Limited Dependent Variables & Selection: PS #2

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1. Suppose that we observe N iid draws $(y_i, \mathbf{x}_i)$ from a population of interest where $y_i \in \{0, 1\}$ and $\mathbf{x}_i$ is a $(k \times 1)$ vector of dummy variables indicating which of k mutually exclusive "bins" person i falls into. For example, suppose that $k = 2$ and we defined the bins to be "female" and "male." Then $\mathbf{x}_i' = \begin{bmatrix} 1 & 0 \end{bmatrix}$ would indicate that person i is female while $\mathbf{x}_1' = \begin{bmatrix} 0 & 1 \end{bmatrix}$ would indicate that person i is male. Note that $\mathbf{x}_i$ does not include an intercept to avoid the dummy variable trap. The following parts explore the results of fitting the linear probability model $\mathbb{P}(y_i|\mathbf{x}_i) = \mathbf{x}_i'\boldsymbol{\beta}$ by running an OLS regression of y_i on $\mathbf{x}_i$. Following the usual conventions, define

$$\mathbf{X}' = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_N \end{bmatrix}, \quad \mathbf{y}' = \begin{bmatrix} y_1 & y_2 & \cdots & y_N \end{bmatrix}$$

   (a) Let N_j denote the number of individuals in the sample who fall into category j. In other words, if $x_i^{(j)}$ is the jth element of $\mathbf{x}_i$, then $N_j \equiv \sum_{i=1}^N x_i^{(j)}$. Show that

$$\mathbf{X}'\mathbf{X} = \begin{bmatrix} N_1 & & & 0 \\ & N_2 & & \\ & & \ddots & \\ 0 & & & N_k \end{bmatrix}$$

   i.e. that $\mathbf{X}'\mathbf{X}$ is a $(k \times k)$ diagonal matrix with jth diagonal element N_j.

   (b) Substitute the preceding part into $\widehat{\boldsymbol{\beta}} \equiv (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ to obtain a simple, closed-form expression for $\widehat{\beta}_j$. Interpret your result.

   (c) A critique of the LPM is that it can yield predicted probabilities that are greater than one or less than zero. Is this a problem in the present example?

2. This question concerns the Probit regression model $\mathbb{P}(y = 1|\mathbf{x}) = \Phi(\mathbf{x}'\boldsymbol{\beta})$ where Φ is the standard normal CDF.

   (a) Derive the first order conditions for the maximum likelihood estimator $\widehat{\boldsymbol{\beta}}$ based on an iid sample $(y_1, \mathbf{x}), \ldots, (y_N, \mathbf{x}_N)$.

   (b) Suppose that $y = \mathbb{1}\{\mathbf{x}'\boldsymbol{\beta} + u > 0\}$ where $u \sim \mathcal{N}(0, 1)$ independently of $\mathbf{x}$ and $\mathbb{1}(\cdot)$ is the indicator function. Show that this model is in fact *exactly equivalent* to the Probit regression model.

3. Consider a logit-Family model with $P_{ni} = \exp(V_{ni}) / \sum_{j=1}^J \exp(V_{nj})$ and $V_{nj} = \mathbf{x}_{nj}'\boldsymbol{\beta}$.

(a) What *variety* of Logit-family model is this? How can you tell?

(b) Show that the partial effects for this model are given by

$$\frac{\partial P_{ni}}{\partial \mathbf{x}_{ni}} = P_{ni}(1 - P_{ni})\boldsymbol{\beta}, \quad \text{and} \quad \frac{\partial P_{ni}}{\partial \mathbf{x}_{nk}} = -P_{ni}P_{nk}\boldsymbol{\beta} \quad \text{for } i \neq k$$

4. *This question is adapted from Wooldridge (2010).* Consider the Heckman selection model from the lecture slides. Assumption (d) of this model states that the conditional mean of u_1 given v_2 is linear: $\mathbb{E}(u_1|v_2) = \gamma_1 v_2$. In this question, you will explore the consequences of replacing Assumption (d) with a *quadratic* conditional mean function, in particular

$$\text{Assumption (d*)} \quad \mathbb{E}(u_1|v_2) = \gamma_1 v_2 + \gamma_2(v_2^2 - 1).$$

In your answers to the following parts, assume that all assumptions other than (d) of the Heckman Selection model continue to apply.

(a) Show that Assumption (c) and (d*) imply $\mathbb{E}(u_1) = 0$. Using your answer, explain why the RHS of Assumption (d*) does *not* take the form $\gamma_1 v_2 + \gamma_2 v_2^2$.

(b) Let a be a constant, $z \sim N(0, 1)$ and $\lambda(\cdot)$ be the inverse Mills ratio defined in the lecture slides. It can be shown that:

$$\text{Var}(z|z > -a) = 1 - \lambda(a)\left[\lambda(a) + a\right].$$

Use this result to prove that

$$\mathbb{E}(y_1|\mathbf{x}, y_2 = 1) = \mathbf{x}_1'\boldsymbol{\beta}_1 + \gamma_1\lambda(\mathbf{x}'\boldsymbol{\delta}_2) - \gamma_2\lambda(\mathbf{x}'\boldsymbol{\delta}_2)\mathbf{x}'\boldsymbol{\delta}_2.$$

Hint: $\text{E}(v_2^2|v_2 > -a) = \text{Var}(v_2|v_2 > -a) + \left[\mathbb{E}(v_2|v_2 > -a)\right]^2$.

(c) Using the expression for $\mathbb{E}(y_1|\mathbf{x}, y_2 = 1)$ from the preceding part, explain how to carry out the Heckman Two-step procedure under assumption (d*).

(d) Consider a "naïve" OLS regression of y_1 on $\mathbf{x}_1$ for the subset of individuals with $y_2 = 1$. Without actually running the naïve regression, explain how you could use the estimates from your Heckman Two-step procedure in the preceding part to determine whether or not the naïve OLS of β_1 would be biased.

5. *This question is adapted from Wooldridge (2010).* To answer it you will need to use the dataset `BWGHT.RAW`, which can either be downloaded from the MIT Press website for the text, or loaded directly into R using the package `Wooldridge`. Documentation for the dataset is available in the R package or alternatively at `http://fmwww.bc.edu/ec-p/data/wooldridge/bwght.des`

(a) Create a binary variable called *smokes* that equals one if a woman smokes during pregnancy, zero otherwise. Then estimate a probit regression that uses *motheduc*, *white*, and log(*faminc*) to predict *smokes*. Summarize your results.

(b) Consider two white women with family income equal to the sample mean: Alice has 12 years of education while Beth has 16. What is the estimated difference in the probability of smoking during pregnancy for Alice compared to Beth?

(c) Calculate the average partial effect of log(*faminc*) in your estimated model.

(d) Calculate the pseudo-R-squared of your model. Don't bother trying to interpret it because, as you know, I'm not a fan! (I just want to make sure you can re-produce all the results that appear in STATA's probit output using R.)