

Econ 673: Microeconometrics

Chapter 4: Properties of Discrete Choice Models

Fall 2008

Outline

- 1 Defining the Choice Set
- 2 Deriving Choice Probabilities
- 3 Identification in Choice Models

Readings

Required

- Train, K., (2003), *Discrete Choice Methods with Simulation*, Cambridge, MA: Cambridge University Press, Ch. 2.

Recommended

- McFadden, D. (1981), "Econometric Models of Probabilistic Choice", in C. Manski and D. McFadden (eds.) *Structural Analysis of Discrete Data with Econometric Applications*, Cambridge MA: MIT Press, pp. 198-272.

Discrete Choice Models

Discrete choice models characterize decision making in which the available alternatives are:

- Mutually exclusive
- Exhaustive
- Finite

Defining the relevant choice set is a crucial step in the analysis

Mutually Exclusive

- Not very restrictive - one can usually redefine the choice set to satisfy this restriction.
- Example #1 (Train): Home Heating Fuel Choice
 - Electric
 - Natural Gas
 - Oil
 - Wood
 - Other

Issue: Some households have dual-fuel or multiple systems.

Possible Solutions

- 1 Explicitly include combinations
 - Electric only
 - Natural gas only
 - oil only
 - Wood only
 - Natural gas with electric room heaters, etc.
- 2 Focus on primary heating systems
The potential problems here are:
 - It may be difficult to identify primary system from available data
 - Secondary heaters may be important users of energy (e.g., electric space heaters)

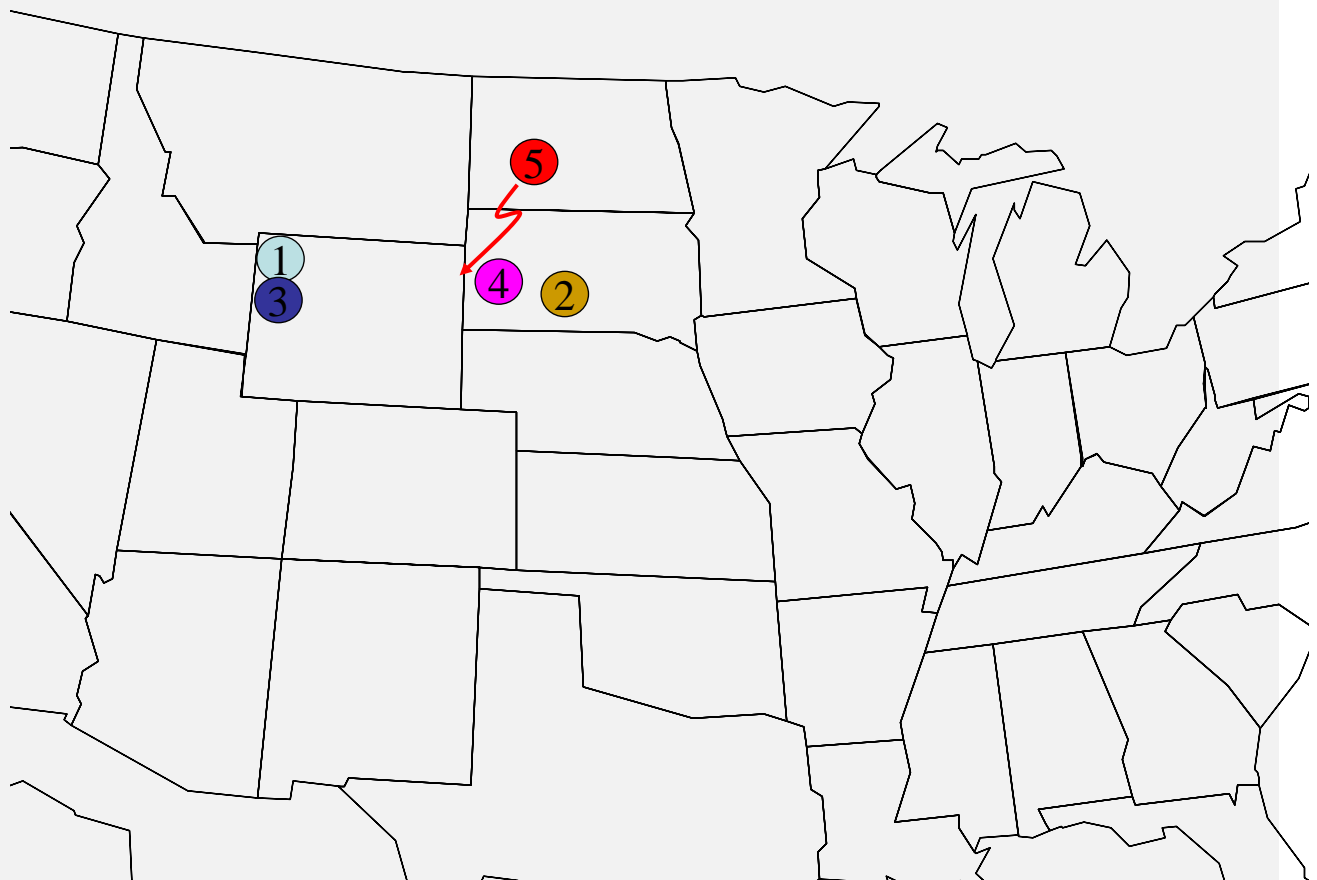
Example #2: Recreation Demand

Consider the following choice set for a summer vacation:

- ① Yellowstone National Park (Idaho, Wyoming, South Dakota)
- ② Badlands National Park (South Dakota)
- ③ Grand Tetons National Park (Wyoming)
- ④ Mount Rushmore National Memorial (South Dakota)
- ⑤ Devil's Tower National Monument (Wyoming)

For many vacationers, the alternatives in this choice set are not mutually exclusive.

Defining the Choice Set



Devil's Tower



Alternative Solutions

- ① Redefine alternatives in terms of portfolios
 - Yellowstone only
 - Yellowstone and Grand Tetons only
 - Grand Tetons and Mount Rushmore only
 - Etc.
- ② Focus on Primary Destination
The potential problems:
 - Identifying primary destination – even in minds of recreationists
 - constructing corresponding explanatory variables (e.g. travel costs)

Exhaustive Criteria

Readily satisfied by including a “none of the above” alternative

- Heating: “no heating”
- Recreation demand: “stay at home” or “all other sites”

Relevance

- Choice set should be defined not only to be mutually exclusive and exhaustive, but also relevant
- Choices must be ones from which agent actually chooses, not just the universe of alternatives

Example: Recreation Demand

- Should the choice set consist of
 - All feasible sites?
 - Nothing is revealed about not visiting an unknown site
 - Computationally intractable
 - Only sites visited in past five years?
 - Useful information is revealed about sites that are not visited.
 - Sites within a given distance?
 - Limits applicability of results to, say, day trips.
- Similar issues emerge in job and career search literature
- Ideally, one would model both choices and accumulation of information about choice set.

Finite or Countable Choice Sets

- This is a restrictive characteristic
 - Excludes the “how much” decision
 - Focuses on the “which” or “how many” decision
- These decisions may be tied
 - Electric power: Choice of rate structure and quantity of electricity consumed
 - Labor: Choice of participation decision and reservation wage or how much to work
 - Recreation: Choice of where to visit and how many trips to take or trip duration

Deriving Choice Probabilities

- Most discrete choice models assume individual agents make choices so as to maximize their utility – the **Random Utility Maximization (RUM) hypothesis**
- Encompasses a wide variety of concepts
 - Producers: profit or costs
 - Consumers: typically conditional indirect utility, but also willingness-to-pay

RUM Model

- The utility individual i receives from choosing alternative j is given by U_{ij} .
- Key: U_{ij} is assumed known to the agent, but unobserved by the analyst.
- Individual i is assumed to choose alternative j if

$$U_{ij} > U_{ik} \forall k \neq j \quad (1)$$

- The probabilistic nature of the problem is from the perspective of the analyst who does not know or observe:
 - All of the factors influencing U_{ij}
 - The functional form of U_{ij}

RUM Model (Cont'd)

The researcher specifies a functional relationship between utility and the observable characteristics of the individual and alternative:

$$U_{ij} = V(\mathbf{x}_{ij}, \mathbf{s}_i) + \epsilon_{ij} \quad (2)$$

\mathbf{x}_{ij} denotes observable characteristics of alternative j for individual i

\mathbf{s}_i denotes observable individual characteristics

$V_{ij} = V(\mathbf{x}_{ij}, \mathbf{s}_i)$ denotes the “representative utility”

ϵ_{ij} captures variations in preferences in the population due to unobservables.

RUM Model (Cont'd)

- The characteristics of ϵ_{ij} (i.e., its distribution) depend critically on what is or is not observable and the functional form of V_{ij} .
- Suppose that

$$U_{ij} = U(\mathbf{x}_{ij}, \mathbf{z}_{ij}, \mathbf{s}_i, \mathbf{t}_i) \quad (3)$$

where

\mathbf{z}_{ij} denotes unobservable characteristics of alternative j for individual i

\mathbf{t}_i denotes unobservable individual characteristics

Then

$$\epsilon_{ij} = U(\mathbf{x}_{ij}, \mathbf{z}_{ij}, \mathbf{s}_i, \mathbf{t}_i) - V(\mathbf{x}_{ij}, \mathbf{s}_i) \quad (4)$$

Example: Recreation Demand

Site Selection may depend upon the equipment owned by the individual (e.g., boats)

- If, say, boat ownership is unobserved, it can induce correlation across alternatives requiring a boat or across choices over time
- If boat ownership is controlled for this source correlation disappears

Measurement Error

- ϵ_{ij} may also capture measurement errors.
- Let $\tilde{\mathbf{x}}_{ij}$ denote the observed characteristics and \mathbf{x}_{ij} denote its true value from the individual's perspective.
- Then

$$\begin{aligned}\epsilon_{ij} &= [U(\mathbf{x}_{ij}, \mathbf{z}_{ij}, \mathbf{s}_i, \mathbf{t}_i) - V(\mathbf{x}_{ij}, \mathbf{s}_i)] + [V(\mathbf{x}_{ij}, \mathbf{s}_i) - V(\tilde{\mathbf{x}}_{ij}, \mathbf{s}_i)] \\ &= \eta_{ij} + \tilde{\eta}_{ij}\end{aligned}$$

where

$\eta_{ij} = U(\mathbf{x}_{ij}, \mathbf{z}_{ij}, \mathbf{s}_i, \mathbf{t}_i) - V(\mathbf{x}_{ij}, \mathbf{s}_i)$ denotes true heterogeneity.

$\tilde{\eta}_{ij} = V(\mathbf{x}_{ij}, \mathbf{s}_i) - V(\tilde{\mathbf{x}}_{ij}, \mathbf{s}_i)$ arises due to measurement error.

Interpretation of errors is important in welfare analysis

Choice Probabilities

The researcher assumes a distribution for $\epsilon_j = (\epsilon_{j1}, \dots, \epsilon_{jJ})'$

$$f(\epsilon_j | \mathbf{x}_j, \mathbf{s}_j) \quad (5)$$

From the analysts perspective, given the observables \mathbf{x}_j and \mathbf{s}_j , the decision makers probability of choosing alternative j becomes:

$$\begin{aligned} P_{ij} &= Pr(U_{ij} > U_{ik} \forall k \neq j | \mathbf{x}_j, \mathbf{s}_j) \\ &= Pr(V_{ij} + \epsilon_{ij} > V_{ik} + \epsilon_{ik} \forall k \neq j | \mathbf{x}_j, \mathbf{s}_j) \\ &= Pr(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik} \forall k \neq j | \mathbf{x}_j, \mathbf{s}_j) \\ &= \int_{D_\epsilon} I(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik} \forall k \neq j | \mathbf{x}_j, \mathbf{s}_j) f(\epsilon_j | \mathbf{x}_j, \mathbf{s}_j) d\epsilon_j. \end{aligned}$$

where D_ϵ denotes the support for the residual's distribution.

Choice Probabilities (cont'd)

- Alternative models appearing in the literature stem from choices of $f(\epsilon_j | \mathbf{x}_j, \mathbf{s}_j)$; e.g., logit, nested logit, and probit)
- Historically, these distributions were chosen for convenience.
- Simulation methods allow for more realistic assumptions.

Alternative Specific Constants

- Alternative specific constants (α_j) are used to capture the mean of unobserved characteristics.
- Specifically, suppose we start with unobserved components capture by ϵ_{ij}^* . Then

$$\begin{aligned}\alpha_j &\equiv E(\epsilon_{ij}^* | \mathbf{x}_{ij}, \mathbf{s}_i) \\ &= E[U(\mathbf{x}_{ij}, \mathbf{z}_{ij}, \mathbf{s}_i, \mathbf{t}_i) - V(\mathbf{x}_{ij}, \mathbf{s}_i) | \mathbf{x}_{ij}, \mathbf{s}_i]\end{aligned}$$

and

$$\epsilon_{ij} \equiv \epsilon_{ij}^* - \alpha_j.$$

Then for

$$U_{ij} = V(\mathbf{x}_{ij}, \mathbf{s}_i) + \alpha_j + \epsilon_{ij} \quad (6)$$

we have that

$$E(\epsilon_{ij} | \mathbf{x}_{ij}, \mathbf{s}_i) = 0. \quad (7)$$

Identification in Choice Models

1 Only Differences in Utility Matter

Suppose that

$$V_{ij} = V(\mathbf{x}_{ij}, \mathbf{s}_i) + \alpha_j \quad (8)$$

Then

$$\begin{aligned}V_{ij} - V_{ik} &= [V(\mathbf{x}_{ij}, \mathbf{s}_i) + \alpha_j] - [V(\mathbf{x}_{ik}, \mathbf{s}_i) + \alpha_k] \\ &= [V(\mathbf{x}_{ij}, \mathbf{s}_i) - V(\mathbf{x}_{ik}, \mathbf{s}_i)] + [\alpha_j - \alpha_k]\end{aligned}$$

Notice that this implies that the alternative specific constants are identified only up to an additive constant.

Identification in Choice Models (cont'd)

2 Factors Affecting Alternatives Equally are Irrelevant

If

$$V_{ij} = V(\mathbf{x}_{ij}, \mathbf{s}_i) = \mathbf{x}'_{ij}\beta + \mathbf{s}'_i\gamma \quad (9)$$

Then the characteristics vector \mathbf{s}_i becomes irrelevant, since

$$\begin{aligned} V_{ij} - V_{ik} &= [\mathbf{x}'_{ij}\beta + \mathbf{s}'_i\gamma] - [\mathbf{x}'_{ik}\beta + \mathbf{s}'_i\gamma] \\ &= \mathbf{x}'_{ij}\beta - \mathbf{x}'_{ik}\beta \\ &= (\mathbf{x}_{ij} - \mathbf{x}_{ik})' \beta \end{aligned}$$

Identification in Choice Models (cont'd)

On the other hand, if

$$V_{ij} = V(\mathbf{x}_{ij}, \mathbf{s}_i) = \mathbf{x}'_{ij}\beta + \mathbf{s}'_i\gamma_j \quad (10)$$

Then the characteristics vector \mathbf{s}_i is still relevant, since

$$\begin{aligned} V_{ij} - V_{ik} &= [\mathbf{x}'_{ij}\beta + \mathbf{s}'_i\gamma_j] - [\mathbf{x}'_{ik}\beta + \mathbf{s}'_i\gamma_k] \\ &= (\mathbf{x}_{ij} - \mathbf{x}_{ik})' \beta + \mathbf{s}'_i(\gamma_j - \gamma_k) \end{aligned}$$

Though again the alternative specific parameters are identified only up to an additive constant.

Identification in Choice Models (cont'd)

3 Only Error Differences Matter, Not Their Levels

Note that:

$$\begin{aligned}
 P_{ij} &= Pr(U_{ij} > U_{ik} \forall k \neq j | \mathbf{x}_{i\cdot}, \mathbf{s}_i) \quad j = 1, \dots, J-1 \\
 &= Pr(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik} \forall k \neq j | \mathbf{x}_{i\cdot}, \mathbf{s}_i) \\
 &= Pr(\eta_{ik} - \eta_{ij} < \Delta_J V_{ij} - \Delta_J V_{ik} \forall k \neq j | \mathbf{x}_{i\cdot}, \mathbf{s}_i) \\
 &= \int_{D_\epsilon} I(\eta_{ik} - \eta_{ij} < \Delta_J V_{ij} - \Delta_J V_{ik} \forall k \neq j | \mathbf{x}_{i\cdot}, \mathbf{s}_i) g(\boldsymbol{\eta}_i | \mathbf{x}_{i\cdot}, \mathbf{s}_i) d\boldsymbol{\eta}_i.
 \end{aligned}$$

where $\eta_{ij} \equiv \epsilon_{ij} - \epsilon_{iJ}$ and $\Delta_J V_{ij} \equiv V_{ij} - V_{iJ}; j = 1, \dots, J$

Identification in Choice Models (cont'd)

4 The Scale of Utility is Irrelevant

$$\begin{aligned}
 P_{ij} &= Pr(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik} \forall k \neq j | \mathbf{x}_{i\cdot}, \mathbf{s}_i) \\
 P_{ij} &= Pr(\lambda [\epsilon_{ik} - \epsilon_{ij}] < \lambda [V_{ij} - V_{ik}] \forall k \neq j | \mathbf{x}_{i\cdot}, \mathbf{s}_i)
 \end{aligned}$$

The original utility specification is indistinguishable from

$$\tilde{U}_{ij} = \lambda U_{ij} = \lambda V(\mathbf{x}_{ij}, \mathbf{s}_i) + \lambda \epsilon_{ij} \quad (11)$$

One must employ a normalizing restriction; e.g., for multivariate probit one often uses

$$\sigma_{11} \equiv \text{Var}(\eta_{11}) = 1 \quad (12)$$

Implications

- Estimation techniques will identify characteristics of $g(\boldsymbol{\eta}_i | \mathbf{x}_i, \mathbf{s}_i)$.
- Without strong distributional assumptions, $f(\boldsymbol{\eta}_i | \mathbf{x}_i, \mathbf{s}_i)$ will not be fully characterized.
- At best, one can hope to identify $J - 1$ means (i.e., the $\alpha_j - \alpha_J$'s) and $\frac{(J-1)(J-2)}{2} - 1$ variance-covariance terms (in addition to any marginal effects).