

MODELS CAPTURING LATENT CONSTRUCTS

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Outline

Introduction

- Two case studies
- Context of research
- New data types
- Research objectives

Data to models

- Specification & analysis
- Validation & forecasting

Models to data

Conclusion

Introduction

Two case studies

Recently work on two case studies:

Case study 1: mode choice study in low-density areas

Case study 2: vehicle choice including electric vehicles

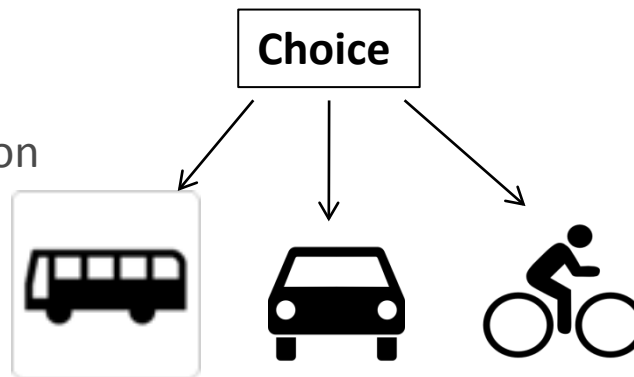
Introduction

Two case studies

Case study 1: mode choice study in low-density areas

Available data:

- Individuals trips (RP)
- Socio-economic information
- Mobility habits
- Opinions
- Perceptions



Work so far:

- Development of hybrid choice models (HCM)
- Focus on analysis of latent variables & integration into choice model (rather than forecasting)

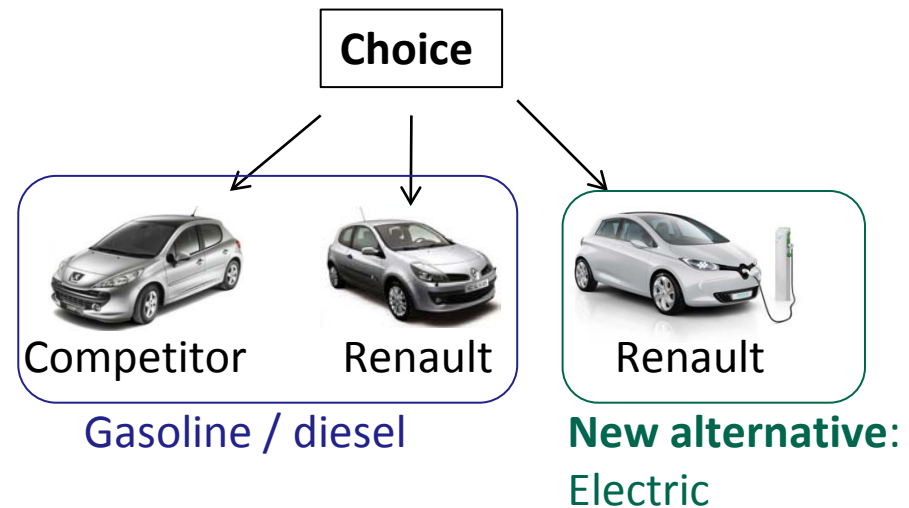
Introduction

Two case studies

Case study 2: vehicle choice including electric vehicles

Available data:

- Vehicle description (RP)
- Vehicle preferences (SP)
- Socio-economic information
- Mobility habits
- Opinions
- Perceptions



Work so far:

- Development of a logit model with multiple alternatives
- Focus on validation & forecasting (no integration of latent attitudes yet)

Context of research: recent progresses in DCM

- Focus on **attitudes** and **perceptions**
- Taken into account to model **choice behavior**

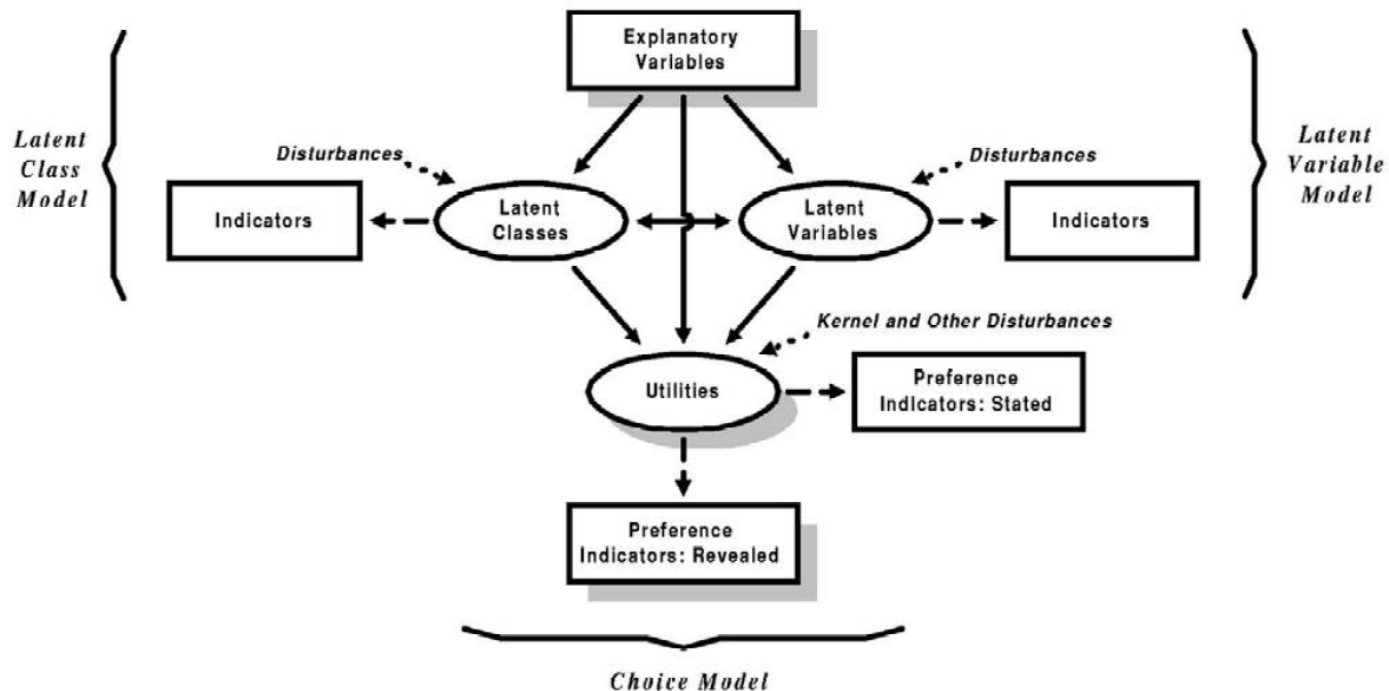
Motivation:

- Choice cannot only be explained by economic indicators (time, price, etc.)
- Important role of attitudes and perceptions in choice behavior

Introduction

Context of research

DCM with **latent constructs** capturing **attitudes** and **perceptions**:
Hybrid choice model (HCM) (Walker, 2001; Ben-Akiva et al., 2002)



Introduction

New data types

Issue:

- Latent aspects must be measured from real data

Recently: **new types of data**

- Data from survey with advanced designs developed by **social scientists**
- Data from **new devices**: smartphones, image analysis, eye-tracking devices, fMRI, etc.

Current drawback:

- Data not necessarily designed for choice models

Objectives of this research:

Investigate potential issues:

Objective 1:

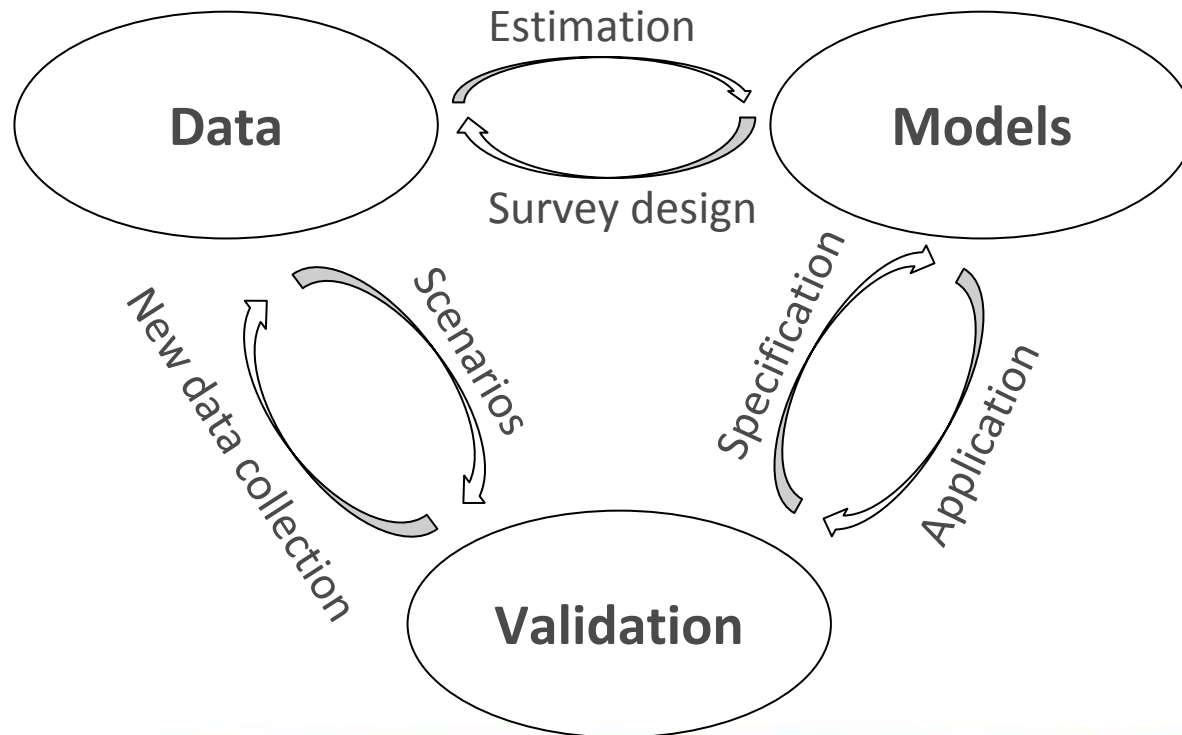
- Developments from **data to models**:
 1. Specification & analysis of HCM
 2. Validation & forecasting of HCM

Objective 2:

- Developments from **models to data**:
 1. Improvement of survey design

Introduction

Research objectives



Data to models

Objective 1: data to models

1. Specification & analysis
 2. Validation & forecasting
- } of HCM

Issues in specification and estimation of HCM:

1. Relation between latent variable and its indicators
⇒ Work on measurement equations:
 1. Non-linear specifications of indicators
 2. Use of indicators from word questions
2. Estimation
⇒ Local optima, Bayesian inference, etc.

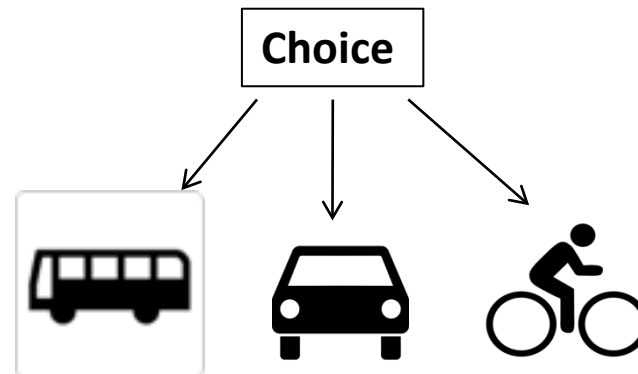
Data to models

1. Specification & analysis

1. Relation between latent variable and its indicators

Non-linear specifications of indicators in **measurement equations**

**Example 1 from
mode choice case
study**



Data to models

1. Specification & analysis

Four themes in statements of opinion:

- **Environment**

The price of gasoline should be increased in order to reduce traffic congestion and air pollution.

- **Mobility**

Taking the bus helps making a town more comfortable and welcoming.

- **Residential choice**

Accessibility and mobility conditions are important in the choice of an accommodation.

- **Lifestyle**

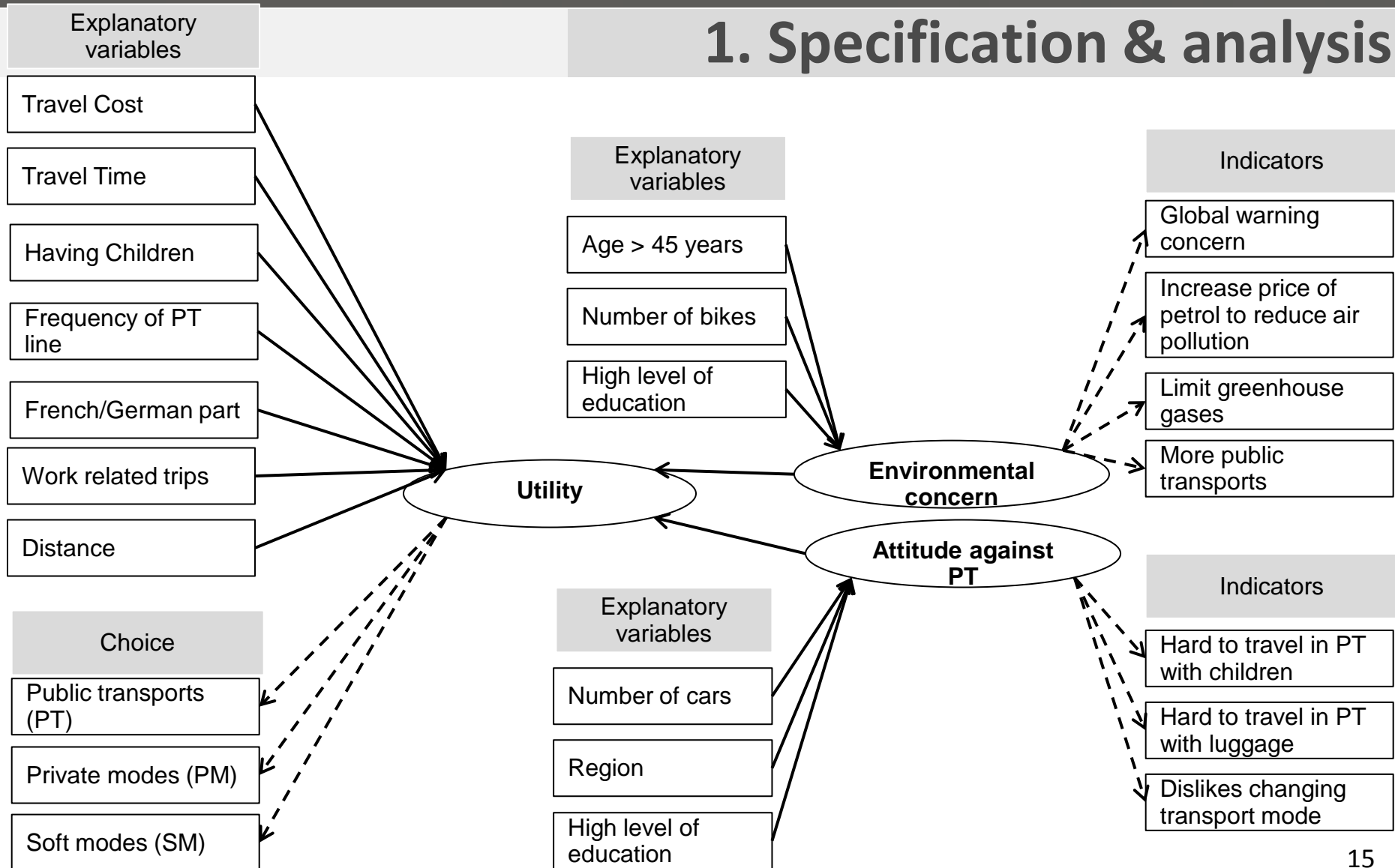
I always plan my activities a long time in advance.

Respondents rate agreement on 5-point Likert scale:

Total disagreement (1) \rightleftarrows Total agreement (5)

Data to models

1. Specification & analysis



Data to models

1. Specification & analysis

Measurement equation of indicators:

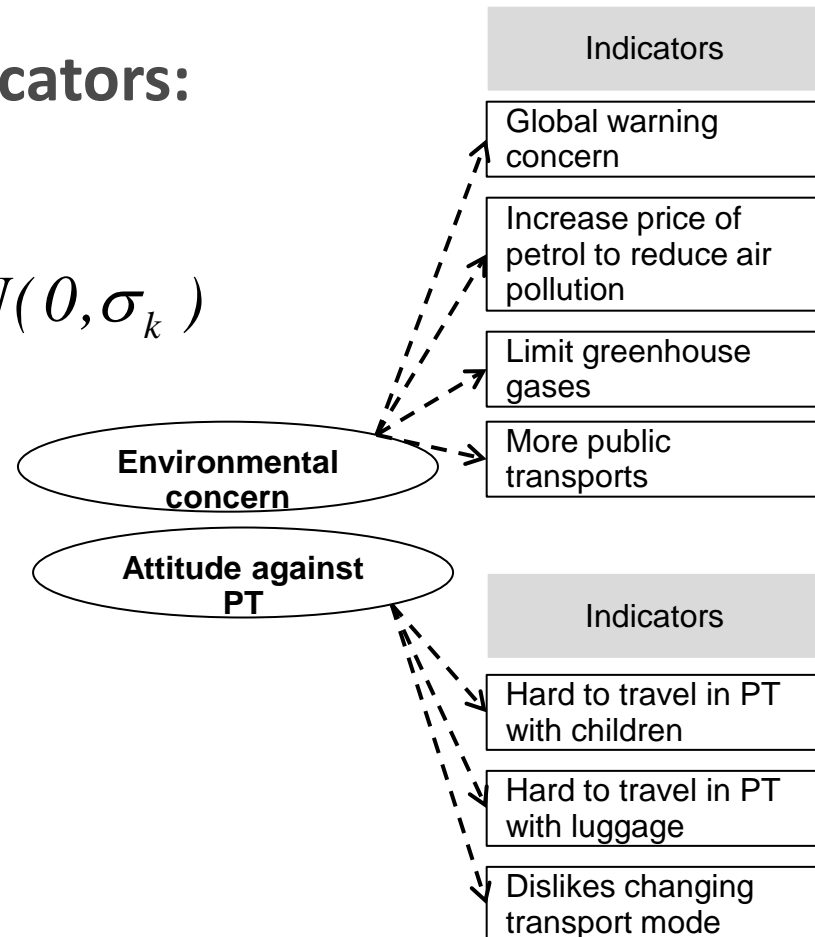
- Currently: **linear**

$$I_k = \alpha_k + \lambda_k A + v_k, \text{ with } v_k \sim N(0, \sigma_k)$$

- Assumption might not always hold

⇒ **Non-linear specification**

- Examples: agreeing-response bias (Schuman and Presser, 1981)



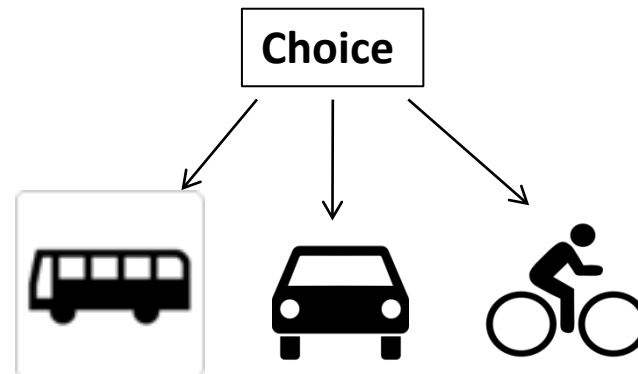
Data to models

1. Specification & analysis

1. Relation between latent variable and its indicators

Use of indicators from word questions in **measurement equations**

**Example 2 from
mode choice case
study**



Data to models

1. Specification & analysis

Adjective data for perception of transport modes

For each of the following transport modes, give three adjectives that describe them best according to you.

		Adjective 1	Adjective 2	Adjective 3
1	The car is:	convenient	comfortable	expensive
2	The train is:	relaxing	punctual	restful
3	The bus, the metro and the tram are:	fast	frequent	cheap
4	The post bus is:	punctual	comfortable	cheap
5	The bicycle is:	stimulating	convenient	cheap
6	The walk is:	healthy	relaxing	independent

Data to models

1. Specification & analysis

Data processing:

- Classification into themes:

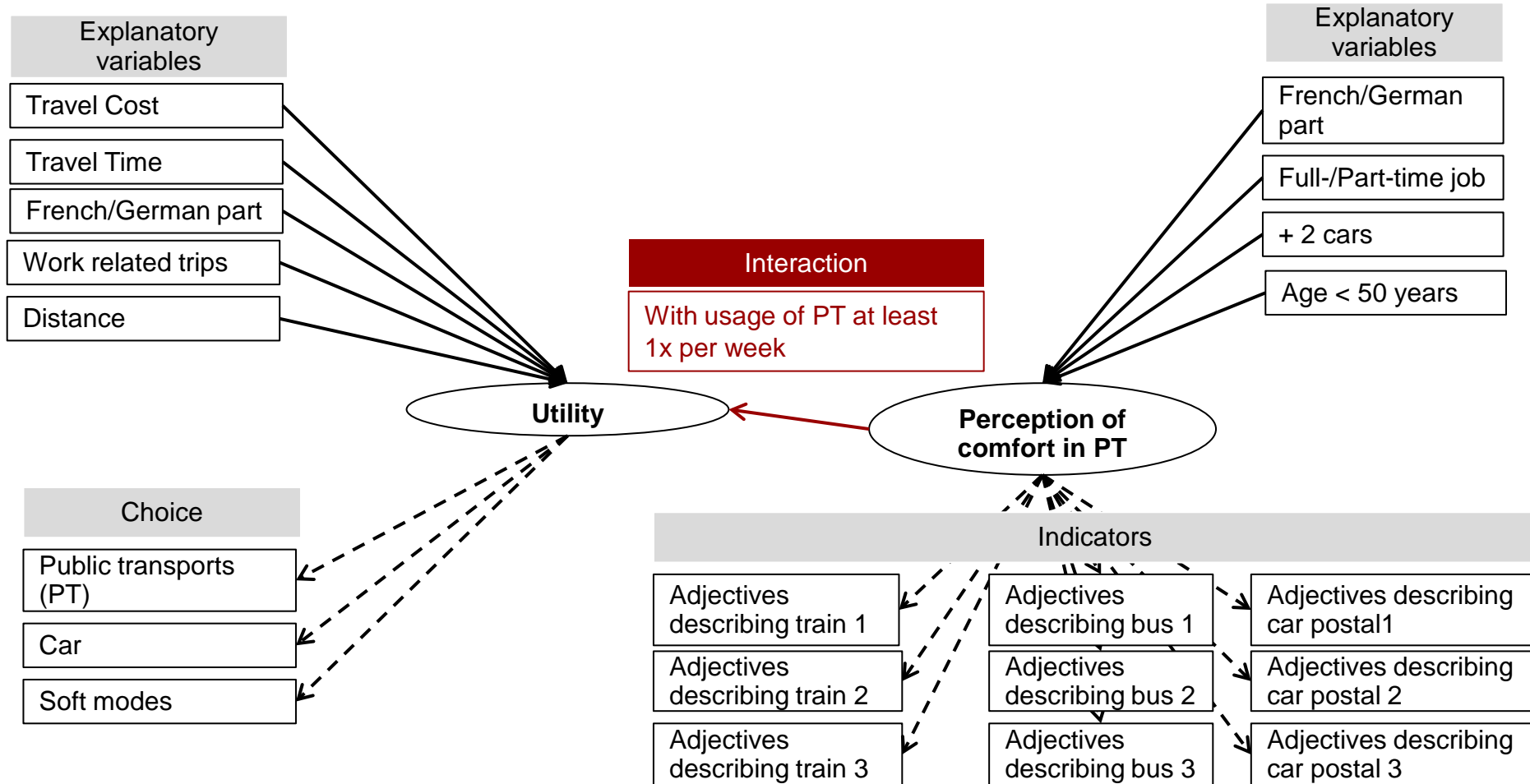
- Perception of cost
- Perception of time
- Difficulty of access
- Flexibility
- Comfort, etc.

- Attribution of scale from -2 to +2

Comfort	Scale
hardly full	1
packed	-1
bumpy	-2
comfortable	1
hard	-1
irritating	-2
tiring	-1
unsuitable with bags	-1
uncomfortable	-1
bad air	-2

Data to models

1. Specification & analysis



Data to models

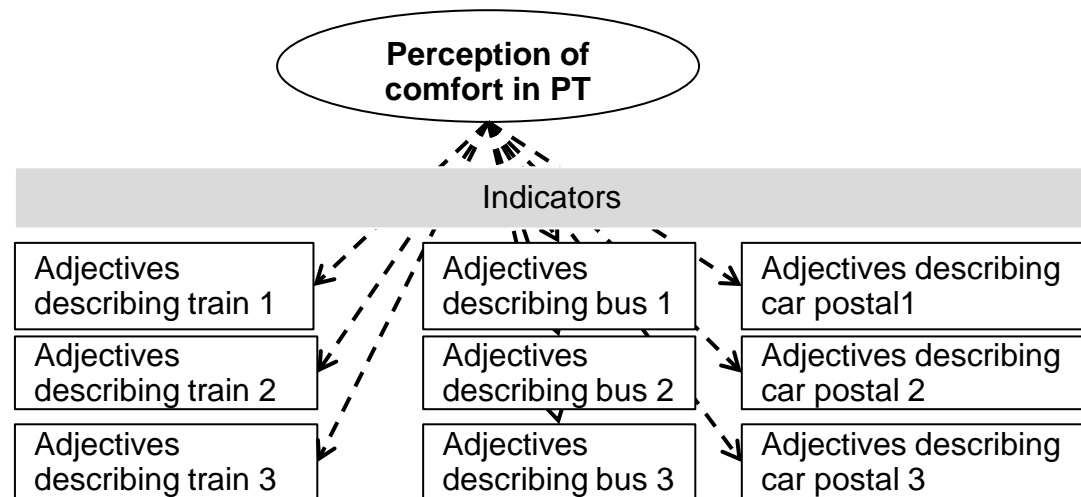
1. Specification & analysis

Measurement equations:

$$I_n = m(X_n^*; \alpha) + v_n$$

with $v_n \sim \text{Logistic}(0,1)$

$$I_n = \begin{cases} -2 & \text{if } -\infty < X_n^* \leq \tau_1 \\ -1 & \text{if } \tau_1 < X_n^* \leq \tau_2 \\ 0 & \text{if } \tau_2 < X_n^* \leq \tau_3 \\ 1 & \text{if } \tau_3 < X_n^* \leq \tau_4 \\ 2 & \text{if } \tau_4 < X_n^* \leq +\infty \end{cases}$$



Data to models

1. Specification & analysis

Issue:

- Scale from -2 to +2 subjective to the modeler

Improvements:

- Order adjectives & obtain distribution with respect to each theme:
 ⇒ Text mining

Data to models

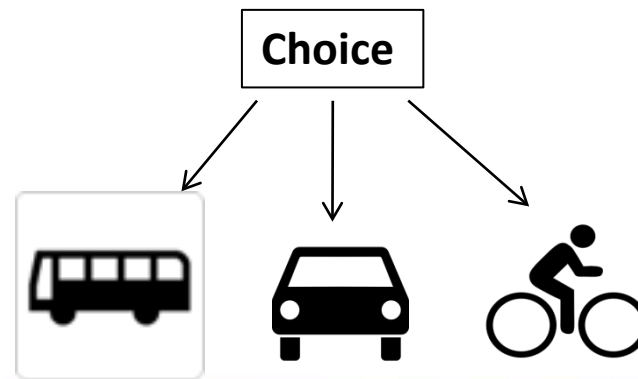
1. Specification & analysis

2. Issues related to estimation

Example:

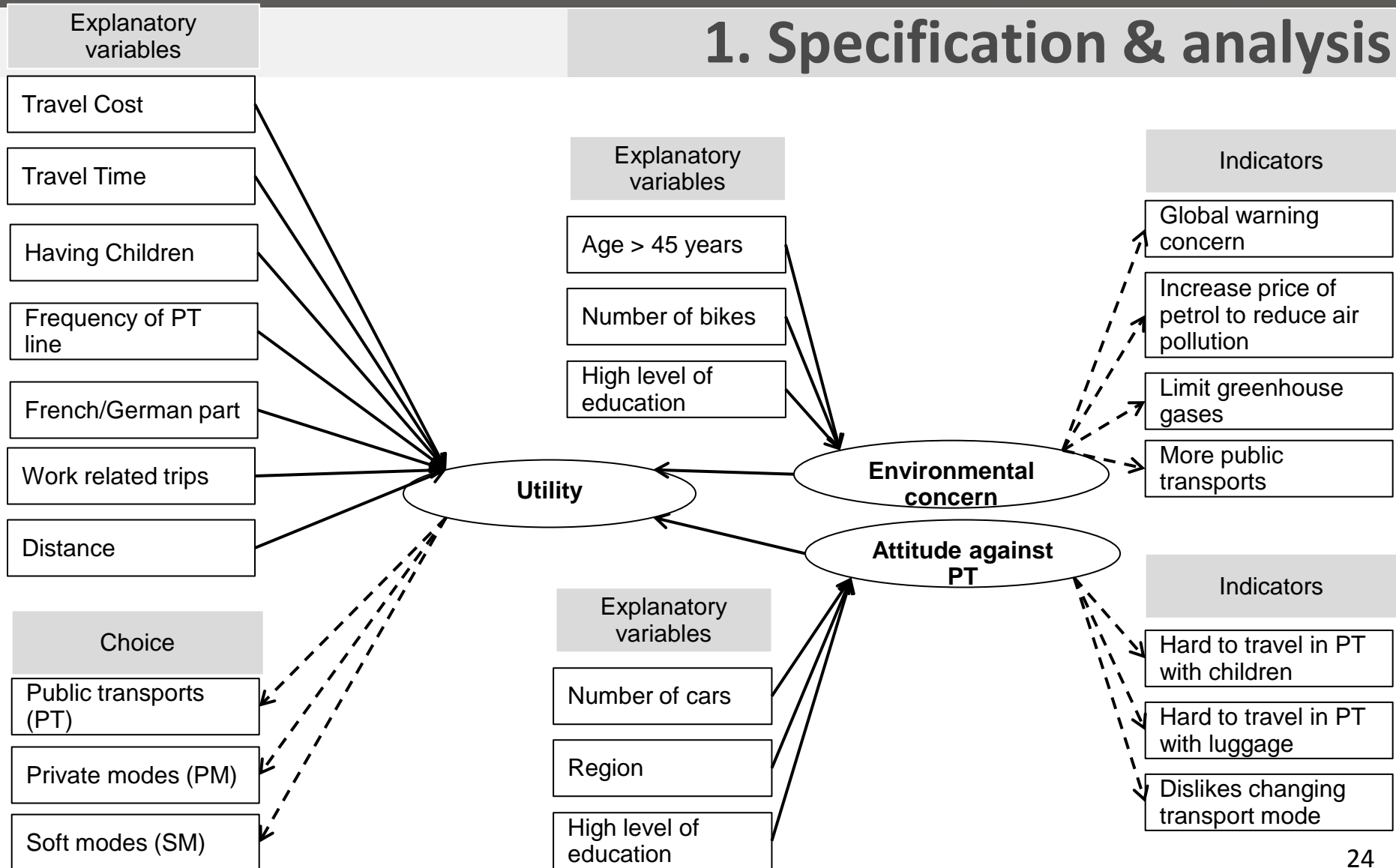
- Difficulty of estimating models including several latent variables:
 - Bayesian inference using Gibbs sampling (Alvarez-Daziano and Bolduc, 2009)
 - Mode choice case study: only 2 latent variables

**Example 3 from
mode choice case
study**



Data to models

1. Specification & analysis



Issues in validation & forecasting of HCM:

1. Analysis of demand indicators built on latent variables
2. Inclusion of aggregate market data for forecasting
3. Absence of market data for new alternatives (SP)

Data to models

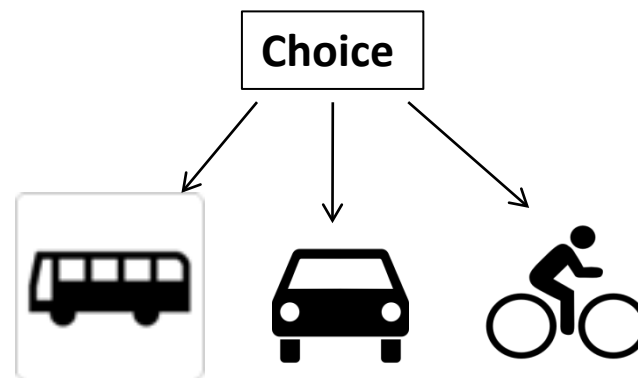
2. Validation & forecasting

1. Analysis of demand indicators built on latent variables

Computation of demand indicators depending on value of latent variable:

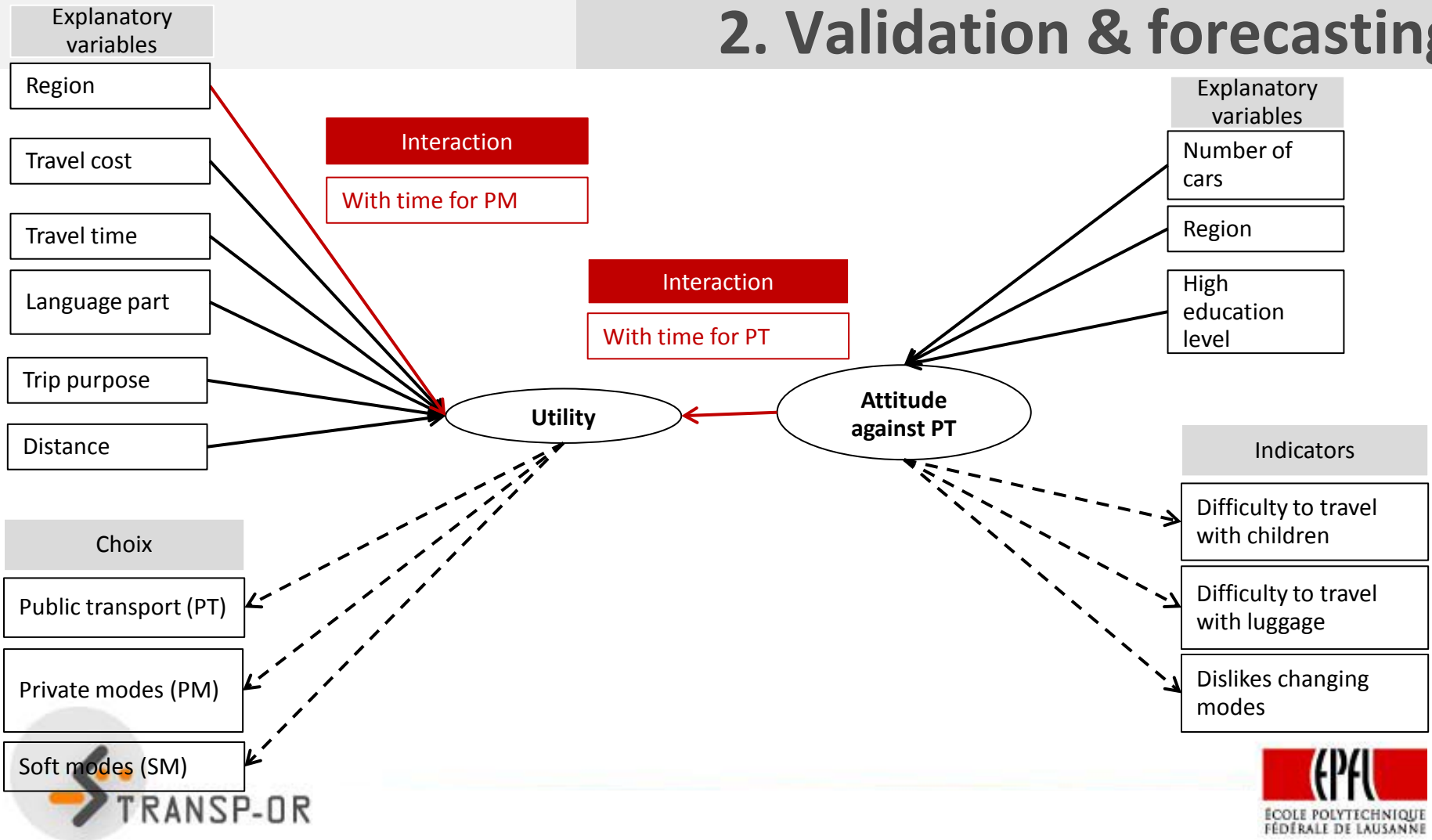
- Capture heterogeneity of value of time (VOT) in population (Abou-Zeid et al., 2010)

**Example 4 from
mode choice case
study**



Data to models

2. Validation & forecasting



Data to models

2. Validation & forecasting

Value of time PT:

$$VOT_{PT,n} = \frac{\beta_{timePT} - \beta_{attPT} \cdot attPT_n}{\beta_{cost}}$$

Result:

- Individuals with more negative attitude against PT
 \implies Increase in TT will **decrease** probability to choose PT
Individuals with more a positive attitude towards PT.
 \implies Increase in TT will **increase** probability to choose PT
- Impacts on VOT

Purpose:

Investigate more indicators & impacts on latent variables

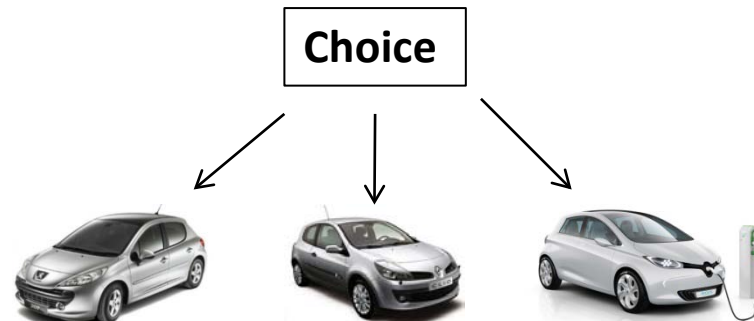
Data to models

2. Validation & forecasting

2. Inclusion of aggregate market data for forecasting

Inclusion of aggregate alternatives in SP survey to deal with missing information

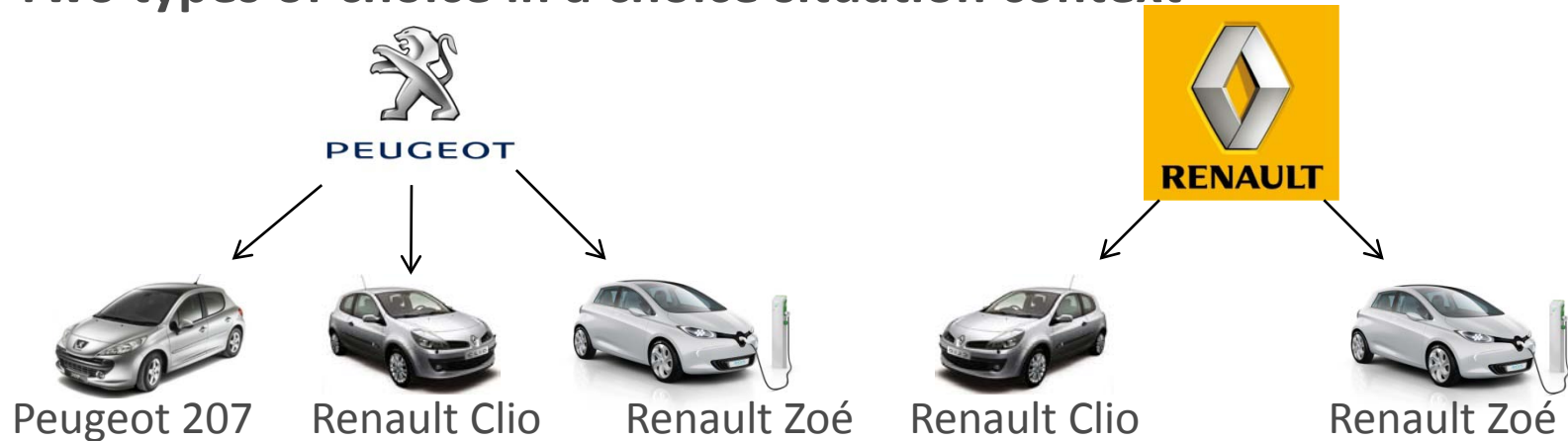
**Example 5 from
vehicle choice case
study**



Data to models

2. Validation & forecasting

Two types of choice in a choice situation context



Issue:

- Choice is supposed to represent all possible alternatives for decision maker
- Not the case for owners of Renault cars

Solution:

- Impute aggregate alternative of gasoline – competitors for these individuals

Data to models

2. Validation & forecasting

Aggregate alternative imputed for Competitors – Gasoline (CG):

$$V_{CG} = \log \sum_{l \in L} \exp V_{ln}$$

$$V_{ln} = C_{CG} + \sum_{s \in S_n} \beta_s \cdot x_s + \beta_{\text{price}_{CG}} \cdot \text{price}_l + \beta_{\text{UseCostGasoline}} \cdot \min(\text{Cost100}_l, 12)$$

Create **aggregate alternative** from **prices** & **operating costs** of new cars on market

(matching segment of 2 other alternatives in choice situation)

Data to models

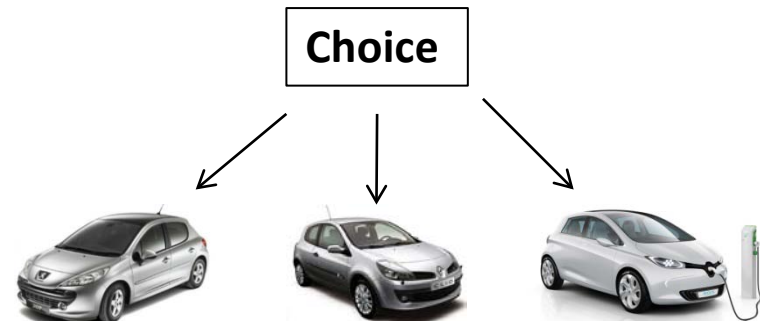
2. Validation & forecasting

3. Absence of market data for new alternatives (SP)

Use:

- Market data of current alternatives
 - SP survey data
- } To estimate possible share for new alternative

**Example 6 from
vehicle choice case
study**



Evaluation of potential market share (MS) for EV

$$MS(RE) = \text{\%}(\text{Choice RE} \mid \text{Owns CG}) \cdot 93.74\% + \text{\%}(\text{Choice RE} \mid \text{Owns RG}) \cdot 6.26\%$$

Acceptance rate EV in the questionnaire for CG owners (weighted)

Acceptance rate EV in the questionnaire for RG owners (weighted)

Market share of competitors

Market share of Renault

Software demo

Illustration: simulation viewer of new version of Biogeme (Bierlaire and Feticarison, 2009)

Market share scenario with:

- Imputation of aggregate alternative
- Integration of market data to compute MS of EV

Variation of price of EV

Models to data

Objective 2: models to data

Design of new surveys from learnings of models

Models to data

Improving design of questionnaires:

- **Semi-open** questions:
 - Lot of information from free report
 - Include more of such questions
- Further modeling developments:
Semi-open → **open** questions

Conclusion

Presented **research agenda** based on expertise from two case studies
⇒ **2 main objectives:**

- **Data to models:**
 - Identify main issues in estimation of HCM
 - Improve specification (measurement equations)
 - Analysis of demand indicators related to latent variables
 - Include aggregate alternatives
 - Include market data
- **Models to data:**
 - Design new surveys for HCM based on learning from models

Thanks