Sheffield Economic Research Paper Series

SERP Number: 2010017

ISSN 1749-8368

Sarah Brown, Mark N. Harris and Karl Taylor

Modelling charitable donations:
A latent class panel approach

September 2010

Department of Economics
University of Sheffield
9 Mappin Street
Sheffield
S1 4DT
United Kingdom
www.shef.ac.uk/economics

Abstract:

We apply a latent class tobit framework to the analysis of charitable donations at the household level where the latent class aspect of the model splits households into two groups, which we subsequently interpret as "low" donators and "high" donators. Then the tobit part of the model explores the determinants of the amount donated by each household conditional on being in that class. We consider both total donations and also separately religious donations. Our findings, which are based on US panel data, suggest that price and labour income elasticities differ substantially across the two classes. The inverse price effect is most pronounced for the "low" donators group for both total and religious donations. The labour income elasticity switches direction of influence upon charitable donations across the two latent classes with a negative influence for the "high" donators group and a positive influence for the "low" donators group, for the case of total donations to charity, a pattern which is reversed in the case of solely religious donations.

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

JEL Classification: D19; H24; H41; H31

Acknowledgements: We are grateful to the Institute for Social Research, University of Michigan for supplying the *Panel Study of Income Dynamics* 1968 to 2007. We are very grateful to Andy Dickerson and Arne Risa Hole for valuable advice. The normal disclaimer applies.

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 US (see, for example, Andreoni, 2006). Given the level of charitable donations in the US, such interest is not unexpected: for example, in 2005, individuals in the US donated more than 260 billion dollars to charity, with 70-80% of individuals in the US making annual contributions to at least one charity (Chhacochharia and Ghosh, 2008).

Empirical analysis of charitable donations has been conducted over the last four decades, which have witnessed methodological advances with respect to econometric techniques as well as increased availability and quality of data. Over this time period, the econometric methodology has increased in sophistication with the early studies adopting a 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.

One problem with the tobit approach, which has been adopted by a number of empirical studies of charitable donations including Kingma (1989) and Auten and Joulfaian (1996), however 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, which allows independent variables to have different effects on the probability of making a donation and the level of donation. Such an approach allows for a two stage decision-making process. Each individual decides whether to donate and, conditional on the decision to donate, then decides how much to donate, where there is potential correlation between the two decision-making processes (see, for example, Yen et al., 1997). An alternative approach taken by Smith et al. (1995) to account for the two levels of decision-making is the Heckman (1979) two-step estimator.

One issue related to such two part models, however, concerns the sharp distinction between participants and non-participants, i.e. those who donate and those who do not donate. Another issue is that it is preferable to identify both parts of the model via exclusion restrictions on data. However, it is often the case that it is difficult to envisage variables that will affect the participation decision and not the amount decision, and *vice versa*. A recent strand of the econometric literature has used latent class models as a means to distinguish between different types of individuals, where the distinction between groups is made on a more flexible basis than in the two part framework. That is, in the double-hurdle framework, there are only two sub-groups of the population identified (participants and non-participants). However, in the latent class framework, there are potentially an infinite number of population sub-groups which can be identified.

In the health economics literature, the latent class framework has been used to distinguish between health groups with high average demand and low average demand for health care (see, for example, Deb and Trivedi, 1997, and Bago d'Uva, 2005). Deb and Trivedi (2002) contrast a two part model that distinguishes between users and non-users of health care with a latent class model that distinguishes between frequent and infrequent users. The findings, which are based on analysis of the RAND Health Insurance Experiment, indicate that individuals in the frequent and infrequent user latent classes can be described as being ill and healthy, respectively.[1] Other areas in which the latent class framework has been applied include consumer behaviour (see, for example, Reboussin et al., 2008, and Swait and Adamowicz, 2001) and transport mode choice (see, for example, Shen, 2009).

In this paper, we apply a latent class tobit framework to the analysis of charitable donations at the household level using US panel data, where the latent class aspect of the model splits households into two groups, which we subsequently interpret as "low" donators and "high" donators. Then the tobit part of the model explores the determinants of the amount donated by each group conditional on being a member of a particular class.

The application of the latent class approach seems well-suited to the analysis of donations since it allows a flexible approach to the analysis of the donating behaviour of individuals and households. In general, latent class models enable us to relatively easily incorporate increased heterogeneity into our empirical models. And then, dependent on the estimation results, they allow for a convenient "labelling" of the classes. Thus, with regard to modelling charitable donations, they appear extremely well-suited as there are undoubtedly several sub-groups of the population with regard to giving behaviour. At the extreme, following a hurdle-type approach, there would simply be "participants" ("givers", or at least potential givers), and "non-participants" (or "non-givers"). However, a much richer characterisation would split the population into "high" and "low" donators (or even more sub-groups). In this way, the non-participants in a hurdle-type setting would necessarily fall into the latter. And now, in the latent class framework, these different classes are allowed to react quite distinctly to the same personal and economic environment. Such class membership is not likely to vary

[1] Jimenez-Martin et al. (2002), however, highlight one particular disadvantage of the latent class approach, which concerns the fact that it is determined by statistical reasoning rather than, in the case of the two part model, being an extension of an economic model such as the principal-agent framework.

significantly over time, especially over the relatively short time scale over which our data is observed, and also we have appropriate (predominantly time-invariant) characteristics by which to parameterise such membership.[2]

In terms of policy aimed at increasing charitable donations, the latent class approach is especially illuminating. If the estimation procedure does, indeed, identify "high" and "low" givers (or indeed, more groups) then effective policy can be targeted at the "high" class of givers. Moreover, say, for example, that the effect of the price of donating on the amount of donations was strong for the low class, but weak or absent for the high class, then this would suggest that a price-based policy may be relatively ineffectual in terms of influencing the overall level of donations.

We analyse both total donations to all charities and separately donations to religious ones (which account for the highest proportion of total donations) in order to ascertain whether our results are sensitive to the type of charitable cause. The majority of existing supply-side empirical studies explore the determinants of total donations to charity at the individual or household level without separately modelling donations made to different types of charity, which may reflect data shortages in this area. It is apparent that, however, as argued by Karlan and List (2007), p.1791, 'perhaps the nature of an organization's activities influences whether donors contribute to gain "moral satisfaction" or to increase the provision of the public good.' Hence, it may be the case that the motivation behind charitable donations and the level of donation may reflect the type of activity associated with the charitable organization.

Finally, as a point of comparison, we also estimate more "standard" models of charitable giving: namely a random effects tobit model and a double-hurdle model. Even though the latent class approach is much less parsimonious than these, it still

[2] It should be acknowledged however that unexpected and/or significant events such as a death in the family or divorce may lead to changes in donating behaviour.

clearly dominates with regard to the information criteria metrics. Thus, we would conclude that our approach is preferable on both *a priori* and statistical grounds. This finding also suggests that policy based on the results where such inherent classes are not allowed for (that is, the tobit and double-hurdle approaches), may be misleading.

II. Econometric Framework: A Latent Class Tobit Model

The hypothesis is that there are inherently two main types of charity donators in the population: “high” and “low” givers. The latter are more likely, for example, to be more 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 (see Greene, 2008, for example). Essentially such approaches implicitly assume that the observed data are drawn from a distinct mix of underlying populations. However, 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 survey of this area), we treat this as a corner solution model, such that we need to employ censored tobit model techniques to take into account the quite significant amount of censoring at zero (Maddala, 1983). In our case the censoring amounts to 43% of observations.

Thus, the set-up we adopt is a latent class tobit model. This approach amounts to first (probabilistically) splitting the sample into two populations (which, prior to estimation we envisage to correspond to “high” and “low” donators); and then for each of these populations separate tobit models apply. In this way, the same explanatory variables in the tobit equation (or “amount of giving” equation) can have differing effects across the different classes (for example, as noted above, price).

The probabilistic splitting of the sample is based on a Multinomial Logit specification (MNL), which can be either a constant across households, or allowed to be a function of observed household and head of household characteristics z_i with associated coefficients ϕ. It is possible to allow for a theoretically large number of such latent classes. However, we restrict ourselves here to just two-classes, as any further number of classes yields an overly heavily parameterised model, and one that is difficult to interpret.[3]

Finally, we have panel data. In the existing literature, the majority of studies of charitable donations at the individual and household level have been based on cross-section data. One important exception is Auten et al., (2002), who exploit a 12 year panel of individual tax returns collected by the US Internal Revenue Service to analyse charitable giving within a lifecycle context.[4] As Greene (2008) points out, the availability of panel data significantly aids in the identification of latent class models. Indeed, following Greene (2008), we parameterise our model such that (largely) time-invariant head of household characteristics 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), determining the amount of giving within each class. In effect, this amounts to parameterising the household's "fixed effect" of being in each class. Let x_{it} be the vector of explanatory variables determining the *level* of donations, and let there be $j = 1, \ldots, J$ latent classes (in our case, J = 2), then there will be J parameter vectors β_j associated with x_{it} in the different classes. Post

[3] Indeed, convergence problems were encountered in the case of the three-class model, clearly indicating that this was an over parameterised model.
[4] One drawback of this panel data source however relates to the fact that the sample is restricted to those tax payers who itemised deductions since there is no information on donations for non-itemisers. Consequently, sample selection bias is a possibility. Within a less general context, Okunade et al. (1994), who analyse a specific type of donation, university alumni giving, also exploit individual level panel data. Panel data has also been analysed within the context of charity level data, see, for example, Khanna et al. (1995) for the UK and Ribar and Wilhelm (2002) for the US.

estimation, based on the estimated β_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. Thus, for a typical group of T_i observations, the joint density of the sequence of y_i is

$$f\left(y_{i1}, y_{i2},\ldots, y_{iT_i} \middle| class = j, x_{it}, \beta_j\right) = \prod_{t=1}^{T_i} f\left(y_{it} \middle| class = j, x_{it}, \beta_j\right) \quad (1)$$

where $f\left(y_{it} \middle| class = j, x_{it}, \beta_j\right)$ is given by the standard tobit formulation (Maddala, 1983). Thus, the overall log-likelihood for a latent class panel of data on charitable donations will be

$$\log L = \sum_{i=1}^{N} \log\left[\sum_{j=1}^{J} p_{ij}\left(\phi, z_i\right) \prod_{t=1}^{T_i} f\left(y_{it} \middle| class = j, x_{it}, \beta_j\right)\right] \quad (2)$$

where $p_{ij}\left(\phi, z_i\right)$ are the MNL probabilities of being in class *j*:

$$p_{ij}\left(\phi, z_i\right) = \frac{\exp\left(z_i'\phi_j\right)}{\sum_{j=1}^{J}\exp\left(z_i'\phi_j\right)} \quad (3)$$

with $\phi_J = 0$ for identification. Note that all parameters of the model, *i.e.*, those in the MNL model determining class membership, and those in the multiple tobit equations, are all jointly estimated.[5] 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 data, probabilities of (Greene, 2008):

[5] Indeed, this must be the case, as we do not observe class membership.

$$P\left(class = j \mid \text{observation } i\right) = \frac{f\left(\text{observation } i \mid \text{class} = j\right) P\left(class\ j\right)}{\sum_{j=1}^{J} f\left(\text{observation } i \mid \text{class} = j\right) P\left(class\ j\right)}$$

$$= \frac{f\left(y_{i1}, y_{i2}, \ldots, y_{iT_i} \mid x_{it}, \beta_j\right) p_{ij}\left(z_i, \phi\right)}{\sum_{j=1}^{J} f\left(y_{i1}, y_{i2}, \ldots, y_{iT_i} \mid x_{it}, \beta_j\right) p_{ij}\left(z_i, \phi\right)}. \tag{4}$$

III. Data

We use data from the US *Panel Study of Income Dynamics* (*PSID*), which is a representative panel of individuals ongoing since 1968 conducted at the Institute for Social Research, University of Michigan.[6] In the *PSID* waves 2001, 2003, 2005 and 2007, there are a series of detailed questions relating to giving to charity.[7] 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 is as follows: 2001, \$38.5 (\$100.5); 2003, \$37.7 (\$103.5); 2005, \$52.9 (\$165.7); and 2007, \$51.9 (\$175.9), with the proportions of households who do not donate in each year being remarkably stable at 44%, 45%, 41% and 42%, respectively. We analyse an unbalanced panel of data, where, on average, households are in the panel for 3 waves, where the minimum (maximum) number of waves is 1 (4). Figure 1 (2) presents the distributions of the natural logarithm of the total amount donated to all charities (religious charities) over the period for all households and for those who donate.[8,9] The distributions are also decomposed by the gender of the head of household. Summary statistics are presented

---

[6] 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. Wilhelm et al. (2008) use the 2001 wave in the *PSID*, as a cross-section, to explore the relationship between the generosity of parents and the generosity of their adult children. Their findings suggest a positive correlation between charitable giving of parents and their children.

[7] 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.

[8] For households reporting zero donations, the value of the natural logarithm of donations is recoded to zero, as there are no reported donations between zero and unity.

[9] Total donations and religious donations are highly positively correlated at 0.791, suggesting that they are complements.

in Table 1, where, on average, the head of household has 12 years of schooling; 70% are male; 24% are aged 40-50; and 50% are married or cohabiting.

In our econometric framework, we include numerous explanatory variables, which have previously been employed in the literature (see, for example, Andreoni 1996 and Auten and Joulfaian, 1996). In terms of the explanatory variables in the latent class component of the model, following Greene (2008), we include (largely) 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, i.e. catholic, protestant and other religion (with no religious denomination as the omitted category); and the following age categories, less than 30 years, 30-39 years, 40-49 years, 50-59 years (above 60 years is our reference category).

Turning to the tobit part of the model, 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; whether the head of household is currently employed or self-employed (unemployed or not currently in the labour market is the reference category); marital status of the head of household (with all states other than married or cohabiting as the base); the natural logarithm of household labour income; the natural logarithm of household wealth; the natural logarithm of household non-labour income (including benefit income); and year dummy variables.

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 US 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.[10] The extent of the tax saving is determined by which marginal tax bracket the individual is in (Schwartz, 1970). In the context of the US, individuals who 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.[11]

We conduct our analysis for total donations to charity and for religious donations only. In addition, we also split the analysis by gender of the head of household in order to explore differences in donating behaviour across males and females.[12] For example, Schokkaert (2006) finds that households with a female head are expected to give more. Indeed, we do find interesting differences across these respective latent class specifications, justifying the increased flexibility that it affords.

IV. Results

Table 2 reports the results of the determinants of class membership and Table 3 reports the (average) expected value of donations within each class (Greene, 2008) denoted by E(V). This is shown for both total donations and religious charitable donations and is also decomposed by gender of the head of household. From these expected values (see

[10] US tax laws specify an upper bound to deductibility with a maximum deductible percentage of the income tax base: 50% of gross income in 2006.

[11] In the *PSID*, households are asked to indicate whether they made an itemized deduction for charitable contributions. Hence, for these households the price of making a donation is less than one, which is the price of donating for those households who did not itemize such donations. Households which itemize are assigned the relevant tax rate using the 'Tax Table' from Internal Revenue Service (US Department of the Treasury) website, http://www.irs.gov, conditional upon total pre tax family income and marital status.

[12] See Yörük (2010) for a comprehensive analysis of the implications of gender differences and household bargaining for charitable donations.

Table 3), it is clear that in each case class 1 are “high” and class 2 “low” givers to charity. In each case we also report the average *ex post* probabilities of being in each class (see Table 2). Again, in each case we can see that probabilities of being in class 2 (or “low” donators), outweigh those of being in class 1. One interpretation of this is that we estimate that most of the population are “low” donators, which is consistent with the means of the donations being less than the medians as detailed in Section III.

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. We can see that there is evidence of both gender and life cycle effects, the latter being particularly evident for households with heads under the age of 40. Interestingly the results suggest that households with a male head, for example, are significantly more likely to be “high” givers than female headed households (although this is not true of the *level* of the donation, see below). Education and religion of the head of household are also clearly significant predictors of class membership for both overall donations and contributions to religious causes only.

Total Donations to Charity

As previously noted, the (average) expected values of donation levels for each class are reported in Table 3. Clearly, the expected value for class 1 (those households subsequently labelled as the “high” contributors group) is considerably larger than that for class 2, at \$122.73 versus \$2.41 (see Table 3).

Having estimated the prior probability for class membership in Table 3, the (log) level of total household donations is modelled via a tobit specification for each predicted class, for all households and also decomposed by gender of the head of household. The column entitled “T.M.E.” gives the overall marginal effect, i.e. across all classes.[13] Coefficients and marginal effects are also reported for each covariate by class.

Due to the possible endogeneity of the price of a donation, which has been discussed in the existing literature (see, for example, Yörük, 2009) following Andreoni (2006), the last dollar tax price is instrumented using the first dollar tax price of donating and household fixed effects. Following Rivers and Vuong (1988), we controlled for potential endogeneity by additionally including the residuals from the first stage regression in the tobit model. However, this procedure did not influence the findings; hence, all results which follow are based upon the last dollar price.[14]

Focusing upon the overall sample, labour income is found to be positively related to the level of the donation, a finding consistent with Auten et al. (2002). Specifically, a one percent increase in labour income is associated with a 0.03 per cent increase in the level of the donation. However, decomposing the marginal effect into the two predicted classes, we find that for class 1, the “high” donators, there is a significant negative inelastic association with the level of the donation, whilst for class 2, the “low” givers, labour income has a positive inelastic association with charitable contributions. Upon decomposing the analysis by gender of the head of household, it becomes clear that this is driven by female headed households, since the direction of the impact of labour income across the classes is unchanged for male headed households.

There are clearly large price effects: the level of the donation is strongly inversely related to the price, which is consistent with the existing literature (see, for example, Glenday et al., 1986). However, it is apparent that those households who are

---

[13] Calculated as probability weighted class specific marginal effects, T.M.E. = $p_1 \times \text{M.E}_1 + p_2 \times \text{M.E}_2$, where p_1 and p_2 are prior probabilities.

[14] The results based on the instrumented price variable are available on request.

in the "high" donator class are far less sensitive to price changes than the corresponding households in the "low" donator class. This is also evident when the sample is decomposed by gender of the head of household, although the price elasticities estimated for female headed households dominate in terms of magnitude.

It is clear from Table 3 that, regardless of class membership, there are gender differences in the level of donations a finding which is consistent with the existing literature, see, for example, Andreoni (2006), with female headed households donating a larger amount on average than their male headed counterparts.

Total Donations to Religious Causes

As with total donations, the expected value for religious donations is lower for those households assigned into class 2 (hence labelled the "low" donator group) at $1.23 compared to an expected value of $18.73 for class 1 (the "high" donator group of givers), see Table 4.

In Table 4 we present the results for religious charitable donations having estimated the prior probability of class membership (see Table 2), where the table has the same structure as Table 3. Similar price and labour income effects are found as in the case of overall donations, whereby there are clear differences between the two types of giver. Interestingly, for each class and across gender of the head of household, overall donations have grown over time. However, this is not evident of religious donations where there is no overall time effect and the only evidence of growth is within the "high" donators class, an effect which is driven by the trend in donations made by male headed households to religious causes.

There is no overall role for household composition either through the number of adults or the number of children, which is consistent with the findings in Table 3. One noticeable difference is that the more children the head of household has the lower is the level of overall (religious) charitable donations for the "low" ("high") donator class members. In accordance with the findings of Yörük (2010), households with married heads, where arguably joint donation decisions are made, donate larger amounts and this is an effect over and above income, i.e. this is not due to the fact that households with a married head potentially have higher income. Interestingly, the influence of marital status upon religious charitable donations is larger for those classified into "low" givers. Moreover, those male heads of household assigned to the "low" donators group, who are married, donate more than double their single counterparts. Splitting the sample by gender reveals that, across the two classes, female headed households have higher average expected donations, which ties in with the existing literature.

Comparison to Alternative Estimators

As discussed in Section I, the existing empirical literature on charitable donations has generally been based on the tobit framework or the double-hurdle approach. The use of the latent class approach was motivated in this paper on the basis of the flexibility that it provides and its ability to identify "high" and "low" donators. This latter point may be especially pertinent from a policy perspective, since socio-economic factors are allowed to have differential impacts across the different groups of donators. It is interesting therefore to compare the results from the latent class framework with those from tobit and double-hurdle specifications in order to ascertain the potential contribution made by applying the latent class approach to the modelling of charitable donations.

In Table 5, the results from estimating a standard random effects tobit model for total donations and religious donations for the sample of all individuals are presented. For each type of donation, two sets of estimates are reported: firstly, including all covariates that were used in the latent class model; and secondly, including only those covariates that affect the level of the donation (i.e. the covariates in the tobit part of the latent class model). In Table 6, the results from adopting a double-hurdle approach to model total donations and religious donations are presented, relating to both the probability of donating and the level of the donation, where the probability of donating is modelled based on the covariates used in the latent class part of the latent class tobit model and the amount of the donation is modelled based on the covariates used in the tobit part of the model. We also compare the various models in terms of their overall statistical performance. In Table 7 the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) statistics are reported for the latent class tobit, the random effects tobit and double hurdle models. Both statistics reveal that statistically the latent class tobit estimator is the preferred approach for modelling both total charitable donations and those donations to religious causes only. Thus, the relative statistical performance of the models endorses our modelling strategy and casts some doubt on the approaches traditionally employed in this area.

Turning to the estimated parameters and their economic intuition, in contrast to the results from the latent class model, the tobit estimates reveal no gender effect for either overall charitable donations or religious donations. In general, the tobit and double-hurdle results are roughly consistent with the "low" donator estimates from the latent class model, which accords with expectations since this group dominates in probabilistic terms. There are instances however of different signs in some cases: for example, the influence of labour market status in the case of religious donations. Such findings suggest that results based on the tobit and double-hurdle approaches may not adequately reflect the determinants of donating behaviour of the "high" donator group. Moreover, these findings also suggest that policy based on such double-hurdle and/or tobit results could be inappropriate.

Moreover, the tobit and double hurdle approaches do not allow covariates to have different effects across the latent groups, which is potentially important. For example, the results from the latent class framework suggested that, although total donations were inelastic with respect to labour income, the direction of influence differed across the "high" and "low" givers. In terms of policy, the latent class results suggest that a price-based policy based on tax incentives may not be particularly effective since the price elasticity of donating is much stronger for the "low" donator class. It should be acknowledged, however, that the amount donated by the "high" donator group is considerably larger than that donated by the "low" donator group. Hence, the weaker price elasticity of the "high" donator group may still be associated with a relatively large level of donations.

V. Conclusion

In this paper we have applied a panel latent class tobit model to the analysis of donations to charity at the household level. Somewhat surprisingly, the latent class approach has not yet been applied to the analysis of donations to charity in the existing literature despite the flexibility of this approach. This econometric framework is such that the latent class aspect of the model splits households into two groups, which can subsequently be interpreted as "low" donators and "high" donators and the tobit part of the model explores the determinants of the amount donated by each group conditional on being a member of that class. In the existing literature, the various econometric frameworks employed have led to a sharp distinction between those who donate to charity and those who do not donate, with the group that donates encompassing a wide range of levels of donation. In particular, within the latent class framework, households who report zero donations within a given time period are labelled as being "low" givers rather than being classified as households that do not give at all as in the traditional approach. Thus, our modelling framework in contrast to the traditional approach does not depend on such a sharp distinction – the importance of which is evident when comparing the expected values of the level of donations for each group. For example, given the low expected values for the “low” givers group, for all donations, $2 to $3 over the entire calendar year, classifying such households in a group of positive donators as in, for example, a double hurdle set-up may mis-classify such households given that such low levels of charitable donations may arguably be related to measurement error. Furthermore, our empirical analysis suggests that there are noticeable differences in the propensity to donate between the “low” and “high” donator groups in particular in relation to differences in price elasticity and labour income elasticity, which potentially yields interesting insights into the economic motivations behind donating behaviour. Finally, in the comparison of the statistical performance of the random effects tobit model, the double-hurdle model and the latent class tobit model, the latent class approach strongly dominates with regard to the information criteria metrics (despite the fact that the latent class approach is much less parsimonious than the approaches traditionally employed in this area). Such findings suggest that policy based on the results where such inherent classes are not allowed for, that is, the tobit and double-hurdle approaches, may be potentially misleading.

References

Andreoni, J. (2006). Philanthropy. Chapter 18 in The Handbook of the Economics of Giving, Altruism and Reciprocity, Volume 2, edited by S. -C. Kolm and J. M. Ythier, Elsevier.

Auten, G. E. and D. Joulfaian (1996). Charitable Contributions and Intergenerational Transfers. *Journal of Public* Economics, 59, 55-68.

Auten, G. E., H. Sieg and C. T. Clotfelter (2002). Charitable Giving, Income, and Taxes: An Analysis of Panel Data. *American Economic Review*, 92, 371-82.

Bago d'Uva, T. (2005). Latent Class Models for Use of Primary Health Care: Evidence from a British Panel. *Health Economics*, 14, 873-92.

Chhacochharia, V. and S. Ghosh (2008). Do Charity Ratings Matter? Department of Economics, College of Business, Florida Atlantic University Working Paper Number 8001.

Deb, P. and Trivedi, P. K. (1997). Demand for Medical Care by the Elderly: A Finite Mixture Approach. *Journal of Applied Econometrics*, 12, 313-36.

Deb, P. and Trivedi, P. K. (2002). The Structure of the Demand for Health Care: Latent Class versus Two-Part Models. *Journal of Health Economics*, 41, 601-25.

Glenday, G., A. K. Gupta and H. Pawlak (1986). Tax Incentives for Personal Charitable Donations. *Review of Economics and Statistics*, 68, 688-93.

Greene, W. (2008). Econometric Analysis. International Edition, 6th Edition, Prentice Hall.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47, 153-61.

Jimenez-Martin, S., Labeaga, J. and Martinez-Granado, M. (2002). Latent Class Versus Two-Part Models in the Demand for Physician Services across the European Union. *Health Economics*, 11, 301-22.

Khanna, J., J. Posnett and T. Sandler (1995). Charity Donations in the UK: New Evidence based on Panel Data. *Journal of Public Economics*, 56, 257-72.

Karlan, D. and J. A. List (2007). Does Price Matter in Charitable Giving? Evidence from a Large-Scale Natural Field Experiment. *American Economic Review*, 97, 1774-93.

Kingma, B. R. (1989). An Accurate Measurement of the Crowd-Out Effect, Income Effect, and Price Effect for Charitable Contributions. *Journal of Public Economics*, 97, 1197-207.

Maddala, G. S. (1983). Limited Dependent and Qualitative Variables in Econometrics. Cambridge University Press.

Okunade, A. A., P. V. Wunnava and R. Walsh (Jr.) (1994). Charitable Giving of Alumni: Micro Data Evidence from a Large Public University. *American Journal of Economics and Sociology*, 53, 73-84.

Reboussin, B. A., Ip, E. and M., Wolfson (2008). Locally Dependent Latent Class Models with Covariates: An Application to Under-Age Drinking in the USA. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 171, 877-97.

Reece, W. S. (1979). Charitable Contributions: New Evidence on Household Behaviour. *American Economic Review*, 69, 142-51.

Ribar, D. C. and M. O. Wilhelm (2002). Altruistic and Joy-of-Giving Motivations in Charitable Behavior. *Journal of Political Economy*, 110, 425-57.

Rivers, D. and Q. Vuong (1988). Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models. *Journal of Econometrics*, 39, 347-66.

Schokkaert, E. (2006). Empirical Analysis of Transfer Motives. Chapter 2 in The Handbook of the Economics of Giving, Altruism and Reciprocity, Volume 1, edited by S. -C. Kolm and J. M. Ythier, Elsevier.

Schwartz, R. A. (1970). Personal Philanthropic Contributions. *Journal of Political Economy*, 78, 1264-91.

Shen, J. (2009). Latent Class Model or Mixed Logit Model? A Comparison by Transport Mode Choice Data. *Applied Economics*, 41, 2915-24.

Smith, V. H., M. R. Kehoe and M. E. Cremer (1995). The Private Provision of Public Goods: Altruism and Voluntary Giving. *Journal of Public Economics*, 58, 107-26.

Swait, J. and W. Adamowicz (2001). The Influence of Task Complexity on Consumer Choice: A Latent Class Model of Decision Strategy Switching. *Journal of Consumer Research*, 28, 135-48.

Wilhelm, M. O., E. Brown, P. M. Rooney and R. Steinberg (2008). The Intergenerational Transmission of Generosity. *Journal of Public Economics,* 92, 2146-56.

Yen, S. T., P. C. Boxall and W. L. Adamowicz (1997). An Econometric Analysis of Donations for Environmental Conservation in Canada. *Journal of Agricultural and Resource Economics*, 22, 246-63.

Yörük, B. (2009). How Responsive are Charitable Donors to Requests to Give? *Journal of Public Economics*, 93, 111-17.

Yörük, B. (2010). Charitable Giving by Married Couples Revisited. *The Journal of Human Resources*, 45, 497-516.

FIGURE 1: The Distribution of the Natural Logarithm of All Charitable Donations

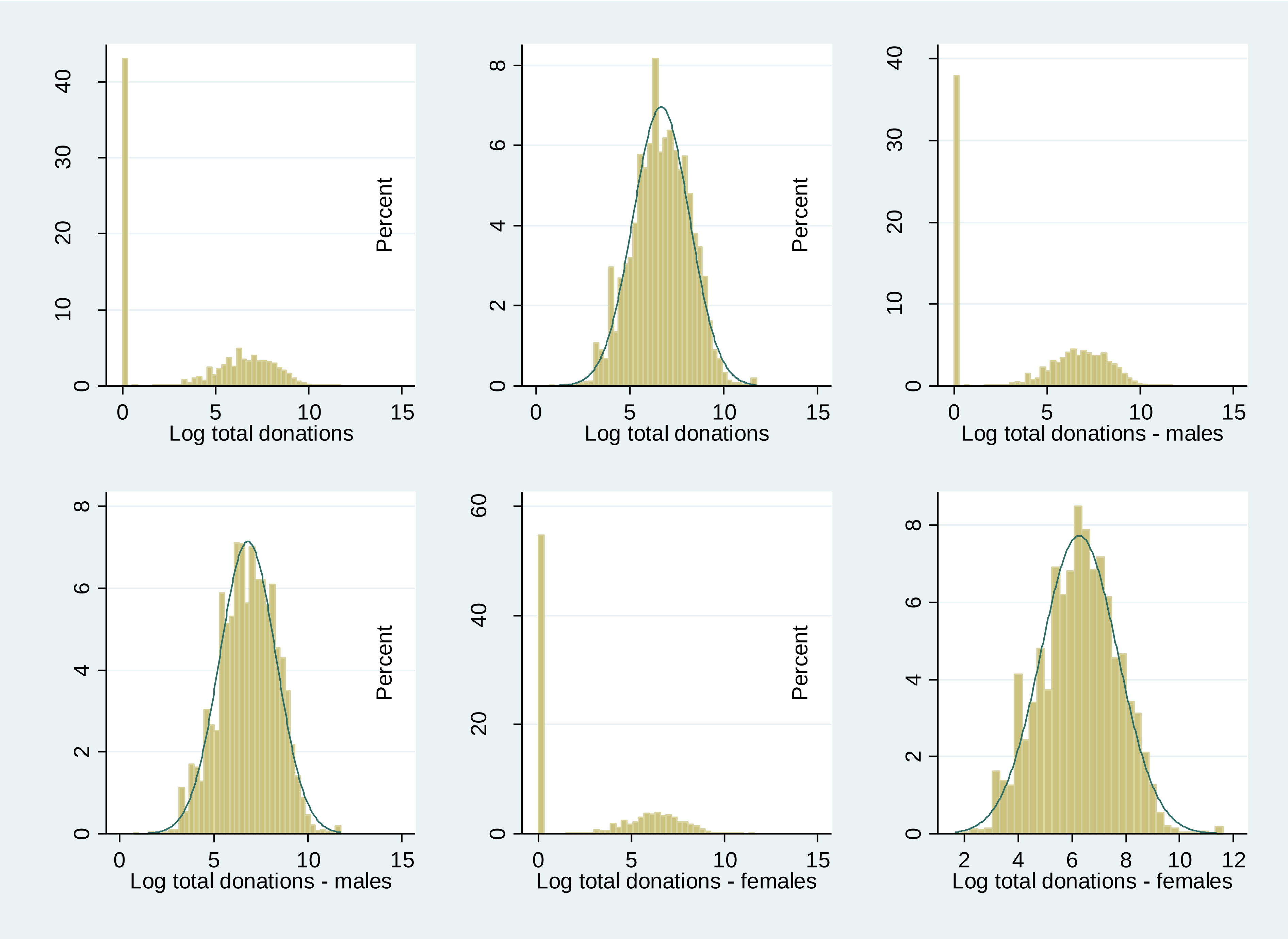

FIGURE 2: The Distribution of the Natural Logarithm of Religious Donations

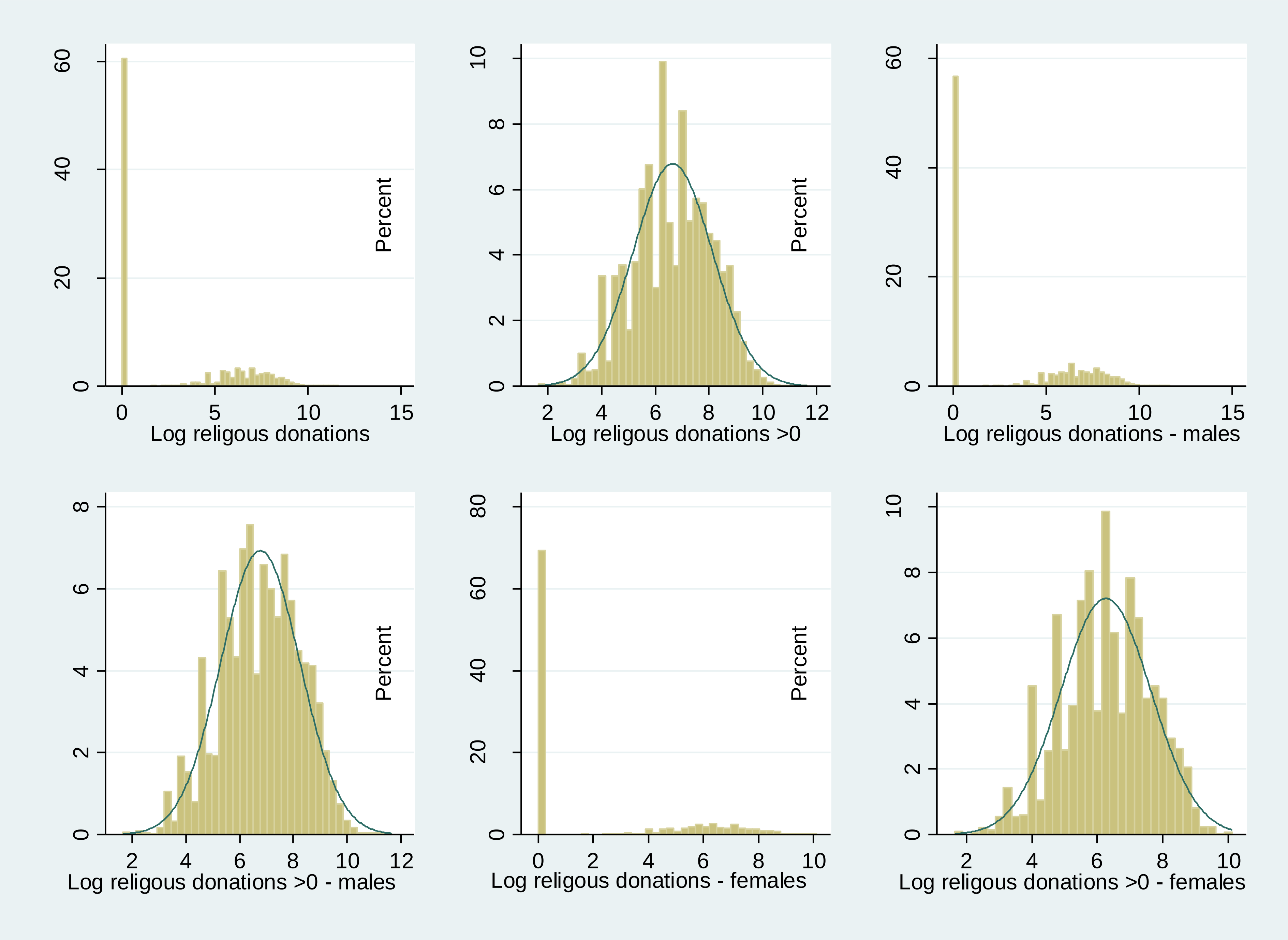

TABLE 1: Summary Statistics

	ALL		FEMALE		MALE	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Log Total Donations	3.805	3.498	2.833	3.263	4.230	3.263
Log Religious Donations	2.621	3.379	2.929	2.983	2.929	3.493
Head of Household Characteristics						
Years of Schooling	12.488	3.417	12.148	3.230	12.637	3.484
Male [0/1]	0.696	0.459	–		–	
White [0/1]	0.602	0.489	0.440	0.496	0.673	0.469
Catholic [0/1]	0.161	0.367	0.122	0.328	0.178	0.382
Protestant [0/1]	0.509	0.499	0.587	0.492	0.475	0.499
Other Religion [0/1]	0.015	0.122	0.043	0.202	0.031	0.173
Aged <30 [0/1]	0.192	0.389	0.213	0.409	0.175	0.379
Aged 30-40 [0/1]	0.213	0.409	0.189	0.391	0.224	0.417
Aged 40-50 [0/1]	0.244	0.429	0.227	0.419	0.252	0.434
Aged 50-60 [0/1]	0.175	0.380	0.136	0.342	0.193	0.394
Employee [0/1]	0.575	0.495	0.484	0.499	0.612	0.487
Self Employed [0/1]	0.099	0.298	0.049	0.215	0.120	0.325
Married or Cohabiting [0/1]	0.503	0.500	0.018	0.131	0.714	0.452
Household Characteristics						
Number of Adults [1+]	1.838	0.766	1.365	0.662	2.045	0.716
Number of Children [0+]	0.862	1.165	0.870	1.208	0.858	1.147
Log Labour Income	7.916	4.443	6.759	4.636	8.421	4.259
Log Wealth	1.896	3.302	1.617	3.075	2.018	3.389
Log Non Labour Income	1.351	3.073	1.937	3.379	1.095	2.892
Price	0.935	0.094	0.971	0.062	0.919	0.101
2003 [0/1]	0.254	0.435	0.250	0.433	0.256	0.436
2005 [0/1]	0.253	0.434	0.265	0.441	0.247	0.431
2007 [0/1]	0.269	0.444	0.270	0.444	0.269	0.443
Number of households ($i=1,..,N$) in unbalanced panel	10,653		3,455		6,972	
OBSERVATIONS ($N\times T$)	30,779		9,357		21,381	

TABLE 2: Estimates of the Determinants of Class Membership

	TOTAL DONATIONS						RELIGIOUS DONATIONS					
	ALL		FEMALE		MALE		ALL		FEMALE		MALE	
	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*
Intercept	-5.179	*0.164*	-5.759	*0.331*	-4.435	*0.192*	-4.654	*0.174*	-5.686	*0.380*	-3.987	*0.199*
Years of Schooling	0.321	*0.011*	0.357	*0.023*	0.299	*0.013*	0.229	*0.012*	0.276	*0.026*	0.208	*0.013*
Male	0.523	*0.057*	–		–		0.495	*0.065*	–		–	
White	0.613	*0.055*	0.457	*0.103*	0.664	*0.068*	0.375	*0.062*	0.244	*0.127*	0.398	*0.077*
Catholic	0.107	*0.079*	0.276	*0.164*	-0.001	*0.091*	0.403	*0.089*	1.023	*0.217*	0.329	*0.102*
Protestant	0.331	*0.059*	0.314	*0.122*	0.286	*0.069*	0.640	*0.067*	1.093	*0.176*	0.563	*0.077*
Other Religion	0.286	*0.129*	0.181	*0.246*	-0.075	*0.169*	0.524	*0.151*	1.384	*0.305*	0.307	*0.190*
Aged <30	-1.415	*0.070*	-1.106	*0.137*	-1.484	*0.107*	-1.633	*0.087*	-1.633	*0.185*	-1.512	*0.122*
Aged 30-40	-0.945	*0.063*	-0.792	*0.140*	-0.951	*0.098*	-1.098	*0.073*	-1.292	*0.184*	-1.000	*0.105*
Aged 40-50	-0.394	*3.980*	-0.582	*0.132*	-0.358	*0.093*	-0.509	*6.324*	-0.837	*0.152*	-0.404	*0.095*
Aged 50-60	-0.187	*2.187*	-0.076	*2.952*	-0.287	*0.099*	-0.379	*3.372*	-0.422	*4.399*	-0.358	*0.101*
Probability Class 1 (p_1)	0.298		0.176		0.336		0.173		0.082		0.195	
Probability Class 2 (p_2)	0.702		0.824		0.664		0.827		0.918		0.805	
OBSERVATIONS	30,779		9,357		21,381		30,799		9,357		21,381	

TABLE 3: Latent Class Tobit Model for Total Charitable Donations

	ALL					FEMALE					MALE				
		CLASS 1		CLASS 2			CLASS 1		CLASS 2			CLASS 1		CLASS 2	
	T.M.E	COEF	M.E.	COEF	M.E.	T.M.E	COEF	M.E.	COEF	M.E.	T.M.E	COEF	M.E.	COEF	M.E.
Number of Adults	-0.03	0.08	0.05	-0.10	-0.06	-0.04	-0.02	-0.01	-0.10	-0.04	-0.03	0.12	0.08	-0.12	-0.08
	[0.38]	*[0.00]*		*[0.19]*		*[0.45]*	*[0.68]*		*[0.47]*		*[0.54]*	*[0.00]*		*[0.20]*	
Number of Kids	-0.13	-0.01	-0.01	-0.31	-0.18	-0.22	-0.04	-0.02	-0.64	-0.27	-0.12	-0.02	-0.02	-0.25	-0.17
	[0.00]	*[0.26]*		*[0.00]*		*[0.00]*	*[0.07]*		*[0.00]*		*[0.00]*	*[0.01]*		*[0.00]*	
Employee	0.19	-0.14	-0.08	0.51	0.30	0.35	0.04	0.01	1.02	0.43	0.03	-0.16	-0.11	0.14	0.10
	[0.13]	*[0.00]*		*[0.01]*		*[0.00]*	*[0.75]*		*[0.00]*		*[0.78]*	*[0.00]*		*[0.51]*	
Self Employed	0.06	0.22	0.13	0.05	0.03	-0.03	0.16	0.07	-0.11	-0.05	0.21	0.25	0.17	0.35	0.24
	[0.46]	*[0.00]*		*[0.78]*		*[0.87]*	*[0.13]*		*[0.81]*		*[0.02]*	*[0.00]*		*[0.09]*	
Married	0.91	0.44	0.25	2.04	1.19	-0.15	0.58	0.24	-0.58	-0.24	1.38	0.64	0.43	2.72	1.85
	[0.00]	*[0.00]*		*[0.00]*		*[0.59]*	*[0.00]*		*[0.49]*		*[0.00]*	*[0.00]*		*[0.00]*	
Log Lab. Income	0.03	-0.01	-0.01	0.07	0.04	0.02	-0.03	-0.01	0.07	0.03	0.04	0.00	0.00	0.09	0.06
	[0.00]	*[0.01]*		*[0.00]*		*[0.05]*	*[0.00]*		*[0.02]*		*[0.00]*	*[0.95]*		*[0.00]*	
Log Wealth	0.10	0.05	0.03	0.23	0.13	0.07	0.04	0.02	0.19	0.08	0.13	0.05	0.03	0.27	0.19
	[0.00]	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*	
Log Oth. Income	0.05	0.01	0.00	0.12	0.07	0.07	0.01	0.01	0.21	0.09	0.03	0.00	0.00	0.06	0.04
	[0.00]	*[0.12]*		*[0.00]*		*[0.00]*	*[0.05]*		*[0.00]*		*[0.02]*	*[0.71]*		*[0.02]*	
Price	-9.38	-3.23	-1.89	-21.53	-12.56	-11.52	-4.46	-1.86	-32.54	-13.58	-9.18	-2.77	-1.88	-18.93	-12.87
	[0.00]	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*	
2003	0.09	0.35	0.21	0.06	0.04	-0.10	0.11	0.05	-0.31	-0.13	0.25	0.39	0.27	0.35	0.24
	[0.35]	*[0.00]*		*[0.77]*		*[0.46]*	*[0.39]*		*[0.42]*		*[0.04]*	*[0.00]*		*[0.19]*	
2005	0.49	0.52	0.30	0.97	0.56	0.13	0.21	0.09	0.35	0.15	0.68	0.52	0.35	1.24	0.84
	[0.00]	*[0.00]*		*[0.00]*		*[0.30]*	*[0.10]*		*[0.35]*		*[0.00]*	*[0.00]*		*[0.00]*	
2007	0.63	0.68	0.40	1.24	0.72	0.25	0.42	0.17	0.64	0.27	0.84	0.70	0.47	1.50	1.02
	[0.00]	*[0.00]*		*[0.00]*		*[0.06]*	*[0.00]*		*[0.09]*		*[0.00]*	*[0.00]*		*[0.00]*	
E(V) Class *j*		4.81	($122.73)	0.88	($2.41)		5.35	($210.61)	1.33	($3.78)		3.22	($25.03)	0.78	($2.18)
Log Likelihood	-51,308.94					-14,433.85					-37,505.42				
OBSERVATIONS	30,779					9,357					21,381				

[.] denotes p value; T.M.E denotes overall marginal effect.

TABLE 4: Latent Class Tobit Model for Religious Charitable Donations

	ALL					FEMALE					MALE				
		CLASS 1		CLASS 2			CLASS 1		CLASS 2			CLASS 1		CLASS 2	
	T.M.E	COEF	M.E.	COEF	M.E.	T.M.E	COEF	M.E.	COEF	M.E.	T.M.E	COEF	M.E.	COEF	M.E.
Number of Adults	0.02	0.10	0.05	0.04	0.02	-0.01	0.01	0.01	-0.03	-0.01	0.03	0.11	0.05	0.09	0.04
	[0.53]	*[0.00]*		*[0.68]*		*[0.86]*	*[0.96]*		*[0.86]*		*[0.30]*	*[0.00]*		*[0.42]*	
Number of Kids	0.01	-0.06	-0.03	0.02	0.01	-0.12	-0.04	-0.01	-0.52	-0.17	0.04	-0.07	-0.03	0.16	0.08
	[0.86]	*[0.00]*		*[0.68]*		*[0.00]*	*[0.21]*		*[0.00]*		*[0.03]*	*[0.00]*		*[0.01]*	
Employee	0.07	-0.18	-0.08	0.31	0.13	0.22	-0.13	-0.04	0.98	0.32	-0.04	-0.18	-0.09	-0.10	-0.05
	[0.26]	*[0.00]*		*[0.20]*		*[0.04]*	*[0.39]*		*[0.02]*		*[0.62]*	*[0.00]*		*[0.73]*	
Self Employed	-0.04	0.17	0.08	-0.18	-0.08	-0.16	0.06	0.02	-0.71	-0.23	0.09	0.18	0.09	0.25	0.12
	[0.50]	*[0.00]*		*[0.40]*		*[0.22]*	*[0.63]*		*[0.20]*		*[0.19]*	*[0.00]*		*[0.27]*	
Married	0.64	0.42	0.18	2.40	1.04	0.07	0.29	0.09	0.29	0.09	1.04	0.62	0.30	3.36	1.61
	[0.00]	*[0.00]*		*[0.00]*		*[0.75]*	*[0.25]*		*[0.77]*		*[0.00]*	*[0.00]*		*[0.00]*	
Log Lab. Income	-0.01	0.01	0.01	-0.05	-0.02	-0.01	-0.01	-0.01	-0.05	-0.02	-0.01	0.01	0.01	-0.03	-0.01
	[0.02]	*[0.06]*		*[0.01]*		*[0.18]*	*[0.69]*		*[0.16]*		*[0.28]*	*[0.02]*		*[0.23]*	
Log Wealth	0.03	0.02	0.01	0.09	0.04	0.03	0.03	0.01	0.13	0.04	0.04	0.02	0.01	0.13	0.06
	[0.00]	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*	
Log Oth. Income	0.02	0.01	0.01	0.09	0.04	0.04	-0.01	-0.02	0.18	0.06	0.01	0.01	0.01	0.04	0.02
	[0.00]	*[0.50]*		*[0.00]*		*[0.00]*	*[0.50]*		*[0.00]*		*[0.15]*	*[0.06]*		*[0.18]*	
Price	-4.31	-2.54	-1.09	-16.13	-6.97	-6.28	-3.32	-1.07	-27.89	-9.04	-4.43	-2.37	-1.14	-14.42	-6.92
	[0.00]	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*		*[0.00]*	*[0.00]*		*[0.00]*	
2003	-0.09	0.29	0.13	-0.39	-0.17	-0.18	0.22	0.07	-0.82	-0.27	0.03	0.29	0.14	0.03	0.01
	[0.26]	*[0.00]*		*[0.18]*		*[0.13]*	*[0.21]*		*[0.11]*		*[0.78]*	*[0.00]*		*[0.93]*	
2005	0.12	0.42	0.18	0.36	0.16	-0.10	0.26	0.09	-0.47	-0.15	0.26	0.40	0.19	0.78	0.38
	[0.13]	*[0.00]*		*[0.22]*		*[0.35]*	*[0.11]*		*[0.32]*		*[0.01]*	*[0.00]*		*[0.02]*	
2007	0.06	0.57	0.25	0.12	0.05	-0.14	0.46	0.15	-0.65	-0.21	0.21	0.56	0.27	0.56	0.27
	[0.41]	*[0.00]*		*[0.68]*		*[0.23]*	*[0.00]*		*[0.19]*		*[0.05]*	*[0.00]*		*[0.10]*	
E(V) Class *j*		2.93	($18.73)	0.21	($1.23)		3.23	($25.28)	0.41	($1.51)		1.78	($5.93)	0.22	($1.25)
Log Likelihood	-41,849.25					-11,321.09					-31,297.32				
OBSERVATIONS	30,779					9,357					21,381				

[.] denotes p value; T.M.E denotes overall marginal effect.

TABLE 5: Random Effects Tobit for Total Charitable Donations and Religious Charitable Donations

	TOTAL DONATIONS				RELIGIOUS DONATIONS			
	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*
Intercept	5.818	*0.425*	11.448	*0.383*	2.995	*0.600*	6.834	*0.519*
Years of Schooling	0.364	*0.012*	–		0.352	*0.019*	–	
Male	-0.181	*0.109*	–		-0.236	*0.170*	–	
White	0.745	*0.085*	–		-0.254	*0.129*	–	
Catholic	0.031	*0.110*	–		0.912	*0.161*	–	
Protestant	0.479	*0.086*	–		1.466	*0.127*	–	
Other Religion	0.372	*0.174*	–		0.819	*0.251*	–	
Aged <30	-2.833	*0.132*	–		-4.173	*0.200*	–	
Aged 30-40	-1.787	*0.130*	–		-2.889	*0.191*	–	
Aged 40-50	-1.083	*0.123*	–		-1.694	*0.177*	–	
Aged 50-60	-0.649	*0.115*	–		-0.931	*0.162*	–	
Number of Adults	-0.096	*0.049*	-0.110	*0.050*	-0.093	*0.069*	-0.021	*0.069*
Number of Kids	-0.024	*0.034*	-0.251	*0.032*	0.160	*0.049*	-0.073	*0.047*
Employee	0.460	*0.087*	0.369	*0.088*	0.361	*0.120*	0.182	*0.120*
Self Employed	0.199	*0.103*	0.315	*0.106*	0.317	*0.144*	0.389	*0.146*
Married	1.988	*0.100*	2.255	*0.089*	2.572	*0.150*	2.638	*0.131*
Log Labour Income	0.072	*0.009*	0.055	*0.009*	0.037	*0.012*	0.002	*0.012*
Log Wealth	0.115	*0.009*	0.171	*0.009*	0.096	*0.013*	0.140	*0.013*
Log Other Income	0.025	*0.009*	0.034	*0.009*	0.017	*0.012*	0.025	*0.012*
Price	-10.087	*0.359*	-12.299	*0.366*	-9.110	*0.495*	-10.822	*0.495*
2003	-0.313	*0.106*	-0.030	*0.093*	-1.189	*0.149*	-0.126	*0.124*
2005	-0.032	*0.107*	0.393	*0.094*	-0.935	*0.150*	0.270	*0.125*
2007	0.367	*0.107*	0.783	*0.094*	-0.824	*0.150*	0.401	*0.127*
Wald Chi Sq. (d)	5,538.29	*p=[0.000]*	3,472.37	*p=[0.000]*	2,534.77	*p=[0.000]*	1,514.61	*p=[0.000]*
OBSERVATIONS				30,779				

d=22 (12) in columns 1 and 3 (2 and 4).

TABLE 6: Double Hurdle Model for Total Charitable Donations and Religious Charitable Donations

	TOTAL DONATIONS				RELIGIOUS DONATIONS			
	Prob. of Donation		Amount of Donation		Prob. of Donation		Amount of Donation	
	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*	COEF	*S.E.*
Intercept	-1.414	*0.038*	9.866	*0.120*	0.895	*0.036*	9.113	*0.309*
Years of Schooling	0.110	*0.002*	–		0.022	*0.001*	–	
Male	0.319	*0.016*	–		-0.074	*0.013*	–	
White	0.313	*0.016*	–		-0.033	*0.011*	–	
Catholic	0.037	*0.024*	–		-0.042	*0.017*	–	
Protestant	0.190	*0.017*	–		0.171	*0.015*	–	
Other Religion	0.050	*0.041*	–		0.098	*0.028*	–	
Aged <30	-0.808	*0.025*	–		-0.341	*0.023*	–	
Aged 30-40	-0.409	*0.024*	–		-0.208	*0.022*	–	
Aged 40-50	-0.200	*0.023*	–		-0.150	*0.020*	–	
Aged 50-60	-0.005	*0.025*	–		-0.108	*0.020*	–	
Number of Adults	–		0.054	*0.017*	–		-0.051	*0.034*
Number of Kids	–		0.005	*0.010*	–		-0.052	*0.022*
Employee	–		-0.032	*0.037*	–		0.240	*0.075*
Self Employed	–		0.189	*0.033*	–		0.285	*0.078*
Married	–		0.334	*0.028*	–		1.588	*0.071*
Log Labour Income	–		-0.006	*0.003*	–		0.034	*0.007*
Log Wealth	–		0.044	*0.003*	–		0.098	*0.009*
Log Other Income	–		0.008	*0.003*	–		0.043	*0.008*
Price	–		-3.770	*0.115*	–		-7.623	*0.336*
2003	–		0.122	*0.041*	–		-0.539	*0.093*
2005	–		0.263	*0.041*	–		-0.329	*0.093*
2007	–		0.510	*0.041*	–		0.028	*0.094*
Wald Chi Sq. (1) test of independence	300.63 *p=[0.000]*				4,083.34 *p=[0.000]*			
OBSERVATIONS				30,779				

TABLE 7: Model Selection Criteria

	TOTAL DONATIONS		RELIGIOUS DONATIONS	
	AIC	*BIC*	*AIC*	*BIC*
Latent Class	3.132	3.139	2.722	2.732
Tobit (all covariates)	3.821	3.287	3.020	3.026
Tobit (subset of covariates)	3.873	3.877	3.052	3.055
Double Hurdle	3.337	3.347	3.880	3.887

Note: AIC $= (-2LL + 2k)/n$, BIC $= (-2LL + k\log(n))/n$; where LL is the log likelihood, k denotes the number of estimated parameters and n denotes the sample size.