

# Multinomial Discrete Choice: Nested Logit and GEV

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Chris Conlon

Fall 2025

Grad IO

The multinomial logit is frequently criticized for producing unrealistic substitution patterns

- ▶ Suppose we got rid of a product  $k$  then  $s_{ij}(\mathbf{J} \setminus k) = s_{ij}(\mathbf{J}) \cdot \frac{1}{1-s_{ik}}$ .
- ▶ Substitution is just proportional to your pre-existing shares  $s_j$
- ▶ No concept of “closeness” of competition!

## Multinomial Probit?

- ▶ The probit has  $\varepsilon_i \sim N(0, \Sigma)$ .
- ▶ If  $\Sigma$  is unrestricted, then this can produce relatively flexible substitution patterns.
- ▶ Flexible is relative: still have normal tails, only pairwise correlations, etc.
- ▶ It might be that  $\rho_{12}$  is large if 1, 2 are similar products.
- ▶ Much more flexible than Logit

## Downside

- ▶  $\Sigma$  has potentially  $J^2$  parameters (that is a lot)!
- ▶ Maybe  $J * (J - 1)/2$  under symmetry. (still a lot).
- ▶ Each time we want to compute  $s_j(\theta)$  we have to simulate an integral of dimension  $J$ .
- ▶ I wouldn't do this for  $J \geq 5$ .

Let's make  $\varepsilon_{ij}$  more flexible than IID. Hopefully still have our integrals work out.

$$u_{ij} = V_{ij} + \varepsilon_{ij}$$

- ▶ One approach is to allow for a block structure on  $\varepsilon_{ij}$  (and consequently on the elasticities).
- ▶ We assign products into groups  $g$  and add a group specific error term

$$u_{ij} = V_{ij} + \eta_{ig} + \varepsilon_{ij}$$

- ▶ The trick putting a distribution on  $\eta_{ig} + \varepsilon_{ij}$  so that the integrals still work out.
- ▶ Do not try this at home: it turns out the required distribution is a special case of **GEV** (more on this later) and the resulting model is known as the **nested logit**.

A traditional (and simple) relaxation of the IIA property is the Nested Logit. This model is often presented as two sequential decisions.

- ▶ First consumers choose a category (following an IIA logit).
- ▶ Within a category consumers make a second decision (following the IIA logit).
- ▶ This leads to a situation where while choices within the same nest follow the IIA property (do not depend on attributes of other alternatives) choices among different nests do not!

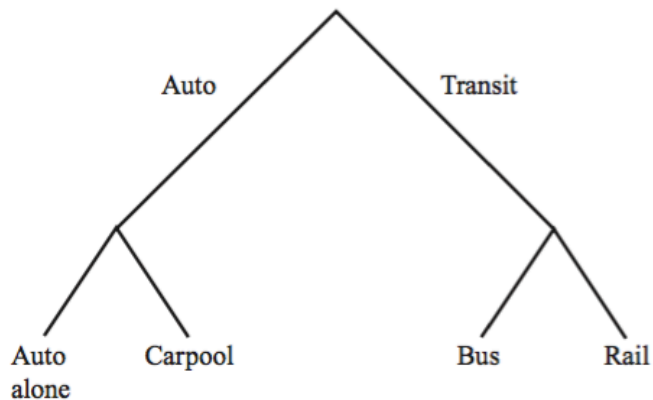


Figure 4.1. Tree diagram for mode choice.

Utility looks basically the same as before:

$$U_{ij} = V_{ij} + \underbrace{\eta_{ig} + \widetilde{\varepsilon}_{ij}}_{\varepsilon_{ij}(\lambda_g)}$$

- ▶ We add a new term that depends on the group  $g$  but not the product  $j$  and think about it as varying unobservably over individuals  $i$  just like  $\varepsilon_{ij}$ .
- ▶ Now  $\varepsilon_i \sim F(\varepsilon)$  where  $F(\varepsilon) = \exp[-\sum_{g=G}^G \left(\sum_{j \in J_g} \exp[-\varepsilon_{ij}/\lambda_g]\right)^{\lambda_g}]$ . This is no longer Type I EV but a special kind of GEV.
- ▶ The key is the addition of the  $\lambda_g$  parameters which govern (roughly) the within group correlation.
- ▶ This distribution is a bit cooked up to get a closed form result, but for  $\lambda_g \in [0, 1]$  for all  $g$  it is consistent with random utility maximization.

The nested logit choice probabilities are:

$$s_{ij} = \frac{e^{V_{ij}/\lambda_g} \left( \sum_{k \in J_g} e^{V_{ik}/\lambda_g} \right)^{\lambda_g - 1}}{\sum_{h=1}^G \left( \sum_{k \in J_h} e^{V_{ik}/\lambda_h} \right)^{\lambda_h}}$$

Within the same group  $g$  we have IIA and proportional substitution

$$\frac{s_{ij}}{s_{ik}} = \frac{e^{V_{ij}/\lambda_g}}{e^{V_{ik}/\lambda_g}}$$

But for different groups we do not:

$$\frac{s_{ij}}{s_{ik}} = \frac{e^{V_{ij}/\lambda_g} \left( \sum_{k \in J_g} e^{V_{ik}/\lambda_g} \right)^{\lambda_g - 1}}{e^{V_{ik}/\lambda_h} \left( \sum_{k \in J_h} e^{V_{ik}/\lambda_h} \right)^{\lambda_h - 1}}$$



We can take the probabilities and re-write them slightly with the substitution that  $\log \left( \sum_{k \in J_g} e^{V_{ik}/\lambda_g} \right) \equiv IV_{ig} = E_\varepsilon[\max_{j \in G} u_{ij}]$ :

$$\begin{aligned} s_{ij} &= \frac{e^{V_{ij}/\lambda_g}}{\left( \sum_{k \in J_g} e^{V_{ik}/\lambda_g} \right)} \cdot \frac{\left( \sum_{k \in J_g} e^{V_{ik}/\lambda_g} \right)^{\lambda_g}}{\sum_{h=1}^G \left( \sum_{k \in J_h} e^{V_{ik}/\lambda_h} \right)^{\lambda_h}} \\ &= \underbrace{\frac{e^{V_{ij}/\lambda_g}}{\left( \sum_{k \in J_g} e^{V_{ik}/\lambda_g} \right)}}_{s_{ij|g}} \cdot \underbrace{\frac{e^{\lambda_g IV_{ig}}}{\sum_{h=1}^G e^{\lambda_h IV_{ih}}}}_{s_{ig}} \end{aligned}$$

This is the decomposition into two logits that leads to the “sequential logit” story.

- ▶  $\lambda_g = 1$  is the simple logit case (IIA)
- ▶  $\lambda_g \rightarrow 0$  implies that all consumers stay within the nest.
- ▶  $\lambda < 0$  or  $\lambda > 1$  can happen and usually means something is wrong. These models are not generally consistent with RUM. (If you report one in your paper I will reject it).
- ▶  $\lambda$  is often interpreted as a correlation parameter and this is almost true but not exactly!
- ▶ Because the nested logit can be written as the within group share  $s_{ij|g}$  and the share of the group  $s_{ig}$  we often explain this model as **sequential choice**. It could just be a **block structure** on  $\varepsilon_i$ .
- ▶ You need to assign products to categories **before you estimate** and you can't make mistakes!

Look at derivatives:

$$\frac{\partial s_{ij|g}}{\partial X_j} = \beta_x \cdot s_{ij|g} \cdot (1 - s_{ij|g})$$

$$\frac{\partial s_{ig}}{\partial X} = (1 - \lambda_g) \cdot \beta_x \cdot s_{ig} (1 - s_{ig})$$

$$\frac{\partial s_{ig}}{\partial J} = \frac{1 - \lambda_g}{J} \cdot s_{ig} \cdot (1 - s_{ig})$$

- ▶ We get  $\beta$  by changing  $x_j$  within group
- ▶ We get nesting parameter  $\lambda$  by varying  $X$
- ▶ We don't have any parameters left to explain changing number of products  $J$ .
- ▶ Estimation happens via MLE. This can be tricky because the model is non-convex. It helps to substitute  $\tilde{\beta} = \beta / (1 - \lambda_g)$

An alternative version of the nested logit is popular in IO (Cardell 1991)  $\sigma \approx 1 - \lambda$ :

$$s_{ij|g} = \frac{e^{V_{ij}/(1-\sigma)}}{D_{ig}}$$

$$s_{ig} = \frac{D_{ig}^{(1-\sigma)}}{\sum_g D_{ig}^{(1-\sigma)}}$$

$$D_{ig} = \sum_{j \in G} e^{V_{ij}/(1-\sigma)}$$

$$s_{ij} = s_{ij|g} \cdot s_{ig} = \frac{\exp\left(\frac{V_{ij}}{1-\sigma}\right)}{D_g^\sigma \left[\sum_g D_g^{(1-\sigma)}\right]}$$

Derivatives for nested logit are complicated and worked out at

<http://www.nathanhmilller.org/nlnotes.pdf>.

It is helpful to define:  $Z(\sigma, s_g) = [\sigma + (1 - \sigma)s_g] \in (0, 1]$  and note that  $Z(0, s_g) = s_g$  and  $Z(1, s_g) = 1$ . If two products are in the same nest or different nests respectively:

$$-\frac{\frac{\partial s_k}{\partial p_j}}{\frac{\partial s_j}{\partial p_j}} \Big| \text{ same} = \frac{s_{k|g}}{Z^{-1}(\sigma, s_g) - s_{j|g}} \equiv D_{jk}^*$$
$$-\frac{\frac{\partial s_k}{\partial p_j}}{\frac{\partial s_j}{\partial p_j}} \Big| \text{ different} = \frac{s_k(1 - \sigma)}{1 - s_{j|g} \cdot Z(\sigma, s_{g(j)})} \equiv D_{jk}^{**}$$

These are related by:

$$D_{jk}^{**} = D_{jk}^* \cdot \frac{s_{g(k)} \cdot (1 - \sigma)}{Z(\sigma, s_{g(j)})}$$

There are more potential generalizations though they are less frequently used:

- ▶ You can have multiple levels of nesting: first I select a size car (compact, mid-sized, full-sized) then I select a manufacturer, finally a car.
- ▶ You can have potentially overlapping nests: Yogurt brands are one nest, Yogurt flavors are a second nest. This way strawberry competes with strawberry and/or Dannon substitutes for Dannon.

In case you are wondering where these things come from...

$$s_{ij}(J) = \frac{y_{ij} \cdot \frac{\partial G_i}{\partial y_j}(y_{i1}, \dots, y_{iJ})}{\mu \cdot G(y_{i1}, \dots, y_{iJ})}$$

With conditions on the **generator function**  $G$ :

1.  $G(\cdot)$  is homogenous of degree  $\mu > 0$  so that  $G(\alpha y) = \alpha^\mu G(y)$
2.  $\lim_{y_j \rightarrow +\infty} G(y_1, \dots, y_j, \dots, y_J) = +\infty$ , for each  $j \in J$
3. the  $k$  th partial derivative with respect to  $k$  distinct  $y_j$  is **non-negative if  $k$  is odd** and **non-positive if  $k$  is even** that is, for any distinct indices  $i_1, \dots, i_k \in J$ , we have

$$(-1)^k \frac{\partial^k G}{\partial x_{i_1} \dots \partial x_{i_k}}(x) \leq 0, \forall x \in \mathbb{R}_+^J$$

The objects are more mathematical than economic...

This is much easier with an example:

$$s_{ij}(J) = \frac{y_{ij} \cdot \frac{\partial G_i}{\partial y_j}(y_{i1}, \dots, y_{iJ})}{\mu \cdot G_i(y_{i1}, \dots, y_{iJ})}$$

- ▶ If  $y_j = e^{V_{ij}}$  and  $G_i = \log \sum_{j \in J} y_{ij}$  we get the IIA logit.
- ▶ If  $y_j = e^{V_{ij}}$  and  $G_i = \sum_{h=1}^H \left( \sum_{j \in B_h} Y_{ij}^{1/\lambda_h} \right)^{\lambda_h}$  we get the nested logit.
- ▶ ... if  $G_i = \sum_{h=1}^H \left( \sum_{j \in B_h} (\alpha_{jh} Y_{ij})^{1/\lambda_h} \right)^{\lambda_h}$  we get **generalized nested logit** (GNL).
- ▶ ... if  $G = \sum_{k=1}^{J-1} \sum_{l=k+1}^J \left( y_{ik}^{1/\lambda_{kl}} + y_{il}^{1/\lambda_{kl}} \right)^{\lambda_{kl}}$  we get **pairwise combinatorial logit** (PCL).
- ▶ there are a number of other **cross nested logit** variants with slightly different setups (from each other).



What's next?

- ▶ Many of these GEV and variants are found in the engineering literature (particularly traffic problems, civil engineering, and industrial engineering).
- ▶ Economists tend to use either nested logit or mixed logit (next lecture).
- ▶ Part of the issue is that it is hard to understand the restrictions on the  $G$  function and the economic meaning of the patterns produced by some of these models.
- ▶ But they may be more parsimonious and easier to estimate than the alternatives.