



A generalized panel data switching regression model



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HIGHLIGHTS

- We consider a generalized switching regression model in the panel data setting.
- Switching is extended to a polychotomous and/or sequential choice.
- The model allows for unobserved effects correlated with covariates.
- We estimate scope economies for the publicly owned US electric utilities in 2001–2003.

ARTICLE INFO

Article history:

Received 22 March 2014

Received in revised form

28 May 2014

Accepted 20 June 2014

Available online 26 June 2014

JEL classification:

C33

C34

Keywords:

Correlated effects

Multinomial logit

Nested logit

Panel data

Polychotomous

Selection

ABSTRACT

This paper considers a generalized panel data model of polychotomous and/or sequential switching which can also accommodate the dependence between unobserved effects and covariates in the model. We showcase our model using an empirical illustration in which we estimate scope economies for the publicly owned electric utilities in the US during the period from 2001 to 2003.

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1. Introduction

Sample selection is a common problem in empirical work. Unobserved heterogeneity among units in the data poses a further challenge for practitioners. However, the increased availability of panel data and some recent developments in the literature have alleviated these challenges. In the case of strictly exogenous covariates, Wooldridge (1995), Kyriazidou (1997) and Rochina-Barrachina (1999) offer several ways to tackle both the selectivity and unobserved effects that are allowed to be correlated with

covariates in the model. For a comparison of these methods, see Dustmann and Rochina-Barrachina (2007).

The above panel data models, as well as their generalizations that followed later (see Semykina and Wooldridge, 2010 and the references therein), largely focus on *binary* sample selection. However, in many instances researchers face selection (or regime switching) of polychotomous and/or sequential nature. Examples include production technology studies of the industries which contain fully specialized, partly specialized and integrated firms, studies of higher education decisions and many others.

To fill this void, we contribute to the literature by considering a generalized panel data model of polychotomous switching which also allows for the dependence between unobserved effects and covariates in the model. The model we consider can be thought of as a generalization of a standard switching regression model. We show that Wooldridge's (1995) estimator can be readily extended

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to the case of polychotomous and/or sequential selection. For consistency, our method requires strict exogeneity of covariates conditional on unobserved effects. We showcase our model using an empirical illustration in which we estimate scope economies for the publicly owned electric utilities in the US during the period from 2001 to 2003.

2. Model

Consider a generalized panel data switching regression model with correlated unobserved effects:

$$y_{it}^r = \begin{cases} \mathbf{x}_{it}^r \boldsymbol{\beta}^r + \alpha_i^r + u_{it}^r & \text{if } D_{it} = r \\ - & \text{otherwise} \end{cases} \quad (1a)$$

$$D_{it}^{r*} = \mathbf{w}_{it}^r \boldsymbol{\gamma}^r + \xi_i^r + v_{it}^r, \quad i = 1, \dots, N; \quad t = 1, \dots, T; \quad r = 1, \dots, R \quad (1b)$$

where \mathbf{x}_{it}^r and \mathbf{w}_{it}^r are $1 \times K_r$ and $1 \times L_r$ vectors of exogenous covariates (which may overlap)¹ with corresponding conformable parameter vectors $\boldsymbol{\beta}^r$ and $\boldsymbol{\gamma}^r$. (α_i^r, ξ_i^r) are individual-specific unobserved effects that are allowed to be correlated with right-hand-side covariates. The outcome variable y_{it}^r is observed only if the r th regime is selected. The regime selection (switching) is governed by a latent variable D_{it}^{r*} with observable categorical realizations: $D_{it} = r$ if the r th regime is selected. While the disturbances u_{it}^r and v_{it}^r are orthogonal to $(\mathbf{x}_{it}^r, \mathbf{w}_{it}^r)$, their distributions are however allowed to be correlated, namely $\mathbb{E}[u_{it}^r v_{it}^r | \mathbf{x}_{it}^r, \mathbf{w}_{it}^r] \neq 0$.

We first formalize the regime switching equation (1b). For convenience, define $\mathbf{x}_i^r \equiv (\mathbf{x}_{i1}^r, \dots, \mathbf{x}_{iT}^r)$ and $\mathbf{w}_i^r \equiv (\mathbf{w}_{i1}^r, \dots, \mathbf{w}_{iT}^r)$.

Assumption 1. For $i = 1, \dots, N, t = 1, \dots, T$ and $r = 1, \dots, R$, the conditional mean of unobserved effects ξ_i^r in a regime switching equation r is a linear projection on \mathbf{w}_i^r , i.e., $\xi_i^r = \mathbb{L}[\xi_i^r | \mathbf{w}_i^r] + a_i^r$, where $\mathbb{E}[a_i^r | \mathbf{x}_i^r, \mathbf{w}_i^r] = 0$. The composite error $e_{it}^r \equiv v_{it}^r + a_i^r$ is identically and independently distributed, conditional on $(\mathbf{x}_i^r, \mathbf{w}_i^r)$, with the type I extreme value distribution over i .

Specifically, we let the linear projection $\mathbb{L}[\xi_i^r | \mathbf{w}_i^r]$ take Chamberlain's (1980) form, i.e.,²

$$\mathbb{L}[\xi_i^r | \mathbf{w}_i^r] = \mathbf{w}_{i1}^r \delta_{t1}^r + \dots + \mathbf{w}_{iT}^r \delta_{tT}^r \equiv \mathbf{w}_i^r \boldsymbol{\delta}_t^r. \quad (2)$$

Thus, our model allows for dependence between unobserved effects ξ_i^r and right-hand-side covariates \mathbf{w}_i^r . This formulation of correlated effects is essentially the one used in Wooldridge (1995, p. 124).³ One may alternatively permit $\mathbb{L}[\xi_i^r | \mathbf{w}_i^r]$ to take a more restrictive, but parsimonious, specification à la Mundlak (1978) which restricts $\delta_{t1}^r = \dots = \delta_{tT}^r$ (e.g., Semykina and Wooldridge, 2010).⁴ We also note that, unlike Wooldridge (1995) who assumes a normally distributed error in the selection equation, we assume the extreme value distribution, which is dictated by a polychotomous nature of the choice set.

The latent variable D_{it}^{r*} in (1b) can naturally be thought of as measuring an individual's propensity to select the regime r . Hence, the r th regime is said to be selected if and only if

$$D_{it} = r \Leftrightarrow D_{it}^{r*} > D_{it}^{j*} \quad \forall j = 1, \dots, R (j \neq r). \quad (3)$$

While one can treat the regime switching as a system of $(R - 1)$ dichotomous decision rules, we follow an alternative approach by

considering the former in the random utility framework. That is,

$$D_{it} = r \Leftrightarrow D_{it}^{r*} > \max_{j=1, \dots, R (j \neq r)} \{D_{it}^{j*}\}. \quad (4)$$

After substituting for D_{it}^{r*} in (4) from (1b) and making use of Assumption 1, we let

$$\epsilon_{it}^r \equiv \max_{j=1, \dots, R (j \neq r)} \{ \mathbf{w}_{it}^j \boldsymbol{\gamma}_t^j + \mathbf{w}_i^j \boldsymbol{\delta}_t^j + e_{it}^j \} - e_{it}^r. \quad (5)$$

From (5) it then follows that

$$D_{it} = r \Leftrightarrow \epsilon_{it}^r < \mathbf{w}_{it}^r \boldsymbol{\gamma}_t^r + \mathbf{w}_i^r \boldsymbol{\delta}_t^r. \quad (6)$$

Given that e_{it}^r is extreme value distributed, it follows that ϵ_{it}^r is multinomial logistically distributed over i with the corresponding marginal distribution $\Lambda_r(\cdot)$:

$$\begin{aligned} \Pr[D_{it} = r | \mathbf{x}_i^r, \mathbf{w}_i^r] &= \Lambda_r(\mathbf{w}_{it}^r \boldsymbol{\gamma}_t^r + \mathbf{w}_i^r \boldsymbol{\delta}_t^r) \\ &= \frac{\exp(\mathbf{w}_{it}^r \boldsymbol{\gamma}_t^r + \mathbf{w}_i^r \boldsymbol{\delta}_t^r)}{\sum_j \exp(\mathbf{w}_{it}^j \boldsymbol{\gamma}_t^j + \mathbf{w}_i^j \boldsymbol{\delta}_t^j)}. \end{aligned} \quad (7)$$

For some strictly positive monotonic transformation $J_r(\cdot)$, condition (6) is equivalent to

$$D_{it} = r \Leftrightarrow J_r(\epsilon_{it}^r) < J_r(\mathbf{w}_{it}^r \boldsymbol{\gamma}_t^r + \mathbf{w}_i^r \boldsymbol{\delta}_t^r). \quad (8)$$

We can now look at model (1) as a binary selection model, for each given regime r . That is, we can essentially replace the regime switching equation (1b) for each $r = 1, \dots, R$ with its equivalent under Assumption 1:

$$\tilde{D}_{it}^{r*} = J_r(\mathbf{w}_{it}^r \boldsymbol{\gamma}_t^r + \mathbf{w}_i^r \boldsymbol{\delta}_t^r) - J_r(\epsilon_{it}^r), \quad (9)$$

where \tilde{D}_{it}^{r*} is a transformed latent variable such that $D_{it} = r$ if and only if $\tilde{D}_{it}^{r*} > 0$, i.e., condition (8) is satisfied. We follow Lee (1982, 1983) and consider $J_r(\cdot) \equiv \Phi^{-1}[\Lambda_r(\cdot)]$, where $\Phi(\cdot)$ is the standard normal cdf. The advantage of such a transformation is that the random error $J_r(\epsilon_{it}^r)$ in (9) is standard normal by construction, which would later enable us to make use of the truncated moments of the standard normal. Incidentally, the use of Lee's (1982, 1983) transformation as means of relaxing the normality in the selection equation has also been pointed out but not further developed in the panel data setting by Rochina-Barrachina (1999).

We next formalize the treatment of unobserved effects in the outcome equations of interest as well as the dependence between the two disturbances in (1a) and (9), where the latter enables us to correct for selectivity bias in the outcome equations.⁵ For convenience, we define $\tilde{\epsilon}_{it}^r \equiv J_r(\epsilon_{it}^r)$.

Assumption 2. For $i = 1, \dots, N, t = 1, \dots, T$ and $r = 1, \dots, R$:

- (i) $\mathbb{E}[u_{it}^r | \mathbf{x}_i^r, \mathbf{w}_i^r, \tilde{\epsilon}_{it}^r] = \mathbb{E}[u_{it}^r | \tilde{\epsilon}_{it}^r] = \mathbb{L}[u_{it}^r | \tilde{\epsilon}_{it}^r]$
- (ii) $\mathbb{E}[\alpha_i^r | \mathbf{x}_i^r, \mathbf{w}_i^r, \tilde{\epsilon}_{it}^r] = \mathbb{L}[\alpha_i^r | \mathbf{x}_i^r, \mathbf{w}_i^r, \tilde{\epsilon}_{it}^r]$.

Assumption 2 states that the disturbance u_{it}^r is mean independent of $(\mathbf{x}_i^r, \mathbf{w}_i^r)$ conditional on $\tilde{\epsilon}_{it}^r$. The latter holds if u_{it}^r and $\tilde{\epsilon}_{it}^r$ are orthogonal to $(\mathbf{x}_i^r, \mathbf{w}_i^r)$, a standard assumption made in the sample selection models in the presence of strictly exogenous covariates. Unlike Wooldridge (1995), we also condition the expectation of u_{it}^r on \mathbf{w}_i^r , which is necessary because outcome and selection equations are permitted to have different covariates and non-zero cross-equation correlation between unobserved effects. Further, Assumption 2 does not impose any restrictions on temporal dependence of u_{it}^r or in the relationship between u_{it}^r and $\tilde{\epsilon}_{it}^r$.

¹ While our model does not require exclusion restrictions and can accommodate the case of $\mathbf{x}_{it}^r = \mathbf{w}_{it}^r$, in practice it is helpful to have some elements of \mathbf{w}_{it}^r excluded from \mathbf{x}_{it}^r .

² Clearly, δ_{it}^r is not identified here.

³ The formulation of Eq. (1b) under Chamberlain's (1980) specification (2) is also equivalent to a reduced form of the following dynamic regime switching equation: $D_{it}^{r*} = \rho^r D_{it-1}^{r*} + \mathbf{w}_{it}^r \boldsymbol{\gamma}^r + v_{it}^r$.

⁴ In this case, the linear projection in (2) is assumed to be a single index of the time averages of \mathbf{w}_{it}^r .

⁵ For a counterpart in Wooldridge (1995), see his Assumption 3' on p. 126.

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