with no variation in contributions to category in any year

Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.

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

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7 Supplementary Appendix

7.1 Literature review supplement: previous models

List II: Multi-Charity Name,Author, Year	Utility forms and Related Models 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	$u_i = \min(\alpha x_i, \beta_1 g_{i1}, \beta_2 g_{i2}, \ldots, \beta_K g_{iK})$
6. Multi-Stage Budgeting	$U(q_i \ldots q_j) = u(v_1(q_1 \ldots q_{J1}), v_G(q_{J1} \ldots q_J))$

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 et al. (2003), (model 2, above) consider only extreme cases (in the context of couples' decision-making). Andreoni et al. (1996), offer the most useful example, estimating a model of giving and volunteering based on a quadratic utility form.

7.2 Supplementary results, construction of results

Table 17: Pooled cross-section linear regressions

	(1) Total	(2) Relig	(3) Nonrelig	(4) Combo	(5) Needy	(6) Health	(7) Educ	(8) Other
Net income	.0113**	.0045**	.0069**	.0019**	.0019**	6.3e-04**	.0011	.0014**
	(.0014)	(8.8e-04)	(.001)	(3.9e-04)	(2.6e-04)	(1.4e-04)	(6.5e-04)	(4.2e-04)
Square net income	-9.0e-09**	-4.8e-09**	-4.3e-09*	-1.2e-09	-1.5e-09**	-5.2e-10**	1.9e-10	-1.2e-09**
	(2.1e-09)	(1.1e-09)	(2.0e-09)	(7.7e-10)	(3.0e-10)	(1.5e-10)	(1.4e-09)	(2.8e-10)
Bonus income	.0204*	.0057	.0146*	.0021	.0038+	.0058	9.0e-04	.002
	(.01)	(.0041)	(.0072)	(.0019)	(.0021)	(.0036)	(.0015)	(.0015)
Wealth w.o. house	-6.2e-04	2.9e-04	-9.1e-04**	4.1e-05	-2.8e-05	-3.0e-04**	-2.0e-04	-4.4e-04**
	(3.8e-04)	(2.2e-04)	(2.7e-04)	(8.4e-05)	(4.8e-05)	(6.4e-05)	(1.4e-04)	(1.3e-04)
Wealth w. house	.001**	-2.1e-04	.0012**	7.9e-05	3.9e-05	3.2e-04**	3.6e-04**	4.6e-04**
	(3.4e-04)	(2.2e-04)	(2.2e-04)	(5.9e-05)	(4.7e-05)	(6.9e-05)	(9.3e-05)	(1.3e-04)
Price	-3133**	-2412**	-710**	-253**	-241**	-109**	-26.7	-83.9
	(260)	(201)	(147)	(63.3)	(54.5)	(33.9)	(80.9)	(55.7)
Head's age	16.8**	14.5**	2.53**	1.24**	1.15**	.236	-.878+	.83**
	(1.37)	(1.05)	(.804)	(.335)	(.291)	(.196)	(.479)	(.277)
Wife's age	5.9**	5.42**	.461	-.377	.647+	.0378	-.326	.531+
	(1.45)	(1.14)	(.876)	(.374)	(.359)	(.168)	(.557)	(.295)
Nmr. kids in hshld.	56.3*	47.3*	11.2	-.083	20.2**	-8.74**	-1.56	1.08
	(26.1)	(21.3)	(12.4)	(5.77)	(6.05)	(2.95)	(5.34)	(4.55)
Head coll. degree	504**	291**	214**	65.2**	55.3**	5.01	31+	58.4**
	(59.4)	(49.5)	(30.7)	(12.6)	(13.2)	(7.45)	(17.5)	(10.3)
Head is Black	316**	314**	9.84	23.2+	-21.1	5.88	18.9+	-18.8*
	(77.2)	(71)	(27.5)	(13.1)	(13.5)	(8.01)	(10)	(8.43)
Head is married	266**	334**	-67.4+	26	-33.6+	-19.9*	-11.2	-29.4*
	(68.8)	(54.8)	(38.9)	(18.5)	(18.7)	(8.64)	(17.5)	(14.7)
Northeast region	-22.4	192	-214	-30.1	-21.7	15.4	6.71	-183*
	(172)	(123)	(131)	(44.2)	(34.6)	(19)	(17.8)	(91.2)
Northcentral region	502**	588**	-82.8	6.16	-5.37	23.1	36.8*	-142
	(172)	(123)	(131)	(44.2)	(33.5)	(18.5)	(16.8)	(91.6)
Southern region	746**	825**	-71.1	-10.7	17.2	17.5	42.5*	-137
	(172)	(123)	(131)	(43.7)	(33.4)	(18.5)	(17.2)	(91.4)
Western region	621**	655**	-30.3	-20.1	44.5	24.2	57.4**	-136
	(176)	(128)	(132)	(44.2)	(35.1)	(20)	(18.1)	(91.6)
Urban	-17.6	-156**	135**	48.8**	63**	-.545	7.76	19.6*
	(47.9)	(40.2)	(24.2)	(10.2)	(11.5)	(5.72)	(9.07)	(9.69)
Constant	1512**	1021**	466*	160+	125+	74.6+	-31.7	139
	(322)	(236)	(211)	(81.7)	(67.9)	(41.5)	(90.6)	(111)
Observations	11560	11518	11518	11513	11508	11510	11533	11549
R^2	0.238	0.117	0.268	0.144	0.062	0.088	0.145	0.071

Additional (hidden) controls: year dummies.
Standard errors in parentheses
+ p<0.10, * p<0.05, ** p<0.01
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.
Giving outliers & households with changing composition removed: details in sec. 4

Table 18: **Pooled cross-section Poisson exponential regressions**

	(1) Total	(2) Relig	(3) Nonrelig	(4) Combo	(5) Needy	(6) Health	(7) Educ	(8) Other
Log net income	.51**	.399**	.69**	.695**	.556**	.533**	.853**	.669**
	(4.3e-04)	(5.5e-04)	(7.0e-04)	(.0013)	(.0014)	(.0022)	(.0019)	(.0015)
Log bonus income	.0013**	-.0119**	.0174**	.0238**	.0135**	.0424**	-.001**	.0072**
	(9.1e-05)	(1.2e-04)	(1.3e-04)	(2.5e-04)	(2.6e-04)	(3.9e-04)	(3.5e-04)	(3.2e-04)
Log wealth w.o. house	.0305**	.0232**	.0427**	.0198**	.0447**	.024**	.0865**	.0463**
	(1.4e-04)	(1.6e-04)	(2.5e-04)	(4.4e-04)	(4.4e-04)	(7.9e-04)	(.001)	(5.5e-04)
Log wealth	.0337**	.0267**	.0588**	.0826**	.0193**	.163**	.209**	.0296**
	(1.8e-04)	(2.1e-04)	(3.5e-04)	(6.5e-04)	(5.7e-04)	(.0013)	(.0016)	(7.4e-04)
Log price	-1.45**	-1.66**	-1.1**	-1.09**	-1.04**	-1.98**	-1.08**	-.955**
	(.0018)	(.0023)	(.0029)	(.0055)	(.0057)	(.0091)	(.0074)	(.0064)
Head's age	.0166**	.0182**	.0129**	.011**	.0085**	.0179**	7.9e-04**	.023**
	(2.2e-05)	(2.7e-05)	(3.8e-05)	(7.2e-05)	(7.1e-05)	(1.2e-04)	(1.1e-04)	(8.1e-05)
Nmr. kids in hshld.	.0874**	.116**	.0404**	.0099**	.131**	-.121**	-.0029*	.063**
	(2.6e-04)	(3.3e-04)	(4.5e-04)	(8.5e-04)	(7.9e-04)	(.0015)	(.0012)	(1.0e-03)
Head coll. degree	.28**	.192**	.431**	.419**	.284**	.233**	.83**	.519**
	(5.4e-04)	(6.8e-04)	(9.1e-04)	(.0017)	(.0017)	(.0027)	(.0027)	(.002)
Northeast region	.0994**	.529**	-.441**	-.213**	-.184**	.263**	1.52**	-1.23**
	(.0049)	(.0078)	(.0063)	(.013)	(.014)	(.0226)	(.0592)	(.0093)
N-central region	.446**	1.06**	-.321**	.0258*	-.109**	.11**	1.65**	-1.09**
	(.0049)	(.0078)	(.0063)	(.013)	(.0139)	(.0226)	(.0592)	(.0092)
Southern reg.	.653**	1.34**	-.271**	-.0932**	.0518**	.113**	1.87**	-1.02**
	(.0049)	(.0078)	(.0063)	(.013)	(.0139)	(.0226)	(.0591)	(.0091)
Western reg.	.562**	1.1**	-.099**	-.0895**	.203**	.37**	2.21**	-.855**
	(.0049)	(.0078)	(.0063)	(.013)	(.0139)	(.0226)	(.0591)	(.0092)
Urban	-.0075**	-.224**	.344**	.337**	.422**	.256**	.334**	.317**
	(5.2e-04)	(6.8e-04)	(8.7e-04)	(.0016)	(.0017)	(.0026)	(.0024)	(.0019)
Year 2002	.0856**	.102**	.0576**	-.0627**	.111**	-.0081*	.19**	.121**
	(7.2e-04)	(8.9e-04)	(.0012)	(.0022)	(.0024)	(.0036)	(.0034)	(.0028)
Year 2004	.176**	.147**	.227**	-.0023	.313**	.0458**	.391**	.419**
	(7.1e-04)	(8.9e-04)	(.0012)	(.0022)	(.0023)	(.0036)	(.0033)	(.0026)
Year 2006	.0927**	.0751**	.127**	-.106**	.231**	-.0108**	.213**	.336**
	(7.1e-04)	(8.9e-04)	(.0012)	(.0022)	(.0023)	(.0035)	(.0033)	(.0026)
Constant	-.776**	-.432**	-3.47**	-4.76**	-2.94**	-5.64**	-11.6**	-4.4**
	(.0066)	(.0097)	(.0096)	(.0188)	(.0201)	(.0318)	(.0618)	(.0184)
Observations	11560	11518	11518	11513	11508	11510	11533	11549
Pseudo R^2	0.306	0.183	0.388	0.252	0.183	0.252	0.371	0.231

Standard errors in parentheses

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

Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.

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

Table 19: **Correlations: residuals from Poisson FE regressions.**

Variables	Religion	Combination	Needy	Education	Health	Other
Combination	0.018	1.000				
	(0.056)					
Needy	0.025	-0.022	1.000			
	(0.008)	(0.016)				
Education	0.017	-0.110	0.011	1.000		
	(0.067)	(0.000)	(0.254)			
Health	-0.011	-0.072	-0.014	-0.038	1.000	
	(0.254)	(0.000)	(0.136)	(0.000)		
Other	0.008	-0.051	-0.019	0.041	-0.015	1.000
	(0.399)	(0.000)	(0.041)	(0.000)	(0.109)	

P-values (for standard 2-tailed tests of significance) in parentheses.
Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted, 11,476-11,524 obs.
Giving outliers & households with changing composition removed:
details in sec. 4

Tsunami giving results

Although the Tsunami presents an intuitive example of a temporary "shock" motivating giving to disaster victims in late December 2004 and early 2005,[65]this data offers little help in identifying expenditure substitution. While the Tsunami itself was an exogenous event, and 2005 giving to the Tsunami clearly precedes 2006 giving, the problem of omitted variable bias remains even after controlling for houshold-fixed effects: an increase in generosity or unobserved wealth in 2005 is likely to persist into 2006 and thus lead both to more Tsunami giving in 2005 and to other types of giving in 2006. While a negative coefficient could be interpreted as evidence of expenditure substitution following the "sign of bias" argument of section 1, my own analysis of this data reveals a *positive* relationship between 2005 Tsunami giving and 2006 total giving. Furthermore, the tsunami was a unique event, and news coverage of the tsunami that may have impacted donors' preferences and world view in ways that could have influenced their future philanthropy,

[65]Although the COPPS/PSID typically interviews respondents about their behavior in the previous complete calendar year only, in 2005 respondents were asked to report their donations to help victims of the December 26, 2004 Indian ocean tsunami, While they were asked to report their year-2004 giving for other categories specifically excluding any "tsunami gifts," they were asked to report their total donations to tsunami relief *up to the point of interview.* Interviews ran from March to September 2005; although the amounts reported do differ by month of interview, there is no evidence that later reporters reported more than earlier ones

and this effect may not be the same in future major disasters. Finally, and most crucially, for 2005 only Tsunami-related donations are observed in COPPS; thus the expenditure-substitution effect on other 2005 giving cannot be measured. If 2005 tsunami giving "crowded out" other giving in 2005, households might compensate for this by increasing 2006 giving to the causes they neglected in 2005.

The results in table 20 suggest this did not occur. In this table I present the results of fixed-effect regressions of giving (to various categories) on the standard set of controls and controls for "giving to the tsunami in the previous year," which is naturally set to zero for all years except 2006. These estimates have the advantage that the Furthermore, the news coverage of the tsunami that influence people to donating to this cause may have impacted their preferences and world view in other ways that could have influenced their future philanthropy. As the Tsunami was an unusually deadly and dramatically reported event, we do not know if future disasters will have the same affects on people's motivations. Finally, this measure will be influenced by the "supply response" of charitable organizations that may have increased the strength of their appeals to prevent their fundraising from being overshadowed by the tsunami.[66] Still, the strength of the observed effect suggest that the tsunami did not have a serious detrimental effect on contributions to other causes in the following year.

[66]There is evidence that some charities did respond in this way. "Tsunami aid 'threat' to charities," BBC News, Saturday, 15 January, 2005, 10:31 GMT. <http://news.bbc.co.uk/1/hi/wales/4172203.stm>

Table 20: **Fixed effects regressions: Responses to Tsunami Giving in prior year**

	(1) Total	(2) Relig	(3) Nonrelig	(4) Combo	(5) Needy	(6) Health	(7) Educ	(8) Other
Tsunami gvg	1.06**	.845**	.446*	.124	.0303	.0369	-.0398	.0344
	(.237)	(.161)	(.186)	(.082)	(.0837)	(.0499)	(.0876)	(.0789)
Net income	.0037**	8.8e-04**	.0032**	5.5e-04**	2.9e-04*	2.8e-04**	.0018**	-1.5e-05
	(3.7e-04)	(2.5e-04)	(2.9e-04)	(1.3e-04)	(1.3e-04)	(7.8e-05)	(1.4e-04)	(1.2e-04)
Price	-854**	-568**	-230+	-71.2	-91.7	-74.4*	-14	10.7
	(176)	(120)	(139)	(61.3)	(62.4)	(37.2)	(65.1)	(58.7)
Wealth w.o. house	-2.0e-04	-5.1e-05	-3.9e-04*	3.3e-04**	-1.3e-04+	-6.5e-06	-2.3e-04**	-1.0e-04
	(2.1e-04)	(1.4e-04)	(1.7e-04)	(7.4e-05)	(7.5e-05)	(4.5e-05)	(7.9e-05)	(7.1e-05)
Wealth w. house	1.6e-04	8.4e-05	3.1e-04+	-2.6e-04**	1.2e-04+	-2.5e-05	1.0e-04	1.3e-04+
	(2.1e-04)	(1.4e-04)	(1.7e-04)	(7.4e-05)	(7.5e-05)	(4.5e-05)	(7.9e-05)	(7.0e-05)
Year 2002	91.2**	85.2**	41.5	-12.5	7.11	3.56	11.5	3.43
	(34.2)	(23.3)	(27)	(11.9)	(12.1)	(7.21)	(12.6)	(11.4)
Year 2004	236**	118**	169**	7.55	36.5**	10.1	31.4*	34.5**
	(35.1)	(23.9)	(27.7)	(12.2)	(12.4)	(7.4)	(13)	(11.7)
Year 2006	211**	105**	191**	-1.75	35.1**	11.1	26+	37.5**
	(36.1)	(24.6)	(28.5)	(12.5)	(12.8)	(7.63)	(13.4)	(12)
Constant	1793**	1245**	466**	185**	173**	109**	-16.5	64.4
	(164)	(111)	(129)	(56.9)	(58)	(34.6)	(60.5)	(54.5)
Observations	11404	11255	11255	11301	11278	11339	11366	11390

Standard errors in parentheses

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

Pooled data (2000-2006), 1968 cross-scn sample (SRC), unweighted.

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

7.3 Further results mentioned in text

- "Standard ols regressions on the de-meaned variables (available by request) also lead to similar results"
  - Link to file: "olsdemeaned_online.txt"
- "As shown in table 5, most households donate to more than one category of charity, and many donate to several categories (especially among large givers; details in the online appendix.)"
  - Link to "largegiversnumbercats.txt"
- "This is not surprising, as the predicted values of the charitable gifts are highly correlated across specifications; e.g., the correlation between the predictions for religious giving using zero-inflated Poisson and OLS specifications is above 0.9 (see online appendix)."
  - Link to "similarcrosssecnests.txt"
- "However, none of the key results are sensitive to the the inclusion of wealth in the regression analysis..."
  - Link to "nowealthresults.txt"