A SAMPLE SELECTION MODEL FOR PROTEST NON-RESPONSE VOTES IN CONTINGENT VALUATION ANALYSES

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Abstract: It can be often observed in contingent valuation surveys that some respondents do not agree to pay some money for a public good, for reasons that differ from a genuine indifference to the good. For example, some people may dislike the idea of placing monetary values to public goods like the environment or a historical monument. Some may protest against the inefficiency of the public administration in managing public funds, and refuse to pay a tax. Others may behave strategically, if they think that their answer could influence the actual level of taxation.

A good survey design can effectively reduce them, but protest votes can hardly be completely removed from the dataset. The question is how to deal with them. Sometimes they are considered as true zero values, or, if the dichotomous choice method is used, as if they were below the minimum bid. Obviously, if the unwillingness to pay reflects only a protest and not a low or null valuation of the good, this procedure results in downward biased estimates of the wtp measure. It is of paramount importance that the questionnaire contains a follow up question for individuals that refuse payment, to investigate about their motivations, and interpret the responses.

Alternatively, observations with protest votes are simply cut off the sample, and only the subsample with positive reservation prices is considered in the analysis. This procedure will not have any effect for the validity of the estimates only if there is no sample selection bias. Otherwise, it leads to incorrect estimates for the willingness to pay.

In this paper we present a sample selection model that allows to take into account, and correct, the possible bias due to protest votes. It is shown that selection bias can sensibly affect the estimates for the willingness to pay for the public good. It will be seen that the model may present estimation problems because of flatness of the likelihood function. In some cases confidence intervals around the sample selection coefficient are too wide to give evidence of presence or absence of sample selection bias. It is argued that even in these circumstances the sample selection model with the protest votes should be preferred to the model without protest votes, since it takes into account the uncertainty about the estimates of the willingness to pay.

Introduction

A problem often encountered in contingent valuation analyses is that individuals asked about their willingness to pay for a given good or service may answer that they are not willing to pay anything. A zero value is not a problem if the respondent is sincerely indifferent to the good, since in that case the stated value reflects the true value. However, it can be often observed that respondents place a zero value in the wtp question for reasons that differ from a genuine indifference to the good (Donaldson et al. (1996); Mitchell and Carson (1989, pp.166-7). For example, some people may refuse the idea of placing monetary values to public goods like the environment or a historical monument. Some may protest against the inefficiency of the public administration in managing public funds, and refuse to pay a tax. Others may behave strategically, if they think that their answer could influence the actual level of taxation.

To some extent, distortions can be controlled by a good survey design: strategic behavior can be prevented by making clear that the respondent's action is very important for informative purposes, but is not going to have any influence on the level of fiscal pressure. Protest votes caused by mistrust about the efficiency of the public administration could be removed by using a payment vehicle other than taxes. A device often adopted is the collection of special funds, which should be administered by trusts over which citizens may exercise their control. However, this alternative may cause other problems. If payment to the trust is taken on a voluntary basis, strategic behavior can again affect the answers, especially in social contexts where voluntary contributions to the provision of public goods are not much usual. A compulsory payment to a trust, on the other hand, would presumably cause another type of bias, due to the unrealistic setting. A requirement for reliability of contingent valuation studies is that the scenario should be credible enough to produce sensible answers.

Thus, protest votes can hardly be completely removed from the survey dataset. The question is how to deal with them. Sometimes they are considered as true zero values, or, if the dichotomous choice method is used, as if they were below the minimum bid. Obviously, if the unwillingness to pay reflects only a protest and not a low or null valuation of the good, this procedure results in downward biased estimates of the wtp measure.

Alternatively, and more frequently, observations with protest votes are simply cut off the sample, and only the subsample with positive reservation prices is considered in the analysis (Whitehead et al. (1993); Mitchell and Carson (1989)). As we will see in the next sections, this procedure will not have any effect for the validity of the estimates only if the probability of obtaining a protest response from individuals with specific socioeconomic characteristics is independent of the value they give to the good.

If a continuous type elicitation format is used, a nested Tobit model is the correct specification: its theoretical structure has been introduced by Lee (1992), applied by Howe et al. (1994) to contingent valuation data. We are not aware of any specification proposed in the literature to deal with selectivity when the elicitation question is in the dichotomous choice format.

2. The model

Protest responses can be controlled for by constructing a system of sequential questions about the individual's willingness to pay for the good. For example, when the elicitation method produces a specific value, as in the open ended or the bidding game formats, a follow up question may be posed to those that put a zero value, asking to motivate their answer. Alternatively, and especially when the dichotomous choice format is applied, the elicitation question is preceded by a question asking the individual if he or she would be favorable to the imposition of a tax (or the request to pay a ticket, depending on the payment vehicle that was chosen) to contribute to the provision of the good. If the individual says yes, a follow up question is posed to elicit the individual's wtp. If the individual says no, a follow up question asks to motivate the answer. This structure allows selection of observations with positive wtp, and gathering of enough information to understand the nature of each case of unwillingness to pay for the good: whether it should be treated as a genuine indifference to the public good, or rather as an expression of protest, either against the public administration, or against the interview. When the respondent displays indifference toward the public good, we assume that the reservation price is below the minimum bid proposed.

Together with the responses of the individuals that are favorable to the payment of a tax (ticket) for the public good, these observations give a direct information about the individual willingness to pay.

If the respondent instead displays interest toward the public good, but nevertheless refuses the idea of contributing to the payment because of protest to the management of the public budget, no information about the reservation price can be gathered.

Data produced by this design can be expressed through a dichotomous variable, assuming value 1 if information about the individual's willingness to pay is available, and zero otherwise. When this dummy variable is equal to 1, another dichotomous variable indicates willingness to pay a given amount: the bid that was actually offered to the individual, or the lowest bid for those who showed indifference toward the public good.

These responses can be modelled simultaneously with two equations: the first one is the *selection equation*, and to the second one is the *elicitation equation*. The model proposed applies to the dichotomous choice elicitation method, but a similar procedure can be adopted when the elicitation format provides continuous wtp data, using a tobit instead of the probit in the elicitation equation.

We define the binary variable Y_1 for the selection equation and Y_2 for the elicitation equation, depending, in turn, on two latent variables Y_1^* e Y_2^*:

$$Y_1 = 1 \quad if \quad Y_1^* > 0 \qquad\qquad Y_2 = 1 \quad if \quad Y_2^* > t$$
$$= 0 \quad if \quad Y_1^* \le 0 \qquad\qquad = 0 \quad if \quad Y_2^* \le t$$

The latent variable Y_2^* is the willingness to pay: an individual accepts to pay the amount *t* if his willingness to pay is greater than the proposed bid and refuse to pay the amount *t* otherwise. But Y_2 is observed only if Y_1=1: the observed outcomes of Y_2 are conditioned on Y_1=1. Estimation of willingness to pay based only on observed responses of Y_2 could be incorrect if there is bias introduced by the self-selection of individuals that answered No to the first question.

To check for the presence of sample selection bias we suggest to model the two choices simultaneously. Let x_1 and x_2 be two vectors of socio-economic characteristics of individuals (not necessarily distinct), and assume a linear specification for the two models:

$$\begin{aligned} Y_1^* &= x_1' b_1 + u_1 \\ Y_2^* &= x_2' b_2 + u_2 \end{aligned} \tag{1}$$

where u_1 and u_2 are two error terms with joint c.d.f. $F(u_1, u_2)$.

The model can be summarized as follows:

$$\begin{aligned} Y_1 = 1 \quad if \quad & x_1' b_1 + u_1 > 0 \\ & \qquad Y_2 = 1 \quad if \quad x_2' b_2 + u_2 > t \\ & \qquad\quad = 0 \quad if \quad x_2' b_2 + u_2 \le t \\ = 0 \quad if \quad & x_1' b_1 + u_1 \le 0 \end{aligned} \tag{2}$$

and the likelihood function can be written as follows:

$$L = \prod_{Y_1=0} P(Y_1^* \le 0) \prod_{Y_1=1} \left[\prod_{Y_2=1} P(Y_1^* > 0, Y_2^* > t) \prod_{Y_2=0} P(Y_1^* > 0, Y_2^* \le t) \right]. \tag{3}$$

which implicitly contains the joint probabilities of Y_1^* and Y_2^*, and the marginal probability of Y_1^*.

Usually (u_1, u_2) is assumed to have bivariate normal distribution with mean zero and covariance matrix

$$\Sigma = \begin{bmatrix} 1 & s_{12} \\ s_{21} & s_2 \end{bmatrix};$$

the variance of Y_1^* is set to 1 for normalization while the variance of Y_2^* is estimable due to the variability of the bids among individuals. The log-likelihood can be written in the following way:

$$\begin{aligned} l = & \sum_{i=i}^{n} \Big\{ (1 - Y_{1i}) \ln P(u_{1i} \le -x'_{1i} b_1) + Y_{1i} \big[Y_{21} \ln P(u_{1i} > -x'_{1i} b_1 , u_{2i} / s_2 > -x'_{2i} b_2 / s_2 + t_i / s_2) + \\ & + (1 - Y_{2i}) \ln P(u_{1i} > -x'_{1i} b_1 , u_{2i} / s_2 \le - x'_{2i} b_2 / s_2 + t_i / s_2) \big] \Big\} \\ = & \sum_{i=1}^{n} \Big\{ (1 - Y_{1i}) \ln \big[1 - \Phi_1 (x'_{1i} b_1) \big] + Y_{1i} \big[Y_{2i} \ln \Phi_2 (x'_{1i} b_1 ,\ x'_{2i} b_2 / s_2 - t_i / s_2 ; -r) + \\ & + (1 - Y_{2i}) \ln \Phi_2 (x'_{1i} b_1 , - x'_{2i} b_2 / s_2 + t_i / s_2 ; -r) \big] \Big\} \end{aligned} \tag{4}$$

where we indicate with $\Phi_1(\cdot)$ the c.d.f. of the univariate standard normal distribution and with $\Phi_2(\cdot\,,\cdot\,;r)$ the c.d.f. of the bivariate standard normal distribution with correlation coefficient r.

The correlation r between the error terms in the two equations accounts for the presence of *selection bias* in the estimates of the parameters of the model: if $r = 0$, the two choices are independent among sample observations, and we could obtain unbiased estimates of the parameters simply fitting two separate equations for Y_1 and Y_2; otherwise, if $r \neq 0$, the estimate of the willingness to pay is biased, the sign depending on the sign of the correlation. In particular if $r < 0$ we would under-estimate the willingness to pay while if $r > 0$ we would incur in over-estimation of willingness to pay, when considering only observations with Y_1=1.

Estimates of the parameters b_1, b_2, s_2, r can be obtained simultaneously, by maximizing the log-likelihood with respect to all arguments. However, Copas (1990) notes that the likelihood functions of models like (1)-(2) often shows non-regular behaviour and suggests not to base the judgement on the presence of selection bias exclusively on the asymptotic standard errors estimated by means of the inverse of the information matrix. Because the likelihood is well-behaved for fixed values of ρ, his suggestion is to evaluate the *likelihood profile* $l(r \mid \hat{b}_1, \hat{b}_2, \hat{s}_2)$ for a grid of values of ρ in the interval (-1,+1) and calculate an approximate confidence interval for ρ as $\left\{ r : 2l(\hat{r}) - 2l(r) \le c^2_{1,1-a} \right\}$ around the maximum $l(\hat{r})$. If the interval contains the value zero then we can conclude that there is no selection bias.

Estimates of the mean willingness to pay can be obtained from the estimates of b_2 in this way:

$$E(Y_2^*) = x_2' b_2$$

and a confidence interval for $E(Y_2^*)$ is calculated with the analytical formula suggested by Cameron (1991):

$$CI_{1-a}\left[E(Y_2^*)\right] = x_2' b_2 \pm t_{a/2} \sqrt{x_2' \mathbf{V} x_2}$$

where $\mathbf{V}$ is the variance-covariance matrix of b_2. This is different from calculating the mean willingness to pay from observed responses of Y_2 because:

$$\begin{aligned} E(Y_2^* \mid Y_1 = 1) &= x_2' b_2 + E(u_2 \mid u_1 > -x_1' b_1) \\ &= x_2' b_2 + r \frac{f(x_1' b_1)}{\Phi(x_1' b_1)} \end{aligned}$$

where the term $r \dfrac{f(x_1' b_1)}{\Phi(x_1' b_1)}$ is the bias due to selection of individuals, the sign depending on the sign of ρ: if $r < 0$ we under-estimate the mean *wtp* while if $r > 0$ we over-estimate the mean *wtp*.

3. The Data

We present now an application of the sample selection model introduced in the previous section. We use data from a preliminary stage of a contingent valuation analysis for a urban park in the metropolitan area of Cagliari, Italy.

Since the scope here is only illustrative of the sample selection model, the description of the survey will be limited to the essential. We used a dichotomous choice model for elicitation of the reservation price. Before the elicitation question was posed, the individual was asked if he or she would have been favorable to the imposition of a tax, on the top of the income tax he or she already paid, to help the provision of the public good. For individuals answering yes, a follow up question was posed to elicit the willingness to pay; for individuals answering no, a follow up question was posed to select people indifferent to the public good from people that were giving protest responses. Unfortunately, not enough care was posed in collecting the latter information, and this resulted in many missing or invalid data: therefore, we could not properly select between individuals that were genuinely indifferent to the public good and those that were giving a protest response. It will be our care, for the second stage survey, to be more scrupolous in collecting this information. Since these data do not allow selction between individuals that (directly or indirectly) provided a valuation for the public good, and people that, because of protest, did not evaluate the good, the selection variable in the following application is just the answer to the question about the attitude toward the payment of a tax.

The questionnaire contained questions aimed to gather information about the socioeconomic characteristics of the respondent. Information leaflets were attached to give a description of the project. It was especially emphasized that the park could supply leisure services: sport facilities, playgrounds for children, observation points for birdwatching, and similar services to be consumed in the leisure time.

Our final sample consisted of 184 observations: 102 individuals answered that they would be favorable to the payment of a tax, and were then asked about their willingness to pay.

4. Results

The model estimated had two regressors in the selection equation, and only one regressor in the elicitation equation.

In order to enhance the reliability of the estimates, we followed the procedure suggested by Copas (1990) discussed in section 2: we first obtained a likelihood profile for a grid of parameter values of r in the range [-1,1], and then obtained its maximum likelihood estimate by optimizing the profile.

Results for the parameter estimates are presented in Table 1.

Table 1: Sample selection model and Censored sample model estimates

Parameters	**Sample Selection**			**Censored Sample**		
Selection eq. N.obs. 184	Estimates	S. Error	p-value	Estimates	S. Error	p-value
Constant	0.6423	0.3833	0.0469	--	--	--
Leisure	0.8429	0.2247	0.0001	--	--	--
Age	-0.0141	0.0071	0.0234	--	--	--
Elicitation eq. N.obs. 102						
Constant	357.32	63.37	0.0000	274.34	47.36	0.0000
Inactive	-96.63	56.76	0.0443	-113.59	60.73	0.0307
s	207.52	53.76	0.0001	187.38	50.36	0.0001
r	-0.69			--	--	--

The model reported in Table 1 has been selected against other possible specifications on the basis of Likelihood Ratio tests for nested models, and the Akaike Criterion for non nested models (cfr. Greene (1993)). The variables selected are: *age*, which is a continuous variable ranging from 19 yr. to 80 yr., with a mean of about 50 yr. The variable *leisure* is a dichotomous variable, with value 1 if the individual has an expenditure for leisure activities of more than 20% of his or her personal income; otherwise the value is zero. The percentage of individuals in the sample with higher leisure time expenditure is about 26%. Finally, the dummy variable “inactive” distinguishes students, retired, housewives and unemployed individuals from those that are currently working: the percentage of "inactive" people in the sample is about 36%.

From the coefficients of the sample selection equation we can infer that the probability to consent to the introduction of a tax for the public good is higher for younger people and for people that spend more of their income in leisure. When we look instead at the elicitation equation, we see that the actual level of willingness to pay for the good depends on the professional condition of the individual. As it can be easily guessed, the group of "inactive" people is willing to pay a lower price for the public good. The professional condition can be considered as a proxy for personal income: just as the variable leisure, which when taken alone in the elicitation equation is also significant, with a positive sign.

The dependent variables in the sample selection equation and in the elicitation equation are negatively correlated (conditional on the independent variables), as implied by the sign of the coefficient r, and the magnitude of correlation is not negligible. This result seems counter-intuitive, since it would imply that people that are more favorable to the introduction of a tax to help the provision of the good are also willing to pay less. From the follow up question asking the motivation of their opposition to a tax for the park, many answered that taxation is high enough already, and that the public administration should be more efficient in the budget management. A possible interpretation for the negative sign of the correlation coefficient is that people that protest more for the imposition of taxes are people that already pay high income taxes because of higher incomes. On the other hand, if people in the higher income class decide to accept the payment, they will probably have higher reservation prices than individuals with lower incomes. The effect of income in the two decisions is not entirely taken into account by the independent variable, since they are just approximations. If this interpretation is correct, the sample selection model would effectively account for protest votes.

As it can be seen from Table 2, the 90% confidence interval about r (represented by digits in bold italics) include the r values in the range [–0.9, -0.1]. It can be observed that the log-likelihood in this range is very flat, producing a wide confidence interval that covers almost all negative values. We can anyway confidently exclude the null hypothesis of no sample selection bias ($r = 0$).

Table 2 Log-likelihood for values of ρ in the range [-1,+1]

ρ	Log-likelihood
-1	-199.87214
-0.9	***-168.82186***
-0.8	***-168.50982***
-0.7	***-168.42507***
-0.6	***-168.46207***
-0.5	***-168.57602***
-0.4	***-168.74370***
-0.3	***-168.95261***
-0.2	***-169.19619***
-0.1	***-169.47155***
0	-169.77846
0.1	-170.11881
0.2	-170.49666
0.3	-170.91858
0.4	-171.39464
0.5	-171.94026
0.6	-172.58026
0.7	-173.35826
0.8	-174.36359
0.9	-175.83995
1	-466.38070

The estimates for mean *wtp* (and relative confidence interval) are reported in Table 3 for the specification with and without sample selection. The estimates are reported for different values of the regressor *Inactive* in the elicitation equation. As expected, given the negative sign of the correlation coefficient, the estimates produced by the sample selection model are higher than those obtained from the subsample with positive willingness to pay. It can also be noted that confidence intervals for the estimates of the sample selection model are wider than those obtained from the censored sample model.

Table 3 Mean WTP and confidence intervals for sample selection and censored sample model.

Model	Mean WTP	Confidence interval for mean WTP
Sample selection		
Inactive	260.69 (53.18)	172.52 - 348.34
Active	357.32 (63.37)	252.25 – 462.40
Censored sample		
Inactive	160.76 (44.25)	87.39 – 234.13
Active	274.34 (47.35)	195.82 – 352.87

Conclusions

We saw that estimates from the sample selection model are quite different from those produced by the censored sample model, where the sample selection bias is not accounted for. We presented an application where the confidence interval about the correlation coefficient allows us to exclude the hypothesis of null correlation between the responses of the selection equation and the elicitation equation. In other terms, since the hypothesis of sample selection bias is accepted, use of the censored sample model would lead us to incorrect estimates for the valuation of the public good.

Unfortunately, as shown by Copas (1990), sample selection models are often characterized by very flat likelihood functions, which may cause estimation problems if algorithms do not converge, or, even if they do converge, the standard results of the asymptotic theory cannot be applied to the model. In these situations nothing conclusive can be said about the presence (or not) of sample selection bias. A possible solution could be given by increasing the number of observations: however this is often not feasible, and indeed the same sample selection model is needed to correct for an imperfect design in a completed survey. Alternatively, when the confidence interval around the selection parameter is so wide that nothing conclusive can be said about the presence or not of sample selection bias, the analyst may use *a priori* information to restrict the hypotheses about the value of the correlation coefficient. In any case, when nothing conclusive can be said about the correlation coefficient, it is advisable to accept the sample selection model rather than the censored sample model: this allows to take into account the uncertainty about the wtp estimate. Calculating the central measure for the wtp for different possible values of rho may give quite different values: the confidence interval will be very wide, and allows for more conservative estimates than those obtained with the more precise, but possibly biased, censored sample, model.

References

Cameron, T.A. (1991), “Interval Estimates of Non-Market Resource Values from Referendum Contingent Valuation Surveys”. *Land Economics* 67, pp. 413-21.

Copas, J.B. (1990), "A Likelihood Approach to Sample Selectivity in Multiple and Binary Regression Models for Comparative Studies", School of Mathematics and Statistics working paper, 20/90, University of Birmingham.

Donaldson, C., A.M. Jones, T.J. Mapp, and **J.A. Olson** (1997), “Limited Dependent Variables in Willingness to Pay studies: Applications in Health Care”, mimeo, University of Aberdeen.

Greene, W.H. (1991) *Econometric Analysis (2nd ed.)*. MacMillan Publishing Company.

Howe, C.W., B.J. Lee, and **Lynne L. Bennett** (1994), "Design and Analysis of Contingent Valuation Surveys Using the Nested Tobit Model", *The Review of Economics and Statistics,* 76(2), pp. 385-89.

Lee, B.J. (1992), "A Nested Tobit Analysis for a Sequentially Censored Regression Model", Economic Letters, 38, pp. 269-73.

Mitchell, R. C. and **R.T. Carson** (1989), *Using Surveys to Value Public Goods. The Contingent Valuation Method,* Resources for the Future, Washington.

Whitehead J.C., P.A. Groothuis and **G.C. Blomquist** (1993), "Testing for Non-response and Sample Selection Bias in Contingent Valuation", *Economic Letters,* 41, pp. 215-20.