

# Model specifications

Alternative specific constants, variables, and functional forms

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Mathematical Modeling of Behavior



# Outline

Logit

Alternative Specific Constants

Qualitative attributes

Taste heterogeneity

Heteroscedasticity

Nonlinear specifications

# The logit model

## Specification

$$\begin{aligned}U_{in} &= V_{in} + \eta + \frac{1}{\mu}\varepsilon_{in} \\&= \sum_k \beta_k z_{ink} + \eta + \frac{1}{\mu}\varepsilon_{in},\end{aligned}$$

where  $\varepsilon_{in}$  are i.i.d.  $\text{EV}(0, 1)$ .

# The logit model

## Choice probability

$$P(i|V, \mathcal{C}_n; \mu) = \frac{e^{\mu V_{in}}}{\sum_{j \in \mathcal{C}_n} e^{\mu V_{jn}}},$$

or

$$P(i|z_n, \mathcal{C}_n; \beta, \mu) = \frac{e^{\mu(\sum_k \beta_k z_{ink})}}{\sum_{j \in \mathcal{C}_n} e^{\mu(\sum_k \beta_k z_{jnk})}}.$$

# The logit model: normalizations

Moneymetric utility:  $\beta_c = -1$

$$\mu V_{in} = -\mu \text{cost}_{in} + \sum_k \mu \beta_k z_{ink}.$$

Linear-in-parameters:  $\mu = 1$

$$\mu V_{in} = \beta_c \text{cost}_{in} + \sum_k \beta_k z_{ink}.$$

# Quantitative attributes

## Numerical and continuous

- ▶  $z_{ink} \in \mathbb{R}, \forall i, n, k.$
- ▶ Associated with a specific unit.
- ▶ Vary across both  $i$  and  $n$ .

## Examples

- ▶ Auto in-vehicle time (in minutes).
- ▶ Transit in-vehicle time (in minutes).
- ▶ Auto out-of-pocket cost (in cents).
- ▶ Transit fare (in cents).
- ▶ Walking time to the bus stop (in minutes).

Straightforward modeling

## Quantitative attributes

- ▶  $\beta$  transforms the unit of the corresponding attribute into utility units.
- ▶ Example: consider two moneymetric specifications:

$$\begin{aligned}\mu V_{in} &= -\mu\text{cost} + \mu\beta\text{TT}_{in} + \dots \\ \mu V_{in} &= -\mu\text{cost} + \mu\beta'\text{TT}'_{in} + \dots\end{aligned}$$

- ▶ If  $\text{TT}_{in}$  is a number of minutes, the unit of  $\beta$  is CHF/minute.
- ▶ If  $\text{TT}'_{in}$  is a number of hours, the unit of  $\beta'$  is CHF/hour.
- ▶ Both models are equivalent, but the estimated value of the coefficient will be different

$$\beta\text{TT}_{in} = \beta'\text{TT}'_{in} \implies \frac{\beta'}{\beta} = \frac{\text{TT}_{in}}{\text{TT}'_{in}} = 60.$$

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# Relax the i.i.d. assumption

## i.i.d. assumption

- ▶ Same  $\eta$  for all alternatives  $i$ : relaxed in this lecture.
- ▶ Same  $\eta$  for all observations  $n$ : relaxed in this lecture.
- ▶ Same  $\mu$  for all alternatives  $i$ : relaxed in the lecture on mixtures.
- ▶ Same  $\mu$  for all observations  $n$ : relaxed in this lecture.
- ▶ Independence across alternatives  $i$ : relaxed in the lecture on MEV models.
- ▶ Independence across observations  $n$ : relaxed in the lecture on panel data.

# Motivation



|                  | iPhone | Samsung |
|------------------|--------|---------|
| Price            | \$900  | \$900   |
| Cellular         | 5G     | 5G      |
| Capacity         | 128GB  | 128GB   |
| Display          | 6.6"   | 6.6"    |
| Market shares US | 60 %   | 27%     |

Conclusion: we cannot assume  $E[\varepsilon_{in}] = E[\varepsilon_{jn}]$ .

Source: [gs.statcounter.com/vendor-market-share/mobile](https://gs.statcounter.com/vendor-market-share/mobile)

# Motivation



- ▶ How can we explain the difference?
- ▶ Only the names of the alternatives are different.
- ▶ It means that the names have an important behavioral influence.
- ▶ In marketing, it is called “brand equity”.

# Modeling

## Alternative Specific Constants

- ▶ We define new variables:

$$Z_{i,\text{iPhone}} = \begin{cases} 1 & \text{if } i \text{ is iPhone,} \\ 0 & \text{otherwise.} \end{cases}$$

$$Z_{i,\text{Samsung}} = \begin{cases} 1 & \text{if } i \text{ is Samsung,} \\ 0 & \text{otherwise.} \end{cases}$$

- ▶ We include them with coefficients in the utility function.

# Alternative Specific Constants

Original formulation

$$U_{in} = V_{in} + \eta + \frac{1}{\mu} \varepsilon_{in}.$$

New formulation

$$U_{in} = V_{in} + (\beta_{\text{iPhone}} z_{i,\text{iPhone}} + \beta_{\text{Samsung}} z_{i,\text{Samsung}}) + \eta + \frac{1}{\mu} \varepsilon_{in}.$$

# Alternative Specific Constants

## New formulation

$$U_{\text{iPhone},n} = V_{\text{iPhone},n} + (\beta_{\text{iPhone}} + \eta) + \frac{1}{\mu} \varepsilon_{\text{iPhone},n}.$$

$$U_{\text{Samsung},n} = V_{\text{Samsung},n} + (\beta_{\text{Samsung}} + \eta) + \frac{1}{\mu} \varepsilon_{\text{Samsung},n}.$$

## Location parameters

$$\eta_{\text{iPhone}} = \beta_{\text{iPhone}} + \eta$$

$$\eta_{\text{Samsung}} = \beta_{\text{Samsung}} + \eta$$

# Alternative Specific Constants

## New formulation

$$U_{\text{iPhone},n} = V_{\text{iPhone},n} + \eta_{\text{iPhone}} + \frac{1}{\mu} \varepsilon_{\text{iPhone},n}.$$

$$U_{\text{Samsung},n} = V_{\text{Samsung},n} + \eta_{\text{Samsung}} + \frac{1}{\mu} \varepsilon_{\text{Samsung},n}.$$

## Comments

- ▶ The use of ASCs relaxes the assumption that the location parameters are the same across alternatives.
- ▶ Abuse of language: the coefficients of the ASCs are often called ASCs themselves.
- ▶ In practice, the numbering of alternatives is often consistent with their names (iPhone is always alternative 1, etc.) But it is not required.
- ▶ There is an identification issue.

# Identification

## Issue

For any value of  $\eta$ ,

$$P_n(i|\mathcal{C}_n) = \Pr(V_{in} + \eta + \eta_i + \frac{1}{\mu}\varepsilon_{in} \geq V_{jn} + \eta + \eta_j + \frac{1}{\mu}\varepsilon_{jn}, \forall j \in \mathcal{C}_n).$$

## Normalization

- ▶ Select any arbitrary alternative  $j$ , and normalize  $\eta = -\eta_j$ .
- ▶ It is equivalent to normalize the ASC of alternative  $j$  to zero.
- ▶ If there are  $J_n$  alternatives, only  $J_n - 1$  ASCs are identified.

## Example: binary choice

### Normalization of the iPhone constant

$$U_{\text{iPhone},n} = V_{\text{iPhone},n} + \frac{1}{\mu} \varepsilon_{\text{iPhone},n}.$$

$$U_{\text{Samsung},n} = V_{\text{Samsung},n} + \beta_{\text{Samsung}} + \frac{1}{\mu} \varepsilon_{\text{Samsung},n}.$$

### Normalization of the Samsung constant

$$U_{\text{iPhone},n} = V_{\text{iPhone},n} + \beta_{\text{iPhone}} + \frac{1}{\mu} \varepsilon_{\text{iPhone},n}.$$

$$U_{\text{Samsung},n} = V_{\text{Samsung},n} + \frac{1}{\mu} \varepsilon_{\text{Samsung},n}.$$

# Relax the i.i.d. assumption

## i.i.d. assumption

- ✓ Same  $\eta$  for all alternatives  $i$ : relaxed in this lecture.
- ▶ Same  $\eta$  for all observations  $n$ : relaxed in this lecture.
- ▶ Same  $\mu$  for all alternatives  $i$ : relaxed in the lecture on mixtures.
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# Motivation



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|------------------------|--------|---------|
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| Cellular               | 5G     | 5G      |
| Capacity               | 128GB  | 128GB   |
| Display                | 6.6"   | 6.6"    |
| Market shares (US)     | 60 %   | 27%     |
| Market shares (Europe) | 36 %   | 31%     |
| Market shares (CH)     | 58 %   | 27%     |

Conclusion: ASC may vary across  $n$ . Heterogenous population.

Source: [gs.statcounter.com/vendor-market-share/mobile](https://gs.statcounter.com/vendor-market-share/mobile)

# Modeling heterogeneity

## Behavioral assumption

- ▶ Individuals have different taste parameters.
- ▶ We replace  $\beta_{\text{iPhone}}$  and  $\beta_{\text{Samsung}}$  by  $\beta_{\text{iPhone},n}$  and  $\beta_{\text{Samsung},n}$ .
- ▶ In practice, it is in general statistically impossible to estimate a different  $\beta$  per individual.
- ▶ Instead, the heterogeneity is captured by socio-economic characteristics:

$$\beta_{\text{iPhone},n} = \beta_{\text{iPhone},n}(\text{country}_n; \theta)$$

# Modeling heterogeneity

## ASC function of the socio-economic characteristics

$$\beta_{in} = \theta_{i1} s_n + \theta_{i2} (1 - s_n),$$

where  $s_n = 1$  if  $n$  resides in the USA, 0 otherwise.

## Specification of the utility

$$\begin{aligned} U_{in} &= V_{in} + \theta_{i1} s_n + \theta_{i2} (1 - s_n) + \frac{1}{\mu} \varepsilon_{in}, \\ &= V_{in} + (\theta_{i1} - \theta_{i2}) s_n + \theta_{i2} + \frac{1}{\mu} \varepsilon_{in}, \\ &= V_{in} + \theta_{i,\text{diff}} s_n + \theta_{i2} + \frac{1}{\mu} \varepsilon_{in}. \end{aligned}$$

# Modeling heterogeneity

## Notes

- ▶ Including a socio-economic characteristic in the utility captures an heterogeneous alternative specific constant.
- ▶ The constant normalized to zero must not be segmented. Therefore, no socio-economic characteristic should appear alone in the specification.
- ▶ There are two possible specifications:

$$U_{in} = V_{in} + \theta_{i1} s_n + \theta_{i2} (1 - s_n) + \frac{1}{\mu} \varepsilon_{in},$$

$$U_{in} = V_{in} + \theta_{i,\text{diff}} s_n + \theta_{i2} + \frac{1}{\mu} \varepsilon_{in}.$$

The first is easier to interpret. The second is more appropriate to combine several characteristics.

# Modeling heterogeneity

## Curse of dimensionality

- ▶ Several socio-economic characteristics can be used to segment the population.
- ▶ However, the number of segments may become too large.
- ▶ For example, if  $K$  is the number of binary socio-economic characteristics, the number of segments is  $2^K$ .

## Practical simplification

- ▶ Include a reference parameter.
- ▶ Include one parameter for each binary socio-economic characteristic, capturing the difference with the reference one.
- ▶ Total number of parameters:  $1 + K$ .

# Modeling heterogeneity

## Example

Three characteristics:  $s_1, s_2, s_3$ .

Combinatorial specification:  $2^3 = 8$  parameters

$$\begin{aligned} &\theta_1 s_1 s_2 s_3 + \theta_2 s_1 s_2 (1 - s_3) + \theta_3 s_1 (1 - s_2) s_3 + \theta_4 s_1 (1 - s_2) (1 - s_3) + \\ &\theta_5 (1 - s_1) s_2 s_3 + \theta_6 (1 - s_1) s_2 (1 - s_3) + \\ &\theta_7 (1 - s_1) (1 - s_2) s_3 + \theta_8 (1 - s_1) (1 - s_2) (1 - s_3). \end{aligned}$$

Practical simplification:  $1 + 3 = 4$  parameters

$$\theta_{\text{ref}} + \theta_1 s_1 + \theta_2 s_2 + \theta_3 s_3.$$

# Modeling heterogeneity

Practical simplification:  $1 + 3 = 4$  parameters

$$\theta_{\text{ref}} + \theta_1 s_1 + \theta_2 s_2 + \theta_3 s_3.$$

Value per segment

| $s_1$ | $s_2$ | $s_3$ | $\theta$                                    | $s_1$ | $s_2$ | $s_3$ | $\theta$                                               |
|-------|-------|-------|---------------------------------------------|-------|-------|-------|--------------------------------------------------------|
| 0     | 0     | 0     | $\theta_{\text{ref}}$                       | 1     | 0     | 0     | $\theta_{\text{ref}} + \theta_1$                       |
| 0     | 0     | 1     | $\theta_{\text{ref}} + \theta_3$            | 1     | 0     | 1     | $\theta_{\text{ref}} + \theta_1 + \theta_3$            |
| 0     | 1     | 0     | $\theta_{\text{ref}} + \theta_2$            | 1     | 1     | 0     | $\theta_{\text{ref}} + \theta_1 + \theta_2$            |
| 0     | 1     | 1     | $\theta_{\text{ref}} + \theta_2 + \theta_3$ | 1     | 1     | 1     | $\theta_{\text{ref}} + \theta_1 + \theta_2 + \theta_3$ |

# Extension to all parameters

## Alternative Specific Constants

- ▶ Qualitative variables.
- ▶ Alternative specific coefficient.
- ▶ Heterogeneity: coefficients vary across individuals.

This potentially applies to all coefficients

# Outline

Logit

Alternative Specific Constants

Qualitative attributes

Taste heterogeneity

Heteroscedasticity

Nonlinear specifications

# Qualitative attributes

## Examples

- ▶ Level of comfort for the train.
- ▶ Reliability of the bus.
- ▶ Color.
- ▶ Shape.
- ▶ etc.

# Modeling

Identify all possible levels of the variable

- Comfortable,
- Not comfortable.

Introduce a 0/1 attribute for each level  $k$

$$z_k \in \{0, 1\}, \forall k = 1, \dots, K,$$

$$\sum_{k=1}^K z_k = 1.$$

Example with  $K = 2$

- $z_c$  for comfortable.
- $z_{nc}$  for not comfortable.

|                 | $z_c$ | $z_{nc}$ |
|-----------------|-------|----------|
| comfortable     | 1     | 0        |
| not comfortable | 0     | 1        |

# Modeling

## Utility function with ASC

$$\begin{aligned}\mu V_{in} &= -\mu(\text{cost}_{in} + \beta_c z_c + \beta_{nc} z_{nc} + \beta_i) \\ &= -\mu(\text{cost}_{in} + \beta_c z_c + \beta_{nc}(1 - z_c) + \beta_i) \\ &= -\mu(\text{cost}_{in} + (\beta_c - \beta_{nc})z_c + \beta_{nc} + \beta_i) \\ &= -\mu(\text{cost}_{in} + \beta'_c z_c + \beta'_i)\end{aligned}$$

## Comments

- ▶ The coefficient of one level is confounded with the coefficient of the constant.
- ▶ In the presence of an ASC, only  $K - 1$  binary variables can be included.

# Alternative specific coefficients

## Generic vs alternative specific

$$\begin{aligned}\mu V_{\text{car},n} &= -\mu\text{cost} + \mu\beta_t \text{TT}_{\text{car},n} + \dots \\ \mu V_{\text{bus},n} &= -\mu\text{cost} + \mu\beta_t \text{TT}_{\text{bus},n} + \dots\end{aligned}$$

or

$$\begin{aligned}\mu V_{\text{car},n} &= -\mu\text{cost} + \mu\beta_{\text{car},t} \text{TT}_{\text{car},n} + \dots \\ \mu V_{\text{bus},n} &= -\mu\text{cost} + \mu\beta_{\text{bus},t} \text{TT}_{\text{bus},n} + \dots\end{aligned}$$

**M**odeling assumption: a minute has/has not the same value whether it is incurred on the auto or bus mode.

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# Modeling heterogeneity

## Behavioral assumption

- ▶ Individuals have different taste parameters.
- ▶ The difference is explained by **continuous** socio-economic characteristics.

## Example: one characteristic

$$\mu V_{in} = -\mu \text{cost}_{in} + \mu \beta_n z_{in} + \dots$$

where

$$\beta_n = \beta_n(\text{income}_n).$$

# Modeling heterogeneity

## Interaction

Typical definition of  $\beta_n$ :

$$\beta_n = \beta \text{ income}_n.$$

$$\mu V_{in} = -\mu \text{cost}_{in} + \mu \beta \text{ income}_n z_{in} + \dots$$

$$\mu V_{in} = -\mu \text{cost}_{in} + \mu \beta x_{in} + \dots$$

where

$$x_{in} = \text{income}_n z_{in}.$$

# Modeling heterogeneity

Example: several characteristics

$$\beta_n = \beta_n(\text{income}_n, \text{age}_n).$$

Interaction

$$\beta_n = \beta \text{ income}_n \text{ age}_n.$$

$$\begin{aligned}\mu V_{in} &= -\mu \text{cost}_{in} + \mu \beta_n z_{in} + \cdots \\ &= -\mu \text{cost}_{in} + \mu \beta \text{ income}_n \text{ age}_n z_{in} + \cdots \\ &= -\mu \text{cost}_{in} + \mu \beta x_{in} + \cdots\end{aligned}$$

where  $x_{in} = \text{income}_n \text{ age}_n z_{in}$ .

# Qualitative characteristics

## Examples

- ▶ Sex.
- ▶ Education.
- ▶ Professional status.
- ▶ etc.

# Modeling heterogeneity

## Behavioral assumption

- ▶ Individuals have different taste parameters.
- ▶ The difference is explained by **qualitative/discrete** socio-economic characteristics.

## Example: one characteristic

$$\mu V_{in} = -\mu \text{cost}_{in} + \mu \beta_n z_{in} + \dots$$

where

$$\beta_n = \beta_n(\text{education}_n).$$

# Modeling heterogeneity

## Segmentation

- ▶ Assume that there are  $K$  levels for the qualitative variable (e.g. education).
- ▶ They characterize  $K$  segments in the population.
- ▶ Define

$$\delta_{kn} = \begin{cases} 1 & \text{if individual } n \text{ is associated with segment } k, \\ 0 & \text{otherwise.} \end{cases}$$

- ▶ Introduce a parameter  $\beta^k$  for each level and define

$$\beta_n = \sum_{k=1}^K \beta^k \delta_{kn}.$$

# Modeling heterogeneity

## Segmentation

$$\mu V_{in} = -\mu \text{cost}_{in} + \mu \beta_n z_{in} + \dots$$

$$\mu V_{in} = -\mu \text{cost}_{in} + \mu \sum_{k=1}^K \beta^k \delta_{kn} z_{in} + \dots$$

$$\mu V_{in} = -\mu \text{cost}_{in} + \mu \sum_{k=1}^K \beta^k x_{ink} + \dots$$

where

$$x_{ink} = \delta_{kn} z_{in}.$$

# Segmentation with several variables

## Example

- ▶ Gender (M, F).
- ▶ House location (metro, suburb, perimeter areas).
- ▶ 6 segments:  $(M, m)$ ,  $(M, s)$ ,  $(M, p)$ ,  $(F, m)$ ,  $(F, s)$ ,  $(F, p)$ .

# Segmentation

## Specification

$$\beta_{M,m} TT_{M,m} + \beta_{M,s} TT_{M,s} + \beta_{M,p} TT_{M,p} + \\ \beta_{F,m} TT_{F,m} + \beta_{F,s} TT_{F,s} + \beta_{F,p} TT_{F,p} +$$

$TT_i = TT$  if indiv. belongs to segment  $i$ , and 0 otherwise.

## Remarks

- ▶ For a given individual, exactly one of these terms is non zero.
- ▶ The number of segments grows exponentially with the number of variables.

# Summary

- ▶ Specification may involve both continuous/quantitative and discrete/qualitative variables.
- ▶ Alternative specific constants are qualitative attributes capturing the name of the alternative.
- ▶ Coefficients can be generic or alternative specific.
- ▶ Taste heterogeneity: coefficients are function of socio-economic attributes, both continuous/quantitative and discrete/qualitative.

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**Heteroscedasticity**

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# Relax the i.i.d. assumption

## i.i.d. assumption

- ✓ Same  $\eta$  for all alternatives  $i$ : relaxed in this lecture.
- ✓ Same  $\eta$  for all observations  $n$ : relaxed in this lecture.
- ▶ Same  $\mu$  for all alternatives  $i$ : relaxed in the lecture on mixtures.
- ▶ Same  $\mu$  for all observations  $n$ : relaxed in this lecture.
- ▶ Independence across alternatives  $i$ : relaxed in the lecture on MEV models.
- ▶ Independence across observations  $n$ : relaxed in the lecture on panel data.

# Motivation

## Logit is homoscedastic

- ▶ Error terms have the same variance across  $n$ .
- ▶ Specification involves the same  $\mu$  across  $n$ .
- ▶ But people may have different levels of knowledge (e.g. taxi drivers).
- ▶ Different sources of data:
  - ▶ RP / SP
  - ▶ Different locations.
  - ▶ Different points in time.
- ▶ Homoscedastic assumption should be relaxed.

# Heteroscedasticity

## Data

- ▶  $K$  groups of data.
- ▶ Each individual  $n$  belongs to exactly one group  $k$ .
- ▶ Characterized by indicators:

$$\delta_{kn} = \begin{cases} 1 & \text{if } n \text{ belongs to group } k, \\ 0 & \text{otherwise,} \end{cases}$$

and  $\sum_k \delta_{kn} = 1$ , for all  $n$ .

Each individual is observed at most once. This assumption will be relaxed in the lecture on panel data.

# Heteroscedasticity

Assumption: variance of error terms is different across groups

Consider individual  $n_1$  belonging to group 1, and individual  $n_2$  belonging to group 2.

$$\begin{aligned}U_{in_1} &= V_{in_1} + \frac{1}{\mu_1}\varepsilon_{in_1}, \\U_{in_2} &= V_{in_2} + \frac{1}{\mu_2}\varepsilon_{in_2},\end{aligned}$$

where  $\mu_2 \neq \mu_1$ .

## Equivalent specification

Multiply all utilities for  $n_2$  by  $\mu_2/\mu_1$  so that the error terms are the same:

$$\begin{aligned}U_{in_1} &= V_{in_1} + \frac{1}{\mu_1}\varepsilon_{in_1}, \\ \frac{\mu_2}{\mu_1}U_{in_2} &= \frac{\mu_2}{\mu_1}V_{in_2} + \frac{1}{\mu_1}\varepsilon_{in_2}.\end{aligned}$$

# Heteroscedasticity

Moneymetric utility:  $\beta_c = -1$

$$\begin{aligned}\mu_1 V_{in_1} &= -\mu_1 \text{cost}_{in_1} + \sum_k \mu_1 \beta_k z_{in_1 k}, \\ \mu_2 V_{in_2} &= -\mu_2 \text{cost}_{in_2} + \sum_k \mu_2 \beta_k z_{in_2 k}.\end{aligned}$$

## Comment

- Estimate  $K$  scale parameters, one per group.

# Heteroscedasticity

Linear-in-parameters:  $\mu_1 = 1$

$$\mu_1 V_{in_1} = \beta_c \text{cost}_{in_1} + \sum_k \beta_k z_{in_1 k},$$

$$\mu_2 V_{in_2} = -\mu_2 \beta_c \text{cost}_{in_2} + \sum_k \mu_2 \beta_k z_{in_2 k}.$$

## Comment

- ▶ Estimate  $K - 1$  scale parameters.
- ▶ The scale parameter for one group is normalized to one.
- ▶ Specification not linear-in-parameters anymore.

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**Nonlinear specifications**

# Nonlinear transformations of the variables

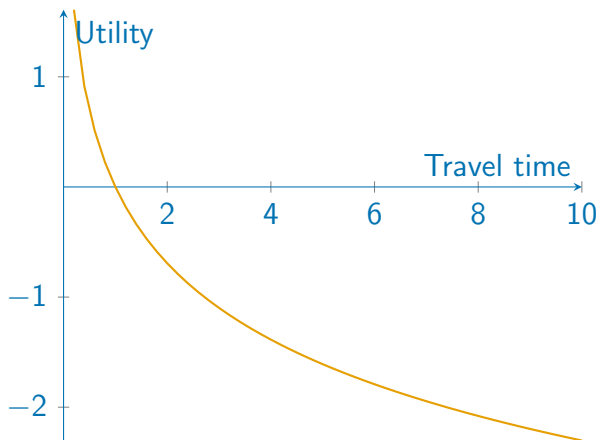
## Example with travel time

- ▶ Compare a trip of 5 min with a trip of 10 min.
- ▶ Compare a trip of 120 min with a trip of 125 min.
- ▶ Utility difference:  $\beta_T \cdot 5$  min, in both cases.

## Behavioral assumption

One more minute of travel is not perceived the same way for short trips as for long trips.

# Nonlinear transformations of the variables



# Nonlinear transformations of the variables

Assumption 1: the marginal impact of travel time is constant

$$V_{in} = \beta_T \text{time}_{in} + \dots$$

Assumption 2: the marginal impact of travel time decreases with travel time

$$V_{in} = \beta_T \ln(\text{time}_{in}) + \dots$$

## Remarks

- ▶ It is still a linear-in-parameters specification.
- ▶ The unit, the value, and the interpretation of  $\beta_T$  are different.

# Nonlinear transformations of the variables

Data can be preprocessed to account for nonlinearities

$$V_{in} = V(h(z_{in}, s_n)) = \sum_k \beta_k (h(z_{in}, s_n))_k$$

It is linear-in-parameter, even with  $h$  nonlinear.

## Note

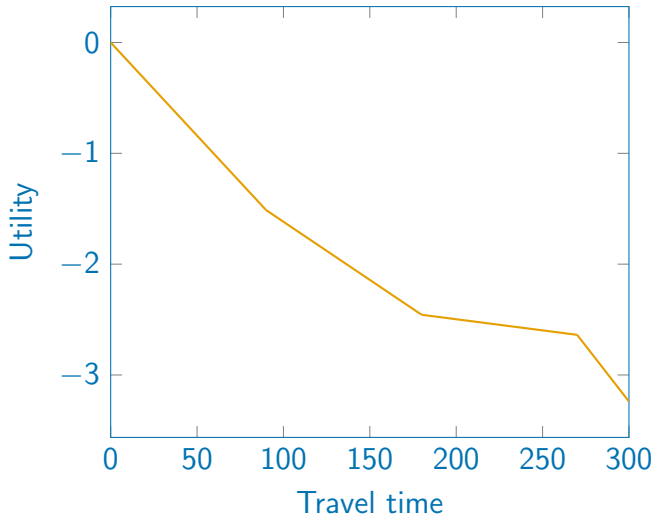
Interactions between attributes and socio-economic characteristics are a special case of  $h$ .

# Piecewise linear specification

Again: sensitivity to travel time varies with travel time

- ▶ Log transform is not the only specification.
- ▶ Another possibility: split the range of values of the variable.
- ▶ Each category is associated with a different coefficient.

# Piecewise linear specification



# Piecewise linear specification

## Procedure

- ▶ Select breakpoints  $\gamma_1 < \gamma_2 < \dots < \gamma_L$ .
- ▶ Define new variables.

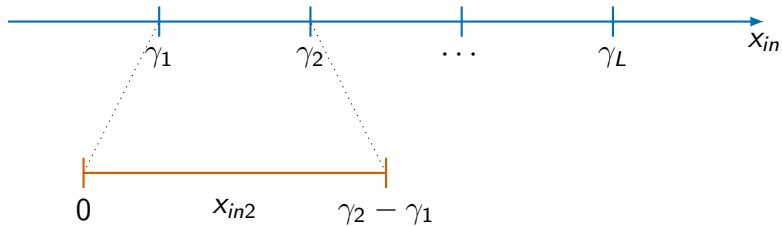
# Piecewise linear specification



# Piecewise linear specification



# Piecewise linear specification



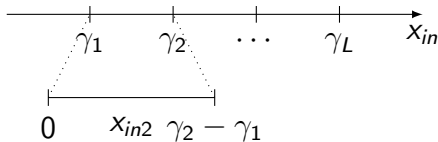
# Piecewise linear specification

## Formulation

$$x_{in1} = \begin{cases} x_{in} & \text{if } x_{in} < \gamma_1, \\ \gamma_1 & \text{otherwise.} \end{cases}$$

$$x_{in\ell} = \begin{cases} 0 & \text{if } x_{in} < \gamma_{\ell-1}, \\ x_{in} - \gamma_{\ell-1} & \text{if } \gamma_{\ell-1} \leq x_{in} < \gamma_{\ell}, \\ \gamma_{\ell} - \gamma_{\ell-1} & \text{otherwise.} \end{cases}$$

$$x_{in(L+1)} = \begin{cases} 0 & \text{if } x_{in} < \gamma_L, \\ x_{in} - \gamma_L & \text{otherwise.} \end{cases}$$



# Piecewise linear specification

## Equivalent formulations

$$x_{in1} = \begin{cases} x_{in} & \text{if } x_{in} < \gamma_1, \\ \gamma_1 & \text{otherwise.} \end{cases} \quad \min(x_{in}, \gamma_1).$$

$$x_{in\ell} = \begin{cases} 0 & \text{if } x_{in} < \gamma_{\ell-1}, \\ x_{in} - \gamma_{\ell-1} & \text{if } \gamma_{\ell-1} \leq x_{in} < \gamma_{\ell}, \\ \gamma_{\ell} - \gamma_{\ell-1} & \text{otherwise.} \end{cases} \quad \max(0, \min(x_{in} - \gamma_{\ell-1}, \gamma_{\ell} - \gamma_{\ell-1})).$$

$$x_{in(L+1)} = \begin{cases} 0 & \text{if } x_{in} < \gamma_L \\ x_{in} - \gamma_L & \text{otherwise} \end{cases} \quad \max(0, x_{in} - \gamma_L).$$

# Piecewise linear specification

## Examples

$\gamma_1 = 90, \gamma_2 = 180, \gamma_3 = 270$ .

| $x_{in}$  | 50 | 100 | 200 | 300 |
|-----------|----|-----|-----|-----|
| $x_{in1}$ | 50 | 90  | 90  | 90  |
| $x_{in2}$ | 0  | 10  | 90  | 90  |
| $x_{in3}$ | 0  | 0   | 20  | 90  |
| $x_{in4}$ | 0  | 0   | 0   | 30  |

$\gamma_1 = 1, \gamma_2 = 5, \gamma_3 = 10$ .

| $x_{in}$  | 0.5 | 4 | 8 | 12 |
|-----------|-----|---|---|----|
| $x_{in1}$ | 0.5 | 1 | 1 | 1  |
| $x_{in2}$ | 0   | 3 | 4 | 4  |
| $x_{in3}$ | 0   | 0 | 3 | 5  |
| $x_{in4}$ | 0   | 0 | 0 | 2  |

## Utility function

$$V_{in} = \sum_{\ell=1}^L \beta_{\ell} x_{in\ell}.$$

# Box-Cox transforms

Box and Cox (1964)

$$V_{in} = \beta B(x_{in}; \lambda) + \dots$$

where

$$B(x_{in}; \lambda) = \begin{cases} \frac{x_{in}^{\lambda} - 1}{\lambda} & \text{if } \lambda \neq 0, \\ \ln x_{in} & \text{if } \lambda = 0, \end{cases}$$

and  $x_{in} > 0$ .

# Box-Cox transforms

## Continuity

The function is continuous and differentiable in  $\lambda$ , because

$$\lim_{\lambda \rightarrow 0} \frac{x_{in}^{\lambda} - 1}{\lambda} = \ln x_{in}.$$

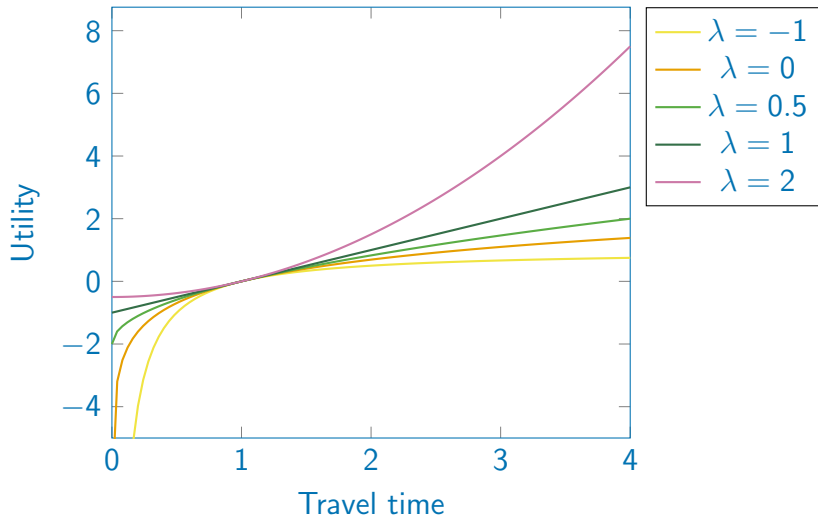
# Box-Cox transforms

## Convexity / concavity

$$\begin{aligned}\partial B(x_{in}; \lambda) / \partial x_{in} &= x^{\lambda-1}, \\ \partial^2 B(x_{in}; \lambda) / \partial x_{in}^2 &= (\lambda - 1)x^{\lambda-2}.\end{aligned}$$

- ▶  $B$  is convex if  $\lambda \geq 1$ .
- ▶  $B$  is concave if  $\lambda \leq 1$ .

## Box-Cox transforms



# Nonlinear interactions

Taste heterogeneity

$$V_{in} = \beta_{in} z_{in} + \dots$$

Linear interaction

$$\beta_{in} = \beta \text{ income}_n.$$

Nonlinear interaction

$$\beta_{in} = \beta \text{ income}_n^\lambda, \text{ where } \lambda = \frac{\partial \beta_{in}}{\partial \text{income}_n} \frac{\text{income}_n}{\beta_{in}}.$$

# Nonlinear interactions

## Remarks

- ▶  $\lambda$  must be estimated.
- ▶ Use a reference value for the socio-economic characteristic:

$$\beta_{in} = \beta \left( \frac{\text{income}_n}{\text{refIncome}} \right)^\lambda.$$

- ▶ Reference value is arbitrary.
- ▶ Several (continuous) characteristics can be combined:

$$\beta_{in} = \beta \left( \frac{\text{income}_n}{\text{refIncome}} \right)^{\lambda_1} \left( \frac{\text{age}_n}{\text{refAge}} \right)^{\lambda_2}.$$

# Example: interurban mode choice in Switzerland

## Sample

- ▶ Revealed preference data.
- ▶ Survey conducted between 2009 and 2010 for PostBus.
- ▶ Questionnaires sent to people living in rural areas.
- ▶ Each observation corresponds to a sequence of trips from home to home..
- ▶ Sample size: 1693.

## Model: 3 alternatives

- ▶ Car,
- ▶ public transportation (PT),
- ▶ slow modes.

# Attributes

## Travel cost

- ▶ Alternatives: car and public transportation.
- ▶ Units: CHF.
- ▶ Specification: linear.
- ▶ Coefficient: generic.

## Travel time

- ▶ Alternatives: car and public transportation.
- ▶ Units: minutes.
- ▶ Specification: Box-Cox.
- ▶ Coefficient: alternative specific, interacted with gender.

# Attributes

## Waiting time

- ▶ Alternative: public transportation.
- ▶ Units: minutes
- ▶ Specification: linear.
- ▶ Coefficient: interacted with income and socio-professional category.

## Distance

- ▶ Alternative: slow mode.
- ▶ Units: kilometers.
- ▶ Specification: linear.
- ▶ Coefficient: piecewise linear interaction with age.

# Parameters of the error terms

## Alternative specific constants

- ▶ Alternatives: car and public transportation.
- ▶ Units: none.
- ▶ Coefficient: interacted with public transportation subscription.

## Scale parameter

Interacted with language region.

# Utility functions

## Public transportation

$$\mu_n V_{pt,n} = \mu_n (\text{asc}_{pt,n} + \beta_c \text{tc}_{pt,n} + \beta_{t,pt,n} \text{boxcox\_tt}_{pt,n} + \beta_{w,n} \text{wt}_n),$$

where

$$\text{asc}_{pt,n} = \text{asc}_{pt} + \text{asc}_{pt,GA} \mathbb{1}(n \in GA),$$

$$\mu_n = \mu_{\text{french}} \mathbb{1}(n \in \text{french}) + \mu_{\text{german}} \mathbb{1}(n \in \text{german}),$$

$$\beta_{t,pt,n} = \beta_{t,pt} + \beta_{t,pt,\text{female}} \mathbb{1}(n \in \text{female}) + \beta_{t,pt,\text{unknown}} \mathbb{1}(n \in \text{gender unknown}),$$

$$\beta_{w,n} = \beta_w + \beta_{w,\text{craftman}} \mathbb{1}(n \in \text{craftman}) + \beta_{w,\text{manager}} \mathbb{1}(n \in \text{manager}) +$$

$$\beta_{w,\text{intellectual}} \mathbb{1}(n \in \text{intellectual}) + \beta_{w,\text{high income}} \mathbb{1}(n \in \text{high income}),$$

$$\text{boxcox\_tt}_{pt,n} = \frac{\text{tt}_{pt,n}^{\lambda_{tt}} - 1}{\lambda_{tt}}.$$

# Utility functions

## Car

$$\mu_n V_{\text{car},n} = \mu_n (\text{asc}_{\text{car},n} + \beta_c \text{tc}_{\text{car},n} + \beta_{t,\text{car},n} \text{tt}_{\text{car},n}),$$

where

$$\text{asc}_{\text{car},n} = \text{asc}_{\text{car}} + \text{asc}_{\text{car},\text{GA}} \mathbb{1}(n \in \text{GA}),$$

$$\mu_n = \mu_{\text{french}} \mathbb{1}(n \in \text{french}) + \mu_{\text{german}} \mathbb{1}(n \in \text{german}),$$

$$\beta_{t,\text{car},n} = \beta_{t,\text{car}} + \beta_{t,\text{car},\text{female}} \mathbb{1}(n \in \text{female}) + \beta_{t,\text{car},\text{unknown}} \mathbb{1}(n \in \text{gender unknown})$$

$$\text{boxcox\_tt}_{\text{car},n} = \frac{\text{tt}_{\text{car},n}^{\lambda_{tt}} - 1}{\lambda_{tt}}.$$

# Utility functions

## Slow modes

$$\mu_n V_{\text{sm},n} = \mu_n (\beta_{d,n} \text{distance}_n),$$

where

$$\mu_n = \mu_{\text{french}} \mathbb{1}(n \in \text{french}) + \mu_{\text{german}} \mathbb{1}(n \in \text{german}),$$

$$\beta_{d,n} = \beta_d (\text{age0-40}_n + \beta_{\text{age40-60}} \text{age40-60}_n + \beta_{\text{age60-100}} \text{age60-100}_n),$$

$$\text{age0-40}_n = \min(\text{age}_n, 40),$$

$$\text{age40-60}_n = \max(0, \min(\text{age}_n - 40, 20)),$$

$$\text{age60-100}_n = \max(0, \min(\text{age}_n - 60), 40).$$

# Parameters

## 22 parameters

|                                      |                                       |
|--------------------------------------|---------------------------------------|
| $\text{asc}_{\text{pt}}$             | $\beta_{t,\text{car},\text{unknown}}$ |
| $\text{asc}_{\text{pt},\text{GA}}$   | $\lambda_{tt}$                        |
| $\text{asc}_{\text{car}}$            | $\beta_w$                             |
| $\text{asc}_{\text{car},\text{GA}}$  | $\beta_{w,\text{craftman}}$           |
| $\mu_{\text{french}}$                | $\beta_{w,\text{manager}}$            |
| $\mu_{\text{german}}$                | $\beta_{w,\text{intellectual}}$       |
| $\beta_{t,\text{pt}}$                | $\beta_{w,\text{high inc}}$           |
| $\beta_{t,\text{pt},\text{female}}$  | $\beta_d$                             |
| $\beta_{t,\text{pt},\text{unknown}}$ | $\beta_{\text{age}40-60}$             |
| $\beta_{t,\text{car}}$               | $\beta_{\text{age}60-100}$            |
| $\beta_{t,\text{car},\text{female}}$ | $\beta_c$                             |

Normalizations: moneymetric:  $\beta_c = -1$ , linear-in-parameters:  $\mu_{\text{french}} = 1$ .

# Estimation results

## General statistics

|                                          | Moneymetric | Linear    |
|------------------------------------------|-------------|-----------|
| Number of estimated parameters           | 21          | 21        |
| Sample size                              | 1785        | 1785      |
| Null log likelihood                      | -1922.909   | -1922.909 |
| Final log likelihood                     | -1007.661   | -1007.644 |
| Likelihood ratio test for the null model | 1830.497    | 1830.531  |
| Rho-square for the null model            | 0.476       | 0.476     |
| Rho-square-bar for the null model        | 0.465       | 0.465     |
| Akaike Information Criterion             | 2057.321    | 2057.287  |
| Bayesian Information Criterion           | 2172.5552   | 2172.518  |
| Number of iterations                     | 74          | 42        |

# Estimation results: moneymetric

| Parameter number | Description              | Coeff. estimate | Robust Asympt. std. error | t-stat | p-value  |
|------------------|--------------------------|-----------------|---------------------------|--------|----------|
| 1                | $asc_{pt}$               | -8.87           | 7.8                       | -1.14  | 0.255    |
| 2                | $asc_{pt,GA}$            | 19.9            | 13.2                      | 1.51   | 0.131    |
| 3                | $\beta_{t,pt}$           | -0.771          | 0.559                     | -1.38  | 0.168    |
| 4                | $\beta_{t,pt,female}$    | 0.407           | 0.317                     | 1.28   | 0.2      |
| 5                | $\beta_{t,pt,unknown}$   | -4.31           | 2.09                      | -2.06  | 0.0392   |
| 6                | $\lambda_{tt}$           | 0.758           | 0.122                     | 6.22   | 4.82e-10 |
| 7                | $\beta_w$                | -0.584          | 0.264                     | -2.21  | 0.0271   |
| 8                | $\beta_{w,craftman}$     | 0.415           | 0.328                     | 1.27   | 0.206    |
| 9                | $\beta_{w,intellectual}$ | 0.314           | 0.3                       | 1.05   | 0.296    |
| 10               | $\beta_{w,manager}$      | -0.661          | 0.445                     | -1.49  | 0.137    |
| 11               | $\beta_{w,high\ inc}$    | -0.658          | 0.342                     | -1.93  | 0.0542   |
| 12               | $asc_{car}$              | 16.3            | 8.04                      | 2.03   | 0.0428   |
| 13               | $asc_{car,GA}$           | -15.4           | 13.9                      | -1.1   | 0.271    |
| 14               | $\beta_{t,car}$          | -2.16           | 1.31                      | -1.64  | 0.101    |
| 15               | $\beta_{t,car,female}$   | 0.847           | 0.591                     | 1.43   | 0.152    |
| 16               | $\beta_{t,car,unknown}$  | 6.08            | 4.01                      | 1.52   | 0.13     |
| 17               | $\beta_d$                | -3.04           | 0.575                     | -5.28  | 1.26e-07 |
| 18               | $\beta_{age40-60}$       | 4.39            | 1.04                      | 4.22   | 2.44e-05 |
| 19               | $\beta_{age60-100}$      | -1.74           | 1.56                      | -1.11  | 0.265    |
| 20               | $\beta_c$                | -1.0            |                           |        |          |
| 21               | $\mu_{french}$           | 0.0725          | 0.0195                    | 3.71   | 0.000203 |
| 22               | $\mu_{german}$           | 0.0373          | 0.00975                   | 3.83   | 0.000129 |

# Estimation results: linear-in-parameters

| Parameter number | Description                     | Coeff. estimate | Robust Asympt. std. error | t-stat | p-value  |
|------------------|---------------------------------|-----------------|---------------------------|--------|----------|
| 1                | $\text{asc}_{\text{pt}}$        | -0.639          | 0.529                     | -1.21  | 0.227    |
| 2                | $\text{asc}_{\text{pt,GA}}$     | 1.48            | 0.874                     | 1.7    | 0.09     |
| 3                | $\beta_{t,\text{pt}}$           | -0.0561         | 0.0354                    | -1.59  | 0.113    |
| 4                | $\beta_{t,\text{pt,female}}$    | 0.0296          | 0.0212                    | 1.39   | 0.163    |
| 5                | $\beta_{t,\text{pt,unknown}}$   | -0.415          | 0.145                     | -2.86  | 0.00429  |
| 6                | $\lambda_{tt}$                  | 0.757           | 0.122                     | 6.22   | 4.91e-10 |
| 7                | $\beta_w$                       | -0.0423         | 0.0153                    | -2.76  | 0.00569  |
| 8                | $\beta_{w,\text{craftman}}$     | 0.03            | 0.0231                    | 1.3    | 0.194    |
| 9                | $\beta_{w,\text{intellectual}}$ | 0.0227          | 0.0208                    | 1.09   | 0.274    |
| 10               | $\beta_{w,\text{manager}}$      | -0.0479         | 0.0297                    | -1.61  | 0.107    |
| 11               | $\beta_{w,\text{high inc}}$     | -0.0477         | 0.023                     | -2.08  | 0.0377   |
| 12               | $\text{asc}_{\text{car}}$       | 1.18            | 0.483                     | 2.45   | 0.0143   |
| 13               | $\text{asc}_{\text{car,GA}}$    | -1.07           | 0.929                     | -1.16  | 0.247    |
| 14               | $\beta_{t,\text{car}}$          | -0.157          | 0.0797                    | -1.97  | 0.0492   |
| 15               | $\beta_{t,\text{car,female}}$   | 0.0615          | 0.0392                    | 1.57   | 0.117    |
| 16               | $\beta_{t,\text{car,unknown}}$  | 0.972           | 0.302                     | 3.21   | 0.00131  |
| 17               | $\beta_d$                       | -0.899          | 0.295                     | -3.04  | 0.00234  |
| 18               | $\beta_{\text{age}40-60}$       | 0.319           | 0.421                     | 0.758  | 0.448    |
| 19               | $\beta_{\text{age}60-100}$      | -0.425          | 0.235                     | -1.81  | 0.0702   |
| 20               | $\beta_c$                       | -0.0724         | 0.0195                    | -3.71  | 0.000209 |
| 21               | $\mu_{\text{french}}$           | 1.0             |                           |        |          |
| 22               | $\mu_{\text{german}}$           | 0.515           | 0.0508                    | 10.1   | 0.0      |

# Estimation results: moneymetric

$$\beta_c = -0.0724$$

| Parameter number | Description              | Coeff. estimate | Robust Asympt. std. error | t-stat | p-value  |
|------------------|--------------------------|-----------------|---------------------------|--------|----------|
| 1                | asc <sub>pt</sub>        | -0.644          | 0.565                     | -1.14  | 0.255    |
| 2                | asc <sub>pt,GA</sub>     | 1.48            | 0.978                     | 1.51   | 0.13     |
| 3                | $\beta_{t,pt}$           | -0.0561         | 0.0406                    | -1.38  | 0.168    |
| 4                | $\beta_{t,pt,female}$    | 0.0296          | 0.023                     | 1.28   | 0.2      |
| 5                | $\beta_{t,pt,unknown}$   | -0.444          | 0.214                     | -2.07  | 0.0381   |
| 6                | $\lambda_{tt}$           | 0.757           | 0.122                     | 6.23   | 4.77e-10 |
| 7                | $\beta_w$                | -0.0423         | 0.0191                    | -2.21  | 0.0272   |
| 8                | $\beta_{w,craftman}$     | 0.03            | 0.0238                    | 1.26   | 0.207    |
| 9                | $\beta_{w,intellectual}$ | 0.0227          | 0.0218                    | 1.04   | 0.297    |
| 10               | $\beta_{w,manager}$      | -0.0479         | 0.0322                    | -1.49  | 0.137    |
| 11               | $\beta_{w,high\ inc}$    | -0.0477         | 0.0248                    | -1.92  | 0.0542   |
| 12               | asc <sub>car</sub>       | 1.18            | 0.583                     | 2.02   | 0.043    |
| 13               | asc <sub>car,GA</sub>    | -1.08           | 1.01                      | -1.06  | 0.288    |
| 14               | $\beta_{t,car}$          | -0.157          | 0.0954                    | -1.64  | 0.101    |
| 15               | $\beta_{t,car,female}$   | 0.0615          | 0.0429                    | 1.43   | 0.152    |
| 16               | $\beta_{t,car,unknown}$  | 1.41            | 0.489                     | 2.89   | 0.00381  |
| 17               | $\beta_d$                | -0.596          | 0.171                     | -3.49  | 0.00048  |
| 18               | $\beta_{age40-60}$       | 0.994           | 0.594                     | 1.67   | 0.0945   |
| 19               | $\beta_{age60-100}$      | -0.645          | 0.69                      | -0.935 | 0.35     |
| 20               | $\beta_c$                | -0.0724         |                           |        |          |
| 21               | $\mu_{french}$           | 1.0             | 0.27                      | 3.71   | 0.000208 |
| 22               | $\mu_{german}$           | 0.515           | 0.135                     | 3.82   | 0.000134 |

# Comments

## Moneymetric vs linear-in-parameters

- ▶ The results are identical, up to numerical precision.
- ▶ Moneymetric is more challenging for the optimization algorithm.

# Alternative specific constants

Moneymetric model

## Public transportation vs. Slow modes

- ▶ Individuals without a GA:  $asc_{pt} = -8.87$ .
- ▶ Individuals with a GA:  $asc_{pt} + asc_{pt,GA} = -8.87 + 19.9 = 11.03$ .

## Car vs. Slow modes

- ▶ Individuals without a GA:  $asc_{car} = 16.3$ .
- ▶ Individuals with a GA:  $asc_{car} + asc_{car,GA} = 16.3 - 15.4 = 0.9$ .

## Public transportation vs. Car

- ▶ Individuals without a GA:  $asc_{pt} - asc_{car} = -8.87 - 16.3 = -25.2$ .
- ▶ Individuals with a GA:  
 $asc_{pt} + asc_{pt,GA} - asc_{car} - asc_{car,GA} = 11.03 - 0.9 = 10.1$ .

# Travel time coefficient

Moneymetric model

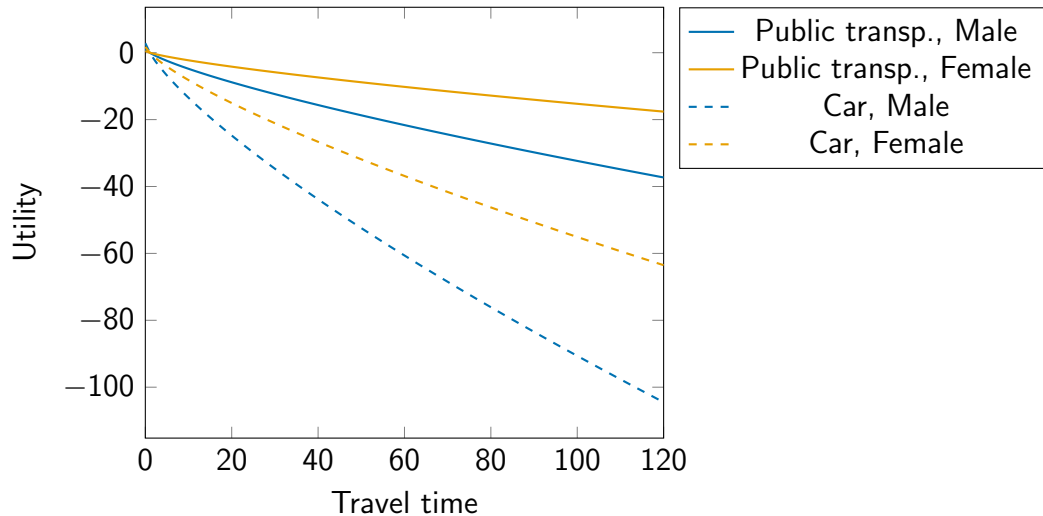
## Public transportation

- ▶ Males:  $-0.771$ .
- ▶ Females:  $-0.771 + 0.407 = -0.364$
- ▶ Unknown gender: irrelevant, never used for applications.

## Car

- ▶ Males:  $-2.16$ .
- ▶ Females:  $-2.16 + 0.847 = -1.31$
- ▶ Unknown gender: irrelevant, never used for applications.

## Travel time



# Waiting time coefficient

Moneymetric model

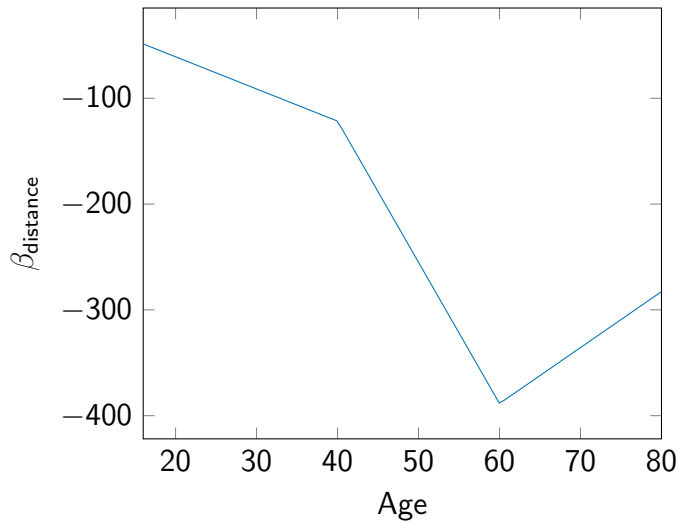
## Individuals with low income

- ▶ Craftman:  $-0.584 + 0.415 = -0.169$ .
- ▶ Intellectual:  $-0.584 + 0.314 = -0.27$ .
- ▶ Manager:  $-0.584 - 0.661 = -1.245$ .
- ▶ Others:  $-0.584$ .

## Individuals with high income

- ▶ Craftman:  $-0.584 + 0.415 - 0.658 = -0.827$ .
- ▶ Intellectual:  $-0.584 + 0.314 - 0.658 = -0.928$ .
- ▶ Manager:  $-0.584 - 0.661 - 0.658 = -1.903$ .
- ▶ Others:  $-0.584 - 0.658 = -1.242$ .

## Distance coefficient



# Choice probabilities

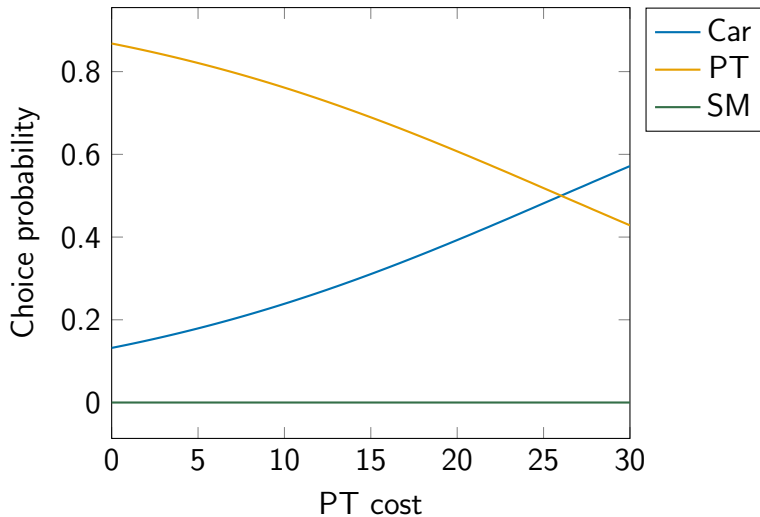
## Attributes

- ▶ Cost of gasoline: 4.54 CHF.
- ▶ Travel time by car: 32 min.
- ▶ Cost PT: 12.4 CHF.
- ▶ Travel time PT: 45 min.
- ▶ Waiting time: 10 min.
- ▶ Distance: 30 km.

## Socio-eco. characteristics

- ▶ French speaking.
- ▶ Age: 27.
- ▶ Gender: female.
- ▶ Subscription: GA.
- ▶ Socio-prof. category: intellectual.
- ▶ Income: low.
- ▶ Car availability: yes.

## Choice probabilities



# Choice probabilities

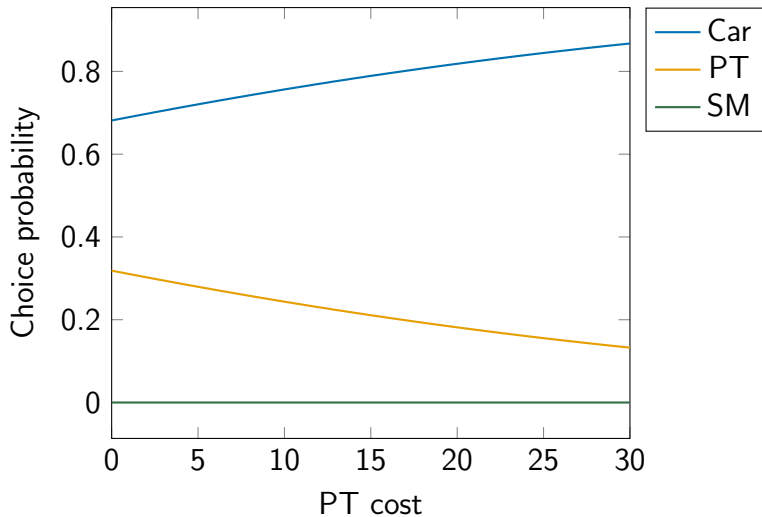
## Attributes (same as before)

- ▶ Cost of gasoline: 4.54 CHF.
- ▶ Travel time by car: 32 min.
- ▶ Cost PT: 12.4 CHF.
- ▶ Travel time PT: 45 min.
- ▶ Waiting time: 10 min.
- ▶ Distance: 30 km.

## Socio-eco. characteristics

- ▶ German speaking.
- ▶ Age: 55.
- ▶ Gender: male.
- ▶ Subscription: no GA.
- ▶ Socio-prof. category: manager.
- ▶ Income: high.
- ▶ Car availability: yes.

## Choice probabilities



# Summary

- ▶ Alternative Specific Constants.
- ▶ Continuous/quantitative vs discrete/qualitative variables.
- ▶ Taste heterogeneity and interactions.
- ▶ Heteroscedasticity.
- ▶ Nonlinear specifications.