Discrete choice (2)

Applied Econometrics for Spatial Economics

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1. Introduction

- Topics:
  1. Discrete choice
     - Random utility framework, estimating binary and multinomial regression models
  2. Spatial econometrics
     - Spatial data, autocorrelation, spatial regressions
  3. Identification
     - Research design, IV, OLS, RDD, quasi-experiments, standard errors
  4. Hedonic pricing
     - Theory and estimation
  5. Quantitative spatial economics
     - General equilibrium models in spatial economics

1. Introduction

Wednesday

09:30-10:30	Lecture 1	Discrete Choice I (The random utility framework)
10:45-11:45	Lecture 2	Discrete Choice II (Estimating discrete choice models)
12:00-13:00	Lecture 3	Spatial Econometrics I (Spatial data)
14:00-15:30	Tutorial 1	Assignment 1

Thursday

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10:45-11:45	Lecture 5	Spatial Econometrics III (Spatial regressions)
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13:30-14:00	Tutorial 2	Discussion of Assignment 1
14:00-15:00	Tutorial 3	Assignment 2

Friday

09:30-10:00	Lecture 7	Identification II (RCTs, OLS, IV, quasi-experiments)
10:00-10:30	Lecture 8	Hedonic pricing I (Theory)
10:45-11:45	Lecture 9	Hedonic pricing II (Estimation)
12:00-12:30	Tutorial 4	Discussion of Assignment 2

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

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2. Linear probability model

Advantages:

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

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2. Linear probability model

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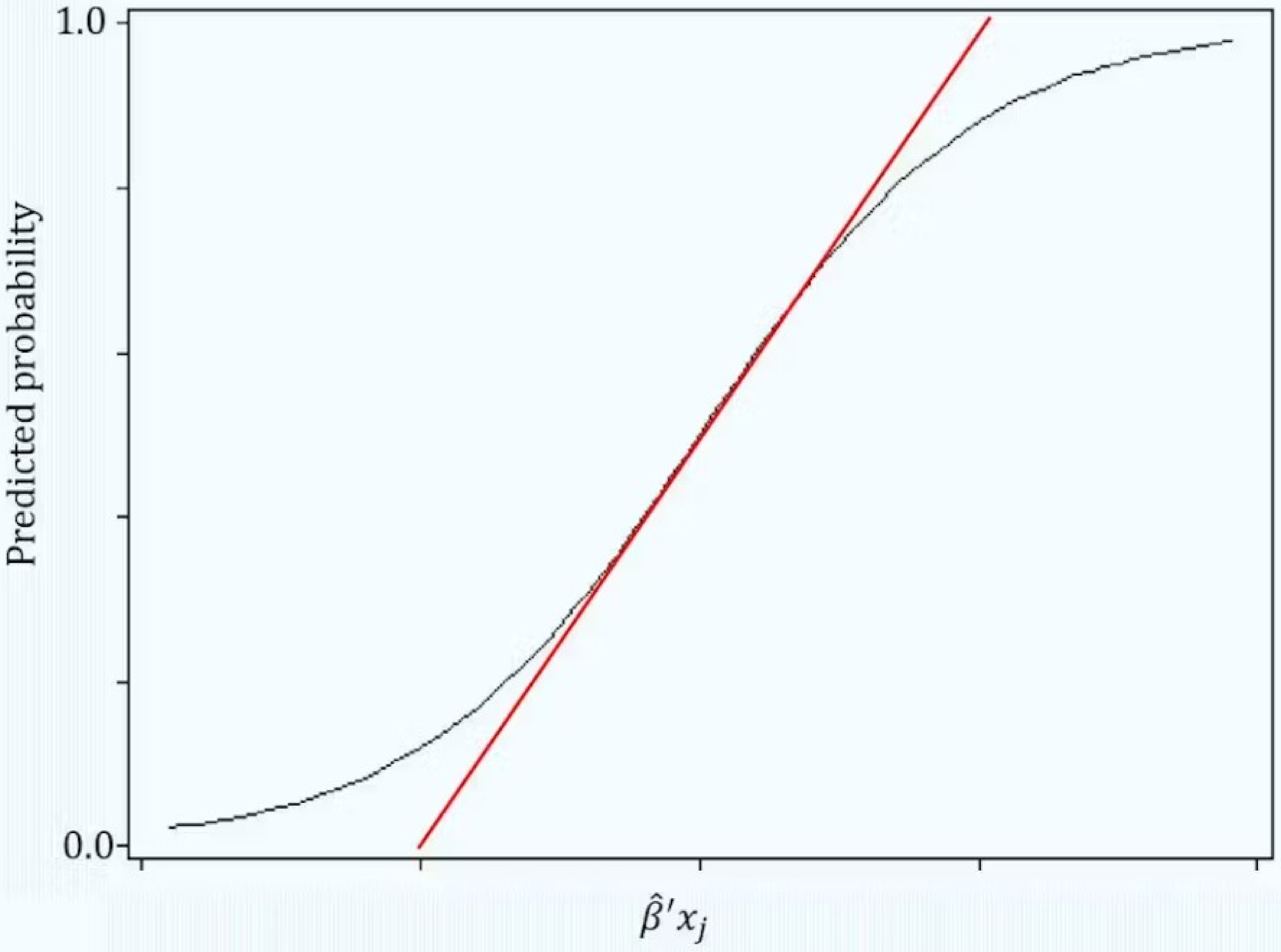
Advantages:

- 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**
  - $\frac{\partial \Pr(d_j = 1)}{\partial x} = \beta$

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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**

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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

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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

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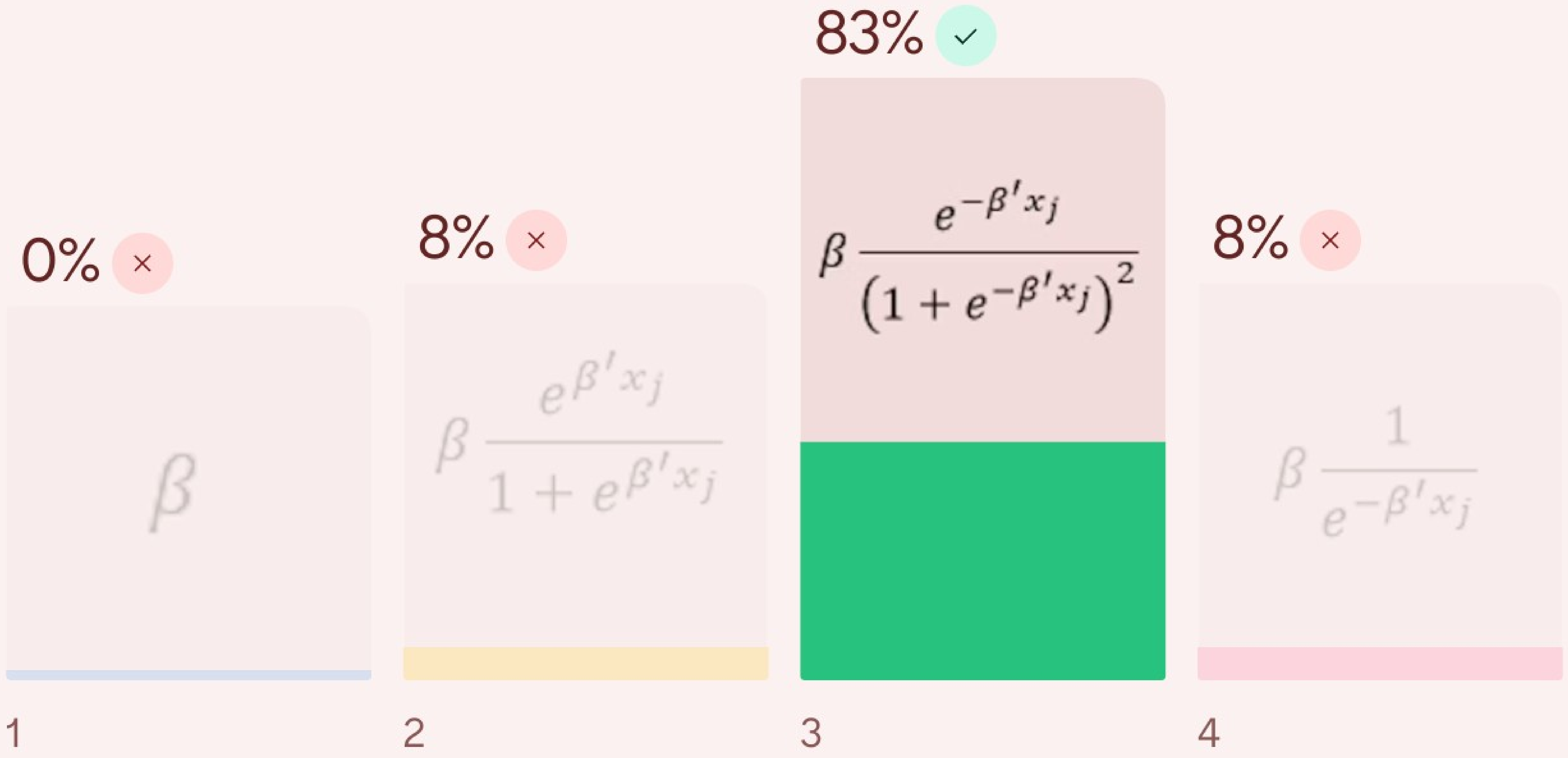
What is the marginal effect on the probabiblity of one unit increase in x, so $\frac{\partial \Pr(d_j=1)}{\partial x_j}$?



3. Logit

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

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3. Logit

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

- **Marginal effect depends on x_j, so is not constant/linear**
  - **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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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. to* control for individual heterogeneity

3. Logit

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

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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

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

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

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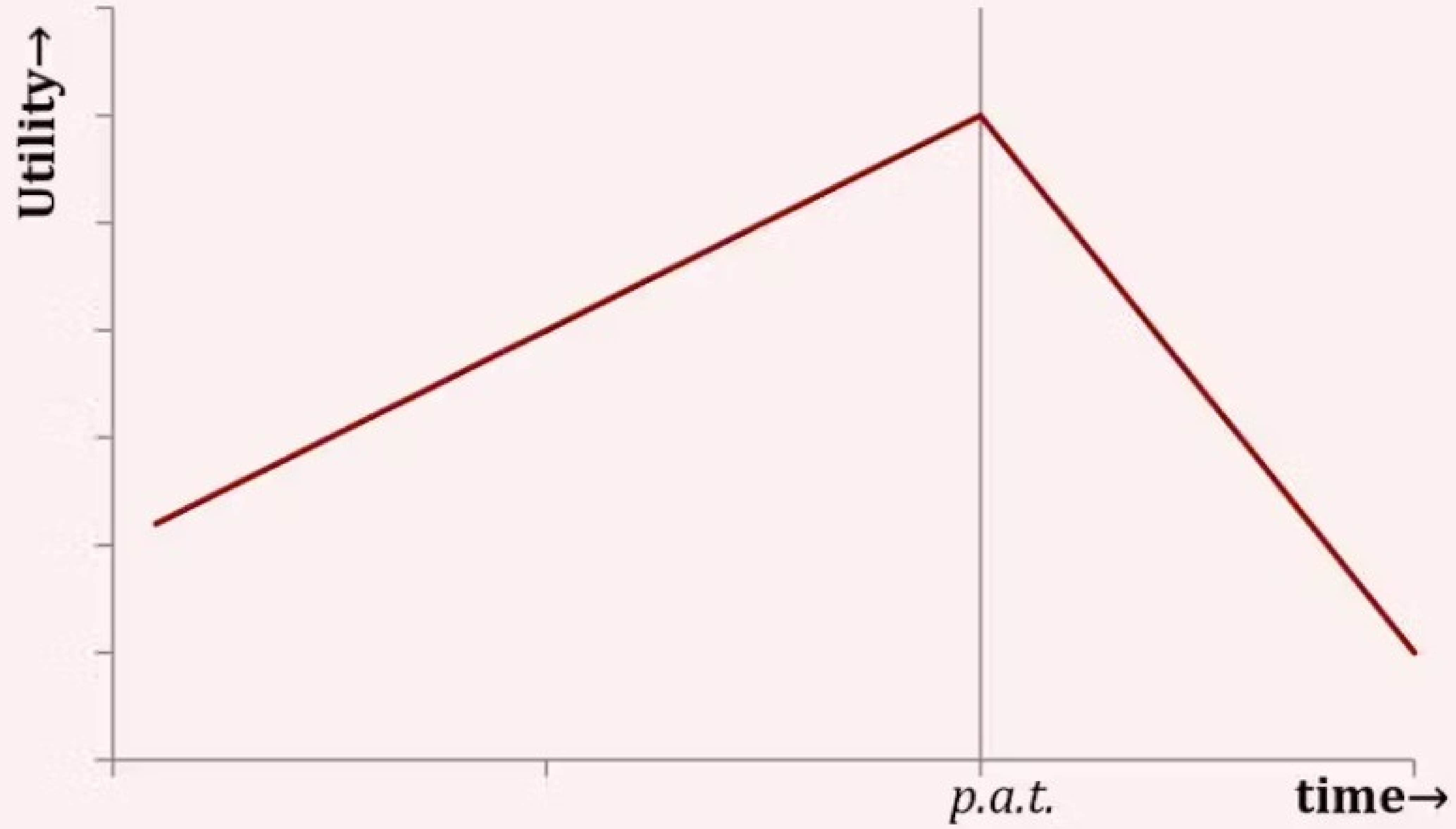
5. Application

- 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**

5. Application

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

- **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 $-\Delta R_{icj}$

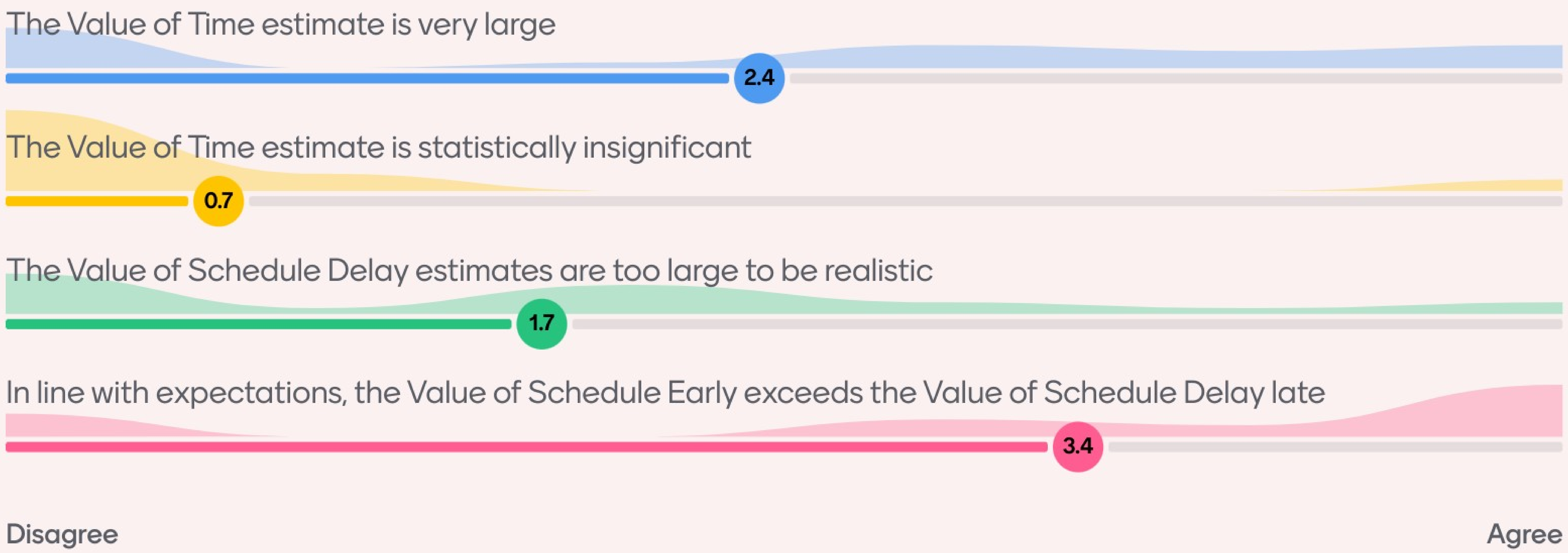
  - **Value of schedule delay early (VSDE):**

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

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

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

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

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

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.:**

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

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:

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

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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)**

4. Conditional logit

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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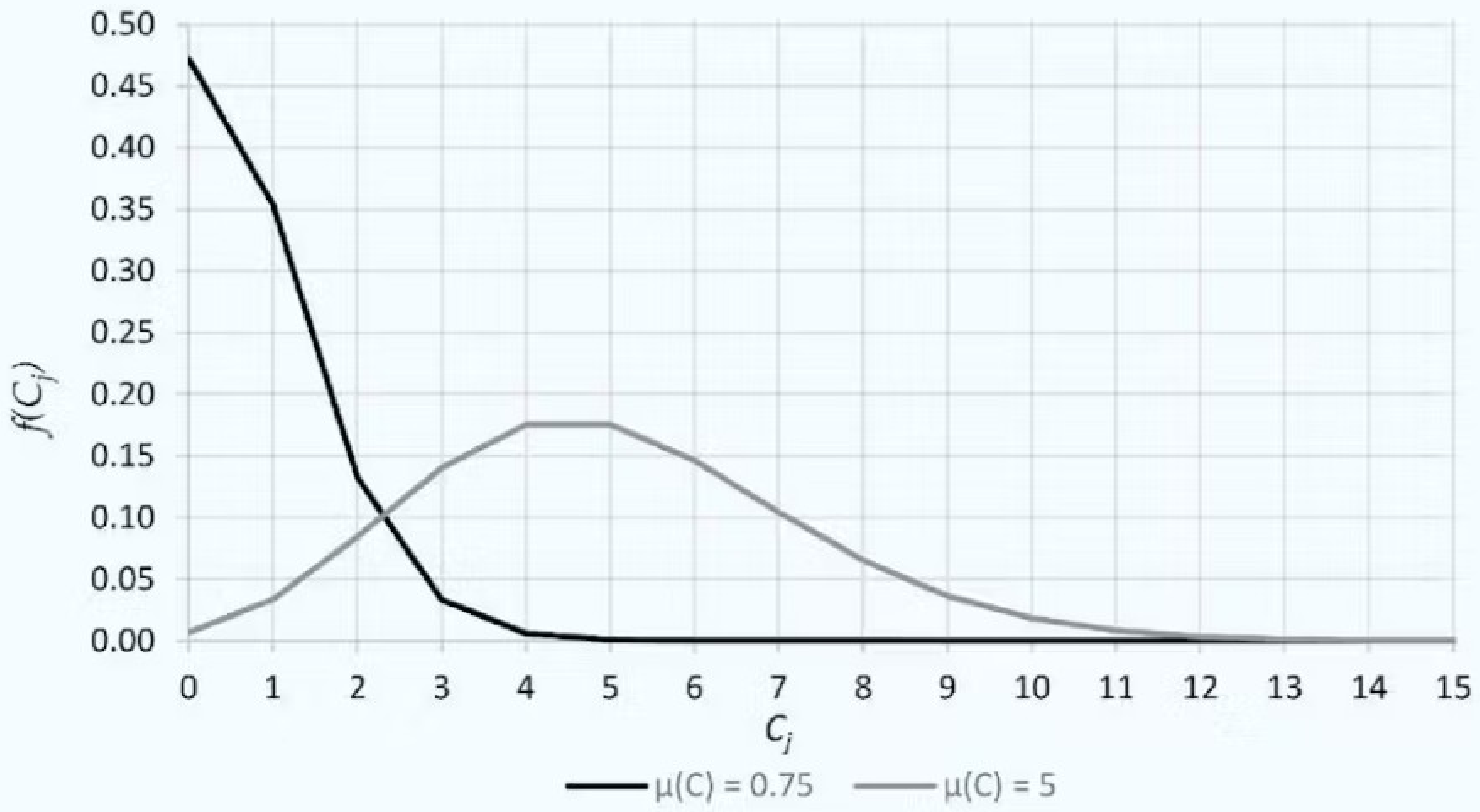
3. Estimate count data models

- 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

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**

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

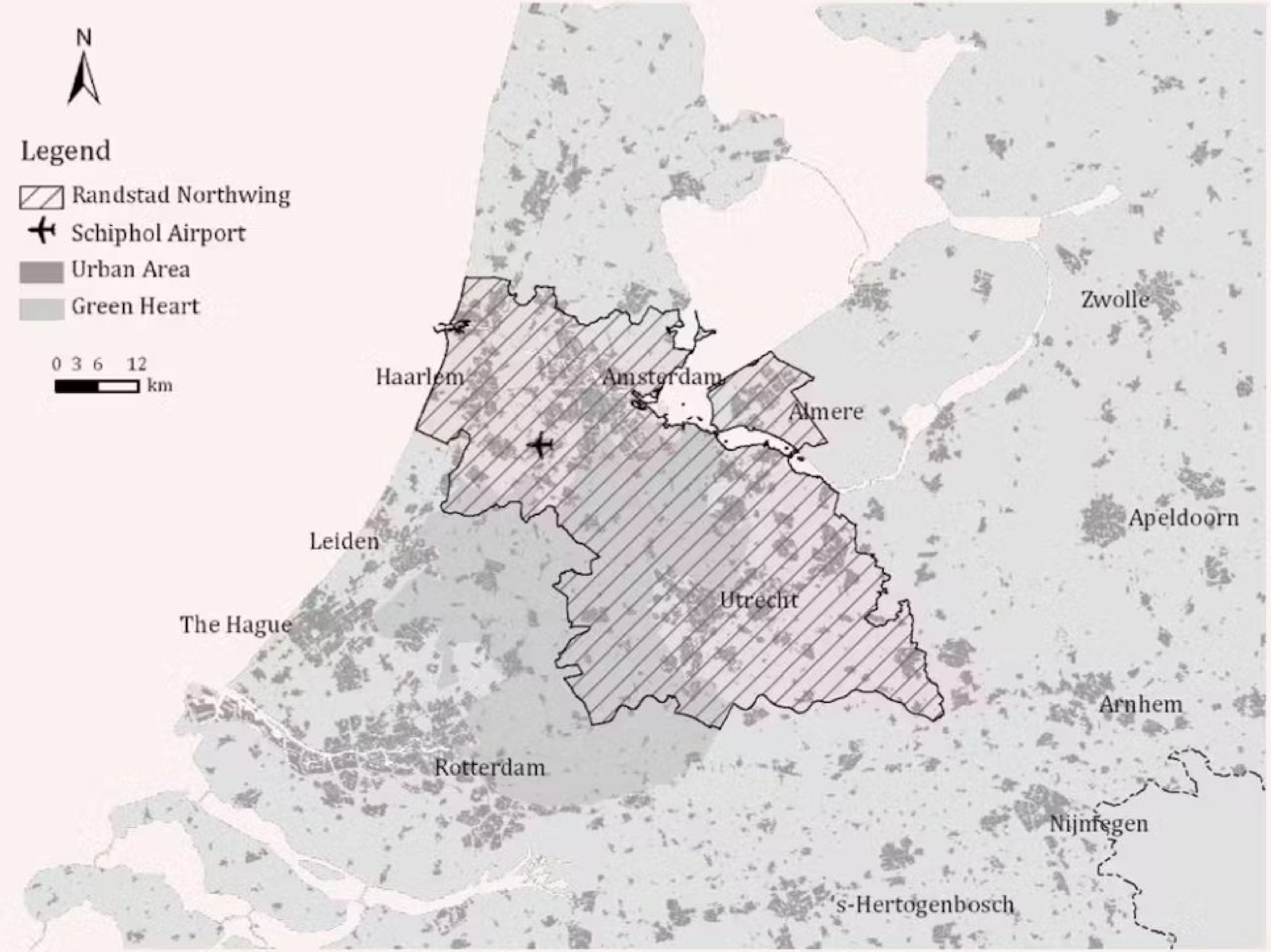
4. Conditional logit

- 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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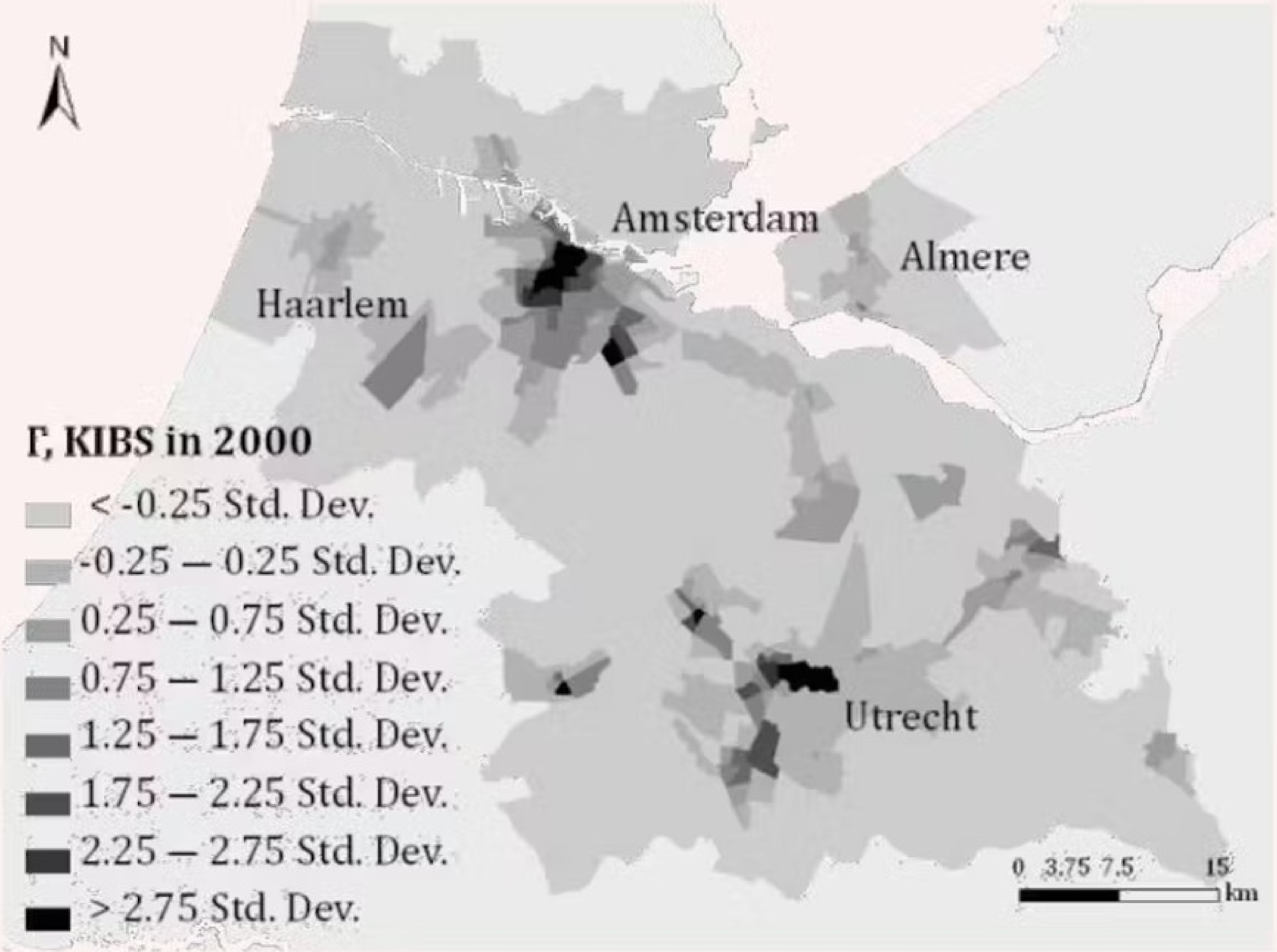
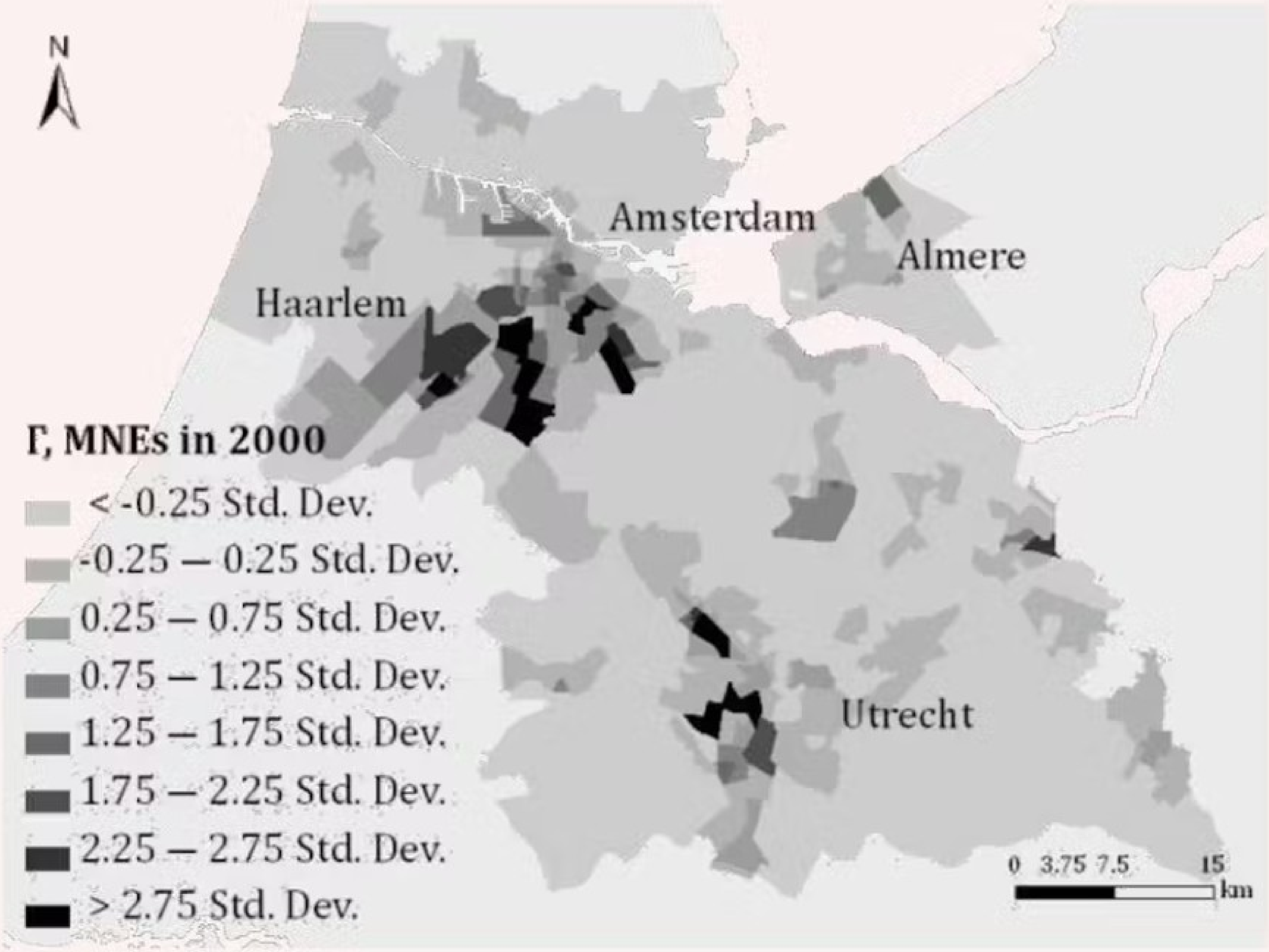
4. Conditional logit

- **Business services in the Randstad Northwing**



4. Conditional logit

- **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**

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4. Conditional logit

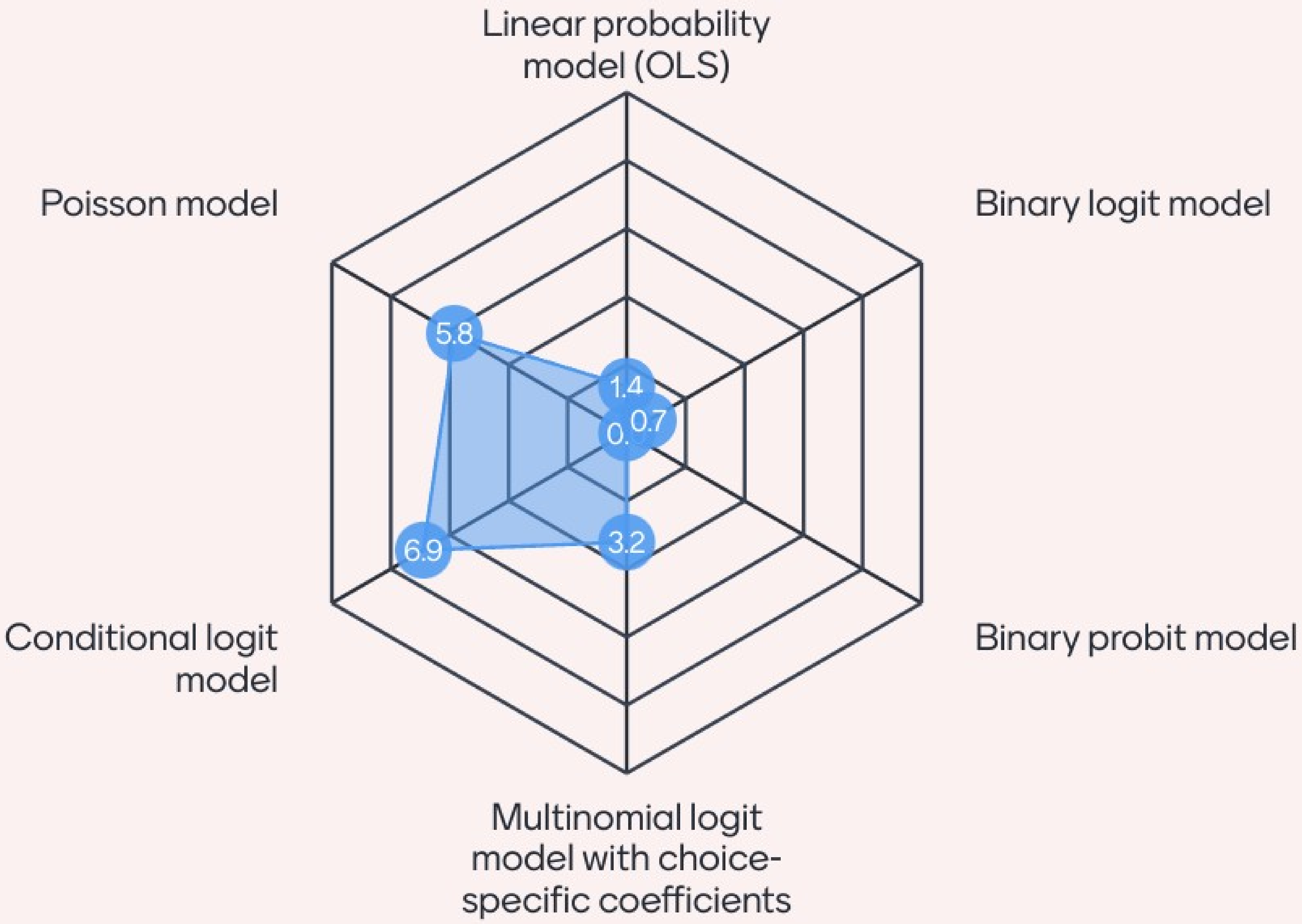
- **Probability Π that i chooses k:**

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

- **There are 13,655 locations**

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

What regression method would you use to estimate this model?



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

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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))

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

Discrete choice (3)

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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

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

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?			

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

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Disadvantages of SP data

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

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

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:

Investigate the preference of households for hydrogen-powered cars

Test the impact of a (past) industrial policy on firm location choices

Measure costs and benefits of the construction of a high-speed rail line to Shikoku

Measure the economic impact of existing power plants on nearby residential neighbourhoods

0.0

Stated preference — **Revealed preference**

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

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

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Discrete choice (3)

Applied Econometrics for Spatial Economics

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