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Modelling charitable donations: A latent class panel inverse hyperbolic sine heteroskedastic tobit approach

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Abstract: We make a methodological contribution to the latent class literature by re-examining censored variable analysis within a panel data context. Specifically, we extend the standard latent class tobit panel approach to include random effects, to allow for heteroskedasticity and to incorporate the inverse hyperbolic sine (IHS) transformation of the dependent variable. The IHS transformation ensures robustness to non-normality in the original (untransformed) dependent variable. We then use this framework to model charitable donations, an interesting application given the potential for divergent groups of individuals in the population with regard to their donating behaviour, which we uncover by a latent class approach. Our findings, which are based on U.S. panel data drawn from five waves of the Panel Study of Income Dynamics, do suggest two distinct classes. There is a clear disparity between the probabilities of zero donations across these classes, with one class dominated by the observed zero givers and associated with relatively low levels of predicted giving. We find clear evidence of both heteroskedasticity and random effects. All IHS parameters were significantly different from zero and different across classes. In combination, these findings endorse the importance of our three modelling extensions.

Key Words: Charity; Donations; Latent Class; Panel Data; Tobit.

JEL Classification: D19; H24; H41; H31

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I. Introduction and Background

An extensive empirical and theoretical literature exists exploring why individuals make contributions to charity, with much of the existing research focusing on charitable donations at the individual and household level in the U.S. (see, for example, Andreoni, 2006). Recent figures from *Giving U.S.A.2011* estimate total charitable contributions in the U.S. in 2011 at $290.89 billion. The figure relates to total charitable contributions from U.S. individuals, corporations and foundations and includes both cash and in-kind donations. Given the economic significance of such donations, such interest in the economics literature is not surprising.

Empirical analyses of charitable donations conducted over the last four decades have witnessed increased availability and quality of data. The econometric methodology has increased in sophistication from the early studies, which typically adopted simple log-linear approach. Reece (1979) made an early methodological contribution by applying the tobit model to the analysis of cross-section data on household donations to charity accounting for the fact that donations cannot be negative: charitable donations are censored at zero. The tobit approach has been adopted by a number of empirical studies of charitable donations including Kingma (1989) and Auten and Joulfaian (1996).

Estimation issues that have arisen, however, with respect to the tobit model include inconsistency in the face of both heteroskedasticity and non-normality; and in panel data variants, the required assumption that the covariates are independent of the unobserved (random) effects. Within the context of modelling charitable giving at the cross-sectional level, Wilhelm (2008) considers alternatives to the tobit approach (such as the censored least absolute deviations and symmetrically censored least squares estimators), which are robust to non-normality and heteroskedasticity. In a panel data setting, Honoré (1992) has also considered estimation of censored regression models in general, where fixed effects are present.

However, a more fundamental problem with the tobit approach, which relates to the treatment of the censored observations, lies in the possibility that the decision to donate and the decision regarding how much to donate, may be characterised by different influences. A double-hurdle model is an alternative econometric specification that has been used in the existing literature (see, for example, Yen et al., 1997), which allows independent variables to have different effects on the probability of making a donation and the level of donation. Such an approach implicitly allows for a two stage decision-making process: an individual decides whether to donate or not; conditional on this decision, he/she then decides how much to give.

In this paper, we make a methodological contribution to the existing literature by a re-examination of censored variable analysis, and the associated treatment of zeros, within a panel data context. The broad approach we follow is a latent class one. Latent class models are finding increasing favour in economics. They have been applied in a wide variety of areas ranging from consumer behaviour (see, for example, Reboussin et al., 2008, and Chung et al., 2011), to health economics (see, for example, Deb and Trivedi, 1997, and Bago d'Uva, 2005) and for transport mode choice (see, for example, Shen, 2009).

In general, the latent class approach (probabilistically) splits the population into a set of homogeneous groups. Within each class, or group, an appropriate econometric model applies: in our case, given the censored nature of charitable donations, this is based upon a tobit specification. Such an approach is advantageous, as it simultaneously introduces heterogeneity into the empirical framework and *ex post* allows for splitting of the population into various sub groups of donating behaviour.

We have extended the "standard" panel data latent class approach to include random effects in the tobit equations of the overall model. We accommodate non-normality by employing the inverse hyperbolic sine (IHS) transformation of the dependent variable (see Burbidge, Magee and Robb, 1988) and allow for heteroskedasticity with an explicit parameterization of the disturbance variance. With these three extensions to the latent class framework, we make a methodological contribution to the latent class literature. We also contribute to the existing literature on modelling charitable donations, which, in our opinion, is an interesting application given the potential for diverse donating behaviour in a population.

The latent class approach potentially offers a richer characterisation of the "zero donation" process than a simple double-hurdle approach, where there is a sharp distinction between participants and non-participants as described above. To illustrate this point, consider the seminal paper by Jones (1989) on the double-hurdle model focusing on expenditure on cigarettes. Observed zero expenditure on cigarettes will arise from two types of individuals: non-smokers and infrequent consumers. For non-smokers, it is unlikely that *any* change in their economic environment (such as income or the price of cigarettes) will induce a switch from non-participation to positive consumption. However, we believe that the same is not true for zero-contributing charity donators. Even for habitual zero-observed donators, it is possible that a significant shock (for example, a very closely related traumatic event) will increase their propensity to donate. However, this increase may be such that effectively this propensity is never actually greater than the threshold required to actually donate, but the potential exists, nevertheless.

Specifically with regard to modelling charitable donations, a latent class approach might also be preferred over a double-hurdle one due to the likely presence of recall bias or mis-reporting or both. Households are asked to report (or recall) their charitable donations over the previous year. For many of the reported zero donations here, it is likely that this number is not identically zero, as individuals may well have forgotten about the "50 cents popped in the collection jar at the supermarket", or the "20 cents to the war veteran in the subway," and so on. The double-hurdle approach treats the observed zeros as a strict representation of the "truth", and will attempt to split these between non-participants and infrequent givers. However, our approach implicitly allows for this recall bias, and will (typically) estimate a non-zero expected value for these households, albeit a very small one.

Moreover, our approach in splitting the population into different types of givers does explicitly allow the probability of zero donating to differ in each class, thereby leading to a layered characterisation of the "zero-donation" outcome. In essence, our suggested latent class approach will "push" some groups towards zero expenditures, whilst "pulling" others away from it. In all situations, there remains a non-zero probability of zero expenditure, which is clearly likely to be higher in the groups pulled towards zero. For example, in the results that follow, we do clearly identify "high" and "low" donor groups: in the former the average probability of zero donations is only 0.02, whereas for the latter this jumps to 0.57.

II. Econometric Framework: A Panel Latent Class Tobit Model

Our hypothesis is that there are inherently more than one type of charity donators in the population; "high" givers and "low" givers is a natural partition. For example, the latter are more likely to be responsive to changes in the price of charitable donations. However, clearly these inherently different types of households will not be directly observed. All that is observed is the amount donated to charity. Thus, the approach we follow here is that of "latent class" or "finite mixture" models (for a comprehensive survey of latent class models see McLachlan and Peel, 2000). Essentially such approaches assume that the observed data are drawn from a mixture of underlying populations. In undertaking such an approach, care needs to be taken of the specific nature of our dependent variable: household charitable donations. As is common in the existing literature on charity (see Andreoni, 2006 for a comprehensive survey of this area), we treat this as a corner solution model (for the reasons outlined above), such that we need to employ censored regression (tobit) model techniques to take into account the quite significant amount of censoring at zero (Maddala, 1983). In our case the censoring amounts to some 40 per cent of observations.

Thus, the general framework we adopt is a latent class tobit model. This approach amounts to first (probabilistically) splitting the sample into two, or more, populations (which, prior to estimation we envisage to correspond to "high" and "low" donators) and then, for each of these subpopulations, separate tobit models apply. In this way, the same explanatory variables in the tobit (or "amount of giving") equation can have differing effects across the different classes.

The probabilistic splitting of the sample is usually based on a logit specification (Greene, 2012), which can be either a constant across households, or allowed to be a function of observed household and head of household characteristics, $\mathbf{z}_i$ with associated coefficients $\boldsymbol{\phi}$. It is possible to allow for a theoretically large number of such latent classes. However, we restrict ourselves here to two, as any greater number of classes yields an overly parameterised model that is difficult to interpret. Indeed, convergence problems were encountered in the case of the three-class model, clearly suggesting that this was the case: one, or more, of the three probabilistic points of support is degenerate. In practice the optimal number of classes is usually determined on the basis of information criteria (see, for example, Deb and Trivedi, 2002).

As Greene (2012) points out, the availability of panel data significantly aids in the identification of latent class models. Essentially this arises as, being time-invariant, we now have several observations (T_i) on each household upon which to base class membership, as opposed to the single one in a cross-section. Following Greene (2012), we parameterise our model such that time-invariant head of household characteristics $\mathbf{z}_i$ affect the probability of being in each class and the remaining head of household and household characteristics, along with any further economic variables (such as price), determine the amount of giving by the household within the class. In effect, this amounts to parameterising the household's "fixed effect" of being in each class. Let $\mathbf{x}_{it}$ be the vector of explanatory variables determining the *level* of donations by household *i* in period *t*, and let there be $j = 1,\ldots,J$ latent classes (in our case, $J = 2$). There will be J parameter vectors $(\boldsymbol{\beta}_j, \sigma_j)$ associated with $\mathbf{x}_{it}$ in the different classes (where σ_j is the standard deviation of the error term within each class). Post-estimation, based on the estimated $(\boldsymbol{\beta}_j, \sigma_j)$ vectors, it is possible to estimate (average) expected values of giving across the classes, and in this way to determine which classes are the "high" and "low" donators.

Conditional on class membership, which is constant over time by definition, the y_{it} observations on charity donations for household *i* $(i = 1,\ldots,N)$ in period *t* $(t = 1,\ldots,T_i)$ are independent – we reconsider this assumption below. For a group of T_i observations, the joint density of the sequence of y_{it} is

$$f\left(\mathbf{y}_i \middle| class = j, \mathbf{X}_i, \boldsymbol{\beta}_j, \sigma_j\right) = \prod_{t=1}^{T_i} f\left(y_{it} \middle| class = j, \mathbf{x}_{it}, \boldsymbol{\beta}_j, \sigma_j\right) \qquad (1)$$

where for household i in period t, $f\left(y_{it}\middle|class=j,\mathbf{x}_{it},\boldsymbol{\beta}_j,\sigma_j\right)$ is given by the tobit formulation (Maddala, 1983) and ($\mathbf{y}_i$, $\mathbf{X}_i$) denotes the T_i periods of observed data on household i.

The density for the it'th observation for the tobit model is derived from the latent regression,

$$\begin{aligned}&y_{it}^{*} \mid (class=j)=\boldsymbol{\beta}_j'\mathbf{x}_{it}+\varepsilon_{it|j},\ \varepsilon_{it|j} \sim N\left(0,\sigma_j^2\right), \text{ with}\\ &y_{it}=y_{it}^{*} \text{ if } y_{it}^{*}>0 \text{ and } y_{it}=0 \text{ otherwise.}\end{aligned} \tag{2}$$

The implied density for the observed y_{it} is

$$f(y_{it} \mid class=j,\mathbf{x}_{it},\boldsymbol{\beta}_j,\sigma_j)=\left[\Phi\left(\frac{-\boldsymbol{\beta}_j'\mathbf{x}_{it}}{\sigma_j}\right)\right]^{1-D_{it}}\left[\frac{1}{\sigma_j}\phi\left(\frac{y_{it}-\boldsymbol{\beta}_j'\mathbf{x}_{it}}{\sigma_j}\right)\right]^{D_{it}} \tag{3}$$

where D_{it} equals 1 if y_{it} is greater than zero, and 0 otherwise.

The log-likelihood for a panel of data on charitable donations will be

$$\log L[(\boldsymbol{\beta}_j,\sigma_j,\boldsymbol{\phi}_j),\ j=1,\ldots,J]=\sum_{i=1}^{N}\log\left[\sum_{j=1}^{J}p_{ij}\left(\boldsymbol{\phi}_j,\mathbf{z}_i\right)\prod_{t=1}^{T_i}f\left(y_{it}\middle|class=j,\mathbf{x}_{it},\boldsymbol{\beta}_j,\sigma_j\right)\right] \tag{4}$$

where $p_{ij}\left(\boldsymbol{\phi},\mathbf{z}_i\right)$ are the logit probabilities of being in class j:

$$p_{ij}\left(\boldsymbol{\phi},\mathbf{z}_i\right)=\frac{\exp\left(\mathbf{z}_i'\boldsymbol{\phi}_j\right)}{\sum_{j=1}^{J}\exp\left(\mathbf{z}_i'\boldsymbol{\phi}_j\right)},\ j=1,\ldots,J;\ \boldsymbol{\phi}_J=\mathbf{0} \tag{5}$$

and $\boldsymbol{\phi}_J=\mathbf{0}$ for identification. Note that all parameters of the model, that is, those in the logit model determining class membership and those in the multiple tobit equations, are jointly estimated (see, for example, Deb and Trivedi, 2002, for maximum likelihood estimation of latent class models). The latent class specification groups the population into two types (classes) of donators. Prior to estimation, we know nothing about which households will be in each class; and nothing about the donating behaviour within each class.

Within each class, donating behaviour follows a corner solution model, whereby each household, in each time period, chooses a utility-maximising level of donation. For some households, in some time-periods, this utility-maximisation choice will be zero. Moreover, this decision process will (primarily) be driven by observed changes in the household's economic and social environment, i.e., $\mathbf{x}_{it}$. Thus, this utility-maximisation process combined with a changing observed (economic and social) environment, $\mathbf{x}_{it}$, means that the econometric model explicitly allows for households to move from zero to positive consumption from year-to-year; or from positive to zero; or from large donations to small; and so on.

Post-estimation, two estimates of the probability of being in each class are available. Prior probabilities can be obtained by simply evaluating the above expression for $p_{ij}\left(\phi, z_i\right)$. However, for prediction purposes it is more useful to look at the posterior, or conditional on the observed data, probabilities (Greene, 2012). Using Bayes Theorem, we obtain

$$
\begin{aligned}
P\left(class = j \middle| observation\ i\right) &= \frac{f\left(observation\ i \middle| class = j\right) P\left(class\ j\right)}{\sum_{j=1}^{J} f\left(observation\ i \middle| \text{class} = j\right) P\left(class\ j\right)} \\
&= \frac{\prod_{t=1}^{T_i} f\left(y_{it} \mid \mathbf{x}_{it}, \boldsymbol{\beta}_j, \sigma_j\right) p_{ij}\left(\mathbf{z}_i, \boldsymbol{\phi}_j\right)}{\sum_{j=1}^{J} \prod_{t=1}^{T_i} f\left(y_{it} \mid \mathbf{x}_{it}, \boldsymbol{\beta}_j, \sigma_j\right) p_{ij}\left(\mathbf{z}_i, \boldsymbol{\phi}_j\right)}.
\end{aligned} \tag{6}
$$

To this point, the specification can be considered a "standard" application of a latent class model where panel data are available (see Greene, 2012, for example). The model can be estimated using standard software, such as *Nlogit*/*Limdep*. We will suggest three important extensions to this basic set-up that significantly increase the complexity of this latent class approach, whilst fully taking advantage of the panel nature of the data.

Heteroskedasticity

As is well-known in the literature (see, Maddala, 1983, for example), if, as is likely with unit-level data, there is heteroskedasticity present in the data and that this is ignored in estimation, biased and inconsistent parameter estimators will result (effectively as a result of maximising the incorrect likelihood function). The conventional assumption in the tobit model, is that

$$E\left(\varepsilon_{it|j}^2 \left|\mathbf{x}_{it}\right.\right) = \sigma_j^2. \tag{7}$$

That is, that the error term in the model in (2) is orthogonal to the covariates and homoskedastic within each class. A common approach to allow for heteroskedasticity is Harvey's (1976) model,

$$\sigma_{ij}^2 = \sigma_j^2\left[\exp\left(\mathbf{w}_i'\boldsymbol{\delta}_j\right)\right]^2. \tag{8}$$

The exponential transformation ensures that the variance(s) under the assumption of heteroskedasticity ($\boldsymbol{\delta} \neq \mathbf{0}$), is (are) both identified and positive. It is also convenient in that a test of $\boldsymbol{\delta}_j = 0,\ j = 1, 2, \ldots$ provides a test of the heteroskedasticity model versus the homoskedastic one. Following the bulk of the censored regression literature (see, for example, Yen and Jones, 1997), the variables chosen to enter into **w** are the household scale variables available to us (income and wealth). With this extension, σ_{ij} in (8) replaces σ_j in the tobit model in (2).

Unobserved Heterogeneity

Although the standard panel data latent class model (described above) allows one to identify the classes more strongly (as opposed to simple cross-sectional data), it is possible to exploit the panel nature of the data even further by using the within household variation through the window of the panel. We will include unobserved time invariant common, or random, effects into the tobit parts of our model specification.

That is, as is common in the panel data literature (see, for example, Baltagi, 2005), we add to ε_{it} a household (and class) varying error $u_{i|j}$ such that the latent regression becomes

$$y^*_{it|j} = \mathbf{x}'_{it}\boldsymbol{\beta}_j + \varepsilon_{it|j} + u_{i|j}\,. \tag{9}$$

These unobserved household specific effects are assumed to be orthogonal to the covariates in the model, and follow a normal distribution with mean zero and variance θ_j^2. Note that as the two unobserved effects implicitly relate to two distinct different groups of the population, they are assumed to be independent. However, due to the presence of the common $u_{i|j}$, observations on the particular household are no longer independent across periods.

The density for the observed $y_{it|j}$ is formed by first conditioning on the unobserved heterogeneity. It is useful to write $u_i = \theta v_i$ where $\theta^2 = \mathrm{Var}[u_i]$ and $v_i \sim N[0,1]$. Then,

$$f(y_{it} \mid class = j, \mathbf{x}_{it}, u_{i|j}, \boldsymbol{\beta}_j, \sigma_j, \theta_j) = \left[\Phi\left(\frac{-\boldsymbol{\beta}'_j\mathbf{x}_{it} - \theta_j v_{i|j}}{\sigma_j}\right)\right]^{1-D_{it}} \left[\frac{1}{\sigma_j}\phi\left(\frac{y_{it} - \boldsymbol{\beta}'_j\mathbf{x}_{it} - \theta_j v_{i|j}}{\sigma_j}\right)\right]^{D_{it}} \tag{10}$$

The density for the observed $y_{it|j}$ is now formed by integrating the unobserved $v_{i|j}$ out of the conditional density. We return to this point below where we obtain the log likelihood for the sample.

Allowing for Non-Normality

If the assumption of normality that is central in the tobit models thus far is invalid, the (pseudo-) maximum likelihood estimator of the parameters will be biased and inconsistent. It is commonplace in models of charitable donations to model the natural logarithm of (one plus) the actual level of donations (see, for example, Yen, 2002). Although often not explicitly stated, this is presumably so that the resulting distribution of charitable donations is more nearly normally distributed. However, it is not clear that a zero in the logarithmic scale is equivalent to the same in the untransformed scale; and moreover, the addition of one is simply an arbitrarily chosen number to ensure that the log transformation is defined for all households. A recently used approach to deal with this issue that originates with Burbidge et al. (1988) is to use the inverse hyperbolic sine (IHS) transformation of the dependent variable. The IHS transformation, $I(y,\gamma)$, of a variable y, takes the form

$$I(y,\gamma)=\frac{1}{\gamma}\sinh^{-1}\left(\gamma y\right)=\frac{1}{\gamma}\log\left[\gamma y+\left(\gamma^{2}y^{2}+1\right)^{0.5}\right] \tag{11}$$

where γ is a scalar parameter to be estimated, and where the transformation is symmetric around zero (so typically only nonnegative values of γ values are considered). The transformation is linear as γ approaches zero. For a wide range of values of γ, the transformation behaves logarithmically, as it does for large values of y. A major advantage of the IHS transformation is that it renders estimation on the transformed variable robust to non-normality of the original error terms. The IHS transformation has been used before in more simple models of charitable donations by, for example, Yen et al. (1997).

With this modification,

$$f(y_{it}\mid class=j,\mathbf{x}_{it},u_{i|j},\boldsymbol{\beta}_j,\sigma_j,\theta_j,\gamma_j)=\begin{array}{c}\left[\Phi\left(\dfrac{-\boldsymbol{\beta}'_j\mathbf{x}_{it}-\theta_j v_{i|j}}{\sigma_j}\right)\right]^{1-D_{it}}\quad\times\\ \left[\dfrac{J(y_{it},\gamma_j)}{\sigma_j}\phi\left(\dfrac{I(y_{it},\gamma_j)-\boldsymbol{\beta}'_j\mathbf{x}_{it}-\theta_j v_{i|j}}{\sigma_j}\right)\right]^{D_{it}}\end{array} \tag{12}$$

where $J(y_{it},\gamma_j)$ is the Jacobian of the transformation from $I(y_{it},\gamma_j)$ to y_{it},

$$J(y_{it},\gamma)=[1+(y_{it}\gamma_j)^2]^{-1/2} \tag{13}$$

We allow γ_j to vary across classes, as it is possible that different transformations are appropriate for the different sub-groups of the population. If the IHS parameters do vary across classes, this would suggest that using a single transformation for all households (as for example, in a simple log-tobit or double-hurdle approach) would be inappropriate.

The suggested extensions (heteroskedasticity, random effects and non-normality) are new to the literature of panel data latent class models. Allowing for unobserved heterogeneity significantly increases the complexity of the estimation. The random effects need to be integrated out of the likelihood function. The approach we take here to evaluate these integrals is to use simulation techniques, using 500 Halton draws. Train (2003) notes that the results based on 500 random draws were essentially identical to those using 100 Halton draws, suggesting that 500 Halton replicates is clearly sufficient. The simulated log likelihood with all extensions in place is

$$\text{LogL}_S = \sum_{i=1}^{N} \log \left\{ \sum_{j=1}^{J} p_{ij}(\boldsymbol{\phi}, \mathbf{z}_i) \left[\frac{1}{R} \sum_{r=1}^{R} \left(\prod_{t=1}^{T_i} f(y_{it} \mid j, \mathbf{x}_{it}, \mathbf{z}_i, v_{ir}, \boldsymbol{\beta}_j, \sigma_j, \boldsymbol{\delta}_j, \theta_j, \gamma_j) \right) \right] \right\} \tag{14}$$

where the simulation is over the R draws on v_{ir}. The simulated log likelihood is maximized using the BFGS (Broyden, Fletcher, Goldfarb, and Shanno) algorithm in NLOGIT 5.0.

Predictions and partial effects are complicated in this model by the presence of the IHS transformation. To assemble this, we note in general, the potentially interesting margin

$$\text{Prob}(y_{it} > 0 \mid class = j, \mathbf{x}_{it}, \mathbf{z}_i, u_i) = \Phi\left(\frac{\boldsymbol{\beta}_j' \mathbf{x}_{it} + \theta_j v_i}{\sigma_j} \right) \tag{15}$$

We will evaluate this probability at the household level, and expected value of v_i, zero. This is then averaged over the households. The expected donation given that the donation is positive is

$$E[y_{it} \mid y_{it} > 0] = \int_0^\infty y_{it} f(y_{it} \mid y_{it} > 0) dy_{it}$$

$$= \left[\Phi\left(\frac{\boldsymbol{\beta}_j'\mathbf{x}_{it}}{\sigma_{ij}}\right)\right]^{-1} \int_0^\infty y_{it} \left[\frac{J(y_{it},\gamma_j)}{\sigma_{ij}} \phi\left(\frac{I(y_{it},\gamma_j) - \boldsymbol{\beta}_j'\mathbf{x}_{it}}{\sigma_{ij}}\right)\right] dy_{it} \tag{16}$$

The unconditional expected donation is

E[y_{it}] = Prob(y_{it} = 0)×0 + Prob(y_{it} > 0)E[y_{it} > 0]

$$= \int_0^\infty y_{it} \left[\frac{J(y_{it},\gamma_j)}{\sigma_{ij}} \phi\left(\frac{I(y_{it},\gamma_j) - \boldsymbol{\beta}_j'\mathbf{x}_{it}}{\sigma_{ij}}\right)\right] dy_{it} \tag{17}$$

There are no closed forms for these integrals, so they must be approximated. We used the built-in Newton-Cotes method (rectangles with end-point correction). Partial effects of these conditional means also require integration. The derivatives of the integrals are simpler than it might appear at first, as in order to differentiate with respect to $\mathbf{x}_{it}$ and $\mathbf{z}_{it}$, it is only necessary to differentiate with respect to $E_{it} = \{[I(y_{it},\gamma_j) - \beta_j'x_{it}]/\sigma_{ij}\}$ and σ_{ij}. Partial effects are then multiples of these primitive derivatives. Standard errors for the partial effects are obtained by the delta method.

III. Data

We use data from the U.S. *Panel Study of Income Dynamics* (*PSID*), which is a panel of individuals ongoing since 1968 conducted at the Institute for Social Research, University of Michigan. As in Reinstein (2011), the sample used for the analysis comprises the *PSID* sample that was nationally representative in 1968. It should be acknowledged that the sample is no longer nationally representative given the changes in the composition of the U.S. population over time. Following Reinstein (2011), the results that we present here, however, do not make use of sampling weights given that their validity rests on a set of assumptions and, hence, arguably is open to debate.

In the *PSID* waves 2001, 2003, 2005, 2007 and 2009, there are a series of detailed questions relating to giving to charity. The definition of a charitable organization in the *PSID* includes ‘religious or non-profit organizations that help those in need or that serve and support the public interest’. It is clearly stated that the definition used does not include political contributions. Households are asked about total donations to charity over the respective calendar years. The mean (median) total value of donations in each of the calendar years are as follows: 2001, $1,181.2 ($160); 2003, $1,170.7 ($114.2); 2005, $1,467.9 ($248.2); 2007, $1,743.9 ($251.8), and 2009 $1,589.6 ($242.2) with the proportions of households who do not donate in each year being remarkably stable at 39 per cent, 42 per cent, 37 per cent, 39 per cent and 40 per cent, respectively. Note that for estimation purposes, donations were entered as a (variance-) standardised variable, and then for the analysis of results, converted back into dollar amounts.

The potential for recall error should be acknowledged given that households are asked to recollect their donating behaviour over the past year. However, Wilhelm (2006) explores the quality of the *PSID* data on charitable donations in terms of two dimensions: missing data and the amounts reported. He compares the *PSID* charitable donations data with data on charitable deductions from the Internal Revenue Service and finds that the reported amounts generally compare well across the data sources except above the 90th percentile. He thus confirms that the *PSID* data on charitable donations are ‘high quality.’ Indeed, as noted previously, the latent class approach adopted here, implicitly allows for such recall bias in any case.

We analyse an unbalanced panel of data, where, on average, households are in the panel for 3 waves and the minimum (maximum) number of waves is 1 (5). Following the existing literature (such as Auten et al., 2002), to avoid changes in income and in charitable donations being related to changes in household composition, households are only included in the sample if their marital status is unchanged over the period. Summary statistics are presented in Table 1, where, on average, the head of household has 12 years of schooling; 71 per cent are male; 48 per cent of household heads are born between 1950 and 1969; and 54 per cent are married or cohabiting. All monetary variables in the analysis are deflated to 2001 prices.

In our econometric framework, we include numerous explanatory variables, which have previously been employed in the literature (see, for example, Andreoni, 2006, and Auten and Joulfaian, 1996). In terms of those in the latent class component of the model, following Greene's (2012) suggestion, we include time invariant head of household characteristics: years of completed schooling; gender; the ethnicity of the head of household (where groups other than white form the reference category); religious denomination, that is, Catholic, Protestant or other religion (with no religious denomination as the omitted category); the natural logarithm of permanent income, which is defined as the average household income prior to the commencement of the estimation sample; and the following year of birth categories, born before 1940, born between 1940-49, 1950-59, 1960-69 and 1970-1979 (born after 1980 is our reference category).

The tobit part of the model is in line with much of the existing literature. Here we include the number of adults in the household, the number of children in the household, the age of the head of household, the employment status of the head of household and their spouse (with unemployed or not currently in the labour market as the reference category), the marital status of the head of household (with all states other than married or cohabiting as the base), the natural logarithm of the income of the head of household and their spouse, and the natural logarithm of household wealth (where we add one to household wealth in order to deal with the values of zero in the logarithmic transformation).

Finally, we also include the price of donating in the tobit model. In an early contribution, Schwartz (1970) analyses the price of donating to charity, which is determined by taxation, as income donated to recognised charities in the U.S. is not subject to income tax. As a consequence, disposable income falls by less than the full amount donated; the price of the donation becomes the donation net of the saving in tax since each dollar donated to a recognised charity leads to less than one dollar sacrificed for consumption purposes. U.S. tax laws do specify an upper bound to deductibility with a maximum deductible percentage of the income tax base: 50% of gross income in 2006. The extent of the tax saving is determined by the household's marginal tax bracket (Schwartz, 1970). In the context of the U.S., households that itemize deductions in their tax return reduce their taxable income in accordance with the level contributed to tax-exempt organisations. Hence, tax deductibility affects the price of donating to charity (Auten et al., 2002). Thus, we also control for the price of making a donation to charity.

For households who itemize charitable donations in their tax return, the price of the donation is defined as one minus the household's marginal tax rate on the contribution made, whereas for households who do not itemize charitable donations, the price of the donation is one; donating one dollar means that there is one dollar less for consumption.

One key advantage of the *PSID* is that it includes households which itemize charitable donations in their annual tax return as well as those who do not. Furthermore, in the *PSID*, households are asked to indicate whether or not they made an itemized deduction for charitable contributions. Households which itemize are assigned the relevant tax rate using the National Bureau of Economic Research (NBER) TAXSIM programme (http://www.nber.org/~taxsim/), which calculates federal state tax liabilities for survey data based on a range of factors such as earnings, marital status and children. The TAXSIM programme includes both state and federal law, which is important given for example changes in federal taxes in 2001, 2003 and 2004 during this period (see Backus, 2010, for recent discussion of the effects of these changes).

One issue, however, which has arisen in the existing literature, is that the decision to itemise is arguably not fully exogenous, that is, the decision to itemise may be influenced by the level of charitable donations. To account for this, as is common in the existing literature (see seminal contributions by Clotfelter, 1980, and Auten et al., 2002), we exclude ‘endogenous itemisers’ who are defined as those who have itemised but would not have done so in the absence of their actual charitable donations. In addition, in order to account for potential measurement error, a household is labelled as an itemiser only if the *PSID* and TAXSIM definitions coincide.

Due to an additional source of possible endogeneity relating to the price of a charitable donation being a function of both the donation and income, which has also been discussed extensively in the existing literature, following Auten et al. (2002), we calculate the price variable firstly by assuming that charitable donations equal zero (i.e. the first dollar price) and then after including a predicted amount of giving set at 1per cent of average income. As stated by Auten et al. (2002), p.376, ‘this procedure yields a tax price consistent with the actual costs of giving, but not endogenous to individual donation decision.’ Following the existing literature, we then take an average of the two price variables.

IV. Results

In this section, we discuss the results from estimating the panel latent class tobit model discussed in Section II above. Table 2 presents the results relating to the determinants of class membership. Out of the 10,002 total observations, 3,276 cases are predicted to be in class 1 and 6,726 in class 2, the sample proportions in each class being 0.3275 and 0.6725, respectively. Note that these class separations are based upon the estimated posterior probabilities (defined previously), as is common in the literature. Note also, that households are assigned to the class that gave them the maximum predicted (posterior) probability. In Table 2, we also present the (average) estimated probability of reporting zero donations in each class. Note that these are the average probabilities of zero-donation across classes once households have been assigned their respective classes.

From Table 2, there is a clear disparity between the probabilities of zero donations across the classes, with class 1 (at 0.0213) being considerably lower than class 2 (at 0.5964). We can use these findings, in part, to help us identify the two classes: so class 2 are clearly dominated by the observed zero givers. To paint a clearer picture of our findings, consider the results presented in Table 3. This table presents the results relating to the analysis of the determinants of the amount of donations. We will return to the estimated coefficients shortly, but for now will focus on the expected values, E(V), of donations. As before, we first split households into class 1 or 2, based upon their estimated posterior probabilities. Within each class, we then consider three expected values of charitable donations: the simple, unconditional, sample average of observed donations for these households; the averaged expected value of donations, conditional on observed personal and household characteristics; and finally the averaged expected value of donations, conditional both on observed personal and household characteristics and also that donations are positive.

From the unconditional expected values, it seems clear that class 1 contains “high” and class 2 contains “low” givers to charity. Average actual donations for the households predicted to be in classes 1 and 2 are $2,166 compared to $1,070. This clearly ties in with the findings presented in Table 2. Households predicted to be in class 1 have a very low probability of making zero donations and are predicted to donate, on average, much more than those predicted to be in class 2. This finding is reinforced when we evaluate the average expected value of the level of donations for each class, conditional on observed characteristics. These predicted expenditure levels are computed following the approach of Yen and Jones (1997) as described in Section II above. We now find that the average predicted level of donations amongst those predicted to be in class 1 is $1,553, almost four times as high as that of class 2, $377.

Finally, the predicted expected values, conditional on both characteristics and that donations are positive, further reinforce the findings that class 1 households are the high donators and class two the low ones. For class 1, this conditional expected value rises marginally (from $1,553 to $1,565) as there are very few predicted zero donators in this class. However, in class 2 the conditional predicted expected value almost doubles (from $377 to $706), as this class has considerably more zero-donators.

After summarising the results in general, we now turn our attention to the specific drivers of both class membership and donation levels.

Class Membership

As the coefficients in Table 2 correspond to class 1 membership (relative to class 2), these coefficients can be interpreted as follows: positive ones being associated with higher probabilities of being in class 1 (relative to class 2); and negative ones being associated with a higher probability of being in class 2. The results suggest that households with a male head are significantly more likely to be in class 2, the low donating group characterised by a relatively high probability of making zero donations, than households with a female head (at the 10% level), which ties in which the existing literature. Life cycle effects are also evident with the likelihood of being in class 1 (relative to class 2) monotonically decreasing in the decade of birth of the head of household, with households with older heads, therefore, more likely to be in class 1, the group of households which is characterised by a relatively low probability of making zero donations. Once again, this finding ties in with the existing literature.

Education and ethnicity of the head of household are also clearly significant predictors of class membership, with the years of schooling of the head of household and having a white head of household being positively associated with being in class 1 (the high donators group). Noticeably, the permanent income of the household has no significant influence upon class membership. Interestingly, having a household head in a Protestant religious denomination is positively associated with being in class 1, whilst being in a Catholic religious denomination is positively associated with being in class 2, thereby highlighting the importance of distinguishing between different religious denominations in modelling donations to charity.

Total Donations to Charity

The results from modelling the level of total household donations via an IHS random effects tobit specification for each predicted class for all households are presented in Table 3, where the coefficients are reported by class. It is apparent that there is no role for household composition either through the number of adults or the number of children. Households comprising a married head of household donate larger amounts. Whether the head of household is employed is also associated with larger donations. Income is found to be positively related to the level of the donation across both classes, a finding consistent with Auten et al. (2002). This is also the case for the level of household wealth. Interestingly, and as commonly found in panel data studies of donations, the price of donating is statistically insignificant. Our findings thus accord with recent studies such as Fack and Landais (2010) who report a relatively small price elasticity for France. Finally, there is no evidence of life cycle effects on the level of the donation as the effects of the age of the head of household are small in magnitude and generally statistically insignificant.

In terms of our ancillary parameters, importantly we find strong evidence of heteroskedasticity, with the variance decreasing with both wealth and income in class 1 (significant at the 5% and 10% levels, respectively). In class 2, the heteroskedastic effects are less pronounced, but the variances still (significantly) decrease with income. This evidence of heteroskedasticity highlights the importance of extending the modelling framework to deal with this issue. Random effects are also significantly present in both classes, and of a similar magnitude, therefore strongly indicating the presence of unobserved heterogeneity and endorsing this novel extension to the modelling framework. Both IHS parameters are significantly different from zero suggesting that a linear approach is clearly inappropriate and that the standard untransformed tobit model, for example, would be mis-specified. Interestingly, these parameters vary quite markedly across classes. This finding suggests that using a *single* transformation for all households, as, for example, in a simple (log) tobit or double-hurdle approach, would also be mis-specified.

Table 4 presents the marginal effects, which are computed separately for each class. For each class we present three sets of marginal effects based on the posterior probabilities of class membership: those relating to the probability of making a positive donation (averaged over households within each class), those relating to the overall expected value of donations (calculated at the means of the explanatory variables within the respective samples), and finally those related to the expected value of donations conditional on a positive value of such (again calculated at the means of the two samples).

In terms of the probability of making positive donations, focusing initially on class 1, it is apparent that the results generally accord with the existing literature with households with older and married heads in class 1, the high donating class, being more likely to make positive donations. The income effects are also statistically significant and positive for class 1. Interestingly, wealth is characterised by the largest marginal effect, around three times larger than income, indicating a positive influence on making a positive donation for the high donators group. The price effects are statistically insignificant, which is in line with the existing panel data studies on charitable donations. Turning to class 2, the low donators group with the associated higher number of zero-donators, it is apparent that all of the marginal effects are predominantly larger in this group, although the effects appear to have been rather imprecisely estimated.

With respect to the marginal effects for the overall expected value of donations, it is apparent that for class 1, the high donators group, having a married head of household and the head of household's age both have relatively large positive effects on the predicted level of donations. Income and wealth are also positively associated the amount of donations albeit with smaller influences. Again, in accordance with the existing literature, the effect of the price is statistically insignificant.

This pattern of results in terms of statistical significance, sign and magnitude is also apparent in the marginal effects for the expected value of donations conditional on the households in class 1 who make non-zero donations. For example, evaluating the effect of a 1 per cent increase in wealth, the expected value of donating (conditional upon donating) increases by \$0.31. Note that as discussed in Section III, the data are standardised by the standard deviation of donations, \$3,632, see Table 1. To calculate the impact of wealth upon the expected value of donations, conditional on being in class 1, the marginal effect is thus multiplied through by the standard deviation and divided through by 100 (since wealth enters into the model in natural logarithms and the dependent variable is not logged); that is, (0.0084×3,632)÷100.

For class 2, the low donators group, the pattern of the marginal effects is similar to those of class 1 for the overall expected value of donations across all households predicted to be in class 2, with, for example, positive income and wealth effects. After conditioning on making non-zero donations, there are some noticeable differences in the marginal effects in terms of changes in sign relating to the effects of having a married head of household, an employed head of household and income. The effects are relatively small: for example, those households with a head who is an employee or self employed and who make positive donations give $13 less over the calendar year than those households with a head of household who is not in employment.

V. Conclusion

In this paper, we make both a methodological contribution to the latent class literature as well as contributing to the existing literature on modelling charitable donations. Our methodological contribution to the panel application of latent class models is threefold. Firstly, we have extended the standard panel data approach to include random effects in the tobit equations of this overall model. Secondly, we have allowed for heteroskedasticity (which if not accounted for when present, would result in biased and inconsistent parameter estimates). Thirdly, we have incorporated the Inverse Hyperbolic Sine (IHS) transformation of the dependent variable into our latent class approach. The advantage of the IHS approach is that the resulting estimator is robust to non-normality in the original (untransformed) variable.

We have applied this new latent class framework to the modelling of donations to charity, an interesting application because of the potential for distinct groups of households in the population to have quite divergent behaviour with respect to their donating behaviour. Our findings, which are based on U.S. panel data drawn from five waves of the Panel Study of Income Dynamics, indicate that there are, indeed, two clearly defined groups of charitable donors: one which gives much more, and has an associated much lower probability of zero-donation; and the other, which donates much less and has a much higher probability of donating nothing. This suggests that treating the population as a single homogeneous group of donors, could well lead to biased parameter estimates and erroneous policy inference.

There was clear evidence of heteroskedasticity, which varied according to both wealth and income levels. Random effects were also found in both classes, and of a similar magnitude across classes. Both IHS parameters were significantly different from zero suggesting that a linear approach is clearly inappropriate and that the standard untransformed tobit model would be mis-specified. As the IHS parameters varied quite dramatically across classes, this suggests that using a single transformation for all households, as, for example, in a simple (log) tobit or double-hurdle approach, would also be inappropriate. Ignoring of any of these issues in estimation, could well have led to biased and inconsistent parameter estimates thereby endorsing the importance of our three extensions to the latent class tobit model.

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TABLE 1: Summary Statistics

	MEAN	STANDARD DEVIATION
Total Donations (2001 prices)	$1,429	$3,632
Head of Household Characteristics		
Years of Schooling	12.81	3.43
Male [0/1]	0.71	0.45
White [0/1]	0.63	0.48
Catholic [0/1]	0.17	0.37
Protestant [0/1]	0.52	0.50
Other Religion [0/1]	0.03	0.18
Born <=1940 [0/1]	0.04	0.19
Born 1940-49 [0/1]	0.11	0.32
Born 1950-59 [0/1]	0.24	0.43
Born 1960-69 [0/1]	0.24	0.43
Born 1970-79 [0/1]	0.23	0.42
Age	45.48	20.07
Employee or Self Employed [0/1]	0.75	0.43
Spouse Employee or Self Employed [0/1]	0.33	0.47
Married or Cohabiting [0/1]	0.54	0.50
Household Characteristics		
Number of Adults [1+]	1.87	0.78
Number of Children [0+]	0.92	1.16
Log Income of Head and Spouse (2001 prices)	10.44	1.08
Log Permanent Income (2001 prices)	9.13	1.14
Log Wealth (2001 prices)	1.71	3.11
Price	0.77	0.08
OBSERVATIONS	10,002	

TABLE 2: Estimates of the Determinants of Class One Membership

	COEF	*S.E.*
Intercept	-7.0569	*0.5823******
Years of Schooling	0.3625	*0.0251******
Male	-0.2514	*0.1338***
White	0.3341	*0.1081******
Catholic	-0.3310	*0.1727*****
Protestant	0.3550	*0.1095******
Other Religion	0.2888	*0.2618*
Log Permanent Income	-0.0141	*0.0419*
Born <=1940	3.2892	*0.3283******
Born 1940-49	2.6315	*0.2559******
Born 1950-59	2.3394	*0.2378******
Born 1960-69	1.3935	*0.2333******
Born 1970-79	0.6752	*0.2359*****
Proportion predicted in Class 1 (p_1)		0.3275
Proportion predicted in Class 2 (p_2)		0.6725
Probability of Class 1 – Zero donations		0.0213
Probability of Class 2 – Zero donations		0.5670
TOTAL OBSERVATIONS		10,002

Notes: ***significant at the 1% level; **significant at the 5% level; and *significant at the 10% level. COEF denotes estimated coefficient and S.E. denotes standard error.

TABLE 3: Random Effects Latent Class Tobit Model

	CLASS 1		CLASS 2	
	COEF	*S.E.*	COEF	*S.E.*
Intercept	-0.1121	*0.0266****	-0.8531	*0.0571****
Married or Cohabiting	0.0729	*0.0095****	0.0728	*0.0076****
Number of Adults	0.0018	*0.0020*	-0.0038	*0.0041*
Number of Children	-0.0008	*0.0015*	-0.0013	*0.0024*
Employed	0.0162	*0.0026****	0.0176	*0.0062***
Spouse Employed	-0.0040	*0.0028*	-0.0010	*0.0055*
Log Wealth	0.0022	*0.0004****	0.0071	*0.0009****
Log Income	0.0204	*0.0024****	0.0718	*0.0044****
Price	0.0013	*0.0109*	0.0249	*0.0284*
Age	-0.0006	*0.0003**	0.0003	*0.0006*
Age Squared /100	0.0005	*0.0003**	-0.0001	*0.0005*
σ	0.3534	*0.0628****	0.3399	*0.0552****
Log Wealth (Heteroskedasticity)	-0.0111	*0.0061**	0.0037	*0.0058*
Log(Income) (Heteroskedasticity)	-0.2075	*0.0169****	-0.0918	*0.0149****
γ (IHS)	14.2604	*1.3955****	11.0396	*0.7088****
θ (RE)	0.0744	*0.0079****	0.0771	*0.0060****
E(V) Class *j*(unconditional)	$2,166		$1,070	
E(V) Class *j* (conditional)	$1,553		$377	
E(V) Class *j* (conditional); Positive donators	$1,565		$706	
Log Likelihood	-6,1107.304			
OBSERVATIONS	10,002			

Notes: ***significant at the 1% level; **significant at the 5% level; and *significant at the 10% level. COEF denotes estimated coefficient and S.E. denotes standard error.

TABLE 4: Random Effects Latent Class Tobit Model – Marginal Effects

PANEL A: CLASS 1

	$Prob(d > 0 \mid class\ 1)$		$E[d]$		$E[d \mid d > 0]$	
	M.E.	*S.E.*	M.E.	*S.E.*	M.E.	*S.E.*
Married or Cohabiting	0.0080	*0.0040***	0.3492	*0.0253****	0.3363	*0.0243****
Number of Adults	0.0002	*0.0002*	0.0087	*0.0053*	0.0083	*0.0051*
Number of Children	-0.0001	*0.0001*	-0.0038	*0.0034*	-0.0037	*0.0033*
Employed	0.0018	*0.0009***	0.0774	*0.0098****	0.0746	*0.0096****
Spouse Employed	-0.0005	*0.0003*	-0.0192	*0.0071***	-0.0185	*0.0068***
Log Wealth	0.0091	*0.0040****	0.0094	*0.0012****	0.0084	*0.0012****
Log Income	0.0030	*0.0012***	0.0749	*0.0079****	0.0613	*0.0076****
Price	0.0001	*0.0009*	0.0060	*0.0400*	0.0058	*0.0385*
Age	0.0023	*0.0005****	0.2107	*0.0775****	0.2030	0.0746**
OBERVATIONS	3,276					

PANEL B: CLASS 2

	$Prob(d > 0 \mid class\ 2)$		$E[d]$		$E[d \mid d > 0]$	
	M.E.	*S.E.*	M.E.	*S.E.*	M.E.	*S.E.*
Married or Cohabiting	0.0614	*0.1130*	0.0390	*0.0027****	-0.0149	*0.0010****
Number of Adults	-0.0032	*0.0062*	-0.0020	*0.0015*	0.0008	*0.0006*
Number of Children	-0.0011	*0.0025*	-0.0007	*0.0008*	0.0003	*0.0003*
Employed	0.0148	*0.0268*	0.0094	*0.0027****	-0.0036	*0.0010****
Spouse Employed	-0.0009	*0.0036*	-0.0006	*0.0020*	0.0002	*0.0008*
Log Wealth	-0.0072	*0.0088*	0.0042	*0.0004****	-0.0007	*0.0007*
Log Income	0.0612	*0.1088*	0.0289	*0.0018****	-0.0336	*0.0021****
Price	0.0210	*0.0422*	0.0007	*0.0122*	-0.0003	*0.0046*
Age	-0.0067	*0.0065*	-0.0053	*0.0200*	0.0020	*0.0076*
OBERVATIONS	6,726					

Notes: M.E. denotes marginal effect; and S.E. denotes standard error. ***significant at the 1% level; **significant at the 5% level; and *significant at the 10% level