

Separability and Substitutability of Charitable Contributions in Individual Utility Functions

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John D. Straub
Department of Economics
Texas A&M University
4228 TAMU
College Station, TX 77843-4228
(979) 845-6929
JDStraub@tamu.edu

Abstract

This paper addresses two questions related to individual preferences for charitable giving and volunteering. The first question is whether individual preferences are consistent with a utility specification that is separable in monetary donations. If utility is weakly separable in monetary donations, collective models of household utility could be readily applied in future work related to household contributions. The second question is whether monetary donations and volunteer labor supply are complements or substitutes. Complementarity enhances the efficiency of the tax code's charitable deduction; substitutability undermines it.

I estimate the parameters of a quadratic utility function. Quadratic utility functions are additively separable under very straightforward parameter restrictions. The moment conditions that define my estimator follow from a theoretical model in which the marginal utility of giving time and/or money depends on labor supply and other observable and unobservable factors. Only preliminary estimates based on a restricted version of the model are available at this time. The preliminary estimates do not permit definitive tests of separability and substitutability, but they do permit illustrative elasticity calculations and policy simulations.

1. Introduction

The goal of this project is to provide empirical evidence on 2 questions related to individual preferences for charitable giving:

(Q1) Assuming individuals derive private utility from their own monetary donations to charity, can their preferences be represented by a utility function that is weakly separable in those donations?

(Q2) Assuming individuals also derive private utility from volunteering their time to charitable organizations, does their volunteer labor complement or substitute for their monetary donations?

My interest in these two somewhat narrowly defined questions about *individual* utility functions is motivated by an interest in more general models of *household* utility. Specifically, I am interested in the applicability of the collective household utility model (Chiappori, 1988 and 1992) to empirical studies of charitable giving and volunteerism. Household utility in the collective framework is built explicitly from the utility functions of individual members (the husband and wife in a married couple, for example). This is significantly more general than assuming a single household utility function for multiple-adult households. Assuming only that household bargaining results in Pareto efficient allocations, Chiappori (1988) shows that the collective model provides testable restrictions on behavior. Subsequent refinements of the collective approach have been very successful at reconciling longstanding disparities between consumer theory and empirical evidence on household labor supply (Browning and Chiappori, 1997; Fortin and Lacroix, 1997). It would be interesting to know if a similar framework could be applied to studies of volunteer labor supply and charitable giving.

Applying the collective model to a study of charitable giving and volunteering poses a number of interesting challenges. One important complication arises from the fact that at least some portion of charitable giving is probably a public good within the household. Chiappori, Blundell, and Meghir (2004) provide identification results for the collective model when public goods are present within the household. Their most important identifying assumption imposes strong restrictions on the complementarity/substitutability between the public good and all other goods. The assumption is that individual utility functions are weakly separable in the public good. When combined with the usual assumption of diminishing marginal utility, for example, weak separability precludes the possibility that separable goods are Hicksian complements

(Silberberg, 1972). In the context of charitable giving and volunteering, this kind of restriction would amount to answering (Q2) by assumption – the assumption that contributions of time and money are substitutes. Unfortunately, previous estimates do not provide a definitive basis for such an assumption. Indeed many previous studies have reached the opposite conclusion, that charitable contributions of time and money are complements.¹

This paper can be seen as an initial test of whether Chiappori, Blundell, and Meghir's approach can be applied to an empirical study of charitable giving and volunteering. My strategy is to assume a very convenient functional form (quadratic utility), and to test for separability (Q1) and substitutability (Q2), using a sample of working single adults. The restricted sample and the functional form assumptions both preclude the use of estimates for inference to the general population. The goal of this paper is not to make inference to the general population. The goal is to see if separability can be rejected for working single individuals. If separability cannot be rejected for working singles, researchers might feel more comfortable assuming separability for individual preferences within multi-adult households in a collective utility framework.

While I make no attempt in this paper to draw inference to the general population, such inference is the ultimate goal of the larger research agenda in which this paper is only a first step. Policy makers care about the answer to (Q2) as it applies to the general population. By allowing households to deduct certain charitable contributions from their taxable income, the federal government and some state governments effectively subsidize the output of recipient organizations. The efficiency of this subsidy depends on the price and income elasticities of giving, which have been the subject of considerable economic research. If charitable contributions of time and money are complements, then tax deductibility of monetary donations should lead to an increase in both types of giving, and traditional elasticity estimates that ignore volunteer labor supply will understate the efficiency of the government's implicit subsidy. If charitable contributions of time and money are substitutes, then tax deductibility increases monetary contributions at the expense of volunteer labor supply, and traditional elasticity estimates will overstate the efficiency of the implicit government subsidy. I do present illustrative elasticity estimates in this paper, but I do not assume these estimates apply to the general population. The elasticities reported in this paper simply summarize the estimates for this particular sample of working singles, and illustrate how similar elasticities could be calculated in future work using more generally representative samples.

¹ Examples include Menchik and Weisbrod (1987), Brown and Lankford (1992), Dye (1980), and Clotfelter (1985).

Questions Q1 and Q2 are both motivated by a presumption that an individual's charitable contributions of time and money are the result of two closely related decisions. These 2 forms of charitable giving are more appropriately studied in conjunction than in isolation. By the same token, decisions about both types of charitable giving may be influenced by other choices. A particularly important choice that I consider is the labor supply choice. The data I study were collected in the first wave of The Center on Philanthropy's Panel Study (COPPS). These data provide information on both types of giving as well as detailed labor supply data, and are described in Section 3 of the paper.

The theoretical model outlined in the next section provides a framework for thinking about how labor supply is related to charitable giving and volunteering. Implications of this theoretical model are used in Section 4 to define moment conditions for the empirical model. Section 5, when completed, will present estimates of the empirical model, test hypotheses related to Q1 and Q2, and describe the results of policy simulations. Estimates based on a restricted version of the model are reported in this preliminary draft. The restricted model does not identify all the parameters necessary to test separability and complementarity. The restricted model does permit illustrative elasticity estimates and policy simulations, however. Section 6 draws preliminary conclusions and discusses the work that lies ahead.

2. Theoretical Framework

Let h denote the number of hours devoted to market work in a year, let d denote dollars donated to charity in a year, and let v denote the number of hours spent volunteering in a year. I model the determination of h , d , and v as a 2-stage recursive system in which labor supply is determined in the first stage, without any explicit consideration of charitable behavior. Given the first-stage realization of h , individuals then decide how much of their remaining time to spend volunteering, and how much of their money to donate to charity. This 2-step process restricts the interaction between labor supply and charitable giving to a one-way street in which h influences the choice of (d, v) , but not the other way around.

The restrictions implied by the recursive system are strong. The model assumes that individuals do not backward induct, and anticipate the optimal values of d and v when choosing h in the first stage. The presumption is that labor supply decisions are much more important to most people than decisions about charitable giving and volunteering. Descriptive statistics discussed in Section 3 are consistent with this presumption (see the discussion of Table 4). Moreover, individuals may have less than complete discretion over hours of work due to exogenous labor demand factors, and contractual restrictions on the number of hours they work.

Many individuals commit to a certain value of h when they choose a career, or match with a particular employer. The model assumes that these labor market commitments are predetermined when the individual chooses d and v . The assumption of a recursive system, like all modeling assumptions, represents an abstraction from reality. The advantage of the assumption is that it permits a very simple and tractable link between the first stage choice of h , and the second stage choice of d and v .

Formally, let an individual's first-stage problem be to maximize the twice differentiable quasi-concave utility function $u_1(e, f)$, where e is the total amount of money available for expenditure in the second stage, and f is the amount of free time available for leisure or volunteering in the second stage. Let $e = \tau(y + wh)$, where y is non-labor income, w is the hourly wage, and $\tau = (1-t)$, where t is the effective marginal income tax rate. The amount of free time available in the second stage is $T-h$, where T is the total number of discretionary hours in a year. Because individuals do not backward induct, or anticipate the optimal choice of d and v , the optimal choice of h in this framework will be a function of the exogenous variables y , t and w . The empirical specification described in Section 4 also conditions on observable demographics, allows for a stochastic component, and allows for endogenous wages and non-labor income that are correlated with the stochastic component.

Given the first-stage realization of h , an individual's second-stage problem is to maximize the twice differentiable quasi-concave utility function $u_2(d, v, c, \ell)$, where d is monetary donations to charity, v is volunteer hours, $\ell = T-h-v$ is leisure, and $c = \tau(y + wh) - pd$ is the amount of money spent on private consumption. The price of monetary donations (p) is one minus the marginal tax rate for people who itemize deductions, and 1 for those who do not. Substituting the definitions of c and ℓ into the utility function defines an unconstrained maximization problem in 2 variables, d and v . The marginal utilities of d and v will be functions of the exogenous variables y , t , and w , as well as the first-stage realization of h . In the empirical model, the marginal utilities also vary according to observable demographic traits and unobservable preference heterogeneity. Unobservable tastes for charitable giving (in the second stage) may be correlated with the stochastic component of the first-stage labor supply problem. The empirical model also addresses the fact that d and v are constrained to be non-negative, and the non-negativity constraints bind for a large portion of the sample.

3. Data and Descriptive Statistics

I use data from the first wave of The Center on Philanthropy's Panel Study (COPPS), which collects data on charitable giving and volunteering as a module added to the University of Michigan's Panel Study of Income Dynamics (Center on Philanthropy, 2001). The first wave of COPPS was fielded with the PSID in 2001, and elicited responses to questions about charitable giving in the previous year.²

Of the 4970 family units responding to the 2001 PSID, 4343 (87%) provided complete information on monetary donations (d), volunteer hours (v), labor supply (h), wages (w), and educational attainment. The analysis focuses on a sub-sample of 885 single men and women who reported working positive hours in 2000.³ Before describing the sub-sample in more detail, I discuss the rationales for dropping couples and non-working individuals from the sample.⁴

To understand the focus on single individuals, recall that questions Q1 and Q2 relate to individual utility functions. Q1, for example, asks if individual utility functions are weakly separable in monetary donations to charity. Monetary donations, however, are only observed at the household level. Hypotheses related to Q1 cannot be tested using data from couples since d is not observed for the individual members in a couple. Estimation based on a sample of single individuals allows me to test Q1 for single individuals. Without additional assumptions, it does not permit inference to married individuals or couples, but the goal of my test is to first see whether such additional assumptions are even worth entertaining. If separability is rejected for single individuals, the case for assuming separable utility for the members of a married couple would be considerably weaker. Restricting the sample to households that were headed by a single adult in 2000 eliminates 2705 couples from the sample, leaving 1638 single individuals.

I also dropped 395 single individuals who reported $h=0$, because I will abstract from censoring of h in the empirical model.⁵ Including individuals who report $h=0$ would introduce 2 significant complications. The first complication is that market wages are not observed for individuals who don't work. The market wage obviously plays a central role in the first-stage determination of labor supply, but it also enters the model's second stage choice of d and v . Intuitively, after-tax wages measure an individual's opportunity cost of time, and therefore determine the price of donating time relative to money. A second complication arises because the

² The PSID is a longitudinal survey that has surveyed members of the sampled "family units" and their descendants each year since 1968. The primary sample (the SRC sample) was designed to be nationally representative in 1968, although additional samples were also added to over-sample racial minorities and low-income households. I restrict attention to the SRC sample to avoid complications . . .

³ I also drop individuals who report income from other family members or who live with working-age children. This is to exclude households that make joint labor supply decisions.

⁴ Provide details on the definition of a couple here.

⁵ The empirical model does, however, explicitly account for censoring of d and v (see Section 4).

marginal utilities of donating time and money depend on the first-stage realization of h in my model. To capture this dependence, my empirical model conditions on residuals from first-stage labor supply regressions. My interpretation of the first-stage residuals relies on the assumption that they represent random disturbances around an interior solution to the first-stage labor supply problem.

Restricting the sample to working individuals reduces the usable sample by 24% (from 1638 to 1243) and raises concerns of sample selection bias. A definitive comparison of charitable giving between working and non-working individuals is beyond the scope of this paper, but Table 1 suggests that excluding non-workers does not significantly affect the binary probabilities of donating money or volunteering time.

Two final restrictions of the sample removed 310 individuals who report income from other family members and 21 individuals who live with working age children. These restrictions ensure that the sample excludes all households that make a joint labor supply decision. The remainder of this paper focuses on the sample of 885 working singles. Summary statistics for the 2705 married couples are provided in the appendix for comparison.

Table 2 shows cross tabulations for binary indicators of donating money and volunteering. Tables 2a and 2b show similar patterns of giving for single men and women. About 40% of the respondents in both groups report no monetary donations or volunteer hours. Of the individuals that do give, most specialize in monetary donations – about a third of the single men and women report positive monetary donations, but zero volunteer hours. Only 4-6% of the respondents in either group report the opposite pattern of specialization (positive volunteer hours without any monetary donations). About 20% of the respondents in both groups report making both types of contribution.

Comparing the patterns of giving for single individuals with those of their married counterparts helps motivate the usefulness of a structural estimation strategy. A comparison of Table 2 with appendix Table A1 shows that married individuals are slightly more likely to report volunteering than their single counterparts, and much more likely to report donating money.⁶ The different patterns of giving are certainly driven by a combination of observable and unobservable factors. Observable factors include family income and the effective price of giving. From Tables 3 and A2, we see that married couples tend to have higher incomes and lower effective prices of

⁶ Twenty-eight percent of the married men report volunteering, compared to only 23% of the single men. Thirty-three percent of the married women report volunteering, compared to only 27% of the single women. Three-quarters of all married households report $d > 0$, while just slightly more than half of the single men and women report the same.

giving.⁷ It could be that higher total family income, combined with economies of scale from living together are more than enough to offset larger family sizes. With higher effective income, and lower effective prices of giving, couples would be able to afford more of all normal goods including charitable contributions. On the other hand, it could simply be the case that married people tend to be more charitable due to unobservable factors. Empirical models in which the stochastic components carry a structural interpretation provide a basis for understanding the relative importance of observable and unobservable factors.

Table 4 presents some additional summary statistics that help develop intuition for the theoretical and empirical modeling framework. The first 3 rows summarize the reported uses of time in the sample of 885 working single adults. Recall that individuals divide their time endowment (T) between three activities, working for pay (h), volunteering (v), and leisure (ℓ). The maximum value of $(h+v)$ observed in the sample is 4774 ($h=4774$, $v=0$). Assuming $\ell = T-h-v = 0$ for this individual, I set $T=4774$ for everyone in the sample. Most individuals spend only a small fraction of their time volunteering, if they volunteer at all. The average value of v is only 28 hours per year, compared to 1918 hours working for pay, and 2829 hours at leisure.⁸ The next 3 rows of Table 4 characterize individual endowments in monetary terms. About 70% of the sample reports at least some non-labor income, with an average after-tax value of \$4940.⁹ Far more important for most individuals is the value of their time, which can be used to generate labor income. The average after-tax value of 4774 hours is \$53,251, implying an average after-tax wage of \$11.15. Of course most individuals choose to work far fewer than $T = 4774$ hours in a year, so average disposable earned income is only \$20,908. When combined with non-labor income, this permits a total expenditure of $\$4,940 + \$20,908 = \$25,848$. On average, only a very small fraction of this amount is spent on monetary donations to charity (\$414). The rest is spent on private consumption. Decomposing the value of time spent on non-market activities results in a similar breakdown. The average value of time spent at leisure is \$31,993; the average value of time spent volunteering is just \$350.

⁷ The lower price of giving for couples is related to the higher family income for couples since higher family income implies higher marginal tax rates for households that itemize deductions. With larger family sizes and higher incomes, couples are also more likely to own their own home and itemize deductions. Note that some of the variation in marginal tax rates is exogenous, however, due to exogenous variation in state income tax rates.

⁸ 75% of the sample reports no volunteer hours at all. 97% report 200 or fewer volunteer hours per year.

⁹ *{Describe my definition of non-labor income.}* Non-labor income is negative for six individuals according to this definition, and zero for 491 individuals.

The relatively small expenditures on d and v motivate the 2-stage modeling strategy outlined in Section 2. It seems clear that both types of charitable giving should depend on labor supply and labor income. But the choices of d and v are relatively low-stakes choices for most people compared to the labor supply decision. When making decisions about labor supply, individuals are effectively allocating tens-of-thousands of dollars. People are free in principle to spend sizable shares of their endowments on d and v , but actual expenditures are very small for most people in practice. Average expenditures on d and v are less than 2% of the average endowment. In fact 83% of the sample spends less than 2% of their full endowment on d and v , and 98% of the sample spends less than 10% (recall from Table 2 that 40% of the sample spends nothing at all on d or v).¹⁰

4. Empirical Model

The primary focus of this paper is on the choice of monetary donations (d) and volunteer hours (v). Following the model of Section 2, I assume that d and v are chosen in the second stage of a 2-stage process. Hours of work (h) are determined in the first stage. The second stage choice of d and v is made conditional on the first stage realization of h . Empirical implementation of the model focuses on 3 concerns: simultaneity of the dependent variables, censoring of d and v at zero, and the endogeneity of important explanatory variables – nonlabor income and the wage.

In the second stage of my model, individuals choose d and v to maximize the utility function $u_2[d, v, c, \ell]$, subject to budget and time constraints, taking the first-stage realization of h as given. This section defines a random utility specification of $u_2[\cdot]$. I estimate the parameters of the stochastic model using a Generalized Method of Moments (GMM) approach.¹¹ The orthogonality conditions that define the GMM estimator are based on implications of the theoretical model. The estimation strategy follows Wales and Woodland's (1983) "Kuhn-Tucker approach" very closely. Wales and Woodland's approach has been applied by Ransom (1987a)

¹⁰ Two observations were dropped from the sample because their reported monetary donations to charity exceeded their total disposable income, as calculated for Table 4. This is of course possible for people who finance monetary donations out of savings or debt, but such behavior cannot be modeled in a static framework. Aside from these 2 observations, no individual's monetary donations to charity exceeded 40% of their full endowment, as calculated for Table 4.

¹¹ Let θ denote the vector of all parameters to be estimated. A GMM estimate, $\hat{\theta}$, minimizes a quadratic form $J_N = m(\hat{\theta})' \mathbf{W} m(\hat{\theta})$, where $m(\hat{\theta})$ is a vector of orthogonality conditions, and \mathbf{W} is a weighting matrix. The orthogonality conditions are defined such that $E[m(\hat{\theta})] = 0$. The weighting matrix could be any positive-definite matrix. The optimal choice of \mathbf{W} is the inverse of the asymptotic covariance matrix for $m(\hat{\theta})$ (Hansen, 1982). The asymptotic covariance of $\hat{\theta}$ is \mathbf{V}/N , where $\mathbf{V} = [\mathbf{M}' \mathbf{W} \mathbf{M}]^{-1}$, and $\mathbf{M} = \partial m(\hat{\theta}) / \partial \theta$.

to estimate the joint labor supply of married couples. My GMM estimator relies on similar, but slightly less restrictive distributional assumptions than Wales and Woodland's maximum likelihood estimator. A more important advantage of GMM over maximum likelihood is the straightforward manner in which instrumental variable techniques can be applied to nonlinear GMM estimators. This is useful in my application since the price of charitable giving is likely to be correlated with unobservable tastes for charitable giving.

My empirical model of the first-stage labor supply decision relies on a standard semi-log specification, which I estimate by two-stage least squares. I allow for the possibility that stochastic components in the model of charitable giving ($\varepsilon_d, \varepsilon_v$) may be correlated with the labor supply model's stochastic component (ε_h).

4.1 The Random Utility Specification

I specify a quadratic functional form for $u_2(\cdot)$:

$$u_2(d, v, c, P) = \alpha Q - (1/2)Q' \beta Q,$$

where α is a 4x1 vector of parameters, Q is a 4x1 vector of arguments from the utility function, and β is a symmetric, positive-definite 4x4 matrix of parameters. Positive-definiteness of β ensures that the utility surface is globally concave. Quadratic utility functions can be interpreted as a second-order approximation to an arbitrary quasi-concave utility function. Quadratic utility also implies very straightforward tests of additive separability. With 4 arguments in $u_2[\cdot]$, there are 6 unique pairs of arguments. A given pair of arguments is additively separable in $u_2[\cdot]$ if the corresponding off-diagonal element of β is zero. For example, d and v are additively separable if $\beta_{12}=0$. Monetary donations are separable from all 3 other arguments if $\beta_{12}=\beta_{13}=\beta_{14}=0$. Additive separability implies weak separability, so the inability to reject additive separability is also an inability to reject weak separability. Rejecting additive separability does not rule out the possibility of weak separability, however (Blackorby et al, 1978).

The time and budget constraints imply that $c = \tau(y + wh) - pd$, and $P = T - h - v$. Taking h as predetermined, we have the following partial derivatives of c and P with respect to d and v : $\partial c/\partial d = -p$, $\partial c/\partial v = 0$, $\partial P/\partial d = 0$, $\partial P/\partial v = -1$. Using the constraints to substitute for c and P , we can define an unconstrained utility maximization problem in 2 variables (d and v). The marginal utilities with respect to d and v are:

$$\partial u_2/\partial d = \alpha_1 - \alpha_3 p - \beta_{11} d + \beta_{33} c p - \beta_{12} v - \beta_{13} (c - p d) - \beta_{14} P + \beta_{23} v p + \beta_{34} P p$$

$$\partial u_2 / \partial v = (\alpha_2 - \alpha_4) - \beta_{22}v + \beta_{44}P + (\beta_{14} - \beta_{12})d - \beta_{24}(P-v) + (\beta_{34} - \beta_{23})c$$

Quadratic utility is convenient for the estimation of demand systems with binding non-negativity constraints since the marginal utility functions are linear in parameters. (See Wales and Woodland, 1983; Ransom 1987a; Ransom 1987b; and Andrioni, Gale, Scholz, and Straub, 2004.) A particularly convenient feature is that a random utility interpretation can be readily applied to additive error terms appended to the marginal utility equations. Specifically, the constant terms α_1 and $(\alpha_2 - \alpha_4)$ can be modeled as linear functions of observable and unobservable characteristics that shift the marginal utility of d and v . For example, $\alpha_1 = s_d \alpha_d + \varepsilon_d$ where s_d is a row-vector of observable characteristics, α_d is a column vector of parameters, and ε_d is a stochastic term representing unobservable preference heterogeneity. An analogous assumption about the marginal utility of volunteering implies $(\alpha_2 - \alpha_4) = s_v \alpha_v + \varepsilon_v$.

If all the observable factors in the marginal utility equations were exogenous, one might assume, for example, that ε_d and ε_v were drawn from a bivariate normal distribution. Recall, however, that c and P are both defined by the time and budget constraints in terms of h . It seems unlikely that ε_d and ε_v would be orthogonal to h . Recall in particular that ε_h – the stochastic component of h – reflects unobservable preferences (work ethic) and demand-side factors from the labor market. It seems especially plausible that unobservable factors affecting the marginal utility of volunteering (ε_v) would be correlated with ε_h . To allow for this possibility, I base my estimation on assumptions about the conditional distribution $(\varepsilon_d, \varepsilon_v | \varepsilon_h)$. Specifically, I assume that $\varepsilon_h, \varepsilon_d$, and ε_v are drawn from a mean-zero trivariate normal distribution with the parameters $\sigma_d, \sigma_v, \sigma_h, \rho_{dh}, \rho_{vh}$, and ρ_{dv} . This implies that $(\varepsilon_d, \varepsilon_v | \varepsilon_h) \sim \text{BVN}(\mu_d, \mu_v, \sigma_{d|h}^2, \sigma_{v|h}^2, \rho_{dv|h})$, with $\mu_d = \rho_{dh}\sigma_d(\varepsilon_h/\sigma_h)$ and $\mu_v = \rho_{vh}\sigma_v(\varepsilon_h/\sigma_h)$. The root-mean squared error of the first-stage labor supply regression provides an estimate of σ_h . Residuals from that regression provide an estimate of ε_{hi} for each observation in the sample. Second stage estimates can condition on the estimates of $(\varepsilon_{hi}/\sigma_h)$ by adding them to the lists of “observable” covariates that shift the marginal utility of d and v . In other words, an individual’s residual from the first-stage labor supply regression is one component of that individual’s s_d vector, and also a component of the individual’s s_v vector. The coefficients on these additional covariates provide estimates of $\mu_d = \rho_{dh}\sigma_d$ and $\mu_v = \rho_{vh}\sigma_v$. Testing the joint significance of these estimates is equivalent to testing the hypotheses that ε_d and ε_v are uncorrelated with ε_h .

The random utility specification is summarized as follows:

$$(1) \quad \begin{aligned} \partial u_2 / \partial d &= s_d \alpha_d - \alpha_3 p - \beta_{11} d + \beta_{33} c p - \beta_{12} v - \beta_{13} (c - p d) - \beta_{14} P + \beta_{23} v p + \beta_{34} P p + \varepsilon_d \\ \partial u_2 / \partial v &= s_v \alpha_v - \beta_{22} v + \beta_{44} P + (\beta_{14} - \beta_{12}) d - \beta_{24} (P - v) + (\beta_{34} - \beta_{23}) c + \varepsilon_v, \text{ with} \end{aligned}$$

$$(\varepsilon_d, \varepsilon_v \mid \varepsilon_h) \sim \text{BVN}(0, 0, \sigma_{d|h}^2, \sigma_{v|h}^2, \rho_{dv|h}).$$

I assume that s_d and s_v each contain the following 5 elements: a constant, age, years of education, a dummy variable that equals 1 if the individual is female, and an estimate of $\varepsilon_{hi}/\sigma_h$.

4.2 Identification

The marginal utility equations (1) define a pair of simultaneous equations in d and v . Identification requires exclusion restrictions or other *a priori* restrictions on the system. Nonlinearities implied by the censoring of d and v provide some identifying power, but identification based only on such nonlinearities would be sensitive to distributional assumptions. Fortunately, a number of additional restrictions follow naturally from the theoretical model. This sub-section discusses these restrictions, as well as other restrictions that are motivated more by convenience or necessity.

The 4 arguments in $u_2(\cdot)$ are $Q = [d, v, c, \ell]'$. With 4 arguments there are 6 unique pairs of arguments, and each pair may or may not be additively separable in $u_2(\cdot)$. I will test additive separability for 3 of the 6 pairs [(d, v), (d, c), and (c, ℓ)], but I will maintain the assumption of additive separability for the other 3 [(v, ℓ), (d, ℓ), and (v, c)]. The maintained separability assumptions imply that 3 of the off-diagonal elements of β are zero (β_{24} , β_{14} , and β_{23}). Note first of all that β_{24} is not identified separately from β_{22} and β_{44} (see equation (1)). If $\beta_{24}=0$, then $u_2(\cdot)$ is additively separable in v and ℓ . Since β_{24} cannot be estimated without observable variation in the “prices” of v and ℓ , I maintain the assumption that $\beta_{24}=0$.¹² Though not technically necessary for identification, I also impose the restrictions $\beta_{14}=\beta_{23}=0$. The assumption that $\beta_{14}=0$ implies that d and ℓ are additively separable in $u_2(\cdot)$; the assumption that $\beta_{23}=0$ implies additive separability between v and c . Restricting β_{14} and β_{23} facilitates estimation and interpretation by reducing the number of free parameters in the model. These restrictions could be relaxed and/or tested, but I maintain them throughout this version of the paper. This allows me to focus attention on other pairs of goods where the possibility of non-zero cross-price effects is more likely and more interesting.

¹² Andreoni, Gale, Scholz, and Straub (2004) define an independent price for v using the responses to a question about the value of volunteer time to the recipient organizations. An analogous question was not asked in the COPPS survey.

Next, note in (1) that the marginal utility of volunteering is not directly affected by the price of monetary donations (p). The “price” of volunteering for an hour in this model is simply an hour of forgone leisure. As more time is volunteered, this price of volunteering rises due to concavity of the utility function. The absence of p in the second equation of (1) is a classic exclusion restriction that follows naturally from the fundamental structure of the problem. This exclusion restriction is sufficient to identify the first equation of (1). The second equation is identified by additional restrictions that also follow from the model, namely the cross-equation restrictions requiring β_{12} and β_{34} to have the same value in both equations.

Under the restrictions, (1) reduces to:

$$(1') \quad \begin{aligned} \partial u_2 / \partial d &= s_d \alpha_d - \alpha_3 p - \beta_{11} d + \beta_{33} c p - \beta_{12} v - \beta_{13} (c - p d) + \beta_{34} P p + \varepsilon_d \\ \partial u_2 / \partial v &= s_v \alpha_v - \beta_{22} v + \beta_{44} P - \beta_{12} d + \beta_{34} c + \varepsilon_v, \text{ with} \end{aligned}$$

$$(\varepsilon_{di}, \varepsilon_{vi} \mid \varepsilon_h) \sim \text{BVN}(0, 0, \sigma_{d|h}^2, \sigma_{v|h}^2, \rho_{dv|h}).$$

Note that c and ℓ do not appear in the first equation, except when interacted with the price of giving. This also helps identify the system.

4.3 Internal Consistency and Identification of Deep Parameters

The pair of simultaneous equations in (1') can be solved for the (potentially latent) optimal values of d and v :

$$(2) \quad \begin{aligned} d^* &= \gamma_d + \eta_d v \\ v^* &= \gamma_v + \eta_v d, \text{ with} \\ d &= d^* \text{ if } d^* > 0. \quad d = 0 \text{ if } d^* \leq 0, \text{ and} \\ v &= v^* \text{ if } v^* > 0. \quad v = 0 \text{ if } v^* \leq 0. \end{aligned} \quad ^{13}$$

¹³ Let c^0 and ℓ^0 be the amounts of private consumption and leisure when $d=v=0$. In other words, let $c^0 = \tau(y + wh) = c + pd$, and let $\ell^0 = T - h = \ell + v$. Then:
 $\gamma_d = (s_d \alpha_d - \alpha_3 p + \beta_{33} c^0 p - \beta_{13} c^0 + \beta_{34} P^0 p + \varepsilon_d) / (\beta_{11} - \beta_{13} 2p + \beta_{33} p^2)$, $\eta_d = (\beta_{12} + \beta_{34} p) / (\beta_{11} - \beta_{13} 2p + \beta_{33} p^2)$,
 $\gamma_v = (s_v \alpha_v + \beta_{44} P^0 + \beta_{34} c^0 + \varepsilon_v) / (\beta_{22} + \beta_{44} + 2\beta_{24})$, and $\eta_v = (\beta_{12} + \beta_{34} p) / (\beta_{44} + 2\beta_{24})$.

Maddala (1983, pg. 214) shows that this kind of system is only consistent if $\eta_d\eta_v < 1$. Ransom (1987b) shows that with quadratic utility, the economic interpretation of this condition amounts to diminishing marginal utility, and that the condition will be satisfied when β is positive definite.

Equations (2) also clarify the difference between my structural estimation strategy, which identifies elements of α and β , and a reduced form bivariate Tobit estimator. A standard reduced form bivariate Tobit assumes that d^* and v^* are determined by 2 index functions of the form:

$$(3) \quad \begin{aligned} d^* &= x_d b_d + u_d \\ v^* &= x_v b_v + u_v, \text{ where} \end{aligned}$$

b_d and b_v are parameter vectors and u_d and u_v are stochastic terms drawn from a mean-zero bivariate normal distribution. As in (2), d^* and v^* are left-censored at 0. Some econometrics software like LIMDEP provide bivariate Tobit routines that estimate the parameter vectors b_d and b_v . Equations (2) show the relationship between the coefficients in (3) (the vectors b_d and b_v) and the model's deep parameters α and β . Each element of b_v is a non-linear function of certain elements of α and β . Similar relationships hold for the elements of b_d , but in this case the elements of b_d are nonlinear functions of parameters and the price variable, p . For example, from equation (2) we see that each element of s_d is also an element of x_d (see the footnote attached to equations (2)). The coefficient for each element of s_d in equation (3) is an element of α_d divided by $(\beta_{11} - \beta_{13}2p + \beta_{33}p^2)$. In other words, if the true model is (1'), then the elements of b_d are not deep parameters; they are coefficients that vary with the price variable. Inference based on estimates of b_d could be misleading when the counterfactual situations of interest involve a change in the effective price. The underlying model implies that b_d should change when the price changes, but (3) treats b_d as a vector of constant parameters.

The bivariate Tobit estimator is also suffers from endogeneity bias and heteroskedasticity if (1') is the true model. From equation (2) we see that $u_d = \varepsilon_d / (\beta_{11} - \beta_{13}2p + \beta_{33}p^2)$. In this case u_d is clearly a function of the price variable.

4.4 Empirical Moment Conditions

My GMM estimator is defined by 5 moment conditions of the form $E[e_j] = 0$, $j = 1..5$, where the e_j are functions of the model's variables and parameters. Interacting the 5 moment conditions with K instruments results in $5K$ orthogonality conditions, and permits identification of $5K$ parameters. All 5 of the moment conditions are derived by combining (1') with the assumption of utility maximization. Wales and Woodland (1983) and Ransom (1987a) estimate

very similar models by maximum likelihood. Estimation by GMM allows me to relax some of the distributional assumptions. More importantly, it facilitates the application of nonlinear instrumental variable techniques.

The following binary indicators are useful when defining the moment conditions:

$b_{00} = 1$ if $d=0$ and $v=0$. $b_{00} = 0$ otherwise.

$b_{10} = 1$ if $d=1$ and $v=0$. $b_{10} = 0$ otherwise.

$b_{01} = 1$ if $d=0$ and $v=1$. $b_{01} = 0$ otherwise.

$b_{11} = 1$ if $d=1$ and $v=1$. $b_{11} = 0$ otherwise.

The first three moment conditions are related to the bivariate discrete choice of whether or not to donate money, and whether or not to volunteer. The probability that $b_{00}=1$ is the probability that ε_d and ε_v each fail to exceed some threshold.¹⁴ For each individual i define the following model error:

$$e_{1i} = b_{00i} - \Phi[r_{di}, r_{vi}], \text{ where}$$

$\Phi[\cdot]$ is the mean-zero bivariate normal CDF with parameters $\sigma_{d|h}$, $\sigma_{v|h}$, and $\rho_{d|h}$. The variance and correlation parameters are constant across individuals in the sample, but the thresholds r_d and r_v are functions of α , β , and the observable characteristics of each individual (see the previous footnote). The law of large numbers implies that the proportion of the sample observed in state b_{00} should approach $(1/n)\sum_i \Phi[r_{di}, r_{vi}]$ as the sample size grows to infinity. In other words, $E[e_1] = 0$. This is the model's first moment condition. I also define two analogous moment conditions involving the indicators b_{10} , and b_{01} .¹⁵

The next 2 moment conditions are based on the continuous choices of how much to donate when $d>0$ and how many hours to volunteer when $v>0$. As with all moment conditions, we are looking to define functions of the data, e_4 and e_5 , such that $E[e_4] = 0$, and $E[e_5] = 0$. As with the first three moment conditions, I start with the implications of utility maximization:

$$\partial u_2 / \partial d = 0 \text{ when } d>0 \text{ and } \partial u_2 / \partial v = 0 \text{ when } v>0.$$

¹⁴ Given (1'), the probability that $b_{00}=1$ is:

$\text{Prob}[\varepsilon_d \leq -(s_d \alpha_d - \alpha_3 p + \beta_{33} c^0 p - \beta_{13} c^0 + \beta_{34} P^0 p) \text{ AND } \varepsilon_v \leq -(s_v \alpha_v + \beta_{44} P^0 + \beta_{34} c^0)]$, where c^0 is the level of private consumption when $d=0$ ($\tau y + \tau w h$), and ℓ^0 is hours of leisure when $v=0$ ($T - h$).

¹⁵ b_{11} is perfectly collinear with b_{00} , b_{10} , and b_{01} . Based on the laws of probability, the model error involving b_{10} is: $e_{2i} = b_{10i} - \{1 - \Phi(r_{di}, r_{vi}) - [1 - \Phi(\infty, r_{vi})]\}$. The model error involving b_{01} is defined analogously.

Begin by assuming that d and v are never censored. In this case we would have $\partial u_2/\partial d = 0$ and $\partial u_2/\partial v = 0$ for every individual in the sample, and equation (1') could be solved explicitly for ε_d and ε_v . For example, $\varepsilon_v = -(s_v\alpha_v - \beta_{22}v + \beta_{44}P - \beta_{12}d + \beta_{34}c)$. Using our assumption about the distribution of $(\varepsilon_d, \varepsilon_v)$, we could write moment conditions of the form: $E[\varepsilon_v] + (s_v\alpha_v - \beta_{22}v + \beta_{44}P^0 - \beta_{12}d + \beta_{34}c^0) = 0$. Left-censoring of d and v does not change the basic form of the moment conditions, but it does complicate the expressions for $E[\varepsilon_d]$ and $E[\varepsilon_v]$, which have to be based on the truncated bivariate normal distribution. The moment condition involving ε_v must now take the form:

$$b_{00}E[\varepsilon_v|d=0, v=0] + b_{10}E[\varepsilon_v|d=1, v=0] + b_{01}E[\varepsilon_v|d=0, v=1] + b_{11}E[\varepsilon_v|d=1, v=1] + (s_v\alpha_v - \beta_{22}v + \beta_{44}P^0 - \beta_{12}d + \beta_{34}c^0) = 0.$$

The moment condition based on ε_d is defined analogously. Details will be provided in an appendix.

Additional moment conditions could also be defined. For example, the distributional assumption in (1') also implies expected values for the variance, co-variance, and other higher moments of d and v . Estimating the model without imposing these additional restrictions effectively generalizes the distributional assumption somewhat. I am, in effect, assuming that $(\varepsilon_d, \varepsilon_v)$ are drawn from a bivariate distribution that is very similar to a bivariate normal distribution. The CDF and the conditional expectation functions approach those of the bivariate normal distribution, but conditional variances and other higher moments remain unspecified.

4.5 Instruments and Orthogonality Conditions

The five moment conditions defined in the previous sub-section represent 5 restrictions on the data that permit identification of up to 5 parameters. There are, however, 21 parameters to estimate: $\theta' = [\alpha_d', \alpha_v', \alpha_3, \beta_{11}, \beta_{22}, \beta_{33}, \beta_{44}, \beta_{12}, \beta_{13}, \beta_{34}, \sigma_{d|h}, \sigma_{v|h}, \rho_{d|h}]$, where α_d and α_v are 5×1 vectors. I define additional restrictions in the usual way, by interacting each moment condition with a set of instruments. Let e_i be the 5×1 vector of model errors for observation i . Let z_i be a $1 \times K$ vector of instruments. The instruments must be uncorrelated with the model errors: $E[e_i z_i] = 0$. With the instruments I can define K orthogonality conditions for each of the 5 moment conditions. With 4 instruments I would be able to identify 20 parameters and the model would be under-identified. With 5 or more instruments, the model is over-identified. Immediate candidates for instruments are the exogenous explanatory variables in the model. Specifically, I use various combinations of the following 8 instruments: a constant, age, age squared, the number

of children under 16 in the household, the effective marginal state income tax rate, and 4 binary indicators which respectively equal one if the respondent is female, black, or Hispanic, or if there is at least one child under the age of 6 in the household. I specifically exclude potentially endogenous variables including wages, income, itemization status, years of education, and the federal marginal tax rate.

As usual, the exogeneity of any given instrument is debatable. Children, for example, were not exogenously imposed on the individuals in my sample. Including a variable in the set of instruments implies the assumption that its value is orthogonal to unobservable factors that influence monetary donations and volunteering. After controlling for observable characteristics, some people have an idiosyncratic disposition towards charitable giving, some people do not. My assumption is that these idiosyncratic dispositions, represented by $(\varepsilon_d, \varepsilon_v)$, are not systematically correlated with the instruments. “Charitable” people are not more or less likely to have children, for example. I think assumptions along these lines are defensible, *a priori*, for the variables in my set of instruments. They are also testable in the context of an over-identified model, and I will test the exogeneity of specific instruments in future drafts.

I do not think the necessary exogeneity assumptions would be defensible for wages, income, itemization status, educational attainment or the federal tax rate. High wages and high educational attainment, for example, reflect high ability and high levels of investment in human capital. Unobservable factors that influence human capital investment seem likely to be correlated with $(\varepsilon_d, \varepsilon_v)$, especially ε_v . Income, itemization status, and a person’s federal tax bracket all reflect the endogenous labor supply choice. Similar arguments could be made for state tax rates, but some of the cross-sectional variation in state tax rates is due to exogenous variation in state tax laws.

5. Estimates

5.1 First-stage Labor Supply Estimates

Table 5 shows results for the two-stage least squares labor supply regression. Annual hours of work (h) is the dependent variable. Regressors in the semi-log specification are the log of the net wage, virtual income, age, age squared, and a constant. Virtual income is an estimate of disposable non-labor income obtained by subtracting τ_{wh} from total disposable income.¹⁶

¹⁶ Total disposable income is defined as $faminc01 - fedtax - statetax$. The variable $faminc01$ is the 2001 PSID’s measure of “total family income”. The variables $fedtax$ and $statetax$ are estimates of each person’s federal and state income tax bills in 2000. I used TAXSIM, the NBER’s online tax simulator to estimate $fedtax$ and $statetax$. TAXSIM uses the following input variables, all of which are observable in the PSID: state of residence, marital status, number of exemptions, wage and salary income, dividend

Additional regressors are excluded from the specification, but serve as instruments for the endogenous regressors (log net wage and virtual income). Instruments for the endogenous regressors are age, age squared, years of education, years of education squared, age times years of education, the state unemployment rate in 2000, and dummy variables that equal 1 if the individual is female, black, or Latino. The implicit assumption behind this choice of regressors and instruments is that age and age squared are the only instruments that affect hours of work directly. All the other instruments affect labor supply indirectly by shifting the wage profile and/or the level of non-labor income.¹⁷ First stage IV regression results are reported in Appendix table A3.

The wage and income coefficients in Table 5 are statistically significant, and have the expected signs. Hausman's specification test strongly rejects the hypothesis that the wage and virtual income variables are uncorrelated with ε_h ($\chi^2(2) = 31.9$, $\text{Prob}[\chi^2 > 31.9] < 0.001$). The uncompensated wage elasticity of labor supply is the wage coefficient (755.7) divided by annual hours of work. The income elasticity is the income coefficient (-0.0343) times virtual income divided by annual hours of work. The average wage elasticity of labor supply in my sample is .749. The average income elasticity is -.422. The value of σ_h implied by the labor supply regression is 844.3 hours per year. Individual residuals provide an estimate of ε_h for each person. The average residual is zero by construction; values range from -3362 to 4445 hours per year.

5.2: Second Stage: A Preliminary Bivariate Probit

Table 6 reports estimates for a bivariate probit. The bivariate probit corresponds to a restricted version of my model that is exactly identified. The orthogonality conditions of the restricted GMM estimator correspond exactly with the normal equations of the bivariate probit's maximum likelihood estimator. Since the probit does not condition on d or v , β_{11} , β_{22} , and β_{12} cannot be identified. The bivariate probit implicitly assumes $\beta_{11}=\beta_{22}=1$, and $\beta_{12}=0$. As usual, variance parameters cannot be identified by the probit, so $\sigma_{d|h}$ and $\sigma_{v|h}$ are normalized to 1. The parameters that are identified by the bivariate probit correspond directly with the remaining parameters of my model. The probit reported in Table 6 does not allow for the possibility that some of the explanatory variables may be endogenous.¹⁸

income, other property income, taxable pensions, social security income, non-taxable transfer income, rent paid, property tax paid, itemized deductions, and unemployment compensation received.

¹⁷ See the discussion of Blundell and MaCurdy's (1999) equation 4.48.

¹⁸ The restrictions implied by the bivariate probit are severe. The restriction that $\beta_{12}=0$, for example, precludes separability tests, which are of central concern. Estimating the bivariate probit serves 2 purposes.

The estimates of α_d and α_v imply that women are more likely to make both kinds of contributions. The estimates also imply that education is positively correlated with tastes for both types of giving. The age coefficient is positive and significant in the monetary donations equation, but insignificant in the volunteer equation. The labor supply residual coefficients do not permit rejection of the hypothesis that ε_d and ε_h are uncorrelated, but they do provide some evidence that ε_h and ε_v are positively correlated (people who like to work for pay also tend to like volunteering).

The negative and significant price coefficient implies that the marginal utility of d is inversely related to the price of monetary donations. The estimates of β_{33} and β_{44} are analogous to income coefficients. The positive and significant estimate of $\beta_{33} = .0298$ implies that the marginal utility of d goes up when people have more money to spend (d is a normal good). The positive and significant estimate of $\beta_{44} = .000198$ implies that the marginal utility of volunteering goes up when people have more free time on their hands (volunteering is also a normal good). The estimates of β_{13} and β_{34} relate to the separability between d and c (β_{13}) and between c and ℓ (β_{34}). Statistically significant estimates would be evidence against separability. The p-value of .26 for β_{13} does not permit rejection of the hypothesis that d is separable from c . The p-value of .11 for β_{34} suggests that separability between c and ℓ might be rejected if the estimates were based on a larger sample. Point estimates are consistent with the hypothesis that the β matrix is positive definite, as required for concavity of the utility function.

The positive and significant estimate of $\rho_{d|v|h}$ implies that unobservable tastes for d and v are positively correlated. This is consistent with the positive correlation between d and v that is often observed in raw data (including my sample), but leaves open the question of whether or not the two types of giving are complements or substitutes at the margin. The key parameter in my model for addressing that question is β_{12} . β_{12} is also the parameter that determines whether d and v are separable. Unfortunately, β_{12} is not identified by the binary probit estimates. Intuitively, the probit reported in Table 6 conditions on the level of each person's of private consumption and leisure before they make any donations or volunteer any hours. Conditional on that information, and other factors, the estimates imply 4 probabilities for each person: $\text{Prob}[d=0, v=0]$, $\text{Prob}[d>0, v=0]$, $\text{Prob}[d=0, v>0]$, and $\text{Prob}[d>0, v>0]$. My next step will be to condition on additional information: the amounts of d and v for people that make positive contributions of either type.

First, it provides the basis for some initial price and income elasticity estimates (but not for cross-price elasticity estimates). Second, it provides a set of initial parameter estimates to be replicated by my GMM programs. Once my GMM estimation programs replicate the results in Table 6 (estimated with Stata), I can generalize the estimation problem. The estimates in Table 6 also provide a set of starting values for my GMM programs.

This will allow me to impose additional moment conditions, and to identify the rest of the model's parameters.

5.3 Illustrative Elasticity Estimates and Policy Simulations

The estimates in Table 6 do permit illustrative calculations of income and price elasticities, and a number of illustrative policy simulations. I stress at the outset that these calculations are based estimates for a sample of working singles, and do not necessarily apply to the more general population.

Because the estimates imply a probability of giving and volunteering for each individual in the sample, they also imply an expected number of contributors and volunteers in the sample. These model predictions can be computed and re-computed after varying prices, incomes, or any other quantity of interest. The results of such calculations imply that a 10% increase in each person's price of giving would reduce the number of people making positive contributions by 8.5%. Exogenously increasing everyone's disposable income $\tau(y + wh)$ by 10% would increase the number of contributors by 2.5%.

The price and income elasticities reported in the previous paragraph permit comparisons with previous estimates based on different models and datasets. Perhaps more interesting to policy makers, are the results of concrete policy simulations. For example, recall that the price of monetary donations is $1 - t^f - t^s$ for people who itemize charitable deductions, where t^f is the effective federal marginal tax rate, and t^s is the effective state marginal tax rate. (The price is 1 for people who do not itemize deductions.) I consider 2 policy changes that would affect the price of giving. The first is an elimination of the charitable deduction, which would increase the price of giving to 1 for everyone who currently itemizes. The second policy simulation is an across-the-board 10% increase in the federal marginal tax rate. This would reduce the price of giving for all itemizers, but it would also affect labor supply and disposable income for everyone in the sample. The net effect of the tax increase depends on the relative magnitudes of these potentially countervailing price and income effects.

Of the 885 individuals in my sample, only 257 (29%) report that they itemize deductions. The average price of giving is 0.733 for these people. (The price is 1.0 for non-itemizers.) Eliminating the charitable deduction raises the price of giving to 1.0 for the 257 itemizers, and reduces the predicted number of contributors in the sample by 4.1%.¹⁹ The prediction assumes

¹⁹ The predicted number of contributors, before eliminating the deduction, is 473.6. After eliminating the deduction, the predicted number of contributors is 454.0. The predictions are made by computing the

that labor supply would be unaffected by elimination of the charitable deduction, which is consistent with the recursive model's assumption that labor supply is chosen without explicit consideration of charitable giving. Labor supply would be affected by an across-the-board increase in the federal marginal tax rate, however, since this would reduce the effective wage of everyone in the sample. Average predicted hours of work fall by 21 hours in response to a 10% increase in the federal marginal tax rate. This implies that potential hours of leisure (when $v=0$) rise by 21 hours on average. Increasing the tax rate reduces the average price of giving from 0.923 to 0.916, but also reduces disposable income about \$1,150 on average. These countervailing price and income effects offset each other almost exactly. The net effect is a negligible reduction in the predicted number of people making monetary donations, and a negligible increase in the number of people volunteering.²⁰

6. Conclusions and Future Work

The estimates and policy simulations reported in this preliminary draft are encouraging, but do not provide definitive evidence related to (Q1) and (Q2). Testing separability (Q1) will involve testing the statistical significance of the parameters β_{12} and β_{13} .²¹ β_{12} relates to separability between monetary donations (d) and volunteer labor supply (v). This is perhaps the most interesting parameter in the model, but it is not identified by the restricted version of the model for which this draft presents estimates. Estimating a more general model is the next priority in this project. Table 6 does provide an estimate of β_{13} . The p-value of 0.26 does not permit rejection of the hypothesis that $\beta_{13}=0$, and that monetary donations are separable from private consumption. It remains to be seen whether similar conclusions will be possible after testing β_{12} and β_{13} jointly.

The second central question relates to the complementarity/substitutability of d and v . The answer to (Q2) also relies critically on β_{12} , so the question cannot be answered with the preliminary estimates currently available. The positive and statistically significant estimate of correlation between ε_d and ε_v ($\rho_{dv|h} = .494$) implies that unobservable tastes for d and v are

probability that $d>0$ for each individual in the sample and summing across individuals. The actual number of contributors observed in the sample is 467.

²⁰ The predicted number of individuals with $d>0$ falls from 473.6 to 470.6, a 0.64% reduction. The predicted number of individuals with $v>0$ rises from 225.8 to 227.0, a 0.53% increase. The elasticities with respect to the federal marginal tax rate are therefore -0.0064 and 0.0053. The actual number of volunteers in the sample is 224.

²¹ The parameter β_{14} determines separability between d and ℓ . I maintain the assumption that $\beta_{14}=0$. This assumption is testable, although I do not focus on that possibility here.

positively correlated. This leaves open the question, however, whether the two types of giving are complements or substitutes at the margin.

Even with definitive estimates for a sample of working singles, we would still not be in a position to draw inference to the general population. Estimates that apply to the general population will rely (implicitly or explicitly) on assumptions about how decisions are made in multi-adult households. Collective models of household utility rely on weak but testable assumptions, and have proven successful in the labor supply literature. Collective utility models could be readily applied to studies of charitable giving under the separability assumptions I propose to test. If separability cannot be rejected for a sample of single adults, it becomes an attractive assumption for individuals within married couples. If separability can be rejected, we will know better than to base future estimates on a convenient, but erroneous assumption.

Table 1: Sample Proportions with $h>0$, $d>0$, and $v>0$

All Single Individuals (n=1638)		
	Single Men (n=614)	Single Women (n=1024)
$h>0$.855	.706
$d>0$.531	.560
$v>0$.219	.253
Working Singles ($h>0$) (n=1243)		
	Single Men (n=524)	Single Women (n=719)
$h>0$	1.000	1.000
$d>0$.520	.551
$v>0$.221	.268

Table 2a: Cross-Tabulation of Monetary Giving and Volunteering for Working Single Men

	does not donate money ($d=0$)	does donate money ($d>0$)	Total
does not volunteer ($v=0$)	184 (46%)	128 (32%)	312 (77%)
does volunteer ($v>0$)	18 (4%)	74 (18%)	92 (23%)
Total	202 (50%)	202 (50%)	404

All percentages are with respect to the total sample size of 404.

Table 2b: Cross-Tabulation of Monetary Giving and Volunteering for Working Single Women

	does not donate money ($d=0$)	does donate money ($d>0$)	Total
does not volunteer ($v=0$)	185 (38%)	164 (34%)	349 (73%)
does volunteer ($v>0$)	31 (6%)	101 (21%)	132 (27%)
Total	216 (44%)	265 (55%)	481

All percentages are with respect to the total sample size of 481.

Table 3a: Summary Statistics for Working Single Men (n=404)

Variable	Sample Mean (std deviation)	Sample Min	Sample Max
monetary donations (d)	444 (1051)	0	10,000
binary indicator of d > 0	.500 (.500)	0	1
volunteer hours (v)	24.0 (115.8)	0	2000
binary indicator of v > 0	.221 (.415)	0	1
annual hours worked (h)	2071 (696)	60	4629
wage (w)	18.2 (15.8)	1.1	171.9
virtual non-labor income (y)	7213 (10,269)	-428	111,346
earned income (wh)	37,130 (32,886)	700	490,000
binary indicator of itemization	.277 (.456)	0	1
effective federal marginal tax rate (t ^f)	.261 (.099)	-.4	.518
effective state marginal tax rate (t ^s)	.045 (.026)	-.034	.095
price of monetary donations (p)	.924 (.162)	.482	1
age	37.0 (12.4)	17	79
years of education	13.4 (2.2)	6	17
<u>Race indicators</u>			
black	.103 (.304)	0	1
Latino	.007 (.086)	0	1
Asian	.011 (.104)	0	1
missing	.006 (.074)	0	1
number of children under 6	.068 (.299)	0	2
number of children between 6 and 16	.171 (.513)	0	4
number of dependents in college	.015 (.120)	0	1

Table 3b: Summary Statistics for Working Single Women (n=481)

Variable	Sample Mean (std deviation)	Sample Min	Sample Max
monetary donations (d)	569 (1341)	0	14,000
binary indicator of d > 0	.551 (.498)	0	1
volunteer hours (v)	31.2 (105.8)	0	1120
binary indicator of v > 0	.268 (.443)	0	1
annual hours worked (h)	1809 (672)	8	4774
wage (w)	15.5 (14.0)	.36	162.5
virtual non-labor income (y)	9091 (10,481)	-4	106,354
earned income (wh)	28,097 (27,147)	45	325,000
binary indicator of itemization	.301 (.454)	0	1
effective federal marginal tax rate (t ^f)	.232 (.138)	-.4	.573
effective state marginal tax rate (t ^s)	.042 (.029)	-.06	.157
price of monetary donations (p)	.921 (.153)	.369	1
age	40.4 (13.6)	18	90
years of education	13.3 (2.3)	1	17
<u>Race indicators</u>			
black	.166 (.373)	0	1
Latino	.013 (.114)	0	1
Asian	.003 (.051)	0	1
missing	.007 (.081)	0	1
number of children under 6	.196 (.533)	0	3
number of children between 6 and 16	.459 (.771)	0	4
number of dependents in college	.077 (.304)	0	3

Table 4: “Alternative” Summary Statistics for Working Singles (n=885)

Variable	Sample Mean (std deviation)	Sample Min	Sample Max
Total hours (T)	4774 (0)	4774	4774
annual hours worked (h)	1918 (694)	8	4774
annual volunteer hours (v)	28.2 (110)	0	2000
annual hours of leisure (ℓ)	2829 (699)	0	4766
after-tax non-labor income ($\tau\gamma$)	4940 (23,184)	-9255	623,952
value of time (τwT)	53,251 (42,472)	1334	465,827
value of full endowment ($\tau\gamma + \tau wT$)	58,191 (49,601)	2285	704,255
disposable earned income (τwh)	20,908 (17,255)	45	276,017
disposable income ($\tau\gamma + \tau wh$)	25,848 (29,345)	804	666,845
expenditure on consumption (c)	25,434 (29,176)	54	665,123
expenditure on leisure ($\tau w\ell$)	31,993 (31,066)	0	452,947
expenditure on monetary donations (pd)	414 (969)	0	12,000
expenditure on volunteer time (τwv)	350 (1813)	0	49,285

Table 5: Labor Supply Regression (Two-Stage Least Squares, n=885)

Dependent variable: annual hours of work (h)

	Coefficient
	(s.e.) [p - bold if < .10]
log of net wage * [ln(τw)]	755.7 (180.7) [<.01]
virtual income * [total income - τwh]	-0.0343 (0.0124) [.01]
age	33.5 (14.3) [.02]
age-squared	-.423 (.167) [.01]
constant	-120.7 (319.6) [.71]

Root Mean Squared Error: 844.3

* Error term is not assumed to be orthogonal to the log of the net wage or virtual income.

Instruments: age, age-squared, years of education, years of education squared, age*years of education, state unemployment rate and 3 binary indicators which equal 1 if the person is female, black or Latino.

Hausman's specification test

H₀: Log of net wage and virtual income are uncorrelated with ε_h .

$\chi^2(2) = 31.9$, Prob[$\chi^2 > 31.9$] < 0.001. H₀ rejected at all conventional significance levels.

Table 6: Bivariate Probit Estimates (n=885)

Model Notation

$$\text{Prob}[d>0] = \text{Prob}[\varepsilon_d > -(s_d\alpha_d + \alpha_3p + \beta_{33}c^0p + \beta_{13}c^0 + \beta_{34}P^0p)]$$

$$\text{Prob}[v>0] = \text{Prob}[\varepsilon_v > -(s_v\alpha_v + \beta_{44}P^0 + \beta_{34}c^0)]$$

$$s_d = s_v = [1 \text{ female age eduys } e_h/\sigma_h]$$

$$c^0 = y + \tau wh$$

$$\ell^0 = T - h$$

$$(\varepsilon_d, \varepsilon_v | \varepsilon_h) \sim \text{BVN}(0, 0, 1, 1, \rho_{dv|h})$$

Variable	Parameter	Coefficient (s.e.) [p - bold if <.10]	
Prob[d>0]			
constant	α_{d1}	-0.928 (.727)	[.20]
female dummy	α_{d2}	0.179 (.095)	[.06]
age	α_{d3}	0.023 (.0036)	[<.01]
years of education	α_{d4}	0.128 (.021)	[<.01]
e_h	α_{d5}	-0.077 (.090)	[.39]
price	α_3	-1.75 (.792)	[.03]
c^0 *price	β_{33}	0.0298 (.014)	[.03]
c^0	β_{13}	-0.0127 (.011)	[.26]
ℓ^0 *price	β_{34}	-0.000194 (.000121)	[.11]
Prob[v>0]			
constant	α_{v1}	-3.22 (.426)	[<.01]
female	α_{v2}	0.146 (.097)	[.13]
age	α_{v3}	-.000877 (.0035)	[.80]
years of education	α_{v4}	0.143 (.021)	[<.01]
e_h	α_{v5}	0.150 (.084)	[.07]
ℓ^0	β_{44}	0.000198 (.000103)	[.06]
c^0	β_{34}	-0.000194 (.000121)	[.11]
	$\rho_{dv h}$	0.494 (.0523)	[<0.01]

Log-likelihood: -947.3

Appendix

Table A1: Cross-Tabulation of Monetary Giving and Volunteering for Married Men and Women

Married Men:

	household does not donate money (d=0)	household does donate money (d>0)	Total
head does not volunteer ($v^h=0$)	596 (22%)	1345 (50%)	1941 (72%)
head volunteers ($v^h>0$)	63 (2%)	701 (26%)	764 (28%)
Total	659 (24%)	2046 (76%)	2705

Married Women:

	household does not donate money (d=0)	household does donate money (d>0)	Total
wife does not volunteer ($v^w=0$)	582 (22%)	1228 (45%)	1810 (67%)
wife volunteers ($v^w>0$)	77 (3%)	818 (30%)	895 (33%)
Total	659 (25%)	2047 (75%)	2705

All percentages are with respect to the total sample size of 2705.

Table A2: Summary Statistics for Couples (n=2705)

Variable	Sample Mean (std deviation)	Sample Min	Sample Max
monetary donations (d)	1720 (3921)	0	76,800
binary indicator of $d > 0$.749 (.432)	0	1
volunteer hours of the head (v^h)	33.8 (127.4)	0	3000
volunteer hours of the “wife” (v^w)	43.7 (144.5)	0	2500
binary indicator of $v^h > 0$.281 (.450)	0	1
binary indicator of $v^w > 0$.331 (.471)	0	1
binary indicator of ($v^h > 0$ AND $v^w > 0$)	.195 (.396)	0	1
binary indicator of ($v^h > 0$ AND $v^w = 0$)	.087 (.281)	0	1
binary indicator of ($v^h = 0$ AND $v^w > 0$)	.137 (.343)	0	1
binary indicator of ($v^h = 0$ AND $v^w = 0$)	.582 (.493)	0	1
annual hours worked by head (h^h)	1952 (972)	0	5824
annual hours worked by wife (h^w)	1280 (964)	0	5824
binary indicator of $h^h > 0$.865 (.341)	0	1
binary indicator of $h^w > 0$.752 (.432)	0	1
wage of head (w^h)	21.8 (28.8)	0	472.1
wage of wife (w^w)	12.5 (17.3)	0	500
total family income	87,293 (101,359)	-59,948	2,112,300
earned income of head ($w^h h^h$)	47,846 (66,125)	0	1,156,694
binary indicator of itemization	.563 (.496)	0	1
effective federal marginal tax rate (t^f)	.242 (.132)	-.4	.667
effective state marginal tax rate (t^s)	.042 (.029)	-.077	.154
price of monetary donations (p)	.818 (.181)	.396	1
age of head	45.6 (14.6)	19	93
age of wife	43.3 (14.0)	17	88
head’s years of education	13.5 (2.5)	0	17
wife’s years of education	13.5 (2.3)	2	17
<u>Race indicators for head of household</u>			
black	.050 (.217)	0	1
Latino	.014 (.120)	0	1
Asian	.005 (.071)	0	1
missing	.009 (.096)	0	1
number of children under 6	.314 (.637)	0	4
number of children between 6 and 16	.634 (.961)	0	8
number of dependents in college	.114 (.361)	0	3

Table A3: First Stage IV-Regressions for the Log Net Wage and Virtual Income

Source	SS	df	MS	Number of obs =	885
Model	42.9386849	9	4.77096499	F(9, 875) =	14.79
Residual	282.164763	875	.322474015	Prob > F =	0.0000
				R-squared =	0.1321
				Adj R-squared =	0.1231
Total	325.103448	884	.367764082	Root MSE =	.56787

lnnetwage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
femalehead	-.1433328	.0388846	-3.69	0.000	-.2196509 -.0670147
black	-.0334919	.0596251	-0.56	0.574	-.1505168 .0835331
latino	-.2530205	.1909903	-1.32	0.186	-.6278731 .1218322
ageofhead	.0458595	.0118961	3.86	0.000	.0225113 .0692078
eduyearshhead	-.1645458	.05812	-2.83	0.005	-.2786167 -.0504749
age2	-.0003858	.0000888	-4.35	0.000	-.00056 -.0002116
edu2	.0091811	.0021579	4.25	0.000	.0049457 .0134164
ageedu	-.0004363	.0006439	-0.68	0.498	-.0017 .0008275
unemp	.0249615	.0237515	1.05	0.294	-.021655 .071578
_cons	1.903652	.5000307	3.81	0.000	.9222525 2.885052

Source	SS	df	MS	Number of obs =	885
Model	1.4904e+10	9	1.6560e+09	F(9, 875) =	17.87
Residual	8.1100e+10	875	92686146.3	Prob > F =	0.0000
				R-squared =	0.1552
				Adj R-squared =	0.1466
Total	9.6004e+10	884	108601802	Root MSE =	9627.4

virty	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
femalehead	1359.809	659.2317	2.06	0.039	65.94849 2653.669
black	-1920.709	1010.856	-1.90	0.058	-3904.694 63.27675
latino	-3930.529	3237.959	-1.21	0.225	-10285.6 2424.545
ageofhead	-848.2044	201.6809	-4.21	0.000	-1244.039 -452.3695
eduyearshhead	-1957.287	985.3394	-1.99	0.047	-3891.191 -23.38192
age2	3.359983	1.504755	2.23	0.026	.4066315 6.313334
edu2	16.03398	36.58461	0.44	0.661	-55.76987 87.83782
ageedu	57.86672	10.91626	5.30	0.000	36.44161 79.29182
unemp	67.72352	402.6712	0.17	0.866	-722.5906 858.0377
_cons	27858.37	8477.283	3.29	0.001	11220.18 44496.55

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