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On discrete location choice models☆

Nils Herger[a,*], Steve McCorriston[b]

[a] Study Center Gerzensee, Dorfstrasse 2, P.O. Box 21, 3115 Gerzensee, Switzerland

[b] Department of Economics, University of Exeter Business School, Streatham Court, Rennes Drive, Exeter EX4 4PU, England, UK

HIGHLIGHTS

- Poisson and conditional logit regressions are polar location choice models.
- A dissimilarity parameter λ covers the continuum between these models.
- The dissimilarity parameter is not identified in Schmidheiny and Brülhart (2011).
- We show that a choice consistent normalisation identifies λ.
- With panel data, a Poisson regression approach facilitates the estimation of λ.

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ABSTRACT

When estimating location choices, Poisson regressions and conditional logit models yield identical coefficient estimates (Guimarães et al., 2003). These econometric models involve polar assumptions as regards the similarity of the different locations. Schmidheiny and Brülhart (2011) reconcile these polar cases by introducing a fixed outside option transforming the conditional logit into a nested logit framework. This gives rise to a dissimilarity parameter ($\lambda \in [0; 1]$) equalling 1 in Poisson regressions (with completely dissimilar locations) and 0 in conditional logit models (with completely similar locations). The dissimilarity parameter is not identified in Schmidheiny and Brülhart (2011). We show that a choice consistent normalisation identifies λ and that, with panel data, its estimation is facilitated by adopting a Poisson regression approach.

1. Introduction

This paper extends recent firm location choice models of Schmidheiny and Brülhart (2011) – henceforth SB – to identify a dissimilarity parameter (λ) between alternative locations by using panel Poisson regressions.

Let the firms undertaking a location choice be indexed with $i = 1, \ldots, N$. Source countries are indexed with $s = 1, \ldots, S$. The choice set includes host locations indexed with $h = 1, \ldots, H$. A location choice denoted by $l_{i,sh}$ reveals that a host h with the profit opportunity $E[\Pi_{i,sh}]$ outperforms the other locations h' that could have been chosen instead, that is

$$l_{i,sh} = \begin{cases} 1 & E[\Pi_{i,sh}] > E[\Pi_{i,sh'}] \; \forall \; h \neq h' \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

A conditional logit model employs (1) as the dependent variable. Thereby, choice-specific variables x_{sh} (reported in logarithms) linearly affect profit expectations $E[\Pi_{i,sh}]$ via

$$E[\Pi_{i,sh}] = \delta_s + x'_{sh}\beta + \epsilon_{i,sh}, \tag{2}$$

where δ_s absorbs source-specific factors. Furthermore, β are coefficients to be estimated. The stochastic component $\epsilon_{i,sh}$ follows a Gumbel distribution with location and scale parameter normalised to, respectively, 0 and 1. The probability that a firm of s chooses h equals

$$P_{sh} = \frac{\exp\left(x'_{sh}\beta\right)}{\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\right)} = \frac{E[n^{cl}_{sh}]}{E[\bar{N}]}. \tag{3}$$

* Corresponding author. Tel.: +41 317803114.
E-mail addresses: nils.herger@szgerzensee.ch (N. Herger), s.mccorriston@exeter.ac.uk (S. McCorriston).

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The log-likelihood function equals

$$\ln L^{cl}(\beta) = \sum_{s=1}^{S}\sum_{h=1}^{H} n_{sh}\ln(P_{sh}) = \sum_{s=1}^{S}\left\{\sum_{h=1}^{H} n_{sh}x'_{sh}\beta - \sum_{h=1}^{H}\left[n_{sh}\ln\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\right)\right]\right\} \tag{4}$$

and permits us to estimate β. Guimarães et al. (2003) show that a count regression onto n_{sh} (the number of location choices) provides an alternative to estimate β. To see this, multiply (3) with the denominator, which yields the (panel) Poisson regression

$$E[\widetilde{n}^{pc}_{sh}] = \exp\left(\delta_s + x'_{sh}\beta\right) = \alpha_s E[n^{pc}_{sh}], \tag{5}$$

where $\alpha_s = \ln(\delta_s)$ and $E[n^{pc}_{sh}] = \exp(x'_{sh}\beta)$. Assuming that $\widetilde{n}^{pc}_{sh}$ is Poisson distributed with the conditional mean function $\exp(\delta_s + x'_{sh}\beta)$ of (5) yields a log-likelihood contribution of s given by

$$\ln L^{pc}_s(\alpha_s, \beta) = -\alpha_s\sum_{h=1}^{H}\exp(x'_{sh}\beta) + \ln\alpha_s\sum_{h=1}^{H} n_{sh} + \sum_{h=1}^{H} n_{sh}x'_{sh}\beta - \sum_{h=1}^{H}\ln n_{sh}! \tag{6}$$

Equating the first derivative with respect to α_s with 0, and solving for α_s yields the maximum likelihood estimator of

$$\alpha_s = \frac{\sum_{h=1}^{H} n_{sh}}{\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\right)} = \frac{\overline{n}_s}{E[\overline{n}_s]}. \tag{7}$$

Hence, α_s absorbs the discrepancy between the observed number of location choices $\overline{n}_s$ and the number $E[\overline{n}_s]$ expected from a Poisson distribution. Thereby, $0 < \alpha_s < 1$ implies that the observed number of location choices is "underreported". Substituting (7) into (6) and summing over S yields the log-likelihood function of the fixed effects Poisson regression

$$\ln L^{pc}(\beta) = \sum_{s=1}^{S}\left\{\sum_{h=1}^{H} n_{sh}x'_{sh}\beta - \sum_{h=1}^{H}\left[n_{sh}\ln\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\right)\right]\right\} + \text{constant}, \tag{8}$$

which looks like a multinomial logit model (Hausman et al., 1984, p. 919).[1] Specifically, since (8) differs from (4) only by a constant, the corresponding estimates for β are identical!

SB observe that the elasticity of the Poisson regression, given by

$$\eta^{pc}_k = \frac{\partial E[\widetilde{n}^{pc}_{sh}]}{\partial x_{sh,k}}\frac{x_{sh,k}}{E[\widetilde{n}^{pc}_{sh}]} = \beta_k, \tag{9}$$

differs from the conditional logit model, given by

$$\eta^{cl}_{sh,k} = \frac{\partial E[n^{cl}_{sh}]}{\partial x_{sh,k}}\frac{x_{sh,k}}{E[n_{sh}]} = (1 - P_{sh})\beta_k, \tag{10}$$

whereby β_k denotes the coefficient pertaining to $x_{sh,k}$. This reflects that Poisson regressions deem the locations to be completely dissimilar. Hence, a change of $x_{sh,k}$ affects the number of location choices with h, but not with h'. SB refer to this as a "positive sum world". Conversely, the conditional logit model is a "zero sum world" where the locations represent completely similar options. Hence, when more firms choose h, this triggers an equivalent reduction elsewhere.

SB show that the introduction of an outside option transforms the conditional logit into a nested logit model covering the continuum between the zero and positive sum world. The outside option $h = 0$ is independent of x_{sh}. The corresponding profit equals

$$E[\Pi_{i,s0}] = \delta_s + \epsilon_{i,s0}. \tag{11}$$

Since the outside option contains only one alternative, this nested logit model, depicted in Fig. 1, involves the partial degeneracy discussed in Hunt (2000). The probability P_{sh} depends now on the probability $P_{øs}$ of *not* choosing the outside option and the (conditional) probability $P_{sh|ø}$ to locate in $h > 0$, that is

$$P_{sh} = P_{øs}\cdot P_{sh|ø} = \frac{\left[\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)\right]^{\frac{\lambda^{ø}_s}{\varsigma^{ø}_s}}}{\left[\exp\left(\delta_s\varsigma^{o}_s\right)\right]^{\lambda^{o}_s} + \left[\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)\right]^{\frac{\lambda^{ø}_s}{\varsigma^{ø}_s}}}\cdot\frac{\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)}{\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)} \tag{12}$$

$$= \frac{\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)\left[\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)\right]^{\left(\frac{\lambda^{ø}_s}{\varsigma^{ø}_s}-1\right)}}{\left[\exp\left(\delta_s\varsigma^{o}_s\right)\right]^{\lambda^{o}_s} + \left[\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)\right]^{\frac{\lambda^{ø}_s}{\varsigma^{ø}_s}}}. \tag{13}$$

The inclusive value parameter $(\lambda^{ø}_s/\varsigma^{ø}_s) \in [0, 1]$ measures the dissimilarity between the locations $h > 0$. Specifically,

$$(\lambda^{ø}_s/\varsigma^{ø}_s) = \sqrt{1 - \rho^{ø}_s} \tag{14}$$

where $\rho^{ø}_s \in [0, 1]$ is the correlation between the stochastic profit components $\epsilon_{i,sh|ø}$ of investing in different locations. Consider the outside option o offering only the basic "choice" of $h = 0$. Hunt (2000) observes that the distinction between unconditional and conditional probabilities is here obsolete, as $P_{s0|o} = 1$ and $P_{s0} = P_{os} \times P_{s0|o}$. The probability of choosing $h = 0$ equals

$$P_{os} = P_{s0} = (1 - P_{øs}) = \frac{\exp\left(\delta_s\varsigma^{o}_s\right)^{\lambda^{o}_s}}{\left[\exp\left(\delta_s\varsigma^{o}_s\right)\right]^{\lambda^{o}_s} + \left[\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\varsigma^{ø}_s\right)\right]^{\frac{\lambda^{ø}_s}{\varsigma^{ø}_s}}}. \tag{15}$$

The coefficients β can be estimated by maximum likelihood from (13) and (15). However, empirically, only the correlation $\rho^{ø}_s$, but not the scale parameters $\lambda^{ø}_s$ and $\varsigma^{ø}_s$, can be estimated from the data (Hunt, 2000). This over-identification problem necessitates some normalisation. SB (p. 217) set $\varsigma^{ø}_s = 1$, $\varsigma^{o}_s = 1$, and $\lambda^{o}_s = 1$ wherefore (13) and (15) become

$$P_{sh} = \frac{\exp\left(x'_{sh}\beta\right)\left[\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\right)\right]^{(\lambda^{ø}_s-1)}}{\exp\left(\delta_s\right) + \left[\sum_{s=1}^{S}\sum_{h=1}^{H}\exp\left(x'_{sh}\beta\right)\right]^{\lambda^{ø}_s}} = \frac{\exp(x'_{sh}\beta)(E[N^{ø}])^{(\lambda^{ø}_s-1)}}{\exp(\delta_s) + (E[N^{ø}])^{\lambda^{ø}_s}} \tag{16}$$

[1] For a textbook discussion of the fixed effects Poisson regression, see Cameron and Trivedi (1998, ch. 9.3).