Discrete choice (1)

Applied Econometrics for Spatial Economics

Hans Koster

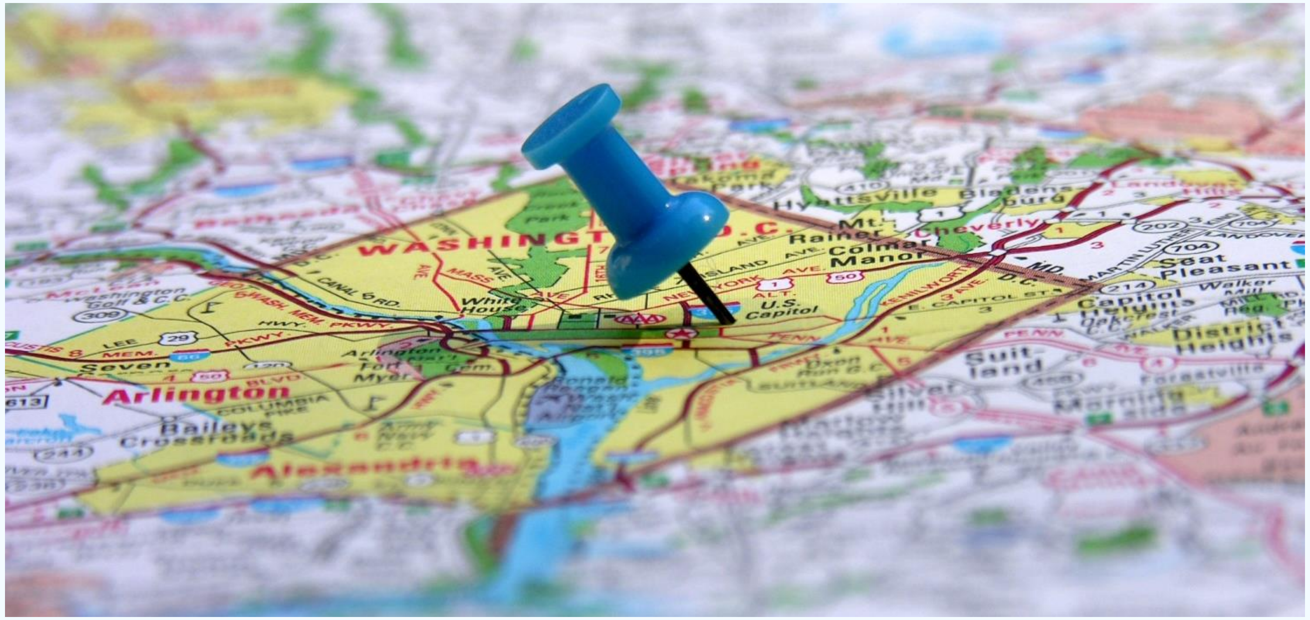
Professor of Urban Economics and Real Estate

VRIJE UNIVERSITEIT AMSTERDAM

tinbergen institute

1. Introduction

1. Introduction



1. Introduction

- **If you have data at your disposal you may use these data to answer practical questions:**
  - **What factors influence the carrier’s selection of a port?**
  - **Which mode do people prefer to travel from A to B?**
  - **Where do people want to live?**

1. Introduction

- *Continuous* choice: estimate marginal changes in behaviour
  - E.g. "when fuel price increases by 10%, the demand for fuel will decrease by 2%"
  - Standard micro-economic theory applies

- Transport demand often has a discrete (binary) nature
  - Some x impacts a discrete y
  - Then use discrete choice methods

VRIJE UNIVERSITEIT AMSTERDAM

1. Introduction

- **Discrete choice methods**
  - ***Dependent* variable y_i is discrete**

- **Why not use OLS?**

- **Let's have the standard OLS equation**

$$y_i = \beta x_i + \epsilon_i \quad (1)$$

where i indexes the individual

VRIJE UNIVERSITEIT AMSTERDAM

1. Introduction

- **OLS may be consistent for binary choice**
  - ***But,*** y_i ***(and therefore*** ϵ**) is *not* normally distributed**
- **Horrace and Oaxaca (2006)**
  - **Leads to biased and inconsistent estimates if $\hat{y}_i$ lies 'often' outside the [0,1] interval**
  - **I show in Clip #9 why that is an issue…**
- **OLS does not necessarily provides a link with economic theory**
- **Not suitable for multinomial choice**

1. Introduction

- This week
  - Learn about how to deal with discrete choices
  - … and stated choice experiments

- Plan:

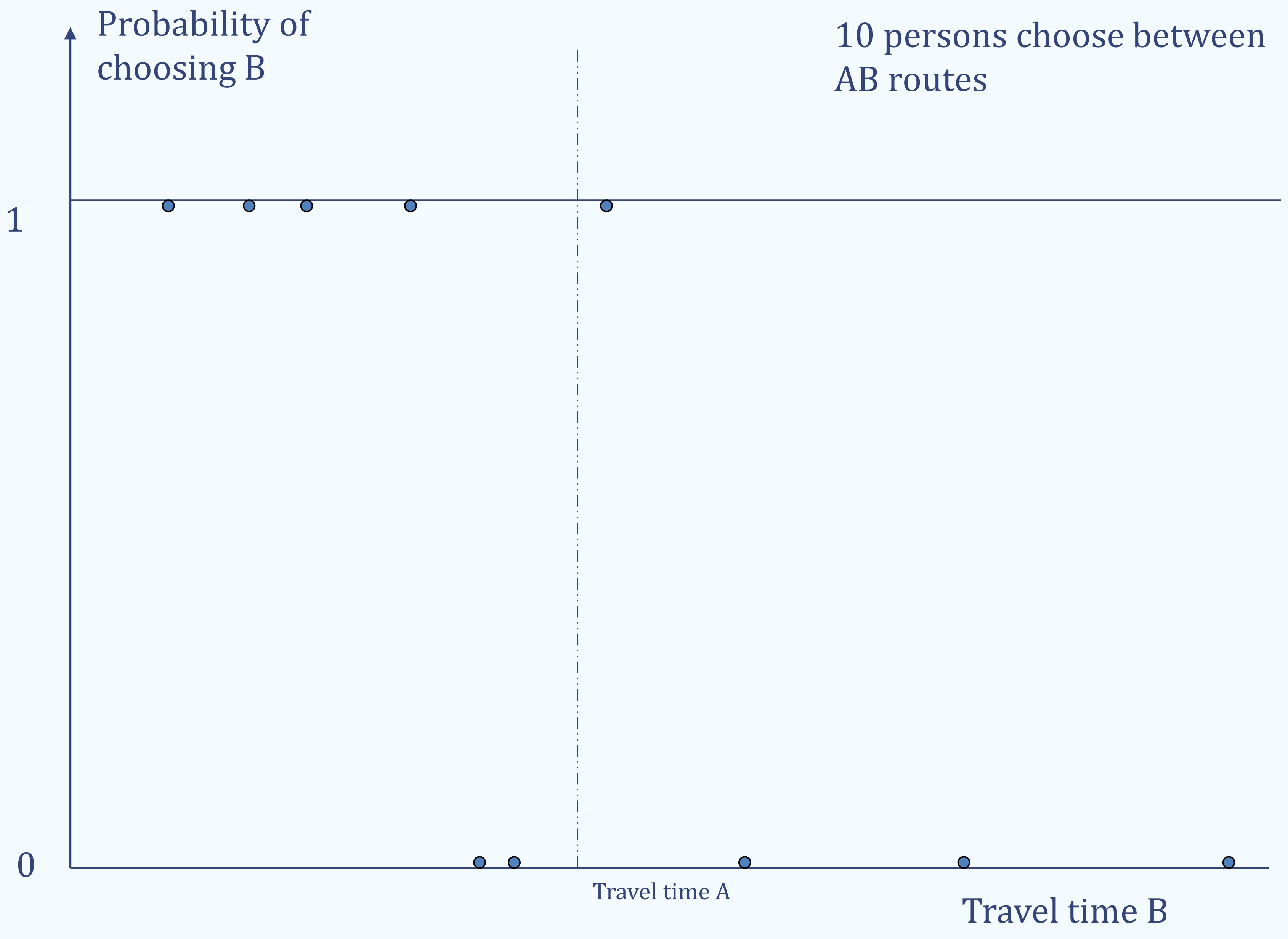
Lecture #1:	The random utility framework
Lecture #2:	Estimating binary choice models
Lecture #3:	Estimating multinomial choice models
	Stated vs. revealed preference data
Assignment:	Estimate the value of time

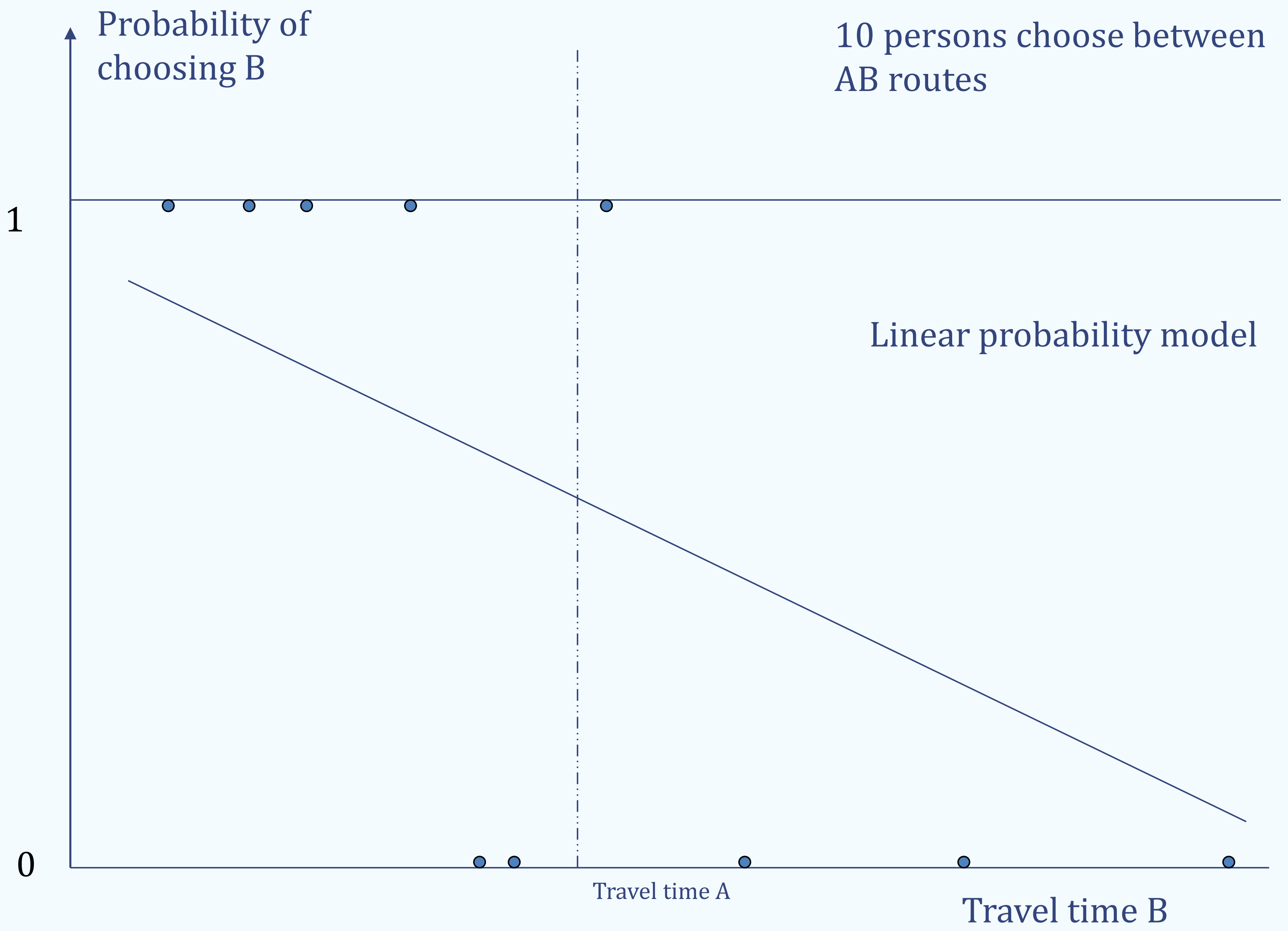
VRIJE UNIVERSITEIT AMSTERDAM

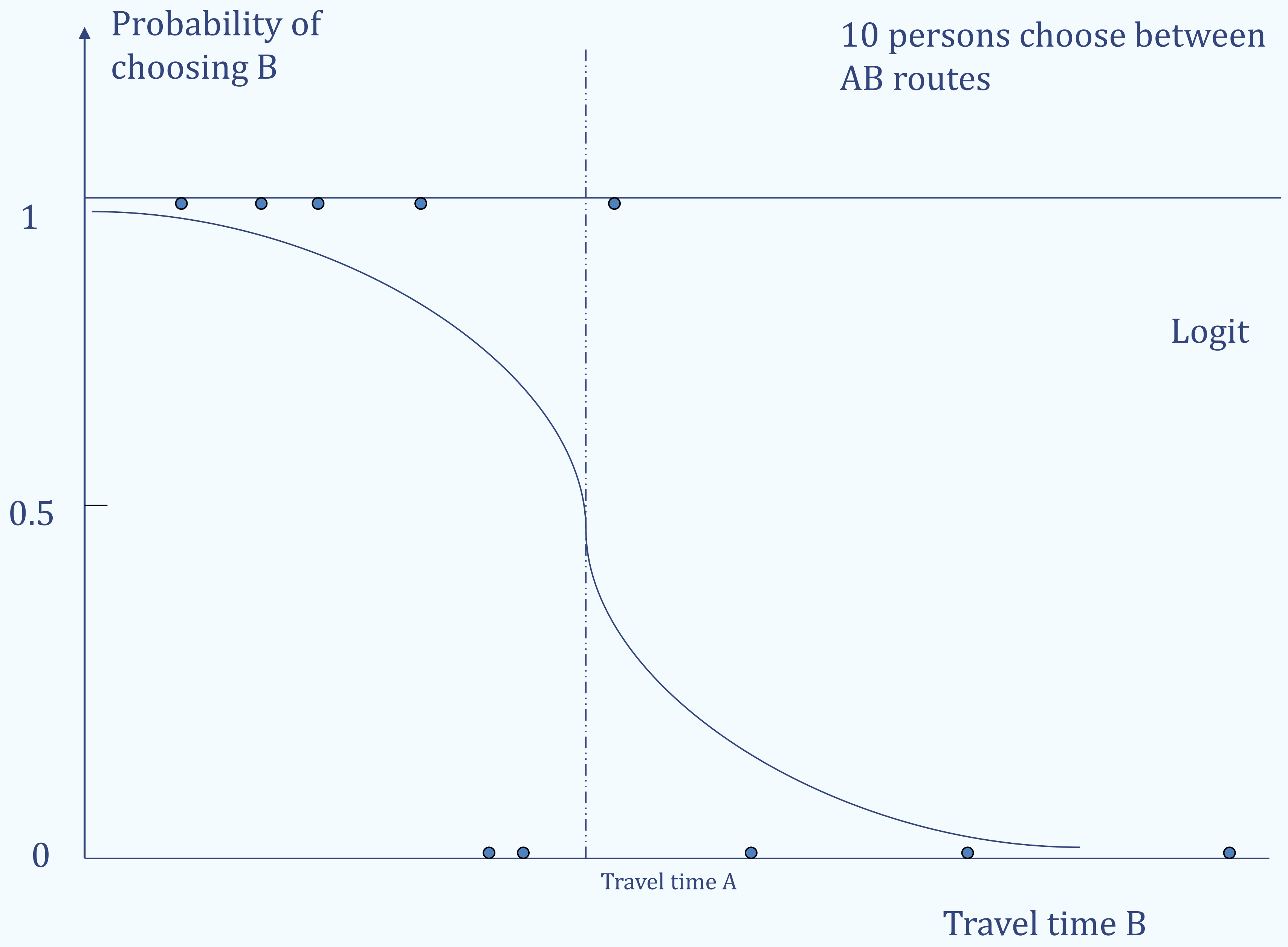
2. The random utility framework

- Consider you have 10 individuals that choose between two routes A en B
- Travel time of A is 9 and of B is 10 minutes
- Some people take route B
  - E.g. because they like particular features of ,
    or they misjudge the travel time

- Let's do a regression of whether or not you have chosen B on the difference between the travel time of A and B:
  $y_B = f\big(\alpha + \beta(travel\ time_B - travel\ time_A)\big) + \epsilon$
  where $y_B = 1$ if you choose B and zero otherwise


Probability of choosing B
10 persons choose between AB routes
1
0
Travel time A
Travel time B


Probability of choosing B
10 persons choose between AB routes
1
Linear probability model
0
Travel time A
Travel time B



Probability of choosing B
10 persons choose between AB routes
1
Logit
0.5
0
Travel time A
Travel time B

2. The random utility framework

- **Indirect utility may be given by:**

  $U_{iA} = V_A(travel\ time_A) + \epsilon_{iA}$ (2)

  $U_{iB} = V_B(travel\ time_B) + \epsilon_{iB}$ (3)

  - V_A, V_B ➔ **deterministic utility**

- **Random terms:** $\epsilon_{iA}, \epsilon_{iB}$**:** **random taste variation**
  - **Random utility model (RUM)**
  - **Note that the levels of** U_{iA} **and** U_{iB} **are not directly observed!**

- $\Pr(Y = A) = \Pr(U_{iA} > U_{iB})$
- $\Pr(V_A + \epsilon_{iA} > V_B + \epsilon_{iB}) = \Pr(V_A - V_B > \epsilon_{iB} - \epsilon_{iA})$

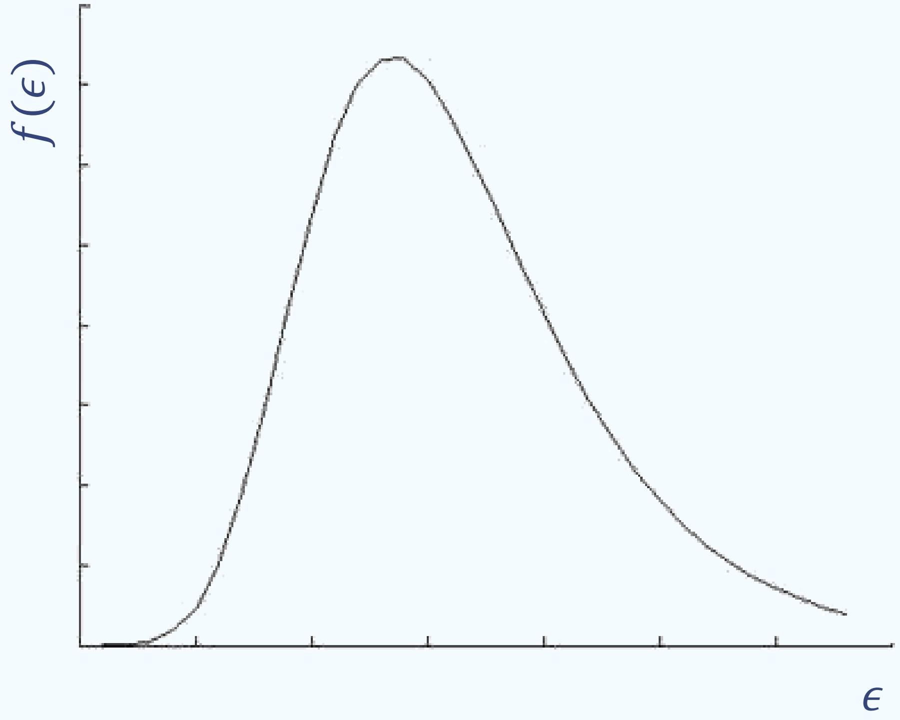
2. The random utility framework

- **Two things are unknown**
  - **Which distribution for ϵ's?**
  - **What is the functional form for V_A and V_B?**

2. The random utility framework

- **Which distribution for ϵ's?**
  - **ϵ's are unobserved**
  - **You draw them from a distribution**

  - **Logit: Extreme Value Type I distribution**



2. The random utility framework

- **Which distribution for ϵ's?**
  - **Extreme Value Type I distribution**
  - **Generates simple closed-form solutions!**

    → $\Pr(V_A - V_B > \epsilon_{iB} - \epsilon_{iA})$
  - **Daniel McFadden (1964)**

2. Random utility framework

- **It appears that:**

$$\Pr(Y = A) = \frac{e^{V_A}}{e^{V_A} + e^{V_B}} \qquad (4)$$

- **With two alternatives this can be written as:**

$$\Pr(Y = A) = \frac{1}{1 + e^{V_B - V_A}}$$

2. The random utility framework

- **Which functional form for V_A and V_B?**
  - **Can be any function**
  - **Linear function is often assumed**
  - **Can be extended with multiple variables**

    $$U_{jA} = \beta p_{jA} + \kappa t_{jA} + \epsilon_{jA} \quad (5)$$

    $$U_{jB} = \beta p_{jB} + \kappa t_{jB} + \epsilon_{jB} \quad (6)$$

    where p_{jA} is the price of a trip and t_{jA} is travel time of alternative j
  - $\beta < 0, \kappa < 0$

- **Recall (from previous slide):**
  - $\Pr(Y = A) = \frac{1}{1+e^{\beta(p_{jB}-p_{jA})+\kappa(t_{jB}-t_{jA})}}$

VRIJE UNIVERSITEIT AMSTERDAM

3. Value of time

- **Important concept in Transport Economics: *Value of Time* (VOT)**
  - **"How much are you willing to pay to reduce your travel time with one hour, *holding utility constant*"**

- **Let's take the deterministic utility function**

$$U_{jA} = \beta p_{jA} + \kappa t_{jA} + \varepsilon_{jA} \quad (7)$$

- **When t_{jA} is measured in hours, the VOT can be written as κ/β**

3. Value of time

- **Value of time is often used in cost benefit analyses**

- **VOT depends on trip purpose**
  - **Business €26.25/h**
  - **Commuting €9.25/h**
  - **Social purpose €7.50/h**

- **VOT depends on income**
  - **About 50% of net income**

4. Multiple alternatives

- **The choice probability for two alternatives:**

$$\Pr(Y = A) = \frac{e^{\beta x_A}}{e^{\beta x_A} + e^{\beta x_B}}$$

- **Usually there are more alternatives in the choice set**
  - **Train, bus, car**
  - **Rotterdam, Antwerp, Hamburg**
  - **Routes to the VU**

- **Simply extend the logit formula:**

$$\Pr(Y = A) = \frac{e^{\beta x_A}}{e^{\beta x_A} + e^{\beta x_B} + e^{\beta x_C}}$$

VRIJE UNIVERSITEIT AMSTERDAM

4. Multiple alternatives

- **The aggregate utility derived from the choice set is summarised by the logsum:**

  $$\mathrm{E[CS]} = \frac{1}{\upsilon}\ln\left(\mathrm{e}^{\beta x_A} + \mathrm{e}^{\beta x_B} + \mathrm{e}^{\beta x_C}\right)$$

  - υ **is the marginal utility of income**
  - **Can be used in welfare estimates**

- **Assume** $\beta x_A = \beta x_B = 10$

- **Now alternative** C **is added and** $\beta x_C = 1$

- **The average utility per alternative decreases from** 10 **to** 7 **but** $\mathrm{E[CS]}$ **increase**
  - **'Love of variety' effect**

4. Multiple alternatives

- **Property of logit formula:**
  - **The *ratios* of choice probabilities for A and B do not depend on whether or not C is in the choice set**
  - **Independence of irrelevant alternatives**
  - $$\frac{\Pr(Y=A)}{\Pr(Y=B)} = \frac{\left(\frac{e^{\beta x_A}}{e^{\beta x_A}+e^{\beta x_B}+e^{\beta x_C}}\right)}{\left(\frac{e^{\beta x_B}}{e^{\beta x_A}+e^{\beta x_B}+e^{\beta x_C}}\right)} = \frac{e^{\beta x_A}}{e^{\beta x_B}}$$
  - **Let's find out whether this is a desirable property…**

4. Multiple alternatives

- ‘The *Red Bus-Blue Bus*’ problem

- Choice set 1: Train, red bus, blue bus
- Assume market shares are 70, 15 and 15%

	Train	Red bus	Blue bus
V	2.54	1	1
Prob	0.700	0.150	0.150

- Choice set 2: Train, red bus, so:

	Train	Red bus
V	2.54	1
Prob	0.823	0.177

- Probability to take the bus in choice set 2 is

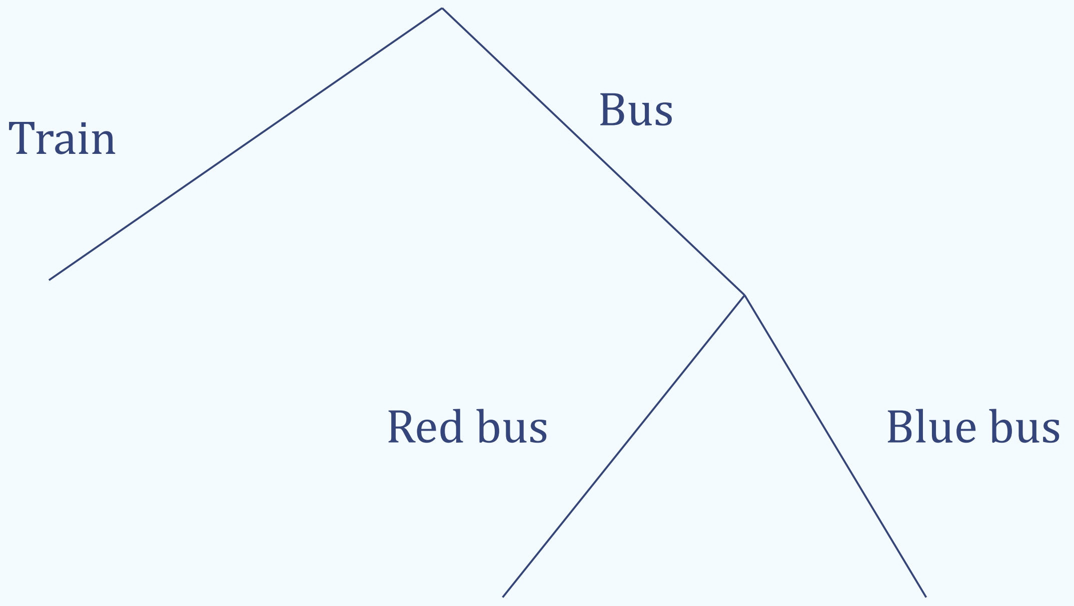
$$\frac{e^1}{e^{2.54}+e^1} = 0.177$$

  - Higher probability – not very realistic as red buses and blue buses are identical

4. Multiple alternatives

- So, when some alternatives are more similar than other alternatives, the use of multinomial choice model may be misleading

- Use nested logit!



4. Multiple alternatives

- **Nested logit takes into account correlation between alternatives**
  - **But define nests yourself!**

2. The random utility framework

- **Let us define utility as follows:**

  $U_{jg} = V_j + W_g + \epsilon_{jg}$

  V_j **only differs within nests between alternatives** j

  W_g **only differs between nests** g

2. The random utility framework

- **We may write the probability to choose an alternative:**
  - $\Pr(d_j = 1) = \Pr(g) \cdot \Pr(j \mid g)$
  - $\Pr(j \mid g) = \frac{e^{V_j/\lambda_g}}{\sum_{k \in g} e^{V_k/\lambda_g}}$
  - $\Pr(g) = \frac{e^{W_g + \lambda_g I_g}}{\sum_{\tilde{g}} e^{W_{\tilde{g}} + \lambda_{\tilde{g}} I_{\tilde{g}}}}$

  with $I_g = \log\left(\sum_{j \in g} e^{V_j/\lambda_g}\right)$

- $\lambda_g = 1 \Rightarrow$ **no correlation (multinomial logit)**
- $\lambda_g \to 0 \Rightarrow$ **perfect correlation (red bus/blue bus)**

- **Hence, when j and k are in the same nest:**

$$\frac{\Pr(d_j = 1)}{\Pr(d_k = 1)} = \frac{e^{W_g + V_j / \lambda_g}}{e^{W_g + V_k / \lambda_g}} = \frac{e^{W_g + V_j}}{e^{W_g + V_k}} = \frac{e^{V_j}}{e^{V_k}}$$

2. The random utility framework

- So, nested logit probability depends on
  - Probability to choose a nest
  - Probability to choose an alternative within the nest

- Note that Nested Logit does not imply a *sequential* choice

5. Summary

Today:

- How to deal with a binary dependent variable?
- Links to economic theory with random taste variation
  - Random utility model
  - Assume distribution of ϵ_i
  - Extreme Value Type I is convenient
- Stated choice experiments can measure value of time

5. Summary

Tomorrow:

- **How to estimate binary choice models?**
  - **Use LPM, Logit or Probit**

- **Application to measure value of time, value schedule delay early and schedule delay late**

VU VRIJE UNIVERSITEIT AMSTERDAM

Discrete choice (1)

Applied Econometrics for Spatial Economics

Hans Koster

Professor of Urban Economics and Real Estate

VRIJE UNIVERSITEIT AMSTERDAM

tinbergen institute

Discrete choice (2)

Applied Econometrics for Spatial Economics

Hans Koster
Professor of Urban Economics and Real Estate

1. Introduction

- This week
  - Learn about how to deal with discrete choices
  - … and stated choice experiments

- Plan:

Lecture #1:	The random utility framework
Lecture #2:	Estimating binary choice models
Lecture #3:	Estimating multinomial choice models
	Stated vs. revealed preference data
Assignment:	Estimate the value of time

1. Introduction

- How to estimate binary discrete choice models?

- Three main options
  1. Linear probability model
  2. Logit
  3. Probit

2. Linear probability model

- **Regress 0/1 variable on characteristics of that choice and use OLS:**
  $\Pr(d_j = 1) = \beta' x_j$

- **Dataset example:**

Chosen	Price	Time
1	14	12
0	25	5
0	15	15
1	15	13
1	4	45
1	3	40
0	20	10

2. Linear probability model

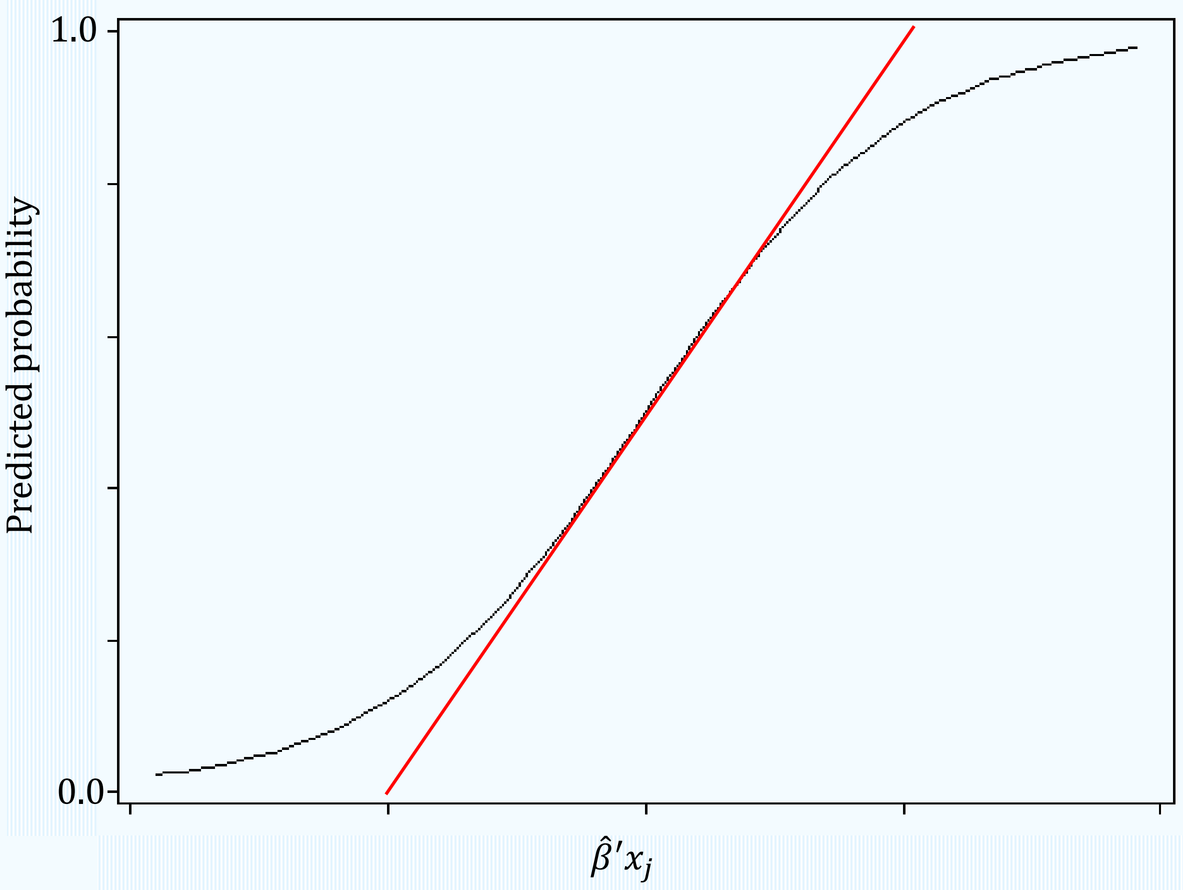
Advantages:

- **Consistent when** $0 \leq \hat{y}_j \leq 1 \; \forall \; j$

2. Linear probability model

Advantages:

- Consistent when $0 \leq \hat{y}_j \leq 1 \; \forall \; j$



2. Linear probability model

Advantages:

- **Consistent when** $0 \leq \hat{y}_j \leq 1 \; \forall \; j$

- **Easy to interpret**
  - **Say that** $\beta = -0.25$ **and** x **is measured in €, then for each euro increase in** x**, the probability to choose alternative** j **decreases by 25 percentage points**
  - $\frac{\partial \Pr(d_j = 1)}{\partial x} = \beta$

VRIJE UNIVERSITEIT AMSTERDAM

2. Linear probability model

Advantages:

- Consistent when $0 \leq \hat{y}_j \leq 1 \; \forall \; j$
- Easy to interpret
  - $\frac{\partial \Pr(d_j = 1)}{\partial x} = \beta$
- Computationally feasible
  - Important for large panel datasets
- In practice, leads to very similar results as Logit and Probit

2. Linear probability model

Disadvantages:

- No direct link with structural parameters of utility function
  - e.g. not able to calculate aggregate utility from choice set
- Biased for small samples and possibly inconsistent marginal effects
  - Linearity?
- Not suitable for multinomial choices

VRIJE UNIVERSITEIT AMSTERDAM

3. Logit

- **Let's define**

$$\Pr(d_j = 1) = \frac{1}{1+e^{-\beta' x_j}}$$

- **Example: regress 0/1 variable on *differences* in characteristics of the alternatives**

Chosen_B	$\text{Price}_B\text{-Price}_A$	$\text{Time}_B\text{-Time}_A$
1	-14	5
0	5	0
0	15	-20
1	-8	13
1	-10	3
1	3	-5
0	20	10

VRIJE UNIVERSITEIT AMSTERDAM

3. Logit

- **Recall**
  - $\Pr(d_j = 1) = \left(1 + e^{-\beta' x_j}\right)^{-1}$

- **The change in the probability for one unit increase in *x***
  - $\frac{\partial \Pr(d_j = 1)}{\partial x_j} = \beta \frac{e^{-\beta' x_j}}{\left(1 + e^{-\beta' x_j}\right)^2}$

- **Marginal effect depends on x_j, so is not constant/linear**
  - **For example, evaluate at mean values of x**

3. Logit

- **Marginal effects:**
  - **Use chain rule of differentiation**
  - $\frac{\partial \Pr(d_j=1)}{\partial x_j} = -\left(1 + e^{-\beta' x_j}\right)^{-2} \times e^{-\beta' x_j} \times -\beta$
  - $\frac{\partial \Pr(d_j=1)}{\partial x_j} = \beta \frac{e^{-\beta' x_j}}{\left(1+e^{-\beta' x_j}\right)^2}$

- **Dependent on x_j, so is not constant/linear**
  - **For example, evaluate at mean values of x**

3. Logit

- **Software**
  - LOGIT **or** LOGISTIC **in STATA**
  - REGRESSION – BINARY LOGISTIC **in SPSS**

- **In STATA you can select to report marginal effects**
  - **Use** MARGINS **after** LOGIT **command**
  - **Choose at which x the values are evaluated (e.g. at means)**

VU VRIJE UNIVERSITEIT AMSTERDAM

3. Logit

Advantages of Logit:

- **Predicted probability is always between one and zero**

- **Clear link to random utility framework**
  - **Log-sum may be used for welfare calculations**

- **Closed-form marginal effects**
  - **Usually leads to very similar results as Probit**

- **Can include 'fixed effects' (XTLOGIT in STATA)**
  - ***e.g.* *t*o control for individual heterogeneity**

VRIJE UNIVERSITEIT AMSTERDAM

Disadvantages of Logit:

- Why Extreme Value Type I distribution for ϵ?
- Maximum likelihood / non linear model

4. Probit

- We may also assume that ϵ_j is normally distributed, so $\epsilon_j = N(0, \sigma^2)$
  - This implies $\Pr(d_j = 1) = \Phi(\beta' x_j)$
  - Central limit theorem?
  - However, no closed-form for cumulative normal distribution!

- Marginal effects:

$$\frac{\partial \Pr(d_j = 1)}{\partial x_j} = \beta \phi(\beta x_j)$$

where $\phi(\cdot)$ is the density function of the normal distribution

4. Probit

Advantages:

- Normal distribution for ϵ_j seems reasonable
  - … Central limit theorem
- Probability is always between one and zero

Disadvantages:

- No closed-form marginal effects
- Hard to include many fixed effects

4. Probit

- **How to choose between the three models?**
  - **Probit estimates ≈ Logit estimates**
  - **Look at goodness of fit**
    → **Use** $|d_j - \hat{d}_j|$
  - **Check for robustness of marginal effects**
  - **Large sample and interested in marginal effects?**
    → **Usually linear probability model!**
    → **There is an ongoing debate in economics on this issue**

VRIJE UNIVERSITEIT AMSTERDAM

6. Summary

Today:

- **How to estimate binary choice models?**
  - **Use LPM, Logit or Probit**

- **Application to measure value of time, value schedule delay early and schedule delay late**

VRIJE UNIVERSITEIT AMSTERDAM

6. Summary

Tomorrow:

- Generalisations of logit models
  - Multinomial logit
  - Nested logit

- Conditional logit models
  - Poisson regression

- Data
  - Stated preference or revealed preference data

Discrete choice (2)

Applied Econometrics for Spatial Economics

Hans Koster

Professor of Urban Economics and Real Estate

Discrete choice (3)

Applied Econometrics for Spatial Economics

Hans Koster
Professor of Urban Economics and Real Estate

1. Introduction

- **This week**
  - **Learn about how to deal with discrete choices**
  - **… and stated choice experiments**

- **Plan:**

Lecture #1:	The random utility framework
Lecture #2:	Estimating binary choice models
Lecture #3:	Estimating multinomial choice models
	Stated vs. revealed preference data
Assignment:	Estimate the value of time

- **How to estimate these types of models?**

- **Overview**

	# Alternatives	Coefficients
1. Binary Logit	2	Homogeneous
2. Multinomial Logit with alternative specific parameters	>2, <~10	Differ between alternatives
3. Nested Logit	>2, <~10	Usually homogeneous
4. Conditional Logit	>2	Homogeneous

2. Multinomial logit

- **Recall:**

  $$\Pr(Y = A) = \frac{e^{\beta x_A}}{e^{\beta x_A} + e^{\beta x_B} + e^{\beta x_C}}$$

  But now let the coefficients be alternative-specific:

  $$\Pr(Y = A) = \frac{e^{\beta_A x_A}}{e^{\beta_A x_A} + e^{\beta_B x_B} + e^{\beta_C x_C}}$$

  - **We cannot identify all the coefficients β_A, β_B, β_C, because <u>we compare the results to a reference category</u>**
    - **Think of dummies**

  - **Illustration: we can write the probability only in terms of differences with respect to one reference category, e.g.:**

    $$\Pr(Y = A) = \frac{1}{1 + e^{\beta_B x_B - \beta_A x_A} + e^{\beta_C x_C - \beta_A x_A}}$$

2. Multinomial logit

- **What demographic factors explain car ownership?**
  - $0 = no\ car;\ 1 = 1\ car;\ 2 \geq 1\ car$

- **Data,** *n=55958*

respid	carown	hhsize	children	...	socallow
100001	1	4	1	...	0
100002	2	2	0	...	0
100004	0	2	0	...	1
100005	1	2	0	...	0
100012	2	5	1	...	0
...	...	...	...	...	...
622410	2	3	1	...	0

2. Multinomial logit

- **What demographic factors explain car ownership?**

- **Start with OLS**
  - **... but car ownership is not really a continuous variable in the data**

Table – EXPLAINING CAR OWNERSHIP
(Dependent variable: The number of cars in the household)

	coeff.	s.e.
Household size	0.1745***	(0.0069)
Number of children in the household	-0.0045	(0.0163)
Social allowance (=1)	-0.6624***	(0.0120)
Male (=1)	0.1093***	(0.0051)
Age	-0.0031***	(0.0002)
Long term illness (=1)	-0.1317***	(0.0060)
Constant	0.7270***	(0.0152)
Number of observations	55,958	
R^2	0.2145	

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

2. Multinomial logit

- *MLOGIT YVAR XVARS , BASEOUTCOME(0)*

Table – EXPLAINING CAR OWNERSHIP

Outcome = 0	coeff.	s.e.
(base outcome)		
Outcome = 1	**coeff.**	**s.e.**
Household size	1.0039***	(0.0196)
Number of children in the household	-0.8290***	(0.0445)
Social allowance (=1)	-2.1039***	(0.0596)
Male (=1)	0.4870***	(0.0233)
Age	-0.0043***	(0.0007)
Long term illness (=1)	-0.3917***	(0.0248)
Constant	-0.6280***	(0.0506)
Outcome = 2	**coeff.**	**s.e.**
Household size	1.3039***	(0.0222)
Number of children in the household	-0.5191***	(0.0522)
Social allowance (=1)	-4.7724***	(0.2219)
Male (=1)	0.5910***	(0.0295)
Age	-0.0171***	(0.0009)
Long term illness (=1)	-0.7218***	(0.0358)
Constant	-1.9361***	(0.647)
Number of observations	55,958	
Log-likelihood	-48,268	
Pseudo R^2	0.1333	

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

2. Multinomial logit

- All the coefficients are compared to one base category!
- Coefficients are different for different alternatives
- Particularly useful when outcomes do not have a logical ordering
  - Bus, car, train
  - Holiday destinations
  - Otherwise: OLS or Ordered Logit
- If the number of alternatives is very large ➔ too many coefficients to interpret meaningfully

VU VRIJE UNIVERSITEIT AMSTERDAM

3. Nested logit

- **Independence of irrelevant alternatives**
  - **Adding an alternative does not affect the relative odds between two other options considered**
  - **Solution: use Nested Logit**
    → **Allows for correlation within nests**

- **Software**
  - NLOGIT **in STATA**
  - **Use Biogeme software**
  - **Limdep/nlogit**

4. Conditional logit

- **Often, the number of alternatives is very large**
  - **Location choice**
  - **Route choice**
  - **Holiday destinations**
  - **Choice of car**
  - **Partner choice**
  - **…**

- **With Multinomial Logit this becomes infeasible**
  - **Unique coefficients for each alternative**
  - **Not necessary for large choice sets**

- **Conditional Logit:**

$$\Pr\left(d_j = 1\right) = \frac{e^{\beta' x_j}}{\sum_{k=1}^{J} e^{\beta' x_k}}$$

4. Conditional logit

- **How to deal with large choice sets?**
  - **Number of observations in your regressions is *number of alternatives* $\times$ *respondents***

1. **Model aggregate choices**
2. **Random selection of alternatives**
3. **Estimate count data models (Poisson)**

VRIJE UNIVERSITEIT AMSTERDAM

4. Conditional logit

1. Model aggregate choices

- Modelling location choice
  - Focus on aggregate areas (municipalities)
- Choice of cars
  - Only distinguish between brands
- However, lack of detail makes results less credible

VRIJE UNIVERSITEIT AMSTERDAM

2. Random selection of alternatives

- McFadden (1978)
  - Choose a random subset of J alternatives for each choice set, including the chosen option
  - This should not affect the *consistency* of the estimated parameters
  - Small-sample properties are yet unclear

- How large should J be?

- Applied in many good papers
  - e.g. Bayer et al. (2007, *JPE*)

VRIJE UNIVERSITEIT AMSTERDAM

4. Conditional logit

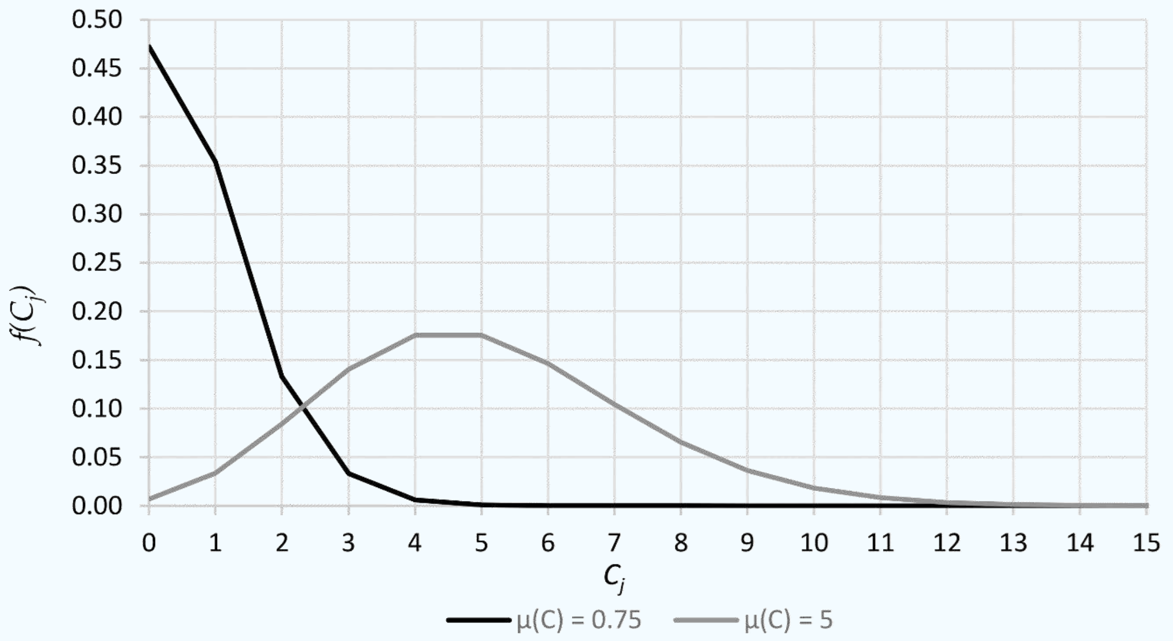
3. Estimate count data models

- Estimate Conditional Logit by means of a Poisson model

- A Poisson regression is a count data model
  - Dependent variable is integer
  - … and should be Poisson distributed

3. Estimate count data models

- **Example of a Poisson distribution**



- **Equidispersion:** $\bar{y} = \sigma_y$

3. Estimate count data models

- Estimate Conditional Logit by means of a Poisson model

- A Poisson regression is a count data model
  - Dependent variable is integer
  - … and should be Poisson distributed
  - $C_j = e^{\beta' x_j} + \epsilon$
    where C_j is the # of decision makers that have chosen a certain alternative

- Convenient interpretation of β
  - When x_j increases with one, C_j increases with $\beta \times 100$ percent

VRIJE UNIVERSITEIT AMSTERDAM

4. Conditional logit

3. Estimate count data models

- **A Poisson model should give identical parameters to the Conditional Logit**
  - **Maximum likelihood functions are identical *up to a constant***
  - **Guimarães et al. (2003)**

- **Hence, group observations based on their chosen alternatives**
  - **… the number of firms choosing a certain location**
  - **… the number of people buying a certain car**

3. Estimate count data models

- Implications
  - You cannot include characteristics of the decision maker *(because you sum up all choices)*!
  - Homogeneous parameters across the population

- Extensions
  - Include fixed effects
  - Negative binomial regression
  - Zero-inflated models
  - See Guimarães et al. (2004) for details

VU VRIJE UNIVERSITEIT AMSTERDAM

5. Revealed preference and stated preference data

Types of data

- Revealed preference (RP) data
  - Observed or reported actual behaviour
- Stated preference (SP) data
  - Respondents are confronted with hypothetical choice sets
- Combinations of RP and SP

VRIJE UNIVERSITEIT AMSTERDAM

5. Revealed preference and stated preference data

Advantages of RP data

- Based on actual behaviour!!
- Use existing (large) data sources
  - Cheaper
  - No expensive experiments
- Panels of the same individuals over a long time

5. Revealed preference and stated preference data

Disadvantages of RP data

- Lack of variability
- Collinearity (e.g. price and travel times)
- Lack of knowledge on the choice set
- Not possible with new choice alternatives
- Actual behaviour may not be first choice
  - University numerus fixus
- Perception errors and imperfect information
  - Airline tickets

VRIJE UNIVERSITEIT AMSTERDAM

5. Revealed preference and stated preference data

- **Example of stated preference question**

Suppose you have to ship a product from A to B			
Option 1		**Option 2**	
Price:	€ 1,000	Price:	€ 750
Handling time:	3 days	Handling time:	1 week
% does not arrive:	1.0%	% does not arrive:	1.3%
What alternative will you choose?			

5. Revealed preference and stated preference data

Advantages of SP data

- New alternatives
- New attributes
- Large variability is possible
- Problems of collinearity can be solved
  - ‘Orthogonal design’
- Choice set is clearly defined

5. Revealed preference and stated preference data

Disadvantages of SP data

- Information bias
- Starting point bias
- Hypothetical bias
- Strategic bias
- Errors

5. Revealed preference and stated preference data

Disadvantages of SP data

- Information bias
  - The respondent has incorrect information on the context
  - Make your experiment as realistic as possible
- Starting point bias
  - Respondents are influenced by the set of available responses to the experiment
  - Test your design and choose realistic attribute values

5. Revealed preference and stated preference data

Disadvantages of SP data

- Hypothetical bias
  - Individuals tend to respond differently to hypothetical scenarios than they do to the same scenarios in the real world.
  - Cognitive incongruity with actual behaviour
  - Again: make your experiment as realistic as possible
  - But otherwise hard to mitigate…

- Strategic bias
  - Respondent wants a specific outcome
  - (S)he fills in answers that are in line with desired outcomes

VRIJE UNIVERSITEIT AMSTERDAM

5. Revealed preference and stated preference data

Disadvantages of SP data

- Unintentional biases
  - Information, starting point, hypothetical bias
- Intentional biases
  - Strategic bias
- Errors
  - Boredom
  - Respondents do not carefully read instructions
  - Respondents do not understand the questions

If there is good data available, I would prefer RP *(personal opinion)*

6. Summary

Today:

- Generalisations of logit models
  - Multinomial logit
  - Nested logit
  - Conditional logit

- Conditional Logit models can be estimated by count data models
  - Cannot include characteristics of the decision maker

- Data
  - Stated preference or revealed preference data

6. Summary

Next week:

- Identification of causal effects