Regression Analysis and Time Use Data A Comparison of Microeconometric Approaches with Data from the Swedish Time Use Survey (HUS)

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JEL-Classification: C24, C34, C52, J22

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Abstract

This study focuses on a comparison and evaluation of models and estimators appropriate for time-use data. The tobit type I as well as different generalizations are used. According to our findings, a simple tobit I method can produce results that are similar and in some cases even better to the much more sophisticated methods. This is especially true if the participation or index equation is incorrectly specified.

1 Introduction

The purpose of this paper is to compare and evaluate statistical models for the analyses of time use data. From our perspective, time use data have important characteristics that have to be considered when they are used in regression analysis. Using market work as an illustration, a measure of work based on time use data typically results in a too large share of individuals reporting zero hours. There are two reasons for this; the individual does not belong to the labor force or the individual does belong to the labor force but did not work, for some reasons, during any of the selected days of interviews. The second reason implies that the design of the time use survey matters. In this study we discuss time use data collected by interviewing the respondents about their activities during the preceding day.

Common with most micro economic modeling a special treatment have to be given to the participation decision, but apart from this, the design of the time use survey also have to be considered. Thus apart from the standard division between genuine non-participators, individuals that never will participate, and individuals who are potentially participators, we also have to be aware of the possibility that the reason they reported zero is that they were asked “wrong” days. The problem of under-reporting in time use surveys is analogous to the well-known problem of under-reporting in consumer expenditure surveys. This is especially true for consumption of durable or other goods like alcoholics and tobacco.

Cragg (1971) suggested the double-hurdle model as an interesting attempt to consider these problems. In order to observe positive value two hurdles must be overcome. First, a positive amount has to be desired (hours of work). Secondly, favorable circumstances have to exist for the positive desire to be realized (the person must be observed working on the interview day).

Deaton & Irish (1984) applied the double-hurdle model on consumer demand. Cragg´s original formulation is based on the assumption of independence between the participation decision and the structural equation, in later applications this assumption have been dropped. The unrestrictive version has been applied to models of labor supply, Blundell & Meghir (1987) and Blundell, Ham & Meghir (1987, 1988) and Carlin & Flood (1997). Jones (1989) used the double hurdle specification for analyzing tobacco expenditure, and Jones (1992) presented a detailed and explicit derivation of the likelihood function for both the models with and without dependence. The double-hurdle model derived in Jones is based on the assumption that the tobit selection is unknown, if the tobit selection is known this information can be utilized in the estimation, both cases will be considered in this study.

The double-hurdle model can be regarded as an extension of Heckman’s (1978) generalized tobit model. Since this model has become a standard framework for studying participation and choice of hours, it is natural to compare this specification with the double-hurdle modification. For the same reason we also include in this comparison the standard tobit (type I) model.

The purpose of this paper is to compare the double-hurdle with the tobit type II model as well as the much simpler standard tobit (type I) model. Whether the more complicated double-hurdle specification is preferred or not depends on how well the index equation can be specified. The difficulty is to specify an index equation that can differ between “true” and “false” zeros. Using available data it can be difficult to specify this equation and therefore it is not obvious that the double-hurdle model is to be preferred or not even that the tobit II is preferred over tobit I.

In section 2 of this paper we introduce the tobit type II and the double-hurdle model. In section 3 these models are used in a labor supply application using Swedish time-use data from the HUS-survey. The last section presents some results based on a Monte Carlo comparison using artificial data.

2 Statistical models

Heckman’s (1978) generalized tobit model (tobit type II), consists of a structural equation (preferred labor supply function), an index equation (labor participation), a threshold equation linking preferred and observed hours and finally a stochastic specification.

(1) Structural equation: $y_i^* = x_{1i}\beta_1 + \varepsilon_i$

(2) Index equation: $d_i^* = x_{2i}\beta_2 + v_i$

(3) Threshold index equation: $d_i = \begin{cases} 1 \text{ if } d_i^* > 0 \\ 0 \text{ if } d_i^* \le 0 \end{cases}$

(4) Threshold structural equation: $y_i = \begin{cases} y_i^* \text{ if } d_i = 1 \\ 0 \text{ else} \end{cases}$

(5) Stochastic specification: $\varepsilon_i, \nu_i \sim N(0,0,\sigma^2,1,\rho)$

y_i* denotes the latent (non-observed) endogenous variable, say preferred hours of market work, and y_i denotes the corresponding observed variable (measured hours of work). x_{1i} and x_{2i} are vectors of explanatory variables, which are assumed to be uncorrelated with the error terms ε_i och ν_i. β_1 and β_2 are vectors of parameters. d_i^* is a latent variable that represents binary censoring and d_i is the observed value (1 if the individual reports market work, else 0). Note that the stochastic specification is quite general in allowing for the error terms to be correlated with the correlation coefficient ρ.

Given the stochastic specification the likelihood function can be derived as

$$(6)\ L = \prod_{y=0} \Phi(-X_2\beta_2) \prod_{y>0} \left\{ \Phi\left(\frac{X_2\beta_2 + \frac{\rho}{\sigma}(y - X_1\beta_1)}{\sqrt{1-\rho^2}} \right) \tfrac{1}{\sigma}\phi((y - X_1\beta_1)/\sigma) \right\}$$

where y=0 denotes the individuals with zero working hours and y>0 the individuals with positive hour, Φ and ϕ denotes the univariate cdf and pdf of the standard normal. Estimation of this model is straightforward and, for instance, software like Limdep can be used.

Instead of using ML, Heckman (1979) suggested a two-stage method (heckit). Thus, estimate the binary regression and obtain estimates of β_2, compute $\lambda_i = \phi(x_{2i}\beta_2)/\Phi(x_{2i}\beta_2)$. Estimate the structural equation based on the sub-sample of participators and using λ_i as an additional right hand side variable. Finally the standard errors and the estimate of σ^2 have to be adjusted.

The double-hurdle represents an interesting modification of the tobit type II model obtained by explicitly consider that y is censored at 0. This model can also be denoted a tobit model with selectivity. The only modification needed is to change the structural threshold function to

$$(7)\qquad y_i = \begin{cases} y_i^* \text{ if } d_i = 1 \text{ and } y_i^* > 0 \\ 0 \text{ else} \end{cases}$$

The derivation of the likelihood function for the double-hurdle model is presented in Jones (1992), after some manipulations it is given as

$$(8)\ L = \prod_{y=0} \{1 - \Phi(X_2\beta_2, X_1\beta_1/\sigma, \rho)\} \prod_{y>0} \left\{ \Phi\left(\frac{X_2\beta_2 + \frac{\rho}{\sigma}(y - X_1\beta_1)}{\sqrt{1-\rho^2}} \right) \tfrac{1}{\sigma}\phi((y - X_1\beta_1)/\sigma) \right\}$$

Thus, this form of the likelihood requires evaluation of the bivariate cdf, and the univariate pdf and cdf. Note that this specification does not use the information that tobit censoring (d=1 and y=0) might be known. An alternative specification that use this information is

$$(9)\ L = \prod_{d=0} \Phi(-X_2\beta_2) \prod_{d=1,y=0} \Phi(X_2\beta_2, -X_1\beta_1/\sigma, \rho) \prod_{y>0} \left\{ \Phi\left(\frac{X_2\beta_2 + \frac{\rho}{\sigma}(y - X_1\beta_1)}{\sqrt{1-\rho^2}} \right) \frac{1}{\sigma}\phi((y - X_1\beta_1)/\sigma) \right\}$$

Thus the first term in (8) is given by two terms in (9), this easily follows by inspection of the probabilities involved. The table below summarizes the relevant selection probabilities

		y		
		= 0	> 0	
d	=0	P_{00}	P_{01}	$P_{0.}$
	=1	P_{10}	P_{11}	$P_{1.}$

The probability of y=0 is given by the following bivariate probabilities $P_{00}+P_{10}+P_{01}$. Instead of evaluating these terms separately Jones (1992) simply used 1-P_{11}. Thus, the first term in likelihood (8) is 1-P_{11}. However, this means that the information that an observation might be observed as d=1 and y=0 is not used explicitly. In order to use this information the sum of the three probabilities could instead be written as $P_{0.}+P_{10}$ (a univariate, and a bivariate probability). These two probabilities are given by the first two terms in (9).

Labor supply is one illustration where it is reasonable to assume known tobit censoring. Let the index equation represent labor force participation and the structural equation hours of work, in many micro databases both participation and hours of work are known. If the case that both d=1 (the individual belongs to the labor force) and y=0 (for instance unemployment) occurs in the data, then the tobit selection is known and the appropriate specification is (9) instead of (8). For an alternative illustration consider expenditure of tobacco. The index equation in this case might be the probability of being a smoker and the structural equation is expenditure on tobacco. Here, it is not obvious that information about whether the respondents are smokers or not is known. The only available information is the expenditure, thus the d-variable is simply coded 1 if y>0 and zero if y=0. For this case the appropriate likelihood function is (8). If the specification (9) is used in this case, the second term in (9) will never be used and the likelihood function (9) is reduced to the likelihood function (6) for a tobit type II model. It should also be noted that specification (9) is included in Limdep but to the best of our knowledge specification (8) is not included in any commercial software.

Finally, the standard tobit (type I), is obtained by dropping the index equation and modifying the threshold function to

$$(10) \qquad y_i = \begin{cases} y_i^* \text{ if } y_i^* > 0 \\ 0 \text{ else} \end{cases}$$

A priori, the standard tobit must be regarded as a very restrictive model since this model does not differ between the participation decision and the structural equation. However, using real data it can be difficult to specify a reasonable model for the decision to participate.

We are going to estimate female labor supply using five different alternatives:

The Standard Tobit model, Type I (Maximum Likelihood)

The Generalized Tobit model, Type II (Heckman's two stage method, Heckit)

The Generalized Tobit model, Type II (Maximum Likelihood)

The Double Hurdle model (Maximum Likelihood using (8))

The Double Hurdle model (Maximum Likelihood using (9))

Usually in these kinds of models the estimated parameters have no natural interpretation. In order to get interpretable results we have used marginal effects. These marginal effects are based on the following expected values;

Double hurdle

(11) $$E(Y) = \Phi_2\left[X_1\beta + \sigma\{\phi(-h)\Phi[\delta(-k+\rho h)] + \rho\phi(-k)\Phi[\delta(-h+\rho k)]\}\right]$$

where Φ_2 denotes the bivariate normal probability and h= $x_1\beta_1/\sigma$, k= $x_2\beta_2$ and δ= $-1/(1-\rho^2)^{1/2}$.

Tobit type II

(12) $$E(Y) = \Phi(k)\left[X_1\beta_1 + \sigma\{\phi(k)/\Phi(k)\}\right]$$

Tobit type I

(13) $$E(Y) = \Phi(h)\left[X_1\beta_1 + \sigma\{\phi(h)/\Phi(h)\}\right]$$

In the following marginal effects are defined as the derivative of E(Y) with respect to the variables in x_1. Note that all effects have been evaluated at the sample means of x_1 and x_2.

3 A labor supply application

In this section we analyze female labor supply based on HUS data 1993. The 1993 wave of the HUS includes a standard survey portion and a detailed time use section. The time use section provides detailed breakdowns of the time devoted to various activities from midnight to the following midnight of the day prior to the survey date.

In the time use survey an effort was made to include one weekday and one weekend day to get as complete a picture as possible of a wide variety of activities. A weighted average of the two reports is used to construct a synthetic week. The weights are 5 and 2 respectively depending on whether the time use day is a weekday or a weekend day. Because of the method used to construct these weeks it is important to emphasize that the time use data give us better information on actual as opposed to normal time use, because the random effects that disrupt normal work and other days are not "washed out" as they are with the typical survey question. On the other hand, because random effects are not systematic and only two days are observed the constructed labor supply figures will be too sensitive to the occurrence of an atypical event.

For example, if time use data are collected for a Tuesday and a Saturday, a mother who normally works 5 days a week, eight hours per day could wind up with a zero hours of work entry if she took Tuesday off to care for a sick child. Because of this one must be careful in comparing the results of this labor supply study with others that rely on traditional data. Over the entire sample we should get a good picture of actual hours worked, but the hours of work for a given individual are too sensitive to random variation.

From the descriptive statistics in table 1 we note that the mean for weekly work hours is about 23 with a standard deviation of about the same size. The 23 hours per week can be interpreted as the average number of hours actually worked in a typical week taking account of abnormal events such as personal sickness, taking care of a sick child, attending some child event, providing substitute child care and so on. The survey data, as is well known, do not present an accurate picture of labor supply because they do not acknowledge enough random and nonrandom variation. The time use data avoid the problem of too little variation but, because of the problem alluded to above, probably take too much account of random variation, especially on an individual basis.

Table 1: Descriptive statistics HUS 1993

Variable	Mean	Standard deviation	Minimum	Maximum
Time-use market work	22.74	22.50	0.00	76.17
Age in years	43.33	11.19	20.00	64.00
Education low	0.49	0.50	0.00	1.00
Education medium	0.30	0.46	0.00	1.00
Education high	0.20	0.40	0.00	1.00
Big city	0.26	0.44	0.00	1.00
Medium city	0.55	0.50	0.00	1.00
Children 0-3	0.18	0.38	0.00	1.00
Children 4-7	0.24	0.43	0.00	1.00
Children 8-12	0.17	0.38	0.00	1.00
Children 13-18	0.24	0.43	0.00	1.00
Organized Child care	0.18	0.39	0.00	1.00
Predicted Net wage	50.76	6.53	32.26	68.89
Predicted Income	129.66	23.66	62.27	250.00
Home owner	0.81	0.39	0.00	1.00
# of household members	3.20	1.14	1.00	9.00
Sunday	0.44	0.50	0.00	1.00
Monday	0.19	0.39	0.00	1.00
Tuesday	0.19	0.39	0.00	1.00
Wednesday	0.18	0.38	0.00	1.00
Thursday	0.16	0.36	0.00	1.00
Friday	0.15	0.35	0.00	1.00
Saturday	0.43	0.49	0.00	1.00

Source: Flood, L.R & Klevmarken, A & Olovsson, P. 1997, Houshold Market and Nonmarket Activities (HUS) Volume 6.

Consider some special characteristics of the exogenous variables that have been used to explain the variation in female labor supply. The net wage used in this study is calculated by $wage_{1993}$(1-(marginal tax rate)$_{1992}$). The income variable is calculated by spouse total net income (92) + household non-labor income (92) + own total net income (92). The maintained assumption is that the individual knows her current wage rate and uses last year's marginal tax rate and income as indicators of the current variables which are unknown. In order to decrease the endogenity problem, the marginal net wage rate and income are then predicted (by OLS) using linear and quadratic terms for age, education, 1992 non labor income and years of experience in the labor market. The predicted mean wage rate after tax is about 50 SEK per hour

Education is measured by dummy variables reflecting three different levels of education. A low education corresponds to about 9 years of schooling while a high education corresponds to at least a university degree. A one for the homeowner dummy indicates ownership of a house.

Dummy variables for the day of the time use interview have been included in the sample selectivity equation for all models except double hurdle with known tobit selection, for this model these variables are used in the structural equation. Sunday is the omitted reference cases for the day dummy variables.

We assume that the presence of children can be considered as exogenous variables. The final sample only includes married/cohabiting females in ages 20-64. Observations with missing values on any variable except wages were also deleted, and a few observations were deleted because of the low quality of the answers to the time use questions, the final sample includes 529 females.

3.1 Results

The marginal effects are presented in Table 2. Inspection of this table shows that; there are very few significant effects and, many of the results are quite similar regardless of the model used. Focusing on the significant effects, we find a strong negative effect of young children: One child in the age 0-3 reduces female working hours by about 12 to 19 hours/week. The double hurdle specification with known censoring produces the strongest effect and the results for the other specifications are rather similar. It is striking that the simple tobit I produce almost exactly the same result as the much more sophisticated double hurdle with unknown censoring.

The tobit I specification produces wage and income effects that are much higher in absolute values compared to the other models. It should be noted that all specifications produce the non-theoretical result of negative wage and positive income elasticity's. This result was also presented in Carlin & Flood (1997).

Despite considerable differences in the specifications, the main results as presented in Table 2 are surprisingly similar. One interpretation of this result is that due to the randomness that characterize time use data it is very difficult to discriminate between different statistical models. This is confirmed by a lagrange-multiplier test of tobit I versus tobit II, which results in a non-rejection of tobit I. (the obtained prob-value is 0.1408709). Unfortunately statistical testing of tobit II versus the double hurdle is not straightforward, and to the best of our knowledge such a test have not been suggested in the literature.

Of course, as usual, the results discussed here might be coincidental and in order to further investigate the differences in these specifications we will use a simulation approach.

Table 2: Marginal effects, market work (hours per week).

Variable	Tobit I	Tobit II, Heckit	Tobit II, ML	Double Hurdle, tobit censoring unknown	Double Hurdle, tobit censoring known
Children 0-3	-11.98 (3.61)	-12.89 (3.74)	-12.81 (3.53)	-12.23 (3.47)	-18.93 (5.16)
Children 4-7	-5.28 (3.80)	-7.46 (4.03)	-6.11 (4.04)	-5.61 (3.88)	-8.26 (5.33)
Children 8-12	-5.98 (3.39)	-3.22 (3.55)	-4.63 (3.63)	-5.49 (3.37)	-3.54 (4.34)
Children 13-18	-3.04 (3.21)	-0.14 (3.43)	0.05 (3.33)	-0.40 (3.29)	1.45 (4.00)
Age	1.10 (0.93)	1.72 (0.88)	1.57 (0.84)	1.29 (0.79)	2.32 (1.24)
Age (sq.)	-1.70 (1.04)	-2.36 (1.02)	-2.18 (0.98)	-1.88 (0.91)	-3.02 (1.41)
Education (low)	4.35 (3.74)	2.10 (3.11)	2.25 (2.96)	3.17 (2.97)	0.91 (4.86)
Education (med)	4.38 (3.11)	0.57 (3.06)	0.57 (2.89)	1.04 (2.82)	1.16 (4.05)
Org. Child care	4.09 (3.27)	4.75 (3.66)	4.01 (3.57)	3.52 (3.45)	5.56 (5.09)
Pred. Net wage	-0.89 (0.43)	-0.40 (0.22)	-0.42 (0.22)	-0.54 (0.25)	-0.50 (0.56)
Pred. Income	0.45 (0.11)	0.20 (0.06)	0.21 (0.06)	0.28 (0.08)	0.20 (0.14)
Home owner	-0.47 (2.78)	-1.51 (2.94)	-0.98 (2.87)	-0.96 (2.72)	0.52 (3.72)
# of househ memb	1.67 (1.66)	1.32 (1.75)	1.56 (1.73)	1.91 (1.68)	0.52 (2.10)
Big city	-2.63 (3.08)	-3.54 (3.26)	-4.28 (3.13)	-4.50 (3.03)	-4.23 (3.93)
Medium city	-1.47 (2.68)	-2.25 (2.81)	-2.37 (2.69)	-2.19 (2.63)	-3.43 (3.40)

Note. Standard deviations are in parentheses.

4 Monte Carlo Simulation

In order to evaluate the differences between our models a Monte Carlo simulation will be used. The specific questions of interest are to evaluate the properties of our models, first using as the data generation process (DGP) the double hurdle and then the tobit type II. Also, what are the consequences if the index equation is incorrectly specified?

The first experiment is based on the following DGP:

(1) Structural equation: $$y_i^* = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i$$

(2) Index equation: $$d_i^* = \gamma_0 + \gamma_1 x_{1i} + \gamma_2 x_{3i} + \upsilon_i$$

(3) Threshold index equation: $$d_i = \begin{cases} 1 \text{ if } d_i^* > 0 \\ 0 \text{ if } d_i^* \leq 0 \end{cases}$$

(4) Threshold structural equation: $$y_i = \begin{cases} y_i^* \text{ if } d_i = 1 \textit{ and } y_i^* > 0 \\ 0 \text{ else} \end{cases}$$

(5) Stochastic specification: $\varepsilon_i, \nu_i \sim N(0,0,\sigma^2,1,\rho)$

Where $\beta = \begin{bmatrix} 1.0 \\ -0.2 \\ 0.2 \end{bmatrix}, \gamma = \begin{bmatrix} 0.7 \\ 0.2 \\ -0.2 \end{bmatrix}$, σ^2=4, ρ= -0.5. The X-variables are generated as uniform (0,5) variables. Note that x_1 is included in both equations, whereas x_2 is included only in the structural equation and x_3 only in the index equation.

The first experiment, presented in table 3a and 3b is based on the sample size 500. As expected, the results based on heckit-estimation produce biased estimates. The bias varies from small (4%) to quite large (126%). The heckit results are rather similar to the ML results (except for the two intercepts and ρ) and together they indicate that if the data is generated by double-hurdle, neglecting this in the estimation leads to a serious problem of bias. This can further be illustrated by the results in Table 3b, which display the bias in the estimated marginal effects. The tobit II results gives a bias with respect to x_1 around 70%. The corresponding error in the marginal effect for x_2 is much smaller, the reason is that x_2 does not appear in the index equation. Table 3b also includes the tobit I model, the bias in the marginal effects for x_1 are smaller and for x_2 similar to the results for tobit II.

A comparison of the two double hurdle results in Table 3 is quite revealing. If the tobit selection is known and this is not utilized in the estimation the resulting bias is substantial. From Table 3b it follows that the bias in the marginal effects range from a negative 25% to a positive 15%. As expected, the bias for the double-hurdle model using the information about tobit censoring is much smaller. Considering that the DGP is double hurdle with known tobit censoring, the bias in some of the parameters is still relatively large. In order to check the importance of the sample size the experiment in table 3 is repeated using 1000 observations. The results reported in Table 4a and b, shows that the double hurdle model converges to the true values. Thus, these results indicate that both (8) and (9) produce consistent estimates, but (9) is much more efficient. The result for the tobit type I and II models however still indicates serious problem of bias.

In Table 5a and b we report results where the DGP is tobit type II. This is easily obtained by increasing the size of the intercept, we choose β_0=10, and with this modification the tobit threshold is never active.

The results show that the efficiency gain by ML-estimation instead of Heckit is very small. Also, as expected, if there is no tobit threshold the double-hurdle results are the same as maximum likelihood estimation of tobit type II. The bias in the marginal effects for the tobit I specification is about the same order of magnitude as in the previous case.

A conclusion is therefore that an advantage of the double hurdle specification is that it is more general than the tobit type II (and of course tobit type I). If the data are generated by tobit type II the double hurdle will still produce correct results and if the DGP is double-hurdle serious bias can be avoided using double-hurdle instead of tobit II.

So far the design of the experiments have favored the double hurdle model. It is important to evaluate the properties using a data generation process that is not in agreement with this model in order to verifying the robustness, or lack of robustness, of this specification. In the last experiment we ask the question, what happens if the index equation is incorrectly specified?

In Table 6a-b the DGP is double hurdle and in Table 7a-b it is tobit II. Both these experiments have used the same index equation as before in order to generate the data. However, in the estimation the γ_1 parameter has been restricted to zero. The consequences are quite dramatic, and all methods produce biased results. From table 6b it follows that the bias in the estimated marginal effects for X_1 and X_2 range from 3 to 70%. As expected, the double hurdle specifications performs much better than tobit II, for instance the β_1 parameter is estimated quite accurately and as a consequence there is only minor error in the marginal effect for X_1. It is interesting to note that the tobit I model produces much smaller bias for X_2, compared to the other models. Since the index equation is not used in tobit I, an error in this relation has no effect on this estimator. Thus the simple tobit I have some advantage compared to the more advanced methods in being more robust regarding error in the specification in the index equation. This result also holds for the experiment presented in Table 7a-b, using tobit II as DGP. Table 7b shows that again the tobit I have the smallest bias in the marginal effect for X_2. However, the tobit II and double hurdle methods (which produce identical results) are better with respect to X_1.

Thus, the results discussed here shows how sensitive the more advanced methods are. An incorrect index or participation equation can cause a serious bias in the estimated parameters. To find robust estimators that can be applied on models for time use as well as other micro data is an important topic for further research.

Table 3a:Monte Carlo simulation. DGP: Double hurdle, tobit censoring known, 500 observations.

Para-meter	True value	Tobit II, Heckit		Tobit II, ML		Double Hurdle, tobit censoring unknown		Double Hurdle, tobit censoring known	
		Bias %	Rmse	Bias %	Rmse	Bias %	Rmse	Bias %	Rmse
β_0	1.0	125.9	1.607	46.2	1.228	-18.0	0.836	-12.3	0.394
β_1	-0.2	52.8	0.125	58.8	0.136	3.7	0.085	2.3	0.060
β_2	0.2	-68.2	0.194	-25.3	0.141	2.7	0.182	9.0	0.067
γ_0	0.7	-139.7	0.990	-145.1	1.029	175.0	8.065	3.2	0.119
γ_1	0.2	3.6	0.045	4.1	0.044	-44.7	1.325	-1.3	0.032
γ_2	-0.2	34.6	0.080	42.0	0.099	-80.7	0.570	2.0	0.032
σ	2.0	-28.6	0.655	-29.4	0.660	-0.2	0.227	-0.3	0.132
ρ	-0.5	36.7	0.440	97.4	0.686	31.2	0.447	-22.5	0.241

Table 3b: Bias in estimated marginal effects. DGP: Double hurdle, tobit censoring known, 500 observations.

Variable	Tobit I ML %	Tobit II Heckit %	Tobit II ML %	Double Hurdle tobit censoring unknown %	Double Hurdle tobit censoring known %
Intercept	-137.1	-18.3	-49.6	-16.5	-10.0
X1	32.0	67.0	71.2	-24.8	-1.4
X2	-8.3	-5.7	-6.9	14.9	0.6

Table 4a:Monte Carlo simulation. DGP: Double hurdle, tobit censoring known, 1000 observations.

Parameter	True value	Tobit II, Heckit		Tobit II, ML		Double Hurdle, tobit censoring unknown		DoubleHurdle, tobit censoring known	
		Bias %	Rmse	Bias %	Rmse	Bias %	Rmse	Bias %	Rmse
β_0	1.0	151.5	1.744	69.2	1.166	-0.1	0.699	-5.2	0.394
β_1	-0.2	55.0	0.117	58.7	0.124	0.5	0.059	2.1	0.060
β_2	0.2	-82.3	0.194	-36.8	0.129	-11.6	0.160	2.3	0.067
γ_0	0.7	-141.7	0.997	-144.1	1.016	21.3	0.872	0.5	0.119
γ_1	0.2	3.4	0.028	3.1	0.027	7.8	0.113	-0.4	0.032
γ_2	-0.2	38.2	0.082	42.0	0.092	-19.1	0.132	0.3	0.032
σ	2.0	-26.7	0.611	-31.3	0.668	0.2	0.186	0.0	0.132
ρ	-0.5	10.0	0.340	77.2	0.556	9.3	0.266	9.4	0.241

Table 4b: Bias in estimated Marginal effects. DGP: Double hurdle, tobit censoring known, 1000 observations.

Variable	Tobit I ML %	Tobit II Heckit %	Tobit II ML %	Double Hurdle tobit censoring unknown %	Double Hurdle tobit censoring known %
Intercept	-138.9	-8.0	-39.7	3.3	-5.1
X_1	39.3	68.4	70.9	-15.9	2.0
X_2	-7.3	-6.0	-6.9	9.1	-0.4

Table 5a:Monte Carlo simulation. DGP: tobit type II, 1000 observations.

Para-meter	True value	Tobit II, Heckit		Tobit II, ML		Double Hurdle, tobit censoring unknown		Double Hurdle, tobit censoring known	
		Bias %	Rmse	Bias %	Rmse	Bias %	Rmse	Bias %	Rmse
β_0	10.0	0.2	0.445	-0.7	0.367	-0.7	0.367	-0.7	0.367
β_1	-0.2	2.3	0.056	2.4	0.057	2.4	0.057	2.4	0.057
β_2	0.2	-2.1	0.070	3.8	0.060	3.8	0.060	3.8	0.060
γ_0	0.7	-0.3	0.120	0.5	0.118	0.5	0.118	0.5	0.118
γ_1	0.2	0.0	0.032	-0.3	0.032	-0.3	0.032	-0.3	0.032
γ_2	-0.2	1.1	0.033	0.2	0.031	0.2	0.031	0.2	0.031
σ	2.0	2.0	0.156	-0.2	0.092	-0.2	0.092	-0.2	0.092
ρ	-0.5	0.1	0.270	9.3	0.217	9.3	0.217	9.3	0.217

Table 5b: Bias in estimated Marginal effects. DGP: Tobit type II, 1000 observations.

Variable	Tobit I ML %	Tobit II Heckit %	Tobit II ML %	Double Hurdle tobit censoring unknown %	Double Hurdle tobit censoring known %
Intercept	-63.1	0.1	-0.6	-0.6	-0.6
X_1	32.0	2.1	2.3	2.3	2.3
X_2	9.6	-0.3	-0.3	-0.3	-0.3

Table 6a: Monte Carlo simulation. DGP: Double hurdle, 1000 observations. Index equation incorrect.

Para-meter	True value	Tobit II, Heckit		Tobit II, ML		Double Hurdle, tobit censoring unknown		Double Hurdle, tobit censoring known	
		Bias %	Rmse	Bias %	Rmse	Bias %	Rmse	Bias %	Rmse
β_0	1.0	126.5	1.413	64.6	0.908	-106.5	1.105	-25.3	0.386
β_1	-0.2	55.2	0.117	58.9	0.125	4.2	0.058	2.1	0.060
β_2	0.2	-32.8	0.077	-37.3	0.088	118.8	0.244	46.3	0.106
γ_0	0.7	-68.3	0.483	-70.9	0.506	163.5	1.272	64.6	0.460
γ_1	0.2	-------	--------	-------	-------	-------	-------	--------	-------
γ_2	-0.2	39.8	0.084	43.8	0.095	-40.7	0.141	4.6	0.032
σ	2.0	-26.2	0.609	-30.8	0.670	5.5	0.206	1.3	0.160
ρ	-0.5	9.8	0.339	84.2	0.584	-4.8	0.226	5.1	0.225

Table 6b: Bias in estimated Marginal effects. DGP: Double hurdle, 1000 observations. Index equation incorrect.

Variable	Tobit I ML %	Tobit II Heckit %	Tobit II ML %	Double Hurdle tobit censoring unknown %	Double Hurdle tobit censoring known %
Intercept	-63.1	32.6	-0.9	-55.8	2.4
X_1	32.0	67.0	69.5	3.3	3.4
X_2	9.6	-70.3	-72.1	32.4	-13.5

Table 7a: Monte Carlo simulation. DGP: Tobit type II, 1000 observations. Index equation incorrect.

Para-meter	True value	Tobit II, Heckit		Tobit II, ML		Double Hurdle, tobit censoring unknown		Double Hurdle, tobit censoring known	
		Bias %	Rmse	Bias %	Rmse	Bias %	Rmse	Bias %	Rmse
β_0	10.0	-2.1	0.393	-2.5	0.381	-2.5	0.381	-2.5	0.381
β_1	-0.2	2.7	0.057	2.7	0.057	2.7	0.057	2.7	0.057
β_2	0.2	44.2	0.099	44.5	0.100	44.5	0.100	44.5	0.100
γ_0	0.7	64.3	0.458	64.8	0.461	64.8	0.461	64.8	0.461
γ_1	0.2	-------	-------	-------	-------	-------	-------	-------	-------
γ_2	-0.2	5.0	0.033	4.4	0.031	4.4	0.031	4.4	0.031
σ	2.0	2.4	0.166	0.5	0.094	0.5	0.094	0.5	0.094
ρ	-0.5	0.8	0.273	6.3	0.217	6.3	0.217	6.3	0.217

Table 7b: Bias in estimated Marginal effects. DGP: Tobit type II, 1000 observations. Index equation incorrect.

Variable	Tobit I ML %	Tobit II Heckit %	Tobit II ML %	Double Hurdle tobit censoring unknown %	Double Hurdle tobit censoring known %
Intercept	-63.1	12.6	12.2	12.2	12.2
X_1	32.0	3.8	3.8	3.8	3.8
X_2	9.6	-72.2	-72.2	-72.2	-72.2

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