Discrete choice (1)

Applied Econometrics for Spatial Economics

Hans Koster
Professor of Urban Economics and Real Estate

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1. Introduction

- **Today:**
  1. Spatial econometrics
  2. Discrete choice
  3. Identification
- **Tomorrow:**
  4. Hedonic pricing
  5. Quantitative spatial economics

- **Today:**
  1. Spatial econometrics
  2. Discrete choice
     - Random utility framework, estimating binary and multinomial regression models
  3. Identification

- **Tomorrow:**
  4. Hedonic pricing
  5. Quantitative spatial economics

1. Introduction

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1. Introduction

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

1. Introduction

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

- Why not use OLS?

- Let's have the standard OLS equation

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

where i indexes the individual

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 later today why that is an issue…**

- **OLS does not necessarily provides a link with economic theory**

- **Not suitable for multinomial choice**

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2. The random utility framework

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

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

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

  - 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!**

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

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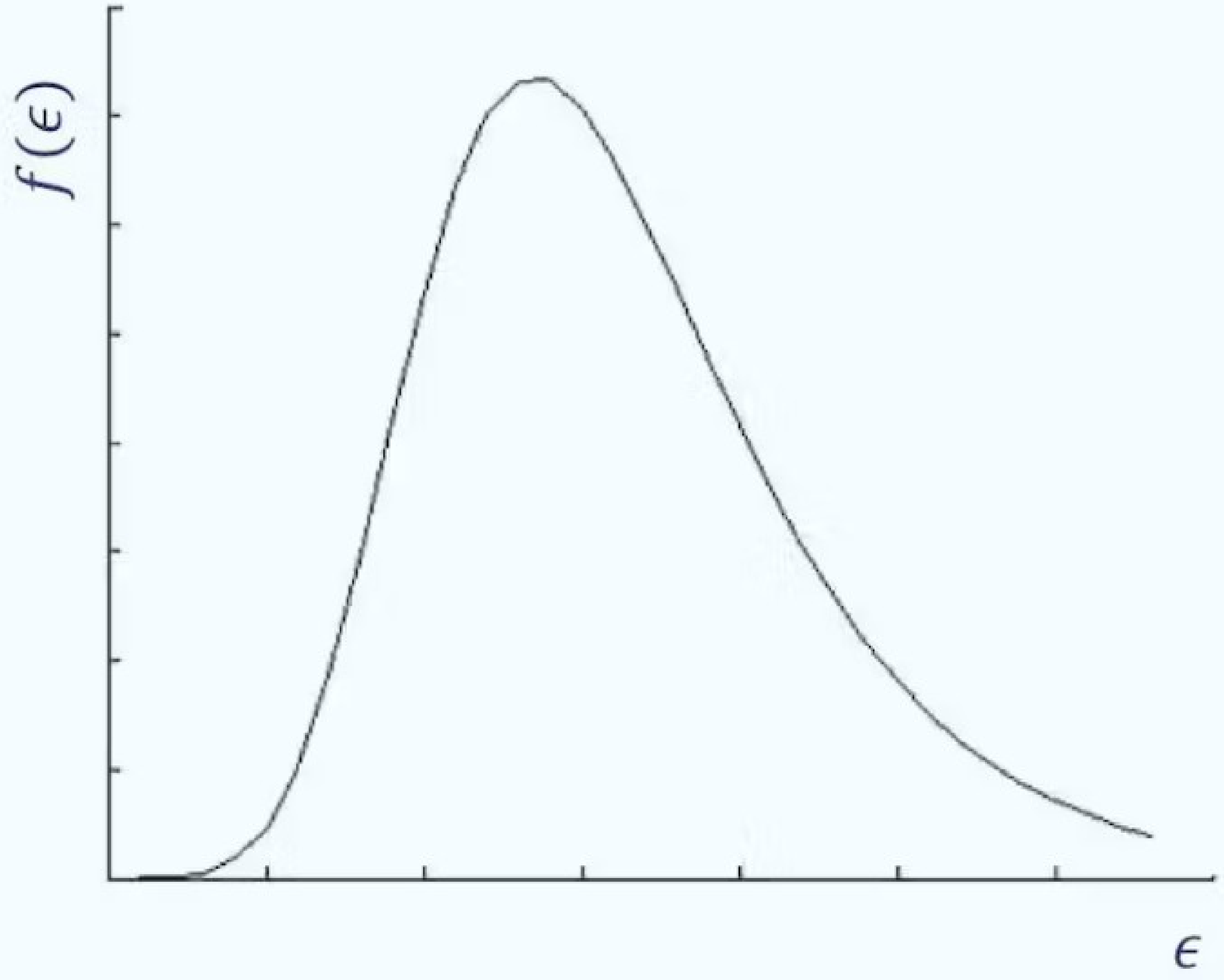
2. The random utility framework

- 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!**

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

2. Random utility framework

- **It appears that:**

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

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

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

- **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**
  $U_{iA} = \beta p_{iA} + \kappa t_{iA} + \gamma x_{iA} + \varepsilon_{iA}$
  - $\Delta U_{iA} = 0$ (7)

→ **Show that when t_{iA} is measured in hours, the VOT can be written as κ/β**

With $U_{iA} = \beta p_{iA} + \kappa t_{iA} + \gamma x_{iA} + \varepsilon_{iA}$, show that when t_{iA} is measured in hours, the Value of Time can be written as κ/β.

7

I'm ready!

7

→ **Show that when t_{jA} is measured in hours, the VOT can be written as κ/β**

Let's look at a change in utility:

$$\Delta U_{iA} = \beta\Delta p_{iA} + \kappa\Delta t_{iA} + \Delta\varepsilon_{iA}$$

- **We hold utility constant, so** $\Delta U_{iA} = 0$
- **Because** $\mathrm{E}[\varepsilon_{iA}] = 0$, $\Delta\varepsilon_{iA} = 0$
- $-\beta\Delta p_{iA} = \kappa\Delta t_{iA}$
- $\Delta t_{iA} = -1$ **(WTP for one hour reduction in travel time)**
- $\Delta p_{iA} = \frac{\kappa}{\beta}$

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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

3. Value of time

- Other applications
  - Value of a Statistical Life (VSL)
    The VSL is the local tradeoff between fatality risk and money
  - Value of schedule delay (VSD)
    The VSD is the local tradeoff between being too early/late and money
  - Etc.
  - … What is necessary is a cost/reward parameter in the discrete choice experiment

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 <u>more alternatives in the choice set</u>**
  - **Train, bus, car**
  - **Rotterdam, Antwerp, Hamburg**
  - **Routes to the VU**

- **Simply extend the logit formula:**

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

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

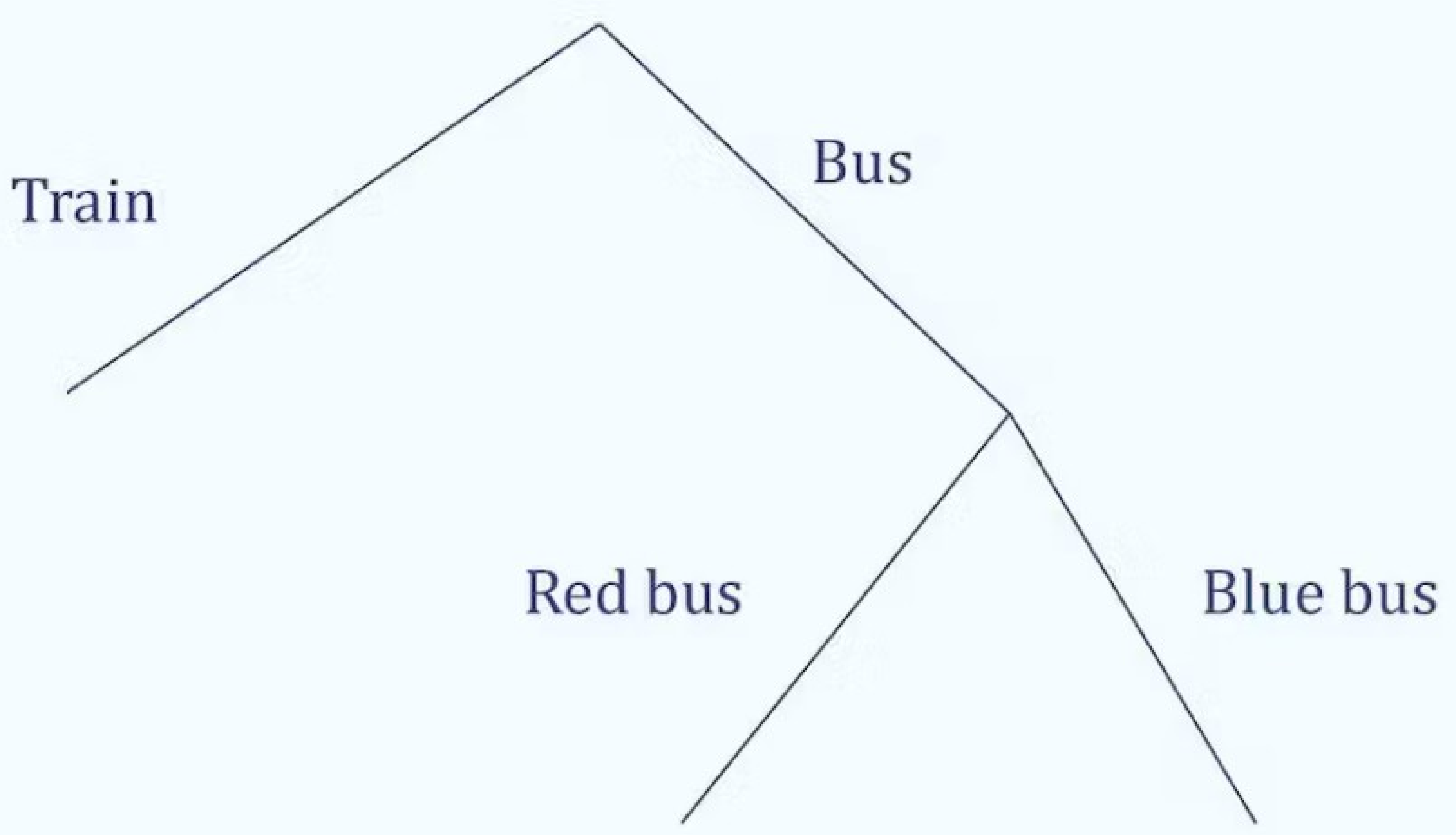
$$\frac{e^{1}}{e^{2.54}+e^{1}} = 0.177$$

  - 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:**
  - $\Pr\left(d_j = 1\right) = \Pr(g) \cdot \Pr(j \mid g)$
  - $\Pr(j \mid g) = \dfrac{e^{V_j/\lambda_g}}{\sum_{k \in g} e^{V_k/\lambda_g}}$
  - $\Pr(g) = \dfrac{e^{W_g + \lambda_g I_g}}{\sum_{\tilde{g}} e^{W_{\tilde{g}} + \lambda_{\tilde{g}} I_{\tilde{g}}}}$

  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)**

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2. The random utility framework

- **When j and k are in the same nest:**

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

  - **IIA property holds *within* nests**

- **When $\lambda_g \to 0$:**

  - $\Pr(j \mid g) = \dfrac{e^{V_j/\lambda_g}}{\sum_{k \in g} e^{V_k/\lambda_g}} = 1/k_g$
  - $\Pr(g) = \dfrac{e^{W_g + \lambda_g I_g}}{\sum_{\tilde{g}} e^{W_{\tilde{g}} + \lambda_{\tilde{g}} I_{\tilde{g}}}} = \dfrac{e^{W_g}}{\sum_{\tilde{g}} e^{W_{\tilde{g}}}}$
  - **Hence, multinomial logit *between* nests**

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

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Discrete choice (2)

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1. Introduction

- How to estimate binary discrete choice models?

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

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

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**

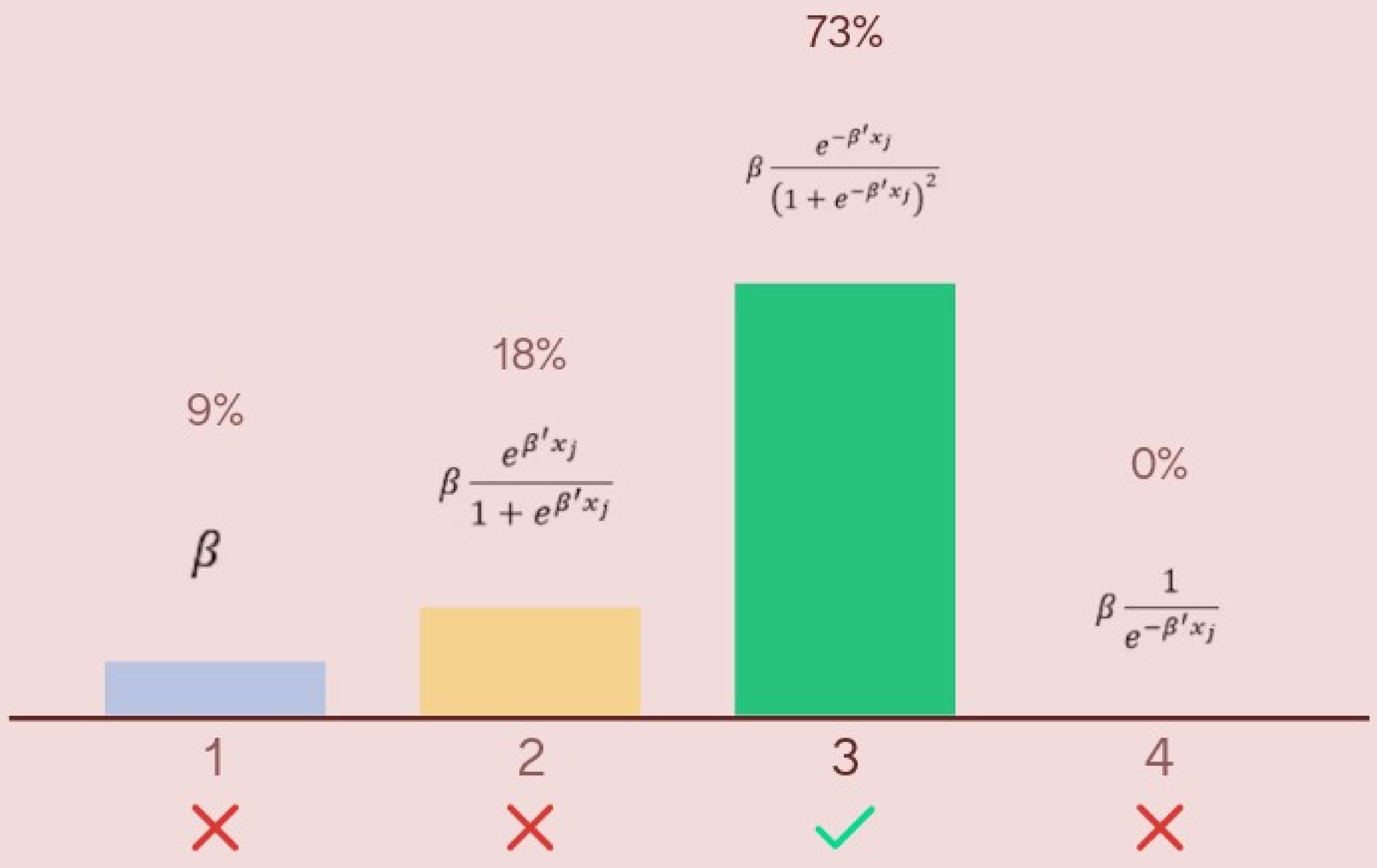
Chosen_B	$\text{Price}_B\text{-Price}_A$	$\text{Time}_B\text{-Time}_A$
1	-14	5
0	5	0
0	15	-20
1	-8	13
1	-10	3
1	3	-5
0	20	10

3. Logit

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

→ **Calculate the marginal effect on probability of one unit increase in x (so $\frac{\partial \Pr(d_j=1)}{\partial x_j}$)**

What is the marginal effect on the probabiblity of one unit increase in x $\left(\frac{\partial \Pr(d_j = 1)}{\partial x_j}\right)$



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

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3. Logit

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

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

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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)**

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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

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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 $\Pr(d_j = 1) = \Phi(\beta' x_j)$
  - 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 may seem more reasonable
- Probability is always between one and zero

Disadvantages:

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

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4. Probit

- How to choose between the three models?
  - Probit estimates ≈ Logit estimates
  - 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

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5. Application

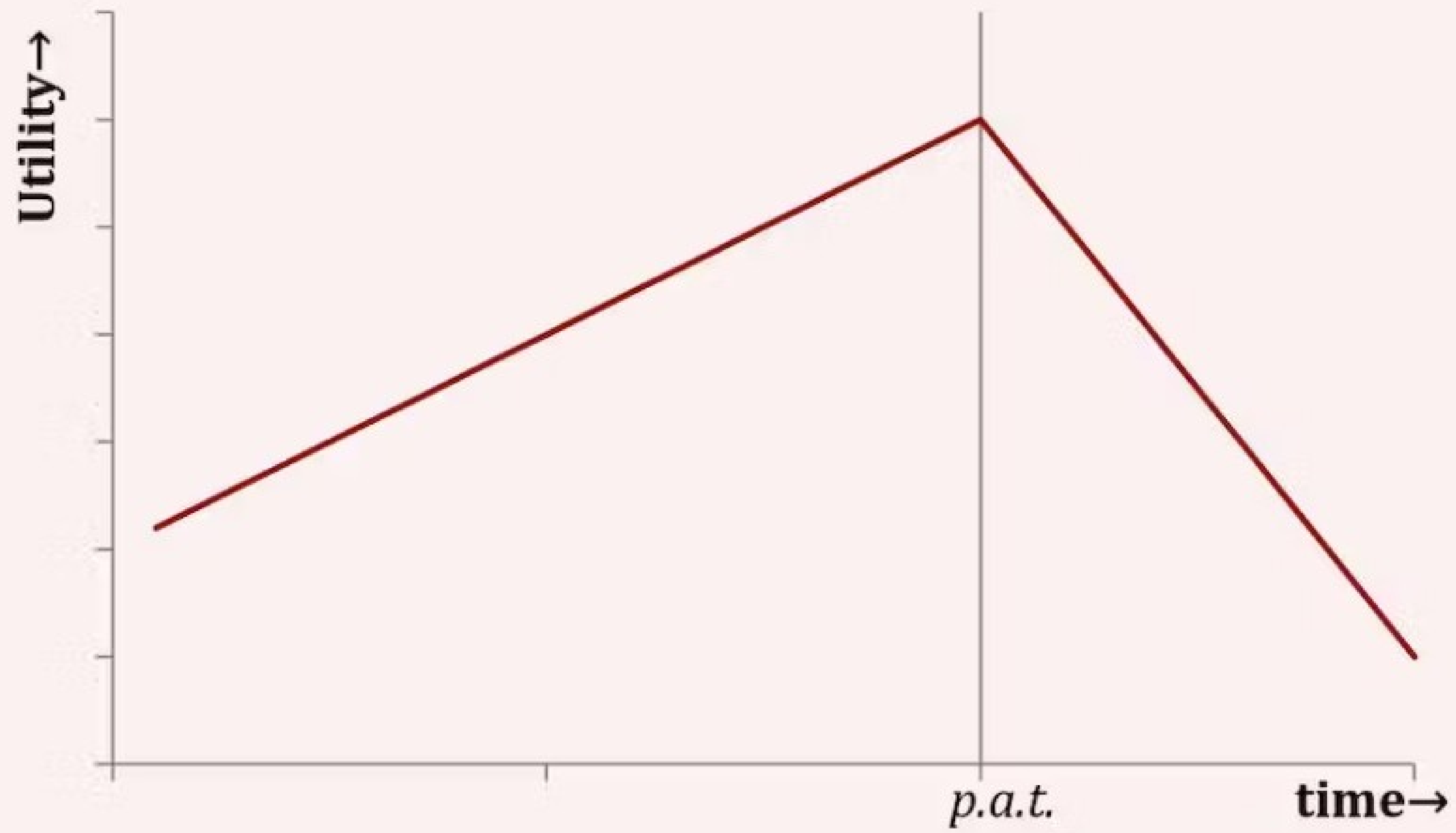
- Koster and Koster (2014)
  - Estimate the value of time and unreliability
  - Uses a stated choice experiment

- Stated-choice experiment about preferences of morning commuters
  - "*Spitsmijden*" (Peak-avoidance project)
  - People get a reward if they avoid the peak

  - But: they may be too early or late at work!
  - Trade-off

5. Application

- Value of time
- Value of schedule delay early
- Value of schedule delay late
  - *p.a.t.* = preferred arrival time



5. Application

- **Example of a choice with two alternatives and uncertainty**

Your preferred arrival time if there is no delay is: 8:40.

	Alternative 1		Alternative 2	
Departure time from home	6:05		6:50	
Probability	*80%*	*20%*	*90%*	*10%*
Total travel time	30 min	40 min	20 min	35 min
Arrival time at work	6:35	6:45	7:10	7:25
Reward	4 euro	4 euro	0 euro	0 euro

5. Application

- **Utility is specified as follows**
  - $U_{icj} = \beta^R R_{icj} + \beta^T T_{icj} + \beta^{SDE} SDE_{icj} + \beta^{SDL} SDL_{icj} + \epsilon_{icj}$

i	**individual**
c	**choice**
j	**alternative**
R_{icj}	**expected *reward***
T_{icj}	**expected travel time**
SDE_{icj}	**expected time before *p.a.t.***
SDL_{icj}	**expected time after *p.a.t.***
ϵ_{icj}	**random taste variation, Extreme Value Type I distributed**

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5. Application

- **Utility is specified as follows**
  - $U_{icj} = \beta^R R_{icj} + \beta^T T_{icj} + \beta^{SDE} SDE_{icj} + \beta^{SDL} SDL_{icj} + \epsilon_{icj}$
  - $\Delta u_{inj} = 0 = \beta^R \Delta R_{icj} + \beta^T \Delta T_{icj} + +\beta^{SDE} \Delta SDE_{icj} + \beta^{SDL} \Delta SDL_{icj}$

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5. Application

- **Estimate the value of time and unreliability**

  - **Value of time (VOT):**

$$-\beta^R \Delta R_{icj} = \beta^T \Delta T_{icj} \rightarrow \Delta T_{icj} = -1 \rightarrow -\Delta R_{icj} = -\frac{\beta^T}{\beta^R}$$

Note that we look at the willingness to pay. Because the experiment focuses on rewards, we have $-\Delta R_{icj}$

  - **Value of schedule delay early (VSDE):**

$$-\beta^R \Delta R_{icj} = \beta^{SDE} \Delta SDE_{icj} \rightarrow \Delta SDE_{icj} = -1 \rightarrow -\Delta R_{icj} = -\frac{\beta^{SDE}}{\beta^R}$$

  - **Value of time (VSDL):**

$$-\beta^R \Delta R_{icj} = \beta^{SDL} \Delta SDL_{icj} \rightarrow \Delta SDL_{icj} = -1 \rightarrow -\Delta R_{icj} = -\frac{\beta^{SDL}}{\beta^R}$$

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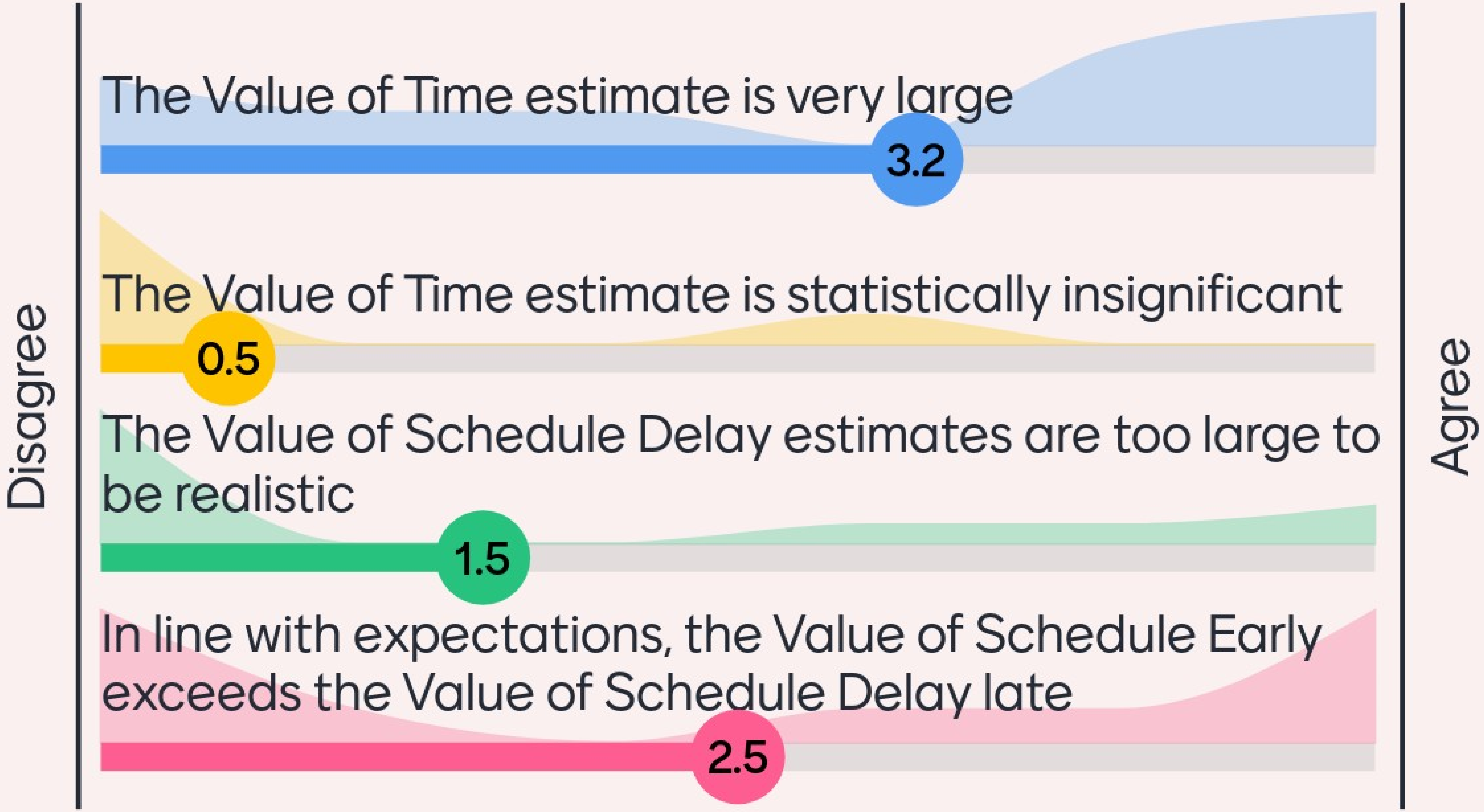
What is your interpretation of the results?



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5. Application

- Results *(s.e.'s between parentheses)*

VOT	€ 35.05 (€ 4.158)
VSDE	€ 23.22 (€ 2.211)
VSDL	€ 17.16 (€ 1.621)

- Willingness to pay estimates are high
  - People are more sensitive to tolls
  - Relatively high share of high income households
- VSDE>VSDL?
  - Constraints in the morning rather than at work

Discrete choice (2)

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Discrete choice (3)

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1. Introduction

- **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

- 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

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

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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:

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

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4. Conditional logit

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

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

1. Model aggregate choices

- Modelling location choice
  - Focus on aggregate areas (*e.g.* municipalities)

- Choice of cars
  - Only distinguish between brands

- However, lack of detail makes results less credible

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*)

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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

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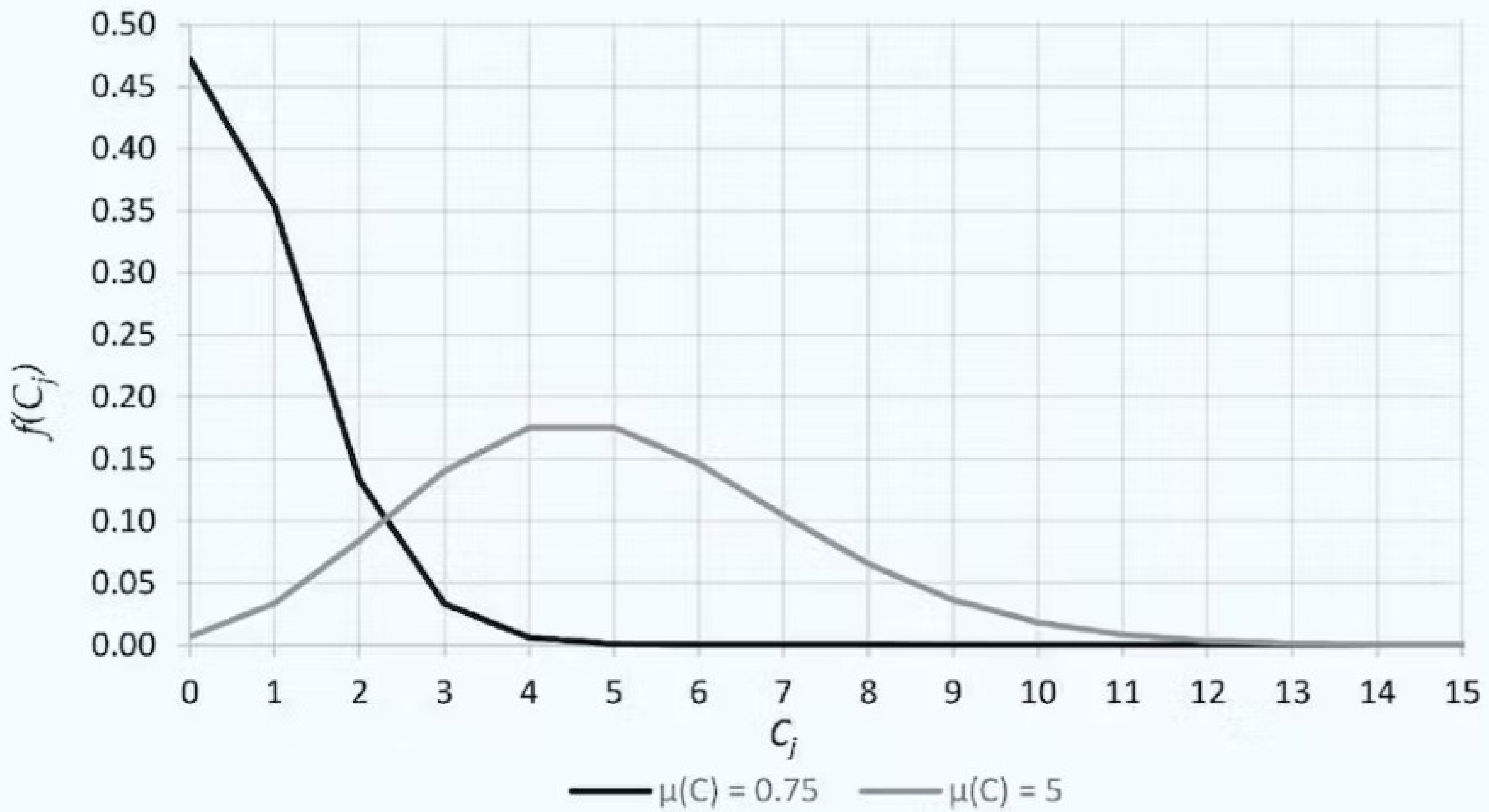
3. Estimate count data models

- **Example of a Poisson distribution**



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

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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**

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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

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4. Conditional logit

3. Estimate count data models

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

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

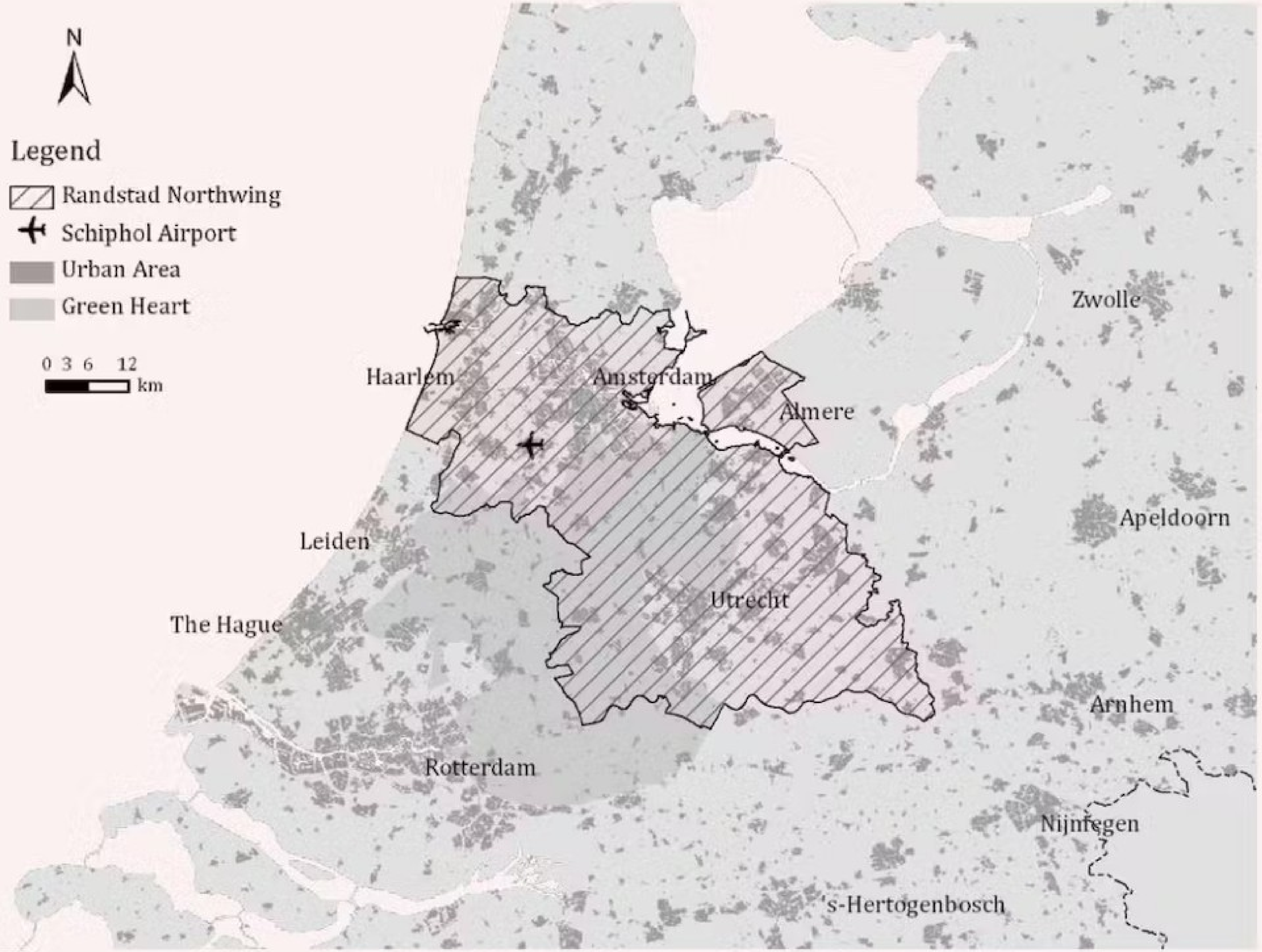
4. Conditional logit

- Jacobs *et al.* (2013)
  - Analyse location choices of business start-ups
  - Investigate the impact of *multinationals* on the number of business start-ups
  - In the Randstad Northwing

- Multinationals may generate:
  - Knowledge spillovers
  - Spin-offs
  - Potential customers *(output sharing)*

4. Conditional logit

- **The Randstad Northwing**



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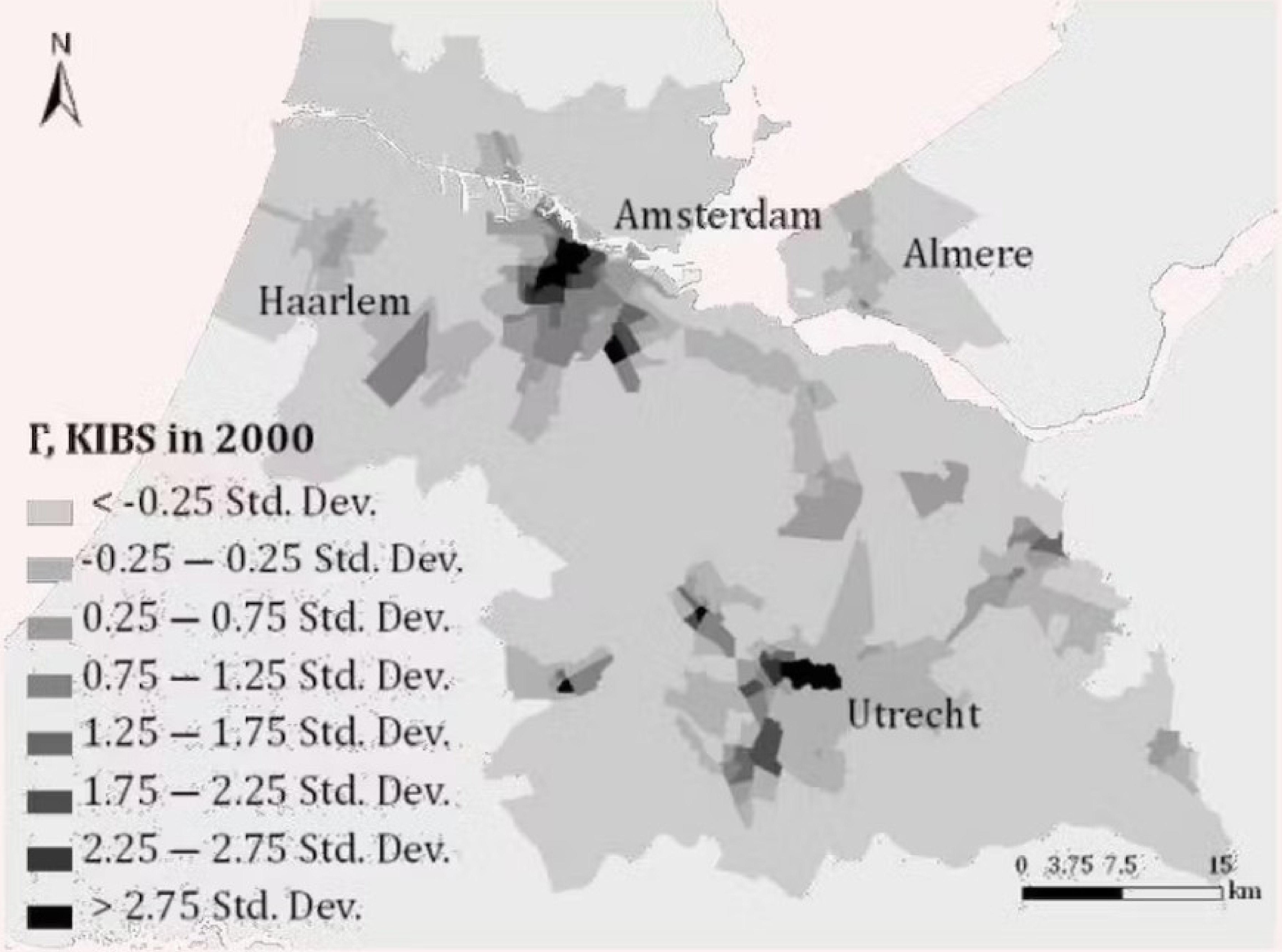
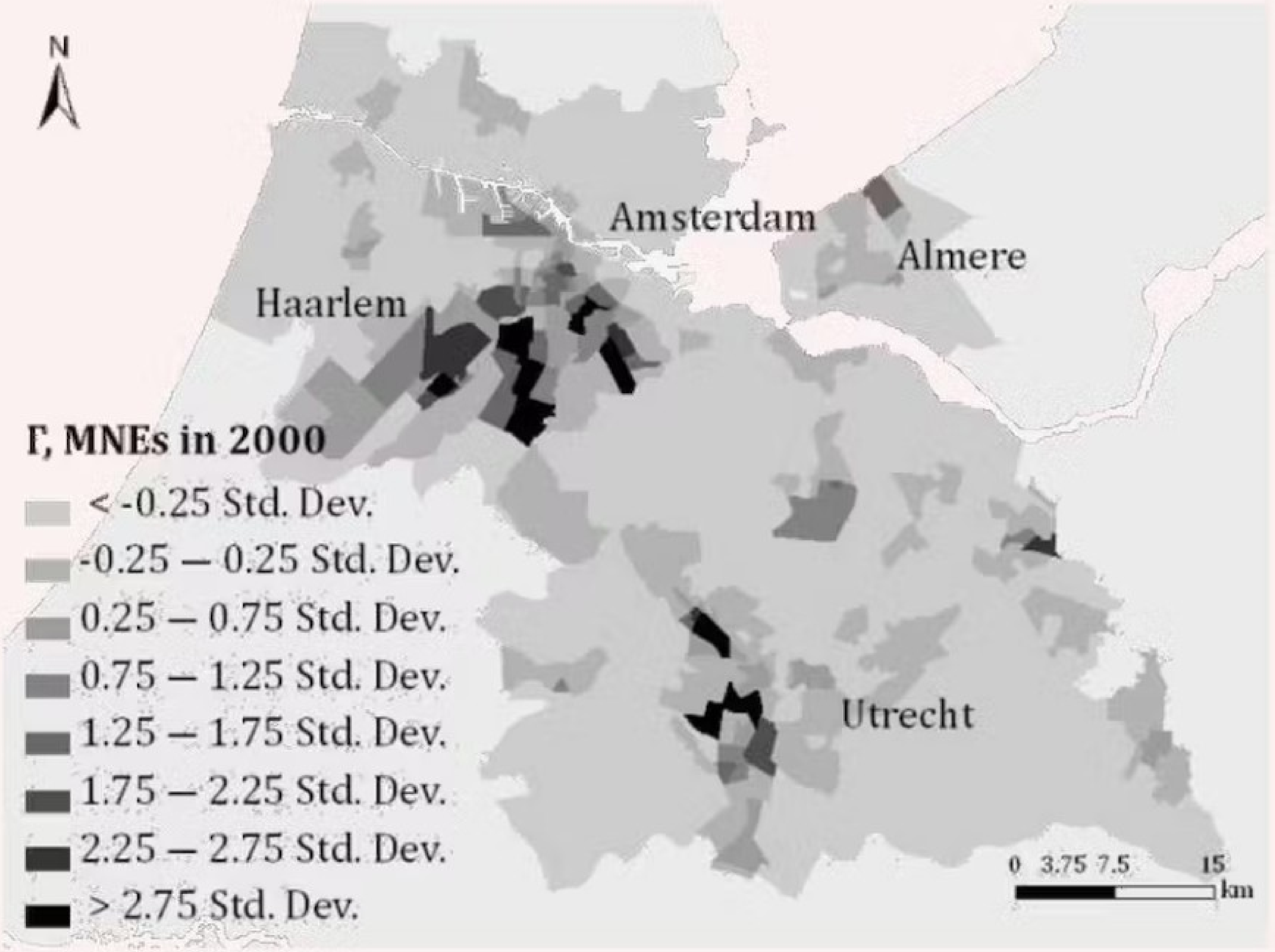
4. Conditional logit

- **Business services in the Randstad Northwing**



- **Multinationals in the Randstad Northwing**



4. Conditional logit

- **Location choice model:**

$$\pi_{ij} = \alpha + \beta e_j^{MNE} + \gamma e_j^{BSF} + \delta e_j^{OF} + \zeta X_j + \eta_{j \in M} + \epsilon_{ij}$$

i	**firm**
j	**PC6 location (alternatives)**
e_j^{MNE}	**multinational employment**
e_j^{BSF}	**business services employment**
e_j^{OF}	**other employment**
X_j	**control variables**
$\eta_{j \in M}$	**municipality fixed effects**

4. Conditional logit

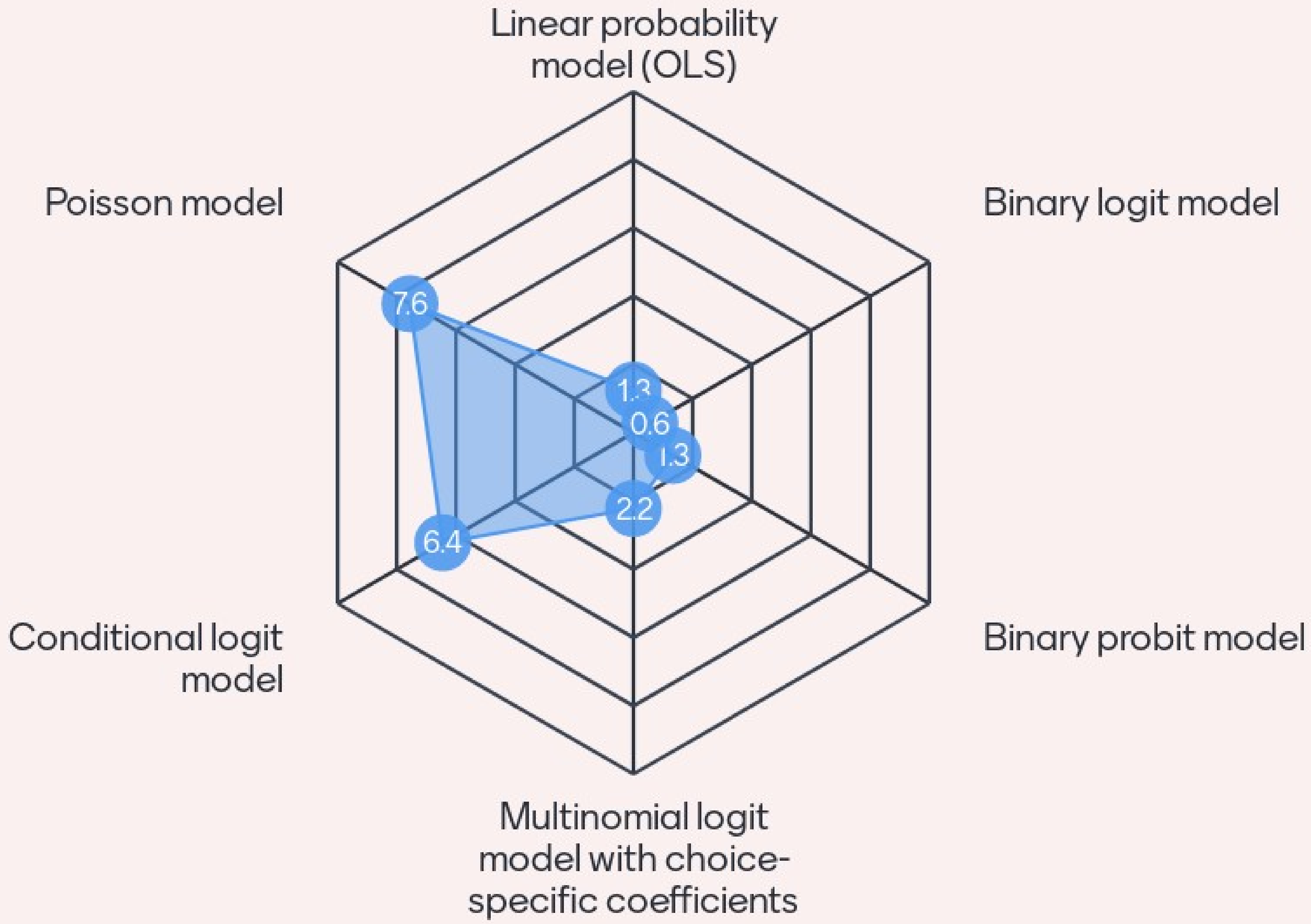
- **Probability Π that i chooses k:**

$$\Pr(d_j = 1) = \frac{e^{\alpha+\beta e_j^{MNE}+\gamma e_j^{BSF}+\delta e_j^{OF}+\zeta X_j+\eta_{j\in M}}}{\sum_{\kappa=1}^{J} e^{\alpha+\beta e_k^{MNE}+\gamma e_k^{BSF}+\delta e_k^{OF}+\zeta X_k+\eta_{k\in M}}}$$

- **There are 13,655 locations**

→ **How would you estimate this model?**

What regression method would you use to estimate this model?



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4. Conditional logit

- Problem: many locations
  - Use count data to estimate this model
    → There are no individual firm characteristics
  - Dependent variable: # start-ups per location

4. Conditional logit

- **Results**

Table – A POISSON MODEL
(Dependent variable: The number of business services start-ups per location)

	(1)	(2)	(3)
Multi-national employment density *(log)*	0.0709***	0.0422***	0.0772***
	(0.0151)	(0.0092)	(0.0121)
Business services employment density *(log)*	0.4304***	0.4374***	0.3821***
	(0.0240)	(0.0162)	(0.0214)
Other employment density *(log)*	-0.2242***	-0.2203***	-0.1352***
	(0.0162)	0.0071	(0.0178)
Control variables (9)	No	Yes	Yes
Municipality fixed effects (61)	No	No	Yes
Number of locations	13,655	13,655	13,655
Log-likelihood	-13,146.903	-13,051.163	-12,709.249

Notes: We include locations with at least 10 employees in 2000. The coefficients can be interpreted as elasticities and differ from Jacobs et al. (2013) because of a slightly different set of controls and because we estimate Poisson models instead of Negative-binomial regressions. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

→ **Please interpret the results in column (3)**

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4. Conditional logit

- Multinationals attract new business services
  - The effect of other business services on start-ups, is however, much larger

- Coefficients are convenient to interpret
  - *e.g.* a 1% increase in multinational empl. leads to an increase of start-ups of 0.077% (in Column (1))

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

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

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5. Revealed preference and stated preference data

- Example of stated preference question
  - Different from contingent valuation!

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?			

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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
  - 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

- <u>Hypothetical bias</u>
  - 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…

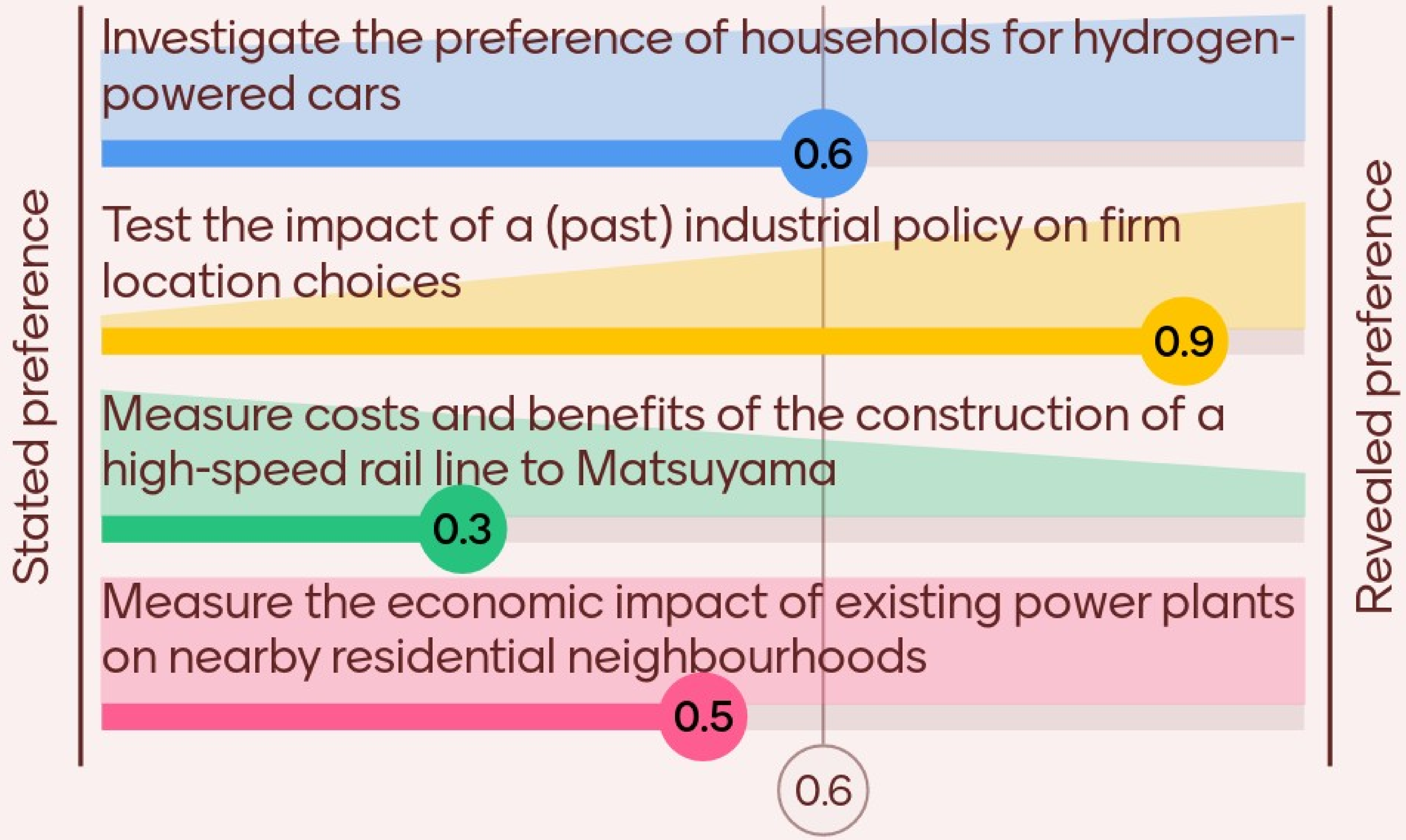
- <u>Strategic bias</u>
  - Respondent wants a specific outcome
  - (S)he fills in answers that are in line with desired outcomes

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)*

Would you use SP or RP in the following cases:



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6. Summary

Discrete choice:

- Random utility framework

- Generalisations of logit models
  - LPM ($J = 2$)
  - Binary logit/probit ($J = 2$)
  - Multinomial logit ($2 < J < 10$)
  - Nested logit ($2 < J < 10$)
  - Conditional logit ($J > 2$)

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

- Data
  - Stated preference or revealed preference data

Discrete choice (3)

Applied Econometrics for Spatial Economics

Hans Koster
Professor of Urban Economics and Real Estate