

CHOICE MODELING IN R

CLASS 7

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CHOICE MODELING

MIXED LOGIT: INTRODUCTION

MIXED LOGIT

Mixed logit (MXL) is an extension of the standard multinomial logit, which utilizes random parameters

- Allows for preference heterogeneity (taste variation)
- Accounts for other effects, like correlated error terms and heteroskedasticity (error components)
- It recognizes the panel structure of the data (really important for the SP data)
- Unfortunately, also computationally intensive and requires simulations

Idea is similar to the LCM, but instead of discrete latent segments it assumes continuous heterogeneity

- Sometimes called Random Parameters logit

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Parameters in the utility function are individual-specific:

$$U_{ij} = \boldsymbol{\beta}_i \mathbf{X}_{ij} + \varepsilon_{ij}$$

- Parameters follow a certain distribution
- They are also independent across individuals

If we would know the values of these parameters, then choice probability would be given by the MNL formula

$$P(y_i = j | \boldsymbol{\beta}_i) = \frac{\exp(\boldsymbol{\beta}_i \mathbf{X}_{ij})}{\sum_l \exp(\boldsymbol{\beta}_i \mathbf{X}_{il})}$$

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Problem: we do not know what these values are, and we usually do not have enough data to estimate a separate vector of coefficients for each individual

Solution: we assume a specific (multivariate) distribution of these coefficients and estimate the parameters of this distribution

To calculate the unconditional probability we calculate the expected value over the parameters

$$L_i = P(y_i = j) = \mathbf{E} \left[P(y_i = j \mid \boldsymbol{\beta}_i) \right] = \int P(y_i = j \mid \boldsymbol{\beta}_i) f(\boldsymbol{\beta}_i \mid \Omega) d\boldsymbol{\beta}_i$$

$f(\boldsymbol{\beta}_i \mid \Omega)$ is a pdf function of a given distribution, Ω are parameters to be estimated

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Solving multidimensional integrals is hard, so usually we simulate this expected value using Monte Carlo methods

- We take R draws from the distribution defined by $f(\boldsymbol{\beta}_i | \Omega)$, let denote them by $\boldsymbol{\beta}_i^r$
- We then simply take the average

$$L_i = P(y_i = j) = \mathbf{E}\left[P(y_i = j | \boldsymbol{\beta}_i)\right] \approx \frac{1}{R} \sum_{r=1}^R P(y_i = j | \boldsymbol{\beta}_i^r)$$

If data have panel structure, then it needs to be accounted for by taking a product of probabilities first

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If data have panel structure
product of probabilities

Let's go to  

MIXED LOGIT

Computational consideration:

- Maximum Likelihood method relies on numerical optimization, which updates model coefficients at each iteration
- Generally, we do not want to generate a new set of draws β_i^r at each iteration, as it would be very computationally intensive
- Instead, we want to generate some draws before optimization, and then transform them using model coefficients to the intended distribution, during optimization

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Examples:

- For the normal distribution we can generate draws from the standard normal distribution, $D_i^r \sim N(0,1)$ and then transform them with mean, and std. dev. coefficients:

$$\beta_i^r = \mu + \sigma D_i^r$$

- For the log-normal distribution we can use the same draws but with different transformation:

$$\beta_i^r = \exp(\mu + \sigma D_i^r)$$

- We can obtain any distribution by transforming draws from uniform distribution $D_i^r \sim U(0,1)$

$$\beta_i^r = F^{-1}(D_i^r | \Omega)$$

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Some simple examples of the MXL/random parameter framework:

Error component model

$$U_{ij} = \beta \mathbf{X}_{ij} + \alpha_{ij} + \varepsilon_{ij}$$

- Only alternative-specific constants are random parameters
- Could be used instead of nested logit to control for error terms correlations

Random scale MNL

$$U_{ij} = \alpha_i(\beta \mathbf{X}_{ij}) + \varepsilon_{ij}$$

- Only scale is heterogenous

EXERCISE

	Alternative A New protection levels	Alternative B New protection levels	Status Quo Current policy
Passive protection % of TPN forests	75%	65%	45%
Active protection % of TPN forests	25%	35%	45%
Annual cost for the household	10 zł	5 zł	0 zł
Your choice	☐	☐	☐

Estimate basic random parameters models on the TPN dataset

- Error component model
- MNL with scale heterogeneity
- MXL with all coefficients random and uncorrelated
 - Try normal and log-normal distribution for cost coefficient

Let's go to  