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RESEARCH MEMORANDUM

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ON THE ESTIMATION OF A FIXED EFFECTS MODEL WITH SELECTIVE NON-RESPONSE

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ON THE ESTIMATION OF A FIXED EFFECTS MODEL WITH SELECTIVE NON-RESPONSE

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Abstract: *If non-response is selective the maximum likelihood estimator of the parameters in a model with fixed effects will not be consistent when the number of time periods is small. In this note, we present a transformation to eliminate the fixed individual effects and show that the corresponding marginal maximum likelihood estimator can be used to estimate the remaining parameters consistently, even if the sample is selective. This consistency also holds when only a few time series observations are available.*

Key words: *panel data, selectivity bias, fixed effects, marginal maximum likelihood.*

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1. Introduction

In the econometric literature of the last two decades, much attention has been paid to the estimation and testing of fixed effects and random effects models using panel data (see Hsiao [1986] for a survey). Relatively little attention, however, seems to have been paid to the phenomenon of missing observations, a problem of frequent occurrence in panel data. (see Biørn [1981], Baltagi [1985] and Wansbeek and Kapteyn [1986]). Using the available complete observations only (i.e. creating a balanced panel) often implies a substantial loss of information compared to using the unbalanced panel. Moreover, both procedures are likely to result in biased estimators if there is selective non-response. For a model with random individual effects, Hausman and Wise [1979] discuss maximum likelihood estimation in case of selective attrition, a generalization of which is recently given by Ridder [1988].

In this note attention will be paid to the model with fixed individual effects. We show how the parameters of the model can be consistently estimated if the non-response is selective. It appears that straightforward extension of the methods suggested by Hausman and Wise [1979] for the random effects model only leads to consistent estimators for the number of time periods (T) tending to infinity and not for the number of units tending to infinity. In practice however, a panel data set typically consists of observations of a large number of individuals over a small number of periods, so the assumption of infinite T will not be a valid approximation.

2. Estimation of the model

Consider the following linear model

$$y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it}, \qquad t = 1,\dots,T,\ i = 1,\dots,N \tag{1}$$

where X_{it} is a row vector of (non-stochastic) values for the (strictly) exogenous variables, β a column vector of unknown parameters of interest and the α_i are fixed unknown parameters. An alternative commonly made assumption for the α_i would be to assume that they are independently identically distributed, in which case we arrive at the random effects model, as considered by, e.g., Baltagi [1985] and Hausman and Wise [1979]. One could prefer to work with a model with fixed rather than random individual effects for several reasons, for example because the fixed effects estimator is consistent even if the unobserved individual effects are correlated with the explanatory variables. A classical example of this topic is the estimation of production functions free of management bias, see e.g. Mundlak [1961].

Following Hausman and Wise [1979] and Ridder [1988], we assume that observations for y_{it} are only available if an unobserved variable r^*_{it} is nonnegative, for which we assume

$$r^*_{it} = Z_{it}\gamma + \xi_i + \eta_{it}, \qquad t = 1,\dots,T;\ i = 1,\dots,N \tag{2}$$

where Z_{it} is a row vector of non-stochastic values for the exogenous variables, possibly containing (partly) the same variables as X_{it}, and ξ_i is an individual specific component of the error term. Because it is well known that a fixed effect probit model is computationally hard to implement since the fixed effects cannot be eliminated (see e.g. Maddala [1987]), we choose a priori for a random effects probit specification. The (observed) indicator variable r_{it} is defined as $r_{it} = 1$ if $r^*_{it} \geq 0$ and $r_{it} = 0$ if $r^*_{it} < 0$.

Letting $\varepsilon_i = (\varepsilon_{i1},\dots,\varepsilon_{iT})'$ and $\eta_i = (\eta_{i1},\dots,\eta_{iT})'$, we assume that the error terms in (1) and (2) are normally distributed according to

$$\begin{bmatrix} \varepsilon_i \\ \eta_i \\ \xi_i \end{bmatrix} \sim N \left[0, \begin{bmatrix} \sigma_\varepsilon^2 I_T & & \\ \rho\, \sigma_\varepsilon \sigma_\eta I_T & \sigma_\eta^2 I_T & \\ 0 & 0 & \sigma_\xi^2 \end{bmatrix} \right] \tag{3}$$

For identification purposes $\sigma_\eta^2 + \sigma_\xi^2$ is usually set to one.

Verbeek and Nijman [1989] give conditions under which the standard fixed effects (or 'within') estimator of β in (1) is consistent, in particular this is the case if both $\rho \neq 0$ and $Z_{it}\gamma$ varies over time. If this is known to be true, an alternative estimator has to be used, which will be derived below. For ease of presentation we assume for the moment that there is no autocorrelation in the error term of the probit equation, i.e. we assume that $\sigma_\xi^2 = 0$. This assumption simplifies the algebra a lot and does not affect the point we want to make. At the end of the present section we will extend the results to the case of nonzero σ_ξ^2.

An obvious alternative to the standard fixed effects estimator (or within estimator) is to use the maximum likelihood estimator incorporating selectivity. This is a straightforward extension of the method of Hausman and Wise [1979], but instead of treating the α_i as random errors we treat them as fixed unknown parameters. The likelihood contribution of individual i is given by

$$\ell_i(\vartheta, \alpha_i) = \prod_{t \in \mathcal{T}_i} P\{ r_{it}^* \geq 0 \mid y_{it} \}\, f(y_{it}) \times \prod_{t \notin \mathcal{T}_i} P\{ r_{it}^* < 0 \}, \tag{4}$$

where $\mathcal{T}_i = \{ t \in \{ 1,\ldots,T \} ;\ r_{it} = 1 \}$ $(i=1,\ldots,N)$ is the set of time indices for the periods in which individual i is observed and $\vartheta = (\beta, \gamma, \rho, \sigma_\varepsilon, \sigma_\eta)'$ is the vector of parameters excluding the individual effects. Straightforward elaboration yields that

$$P\{ r_{it}^* \geq 0 \mid y_{it} \} = \Phi\left[\frac{Z_{it}\gamma + (\rho/\sigma_\varepsilon)(y_{it} - X_{it}\beta - \alpha_i)}{\sqrt{(1-\rho^2)}} \right] \tag{5}$$

$$P\{ r_{it}^* < 0 \} = 1 - \Phi(Z_{it}\gamma) \tag{6}$$

$$f(y_{it}) = \sigma_\varepsilon^{-1}\varphi\left[\frac{y_{it}-X_{it}\beta-\alpha_i}{\sigma_\varepsilon}\right], \tag{7}$$

where φ and Φ are the standard normal density and distribution function respectively, and where σ_η^2 is normalized to one (remember that $\sigma_\xi^2 = 0$). In general, maximizing this likelihood function for all observations does not lead to consistent estimators for finite T since the number of parameters rises with the number of observations. Moreover, one has to optimize with respect to a large number of parameters, which is computationally infeasible. The usual solution to this incidental parameters problem is to condition the likelihood upon some (minimal) sufficient statistics for the incidental parameters resulting in a conditional likelihood function which is independent of the incidental parameters (Andersen [1970], Chamberlain [1980]). Maximizing the conditional likelihood function with respect to the remaining parameters yields (under suitable regularity conditions (see Andersen [1970])) consistent though not necessarily efficient estimators which are asymptotically normal.

In general there is no guarantee that these sufficient statistics exist. In the fixed effects model (1) with no selectivity bias minimal sufficient statistics for α_i are $\bar{y}_{i.}$, the observed individual averages of y_{it} (see e.g. Chamberlain [1980]). Moreover, it can be shown (e.g. Cornwell and Schmidt [1987]) that the maximum likelihood method (ML) and the conditional maximum likelihood method lead to the same estimator for β (the OLS-estimator), which explains why the incidental parameters cause no problem in the standard fixed effects model.

Unfortunately, in the model with selectivity $\bar{y}_{i.}$ is no longer a sufficient statistic for α_i. The conditional likelihood contribution of individual i is given by

$$\begin{aligned} \ell_i^c(\vartheta, \alpha_i) = & \prod_{t \in \mathcal{T}_i} P\{ r_{it}^* \geq 0 \mid y_{it}, \bar{y}_{i.}\} f(y_{it} \mid \bar{y}_{i.}) \\ & \times \prod_{t \notin \mathcal{T}_i} P\{ r_{it}^* < 0 \mid \bar{y}_{i.}\}. \end{aligned} \tag{8}$$

However, it is readily verified that

$$P\{ r_{it}^{*} \geq 0 \mid y_{it}, \bar{y}_{i.} \} = P\{ r_{it}^{*} \geq 0 \mid y_{it} \}, \tag{9}$$

which therefore still contains the incidental parameters α_i unless $\rho = 0$. Thus it follows that maximizing this conditional likelihood function does not lead to consistent estimators either.

Therefore, one has to look for an alternative way to overcome the incidental parameters problem, which is provided by transforming the data in such a way that the individual effects are eliminated and maximizing the likelihood of the transformed data. This can be seen as an application of marginal maximum likelihood (Kalbfleisch and Sprott [1970]) since (in general) only the likelihood of part of the original data is used. Well known effective transformations for the standard fixed effects model (equation (1) while $\rho = 0$) are taking deviations from individual means (the 'within' transformation) and taking first differences. For the standard model marginal ML is identical to ML and therefore also to conditional ML.

It appears that the 'within' transformation, i.e. taking deviations from observed individual means, works equally well in the model with selectivity bias, since it eliminates the incidental parameters (α_i) and thus yields a consistent estimator which is asymptotically normal.

The marginal likelihood contribution of individual i is given by

$$\ell_i^m(\theta) = P\{ r_{it}^{*} \geq 0,\ t \in \mathcal{T}_i \mid \tilde{y}_i \}\ f(\tilde{y}_i) \times \prod_{t \notin \mathcal{T}_i} P\{ r_{it}^{*} < 0 \}, \tag{10}$$

where a tilde denotes deviation from its observed individual mean, i.e. the individual mean is taken over the available observations,

$$\tilde{y}_{it} = y_{it} - \frac{1}{T_i} \sum_{t \in \mathcal{T}_i} y_{it} = y_{it} - \bar{y}_{i.}, \tag{11}$$

where T_i denotes the number of elements in $\mathcal{T}_i$, and where $\tilde{y}_i$ denotes the T_i-vector of observed $\tilde{y}_{it}$'s.

The difference with the likelihood contribution given in (4) is that the simultaneous density of all observed $\tilde{y}_{it}$'s cannot be written as the product of T_i independent densities, since $\tilde{y}_{is}$ and $\tilde{y}_{it}$ are not uncorrelated, and that the probabilities of being observed are now conditional upon $\tilde{y}_i$ instead of y_{it}, implying a nonzero correlation between these probabilities. In particular, for $t \in \mathcal{T}_i$ and $s \in \mathcal{T}_i$ it holds that

$$E\{ \eta_{it} \mid \tilde{y}_i \} = (\rho/\sigma_\varepsilon)(\tilde{y}_{it} - \tilde{X}_{it}\beta) \tag{12}$$

$$V\{ \eta_{it} \mid \tilde{y}_i \} = 1 - \rho^2 + \rho^2/T_i \tag{13}$$

$$\mathrm{Cov}\{ \eta_{it} , \eta_{is} \mid \tilde{y}_i \} = \rho^2/T_i \quad (s \neq t). \tag{14}$$

Since (12) does not involve α_i the incidental parameters problem is solved (the other terms in (10) do not contain α_i) and maximizing the marginal likelihood function (the product of all $\ell_i^m(\theta)$) will lead to consistent estimators for β.

In general the computation of multivariate probit probabilities implies numerical integration over all dimensions. However, since, from (13) and (14), the error term has a random effects structure (which implies that the error terms are independent conditional upon the individual effect), this can be reduced to numerical integration over one dimension, which is computationally very well feasible, see e.g. Butler and Moffitt [1982].

3. Extension to the model with individual effects in the probit error term

In the previous section, we have assumed that the error term in the probit equation was not correlated over time. If we relax this assumption and allow a random individual effect ξ_i the conditional probability in the likelihood is a T-variate probit. Computation of such multivariate probabilities is known to be intractable unless the structure of the (conditional) covariance matrix is such that the dimension of the integral can be reduced. We will show in the sequel that this is the case.

The conditional distribution of the probit error term is characterized by (see Appendix)

$$E\{ \xi_i + \eta_{it} \mid \tilde{y}_i \} = (\rho\sigma_\eta/\sigma_\varepsilon) r_{it}(\tilde{y}_{it} - \tilde{X}_{it}\beta) = \Delta_{it}, \text{ say}, \tag{15}$$

and

$$V\{ \iota\xi_i + \eta_i \mid \tilde{y}_i \} = \sigma_\xi^2 \iota\iota' + \sigma_\eta^2 I_T - \rho^2\sigma_\eta^2 \mathrm{Diag}(r_i) + \rho^2(\sigma_\eta^2/T_i) r_i r_i' \tag{16}$$

where $r_i = (r_{i1},\ldots,r_{iT})'$. For $\sigma_\xi^2 = 0$, these expressions reduce to (12), (13) and (14). Equations (15) and (16) imply that the conditional distribution of the error term in the probit equation is identical to the distribution of

$$v_{it} + u_{i1} + r_{it}u_{i2}, \tag{17}$$

where v_{it}, u_{i1} and u_{i2} are uncorrelated error terms with $E\{v_{it}\} = \Delta_{it}$, $E\{u_{i1}\} = E\{u_{i2}\} = 0$ and

$$V\{v_{it}\} = \sigma_\eta^2(1-r_{it}\rho^2), \quad V\{u_{i1}\} = \sigma_\xi^2 \quad \text{and} \quad V\{u_{i2}\} = \rho^2\sigma_\eta^2/T_i. \tag{18}$$

Just like in the random effects case analysed by Ridder [1988] the conditional probit error term has an error components structure, which can be used to reduce the dimension of integration. Since conditional upon the two individual effects the error terms are independent, we only have to evaluate a double integral instead of a T-variate one. In particular

$$P\{ r_{it}^* \geq 0,\ t \in \mathcal{T}_i\ ;\ r_{it}^* < 0,\ t \notin \mathcal{T}_i \mid \tilde{y}_i \} =$$

$$\int\int \prod_{t=1}^{T} \Phi\left[(2r_{it}-1)\frac{Z_{it}\gamma + \Delta_{it} + u_1 + r_{it}u_2}{\surd(\sigma_\eta^2(1-r_{it}\rho^2))} \right] f(u_1, u_2)\, du_1 du_2, \tag{19}$$

where $f(u_1, u_2)$ is the (normal) density function of u_1 and u_2, equal to $\varphi(u_1)\varphi(u_2)/(\rho\ \sigma_\eta\sigma_\xi/\surd T_i)$. If the individual is observed in all periods ($r_i = \iota$) this simplifies further to a single integral. If these integrals can be evaluated numerically, marginal maximum likelihood estimation is feasible in the case of an individual effect in the probit equation as well.

4. Concluding remarks

In summary, we have seen that the well known equality of the ML estimator, the conditional ML estimator and the marginal ML estimator in the fixed effects regression model, no longer holds true for the model which allows for possible selectivity bias (for finite T). We have presented a way to eliminate the fixed individual effects and to estimate the remaining parameters consistently in the situation of selectivity bias, even if the number of time periods is small. The marginal maximum likelihood function was derived for the case of no autocorrelation in the probit equation as well as the case with individual effects in the probit error term.

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APPENDIX : DERIVATION OF (15) AND (16)

Define for each individual a $T_i \times T$ matrix R_i transforming $y_i = (y_{i1},\ldots,y_{iT})'$ into the T_i dimensional vector $\hat{y}_i$, say, of observed y_{it}'s. Furthermore, define a $T_i \times T_i$ matrix Q_i transforming $\hat{y}_i$ into $\tilde{y}_i$, i.e. $Q_i = I_i - \frac{1}{T_i}\iota_i\iota_i'$, where I_i is a $T_i \times T_i$ identity matrix and ι_i a T_i dimensional column vector of ones. Then $\tilde{\varepsilon}_i = Q_i R_i \varepsilon_i$ and it follows from (3) that

$$\begin{bmatrix} \tilde{\varepsilon}_i \\ \iota_T \xi_i + \eta_i \end{bmatrix} \sim N\left[\begin{bmatrix} 0 \\ 0 \end{bmatrix};\begin{bmatrix} Q_i R_i(\sigma_\varepsilon^2 I_i) R_i' Q_i & Q_i R_i(\rho\,\sigma_\varepsilon \sigma_\eta) \\ & \sigma_\eta^2 I_T + \sigma_\xi^2 \iota_T \iota_T' \end{bmatrix}\right],$$

from which it follows that

$$E\{\, \iota_T \xi_i + \eta_i \mid \tilde{\varepsilon}_i \,\} = \rho\, \sigma_\eta / \sigma_\varepsilon R_i' \tilde{\varepsilon}_i$$

and

$$V\{\, \iota_T \xi_i + \eta_i \mid \tilde{\varepsilon}_i \,\} = \sigma_\eta^2 I_T + \sigma_\xi^2 \iota_T \iota_T' - \rho_1^2 \sigma_\eta^2 R_i' Q_i R_i,$$

which prove (15) and (16) if we use the fact that $R_i' R_i = \mathrm{Diag}(r_i)$ and $R_i' \iota_i \iota_i' R_i = r_i r_i'$.

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