INTEGRATED CHOICE AND LATENT VARIABLE MODELS

APPLICATIONS TO VEHICLE AND MODE CHOICE MODELING

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IRE seminar, USI
10th October 2013

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ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

A HYBRID CHOICE MODEL TO FORECAST THE DEMAND FOR ELECTRIC VEHICLES

FROM SURVEY DESIGN TO MODEL APPLICATION

Aurélie Glerum
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OUTLINE

Introduction & motivation

Data collection

Methodology

Model
- SP model
- Choice model for forecasting

Forecasting analysis

Conclusion

INTRODUCTION & MOTIVATION

Aim

- Develop a **comprehensive methodology** to forecast demand for a new technology: **electric vehicles**

Context

- Current situation:
    - Alternative fuel vehicles (LPG, CNG, etc.) on the car market
    - Electric vehicles (EV) being released
- Collaborative project EPFL-Renault Suisse:
    - Renault has launched Zero Emission (Z.E.) product line in 2011-2013
    - **Aim**: analyze demand for two EV models for **private use**

Zoé

Fluence Z.E.

INTRODUCTION & MOTIVATION

Literature

- SP survey design:
  - Personalized choice situations (Bunch et al., 1993, Achtnicht et al., 2008, etc.)
  - Fractional factorial designs (Brownstone et al., 1996, Ewing and Sarigöllü, 2000, Horne et al., 2005)

- Choice models for demand for EVs or alternative-fuel vehicles:
  - Widely applied (Brownstone and Train, 1999, Dagsvik et al., 2002, Mueller and de Haan, 2009, etc.)
  - Integrated choice and latent variable (ICLV) models for environmental concern (Alvarez-Daziano and Bolduc, 2009)

- Model application:
  - Models developed on SP data need adjustments before application (Brownstone et al., 1996)
  - Joint RP-SP estimations (e.g. Brownstone et al., 2000)
  - Lack of examples of applications of models designed to evaluate demand for new alternatives (Daly and Rohr, 1998)

INTRODUCTION & MOTIVATION

Main features of the model

- Customized choice situations using iterative proportional fitting (IPF)
- Include attitudinal dimensions
- Specify model for the whole market, from a model based on SP data

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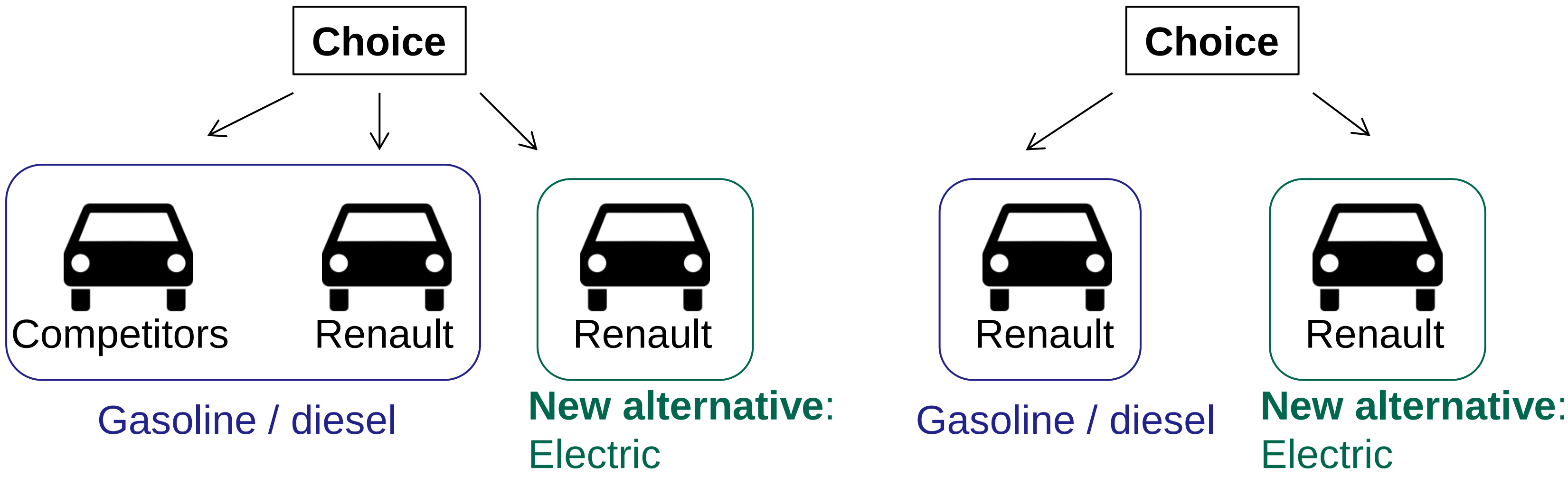
COMPREHENSIVE FRAMEWORK

DATA COLLECTION

Type of survey: **stated preference (SP)** survey

Within same car segment: **hypothetical** choices between

- Own car
- Renault – gasoline (if own car is not Renault)
- Renault – electric



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DATA COLLECTION

STRUCTURE OF THE SURVEY

2 phases:

Phase I:

- Characteristics of respondent's car(s)
- Socio-economic information
- Mobility habits

Phase II:

- Choice situations
- Opinions on topics related to EV
- Perceptions of four categories of vehicles

DATA COLLECTION

STRUCTURE OF THE SURVEY

2 phases:

Phase I:

Characteristics of respondent's car(s)
Socio-economic information
Mobility habits

…used to design…

Phase II:

Choice situations
Opinions on topics related to EV
Perceptions of four categories of vehicles

DATA COLLECTION

STRUCTURE OF THE SURVEY

Opinions on themes related to electric vehicles

- Environmental concern (5 statements)
  Example: An electric car is a 100% ecological solution.
- Attitude towards new technologies (5 statements)
  Example: A control screen is essential in my use of a car.
- Perception of the reliability of an electric vehicle (5 statements)
  Example: Electric cars are not as secure as gasoline cars.
- Perception of leasing (5 statements)
  Example: Leasing is an optimal contract which allows me to change car frequently.
- Attitude towards design (5 statements)
  Example: Design is a secondary element when purchasing a car, which is above all a practical transport mode.

Ratings

- Total disagreement (1)
- Disagreement (2)
- Neutral opinion (3)
- Agreement (4)
- Total agreement (5)
- I don’t know (6)

5 types of respondents sampled in Switzerland:

- Recent buyers
- Prospective buyers
- Renault customers
- Pre-orders
- Newsletter

DATA COLLECTION

SAMPLE

5 types of respondents sampled in Switzerland:

- Recent buyers
- Prospective buyers
- Renault customers
- Pre-orders
- Newsletter

Sampling protocol

All available

Sampling protocol → representativity from:

- 3 language regions of Switzerland (German, French, Italian)
- Gender
- Age category (18-35 years, 36-55 years, 56-74 years)

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DATA COLLECTION

GfK
Ask GfK

0% 25% 50% 75% 100%

Situation de choix 4 de 5

Vous avez ici la description de votre véhicule actuel ainsi que celle de véhicules similaires, thermique et électrique, de la marque Renault. Compte tenu des caractéristiques de chacun de ceux-ci, laquelle des trois solutions choisiriez-vous, si vous deviez changer de voiture aujourd'hui ?

Les valeurs indicatives de leasing sont calculées sur la base d'un apport initial de 20%, d'un kilométrage annuel de 10'000 km et d'une durée de financement de 48 mois.

Caractéristiques	Votre véhicule	Véhicule thermique Renault	Véhicule électrique Renault
Marque	SEAT	RENAULT	RENAULT
Modèle	LEON	MEGANE	FLUENCE
Carburant	Diesel	Diesel	Electricité
Prix d'achat (en CHF)	37510	42739	34008
Prime du gouvernement (en CHF)	0	0	0
Prix total à l'achat (en CHF)	**37510**	**42739**	**34008**
OU : Prix mensuel du leasing (en CHF)	402	435	404
Coûts d'entretien (en CHF par 30'000 km)	850	850	425
Coût en carburant/électricité par 100 km (en CHF)	9.65	10.8	3.55
Leasing de la batterie (en CHF par mois)	0	0	105

précédent suivant

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DATA COLLECTION

An example of choice experiment

Reported by respondent

Characteristics	**Your vehicle**	**Renault vehicle with combustion engine**	**Renault electric vehicle**
Make	Audi	Renault	Renault
Model	A4	Laguna	Fluence
Fuel	Petrol	Petrol	Electricity
Purchase price (in CHF)	42′400	37′200	56′880
Incentive (in CHF)	0	0	−1′000
Total purchase price (in CHF)	42′400	37′200	55′880
OR: Monthly leasing price (in CHF)	477	399	693
Maintenance costs (in CHF for 30′000 km)	850	850	425
Cost in fuel/electricity for 100 km (in CHF)	11.70	13.55	3.55
Battery lease (in CHF per month)	0	0	125

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Deduced from segment of owned car

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DATA COLLECTION

EXPERIMENTAL DESIGN

An example of choice experiment

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Obtained from data base of cars currently sold on market

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DATA COLLECTION

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Fixed attributes

DATA COLLECTION

EXPERIMENTAL DESIGN

An example of choice experiment

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Design variables

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DATA COLLECTION

Design variables

EV variable	Level 1	Level 2	Level 3	Level 4
Purchase price	$(P_{own} + 5'000) * 0.8$	$(P_{own} + 5'000) * 1$	$(P_{own} + 5'000) * 1.2$	-
Governmental incentive	- 0 CHF	- 500 CHF	- 1'000 CHF	- 5'000 CHF
Cost of fuel/electricity for 100 km	1.70 CHF	3.55 CHF	5.40 CHF	-
Battery lease	85 CHF	105 CHF	125 CHF	-

DATA COLLECTION

EXPERIMENTAL DESIGN

Fractional factorial design with sampling weights

Fractional factorial design
- Orthogonal
- Size = 64 (full factorial design has size 108)

Sampling weights:
- Correct for **oversampling** of some levels
- Weights computed with **iterative proportional fitting (IPF)**

	Incentive	Price	Fuel cost of 100 km	Battery lease
1	0	0.80	1.70	85
2	0	1.00	3.55	125
3	0	1.00	5.40	105
4	0	1.20	3.55	105
5	-500	0.80	1.70	125
6	-500	1.00	3.55	85
7	-500	1.00	5.40	105
8	-500	1.20	3.55	105
9	-1000	0.80	3.55	105
10	-1000	1.00	5.40	105
11	-1000	1.00	3.55	85
12	-1000	1.20	1.70	125
13	-5000	0.80	3.55	105
14	-5000	1.00	5.40	105
15	-5000	1.00	3.55	125
16	-5000	1.20	1.70	85

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METHODOLOGY

Hybrid choice model (HCM): DCM with latent constructs.

Allows to capture e.g. attitudes et perceptions

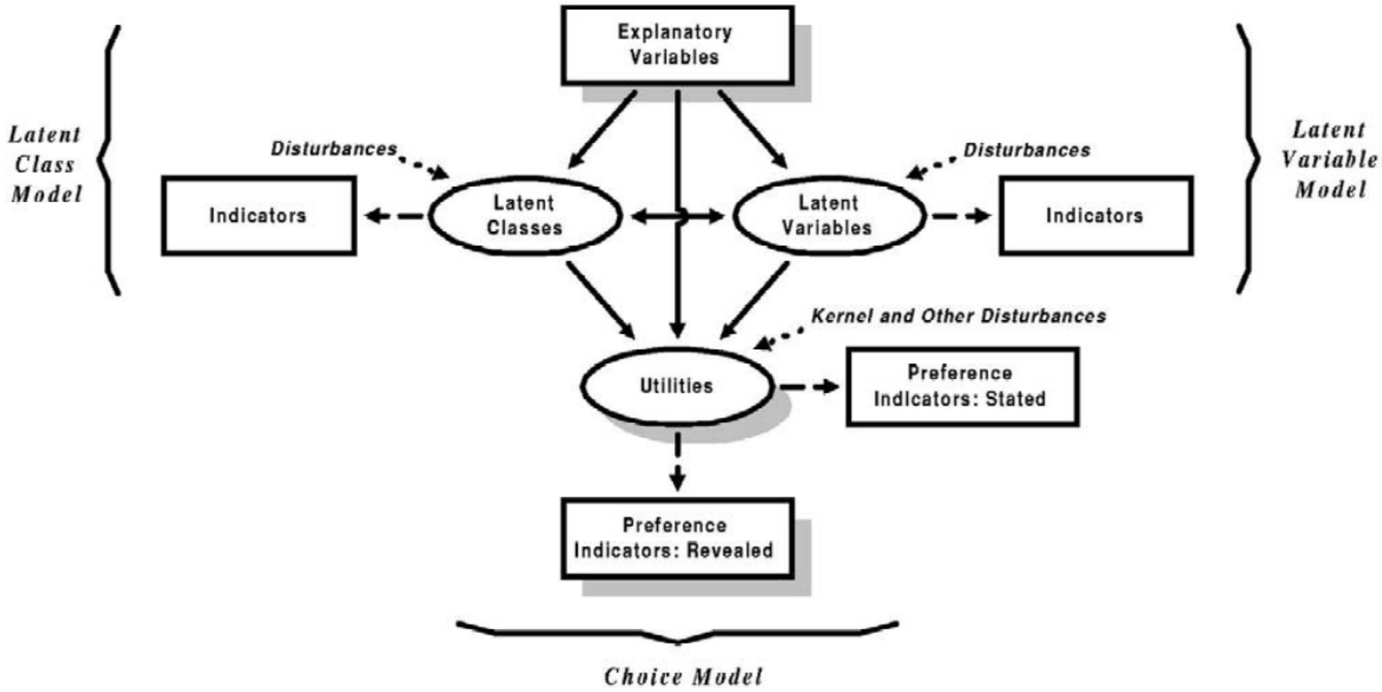
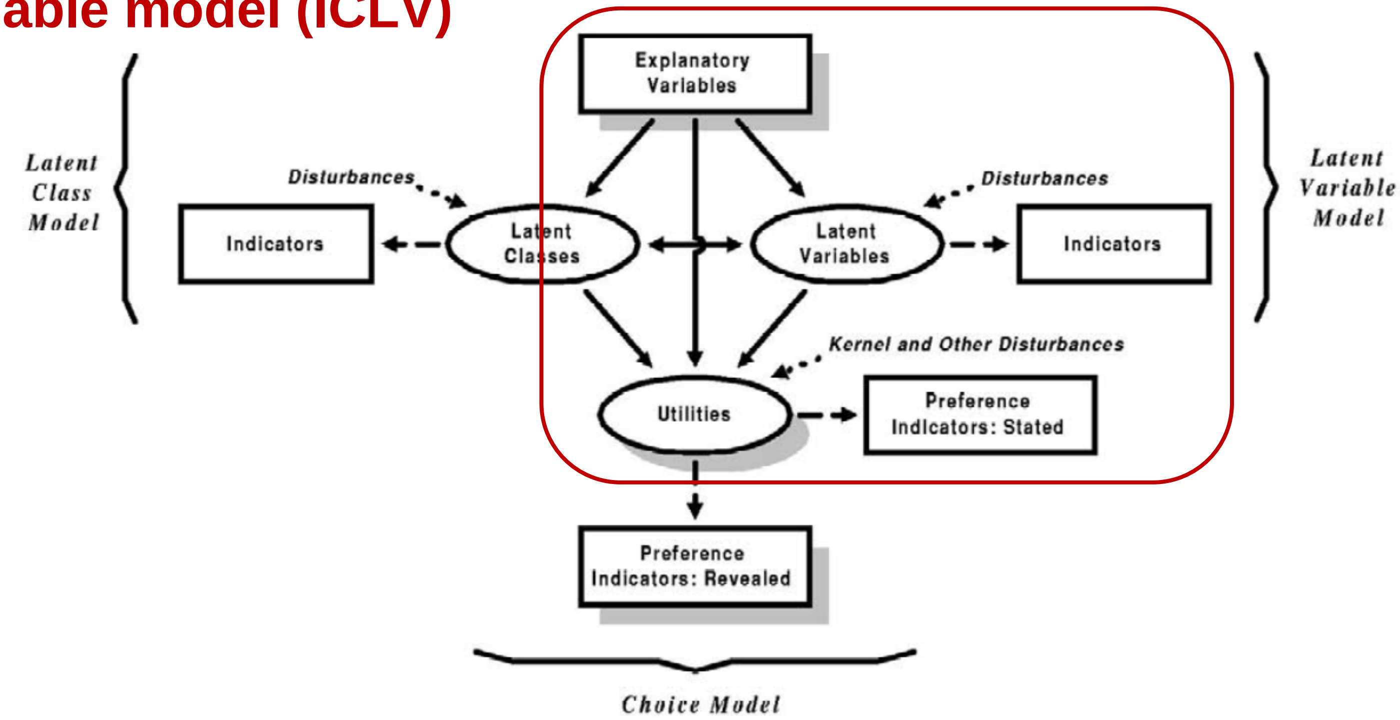


Figure extracted from Walker and Ben-Akiva, 2002.

METHODOLOGY

Hybrid choice model (HCM): DCM with latent constructs.

In this research: focus on the **integration of choice model and latent variable model (ICLV)**



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METHODOLOGY

Hybrid choice model specification

Structural equations:

Choice model:

$U_{in} = V(X_{in}, X_n^*; \beta) + \varepsilon_{in}$ with $\varepsilon_{in} \sim EV(0,1)$

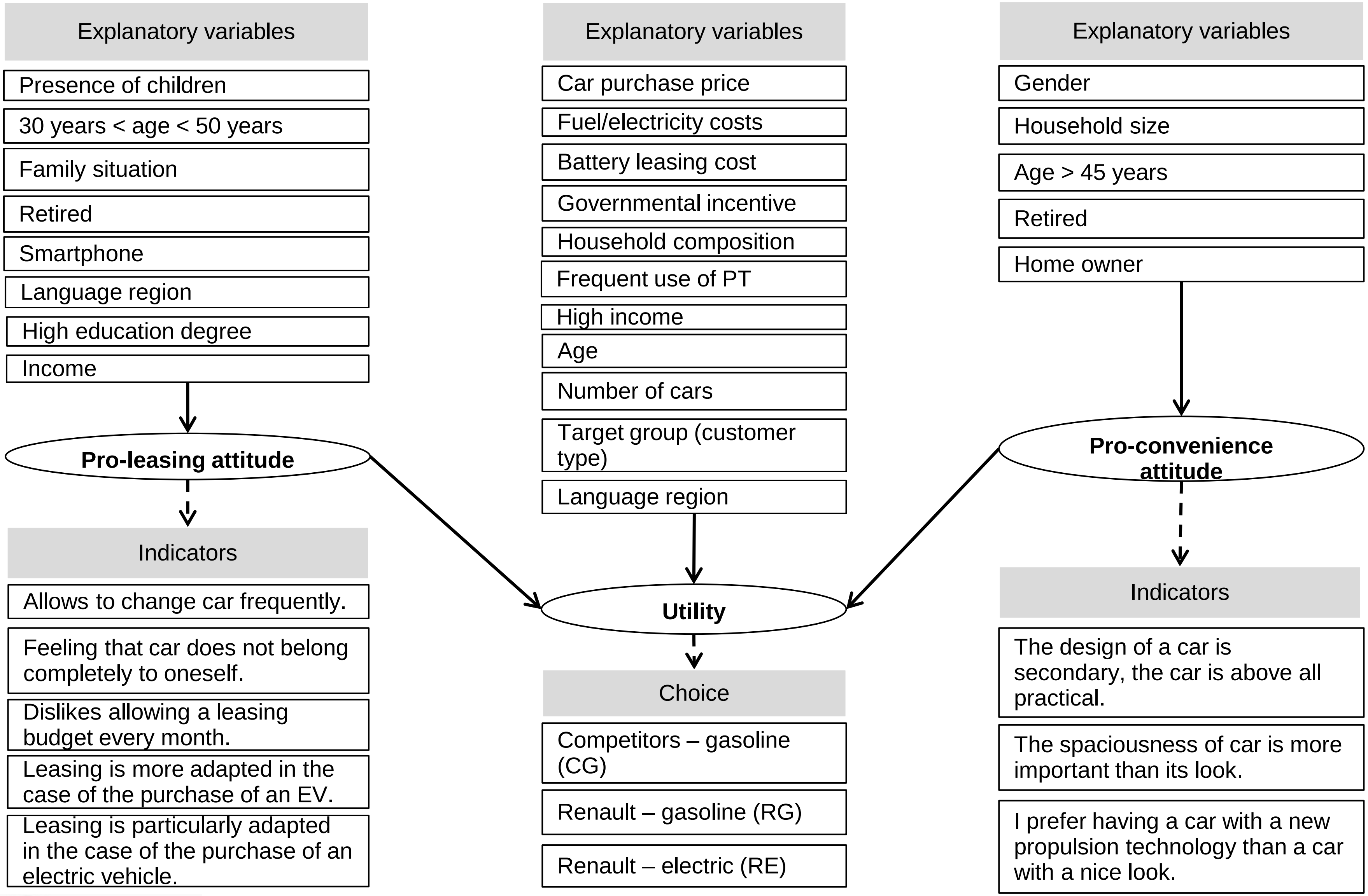
Latent variable model:

$X_n^* = h(X_{in}; \lambda) + \omega_n$ with $\omega_n \sim N(0, \sigma_\omega)$

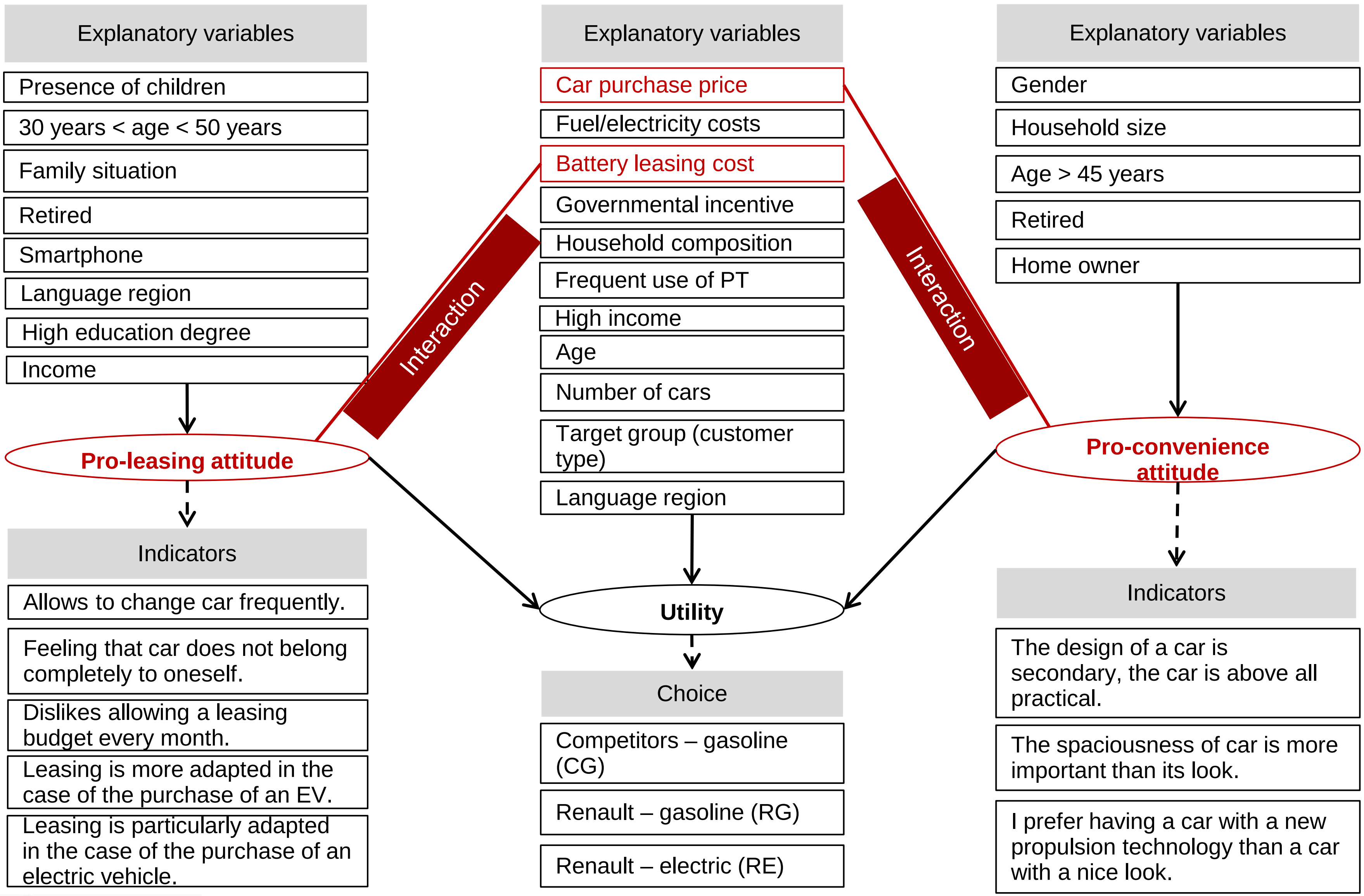
Measurement equations (continuous):

$I_n^* = m(X_n^*; \alpha) + \upsilon_n$ with $\upsilon_n \sim N(0, \sigma_\upsilon)$

SP MODEL


Explanatory variables
Presence of children
30 years < age < 50 years
Family situation
Retired
Smartphone
Language region
High education degree
Income
Pro-leasing attitude
Indicators
Allows to change car frequently.
Feeling that car does not belong completely to oneself.
Dislikes allowing a leasing budget every month.
Leasing is more adapted in the case of the purchase of an EV.
Leasing is particularly adapted in the case of the purchase of an electric vehicle.
Explanatory variables
Car purchase price
Fuel/electricity costs
Battery leasing cost
Governmental incentive
Household composition
Frequent use of PT
High income
Age
Number of cars
Target group (customer type)
Language region
Utility
Choice
Competitors – gasoline (CG)
Renault – gasoline (RG)
Renault – electric (RE)
Explanatory variables
Gender
Household size
Age > 45 years
Retired
Home owner
Pro-convenience attitude
Indicators
The design of a car is secondary, the car is above all practical.
The spaciousness of car is more important than its look.
I prefer having a car with a new propulsion technology than a car with a nice look.

SP MODEL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Interaction
Explanatory variables
Car purchase price
Fuel/electricity costs
Battery leasing cost
Governmental incentive
Household composition
Frequent use of PT
High income
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SP MODEL

SPECIFICATION

Structural equations:

Choice model:

$$U_{CG} = -\exp(\beta_{price_{CG}} + \beta_{AttC} AttC)\, price_{CG} + \sum_k \beta_k X_k + \varepsilon_{CG,n}$$

$$U_{RG} = -\exp(\beta_{price_{RG,TG1245}} TG1245 + \beta_{price_{RG,TG3}} TG3 + \beta_{AttC} AttC)\, price_{RG} + \sum_l \beta_l X_l + \varepsilon_{RG,n}$$

$$U_{RE} = -\exp(\beta_{price_{RE,TG12}} TG12 + \beta_{price_{RG,TG3}} TG3 + \beta_{price_{RG,TG45}} TG45 + \beta_{AttC} AttC)\, price_{RE}$$
$$-\exp(\beta_{Battery} + \beta_{AttL} AttL) Battery + \sum_m \beta_m X_m + \varepsilon_{RE,n} \qquad \text{with } \varepsilon_{in} \sim EV(0,1)$$

Latent variable model:

$$AttL = \beta_{Mean1} + \sum_i \beta_{1,i} \cdot X_{1,i} + \exp(\nu_1) \cdot \Omega_1 \text{ with } \Omega_1 \sim N(0,1)$$
$$AttC = \beta_{Mean2} + \sum_i \beta_{2,i} \cdot X_{2,i} + \exp(\nu_2) \cdot \Omega_2 \text{ with } \Omega_2 \sim N(0,1)$$

Measurement equations (continuous):

$$I_{1,k} = \alpha_{1,k} + \lambda_{1,k} \cdot AttL + \exp(\sigma_{1,k})\, \Omega_{1,k} \text{ with } \Omega_{1,k} \sim N(0,1), \text{ for } k = 1, \ldots, 5$$
$$I_{2,k} = \alpha_{2,k} + \lambda_{2,k} \cdot AttC + \exp(\sigma_{2,k})\, \Omega_{2,k} \text{ with } \Omega_{2,k} \sim N(0,1), \text{ for } k = 1,2,3$$

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SP MODEL

ESTIMATION RESULTS

Name	Value	t-test	Name	Value	t-test
Parameters in linear terms			*Parameters in linear terms (ctd)*		
ASC_{CG}	-2.71	-4.77	$\beta_{\mathrm{Income}_{\mathrm{CG}}}$	-0.223*	-1.92
ASC_{RG}	-2.17	-3.63	$\beta_{\mathrm{Income}_{\mathrm{RG}}}$	-0.259	-2.25
$\beta_{\mathrm{UseCostGasoline}}$	-0.0469**	-1.41	$\beta_{\mathrm{French}_{\mathrm{CG}}}$	0.373	2.94
$\beta_{\mathrm{UseCostElecHigh}_{\mathrm{Fluence}}}$	-0.264	-2.20	$\beta_{\mathrm{French}_{\mathrm{RG}}}$	0.0254**	0.19
$\beta_{\mathrm{UseCostElecHigh}_{\mathrm{Zoé}}}$	-0.802	-4.82	$\beta_{\mathrm{Age}_{\mathrm{CG}}}$	0.0172	3.65
$\beta_{\mathrm{UseCostElecMed}_{\mathrm{Zoé}}}$	-0.514	-3.21	$\beta_{\mathrm{Age}_{\mathrm{RG}}}$	-0.00210**	-0.43
$\beta_{\mathrm{IncentiveHigh}}$	0.799	6.21	$\beta_{\mathrm{TG12}_{\mathrm{CG}}}$	1.60	4.57
$\beta_{\mathrm{IncentiveMed}}$	0.0538**	0.40	$\beta_{\mathrm{TG12}_{\mathrm{RG}}}$	0.664*	1.89
$\beta_{\mathrm{IncentiveLow}}$	0.0164**	0.12	$\beta_{\mathrm{TG3}_{\mathrm{CG}}}$	0.104**	0.11
$\beta_{\mathrm{PT}_{\mathrm{CG,TG1245}}}$	-0.259	-1.96	$\beta_{\mathrm{TG3}_{\mathrm{RG}}}$	2.63	5.18
$\beta_{\mathrm{PT}_{\mathrm{RG,TG1245}}}$	-0.577	-3.67	*Parameters in non-linear terms*		
$\beta_{\mathrm{PT}_{\mathrm{CG,TG3}}}$	-2.64	-3.85	$\beta_{\mathrm{price}_{\mathrm{CG}}}$	-3.60	-4.77
$\beta_{\mathrm{PT}_{\mathrm{RG,TG3}}}$	-1.17	-4.40	$\beta_{\mathrm{price}_{\mathrm{RG,TG1245}}}$	-1.39	-4.33
$\beta_{\mathrm{FamSit}_{\mathrm{CG}}}$	-0.157**	-1.37	$\beta_{\mathrm{price}_{\mathrm{RG,TG3}}}$	-0.290**	-1.06
$\beta_{\mathrm{FamSit}_{\mathrm{RG}}}$	0.183**	1.56	$\beta_{\mathrm{price}_{\mathrm{RE,TG12}}}$	-0.365	-2.57
$\beta_{\mathrm{NbCars}_{\mathrm{CG,TG1245}}}$	-0.207	-2.75	$\beta_{\mathrm{price}_{\mathrm{RE,TG3}}}$	0.342	2.10
$\beta_{\mathrm{NbCars}_{\mathrm{RG,TG1245}}}$	-0.193	-2.32	$\beta_{\mathrm{price}_{\mathrm{RE,TG45}}}$	-0.152**	-1.33
$\beta_{\mathrm{NbCars}_{\mathrm{CG,TG3}}}$	-0.664*	-1.88	β_{AttC}	-0.142	-4.93
$\beta_{\mathrm{NbCars}_{\mathrm{RG,TG3}}}$	-0.945	-6.24	β_{Battery}	2.17	5.87
			β_{AttL}	-0.193*	-1.74

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SP MODEL

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$\beta_{\text{Age}_{\text{CG}}}$	0.0172	3.65
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$\boxed{\beta_{\text{AttC}}}$	$\boxed{-0.142}$	$\boxed{-4.93}$
β_{Battery}	2.17	5.87
β_{AttL}	-0.193*	-1.74

- $\beta_{AttC} < 0$ and significant: pro-convenience individuals less price-sensitive

SP MODEL

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$\beta_{\mathrm{IncentiveMed}}$	0.0538**	0.40	$\beta_{\mathrm{TG12_{RG}}}$	0.664*	1.89
$\beta_{\mathrm{IncentiveLow}}$	0.0164**	0.12	$\beta_{\mathrm{TG3_{CG}}}$	0.104**	0.11
$\beta_{\mathrm{PT_{CG,TG1245}}}$	-0.259	-1.96	$\beta_{\mathrm{TG3_{RG}}}$	2.63	5.18
$\beta_{\mathrm{PT_{RG,TG1245}}}$	-0.577	-3.67	*Parameters in non-linear terms*		
$\beta_{\mathrm{PT_{CG,TG3}}}$	-2.64	-3.85	$\beta_{\mathrm{price_{CG}}}$	-3.60	-4.77
$\beta_{\mathrm{PT_{RG,TG3}}}$	-1.17	-4.40	$\beta_{\mathrm{price_{RG,TG1245}}}$	-1.39	-4.33
$\beta_{\mathrm{FamSit_{CG}}}$	-0.157**	-1.37	$\beta_{\mathrm{price_{RG,TG3}}}$	-0.290**	-1.06
$\beta_{\mathrm{FamSit_{RG}}}$	0.183**	1.56	$\beta_{\mathrm{price_{RE,TG12}}}$	-0.365	-2.57
$\beta_{\mathrm{NbCars_{CG,TG1245}}}$	-0.207	-2.75	$\beta_{\mathrm{price_{RE,TG3}}}$	0.342	2.10
$\beta_{\mathrm{NbCars_{RG,TG1245}}}$	-0.193	-2.32	$\beta_{\mathrm{price_{RE,TG45}}}$	-0.152**	-1.33
$\beta_{\mathrm{NbCars_{CG,TG3}}}$	-0.664*	-1.88	β_{AttC}	-0.142	-4.93
$\beta_{\mathrm{NbCars_{RG,TG3}}}$	-0.945	-6.24	β_{Battery}	2.17	5.87
			$\boxed{\beta_{\mathrm{AttL}}}$	$\boxed{-0.193*}$	$\boxed{-1.74}$

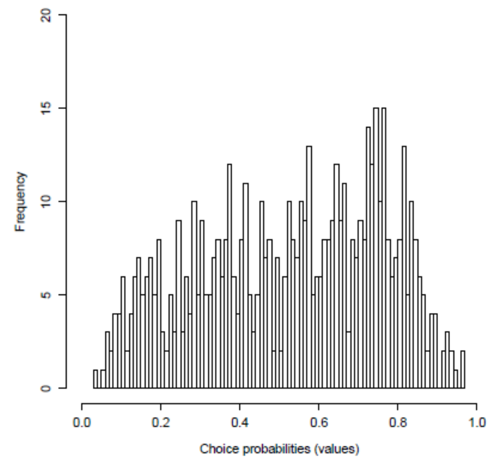
- $\beta_{AttC} < 0$ and significant: pro-convenience individuals less price-sensitive
- $\beta_{AttL} < 0$ and significant: pro-leasing individuals less affected by changes in battery leasing price

SP MODEL

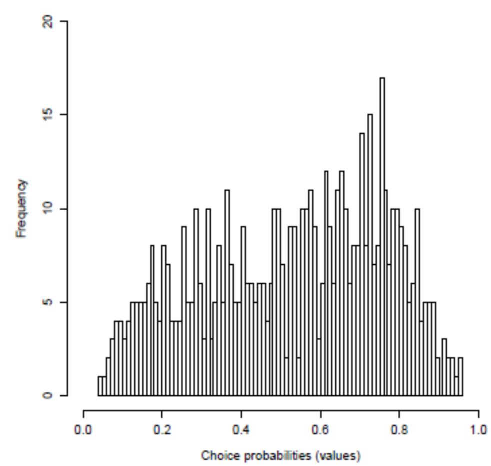
VALIDATION

Histogram of **choice probabilities** predicted by MNL and ICLV (80%/20%)

ICLV



MNL



Value

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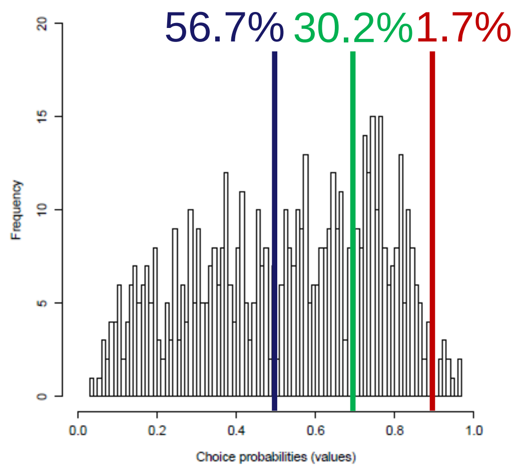
SP MODEL

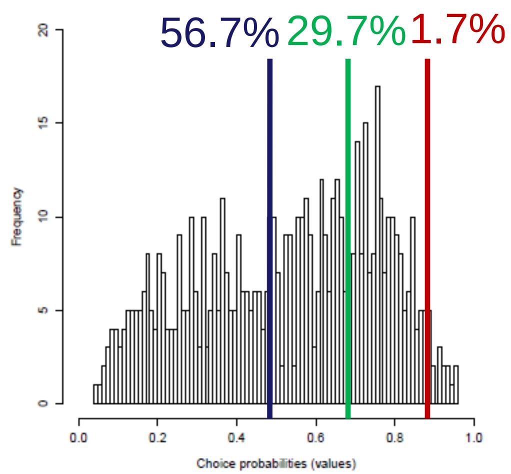
VALIDATION

Histogram of **choice probabilities** predicted by MNL and ICLV (80%/20%)

ICLV



MNL



Value

SP MODEL

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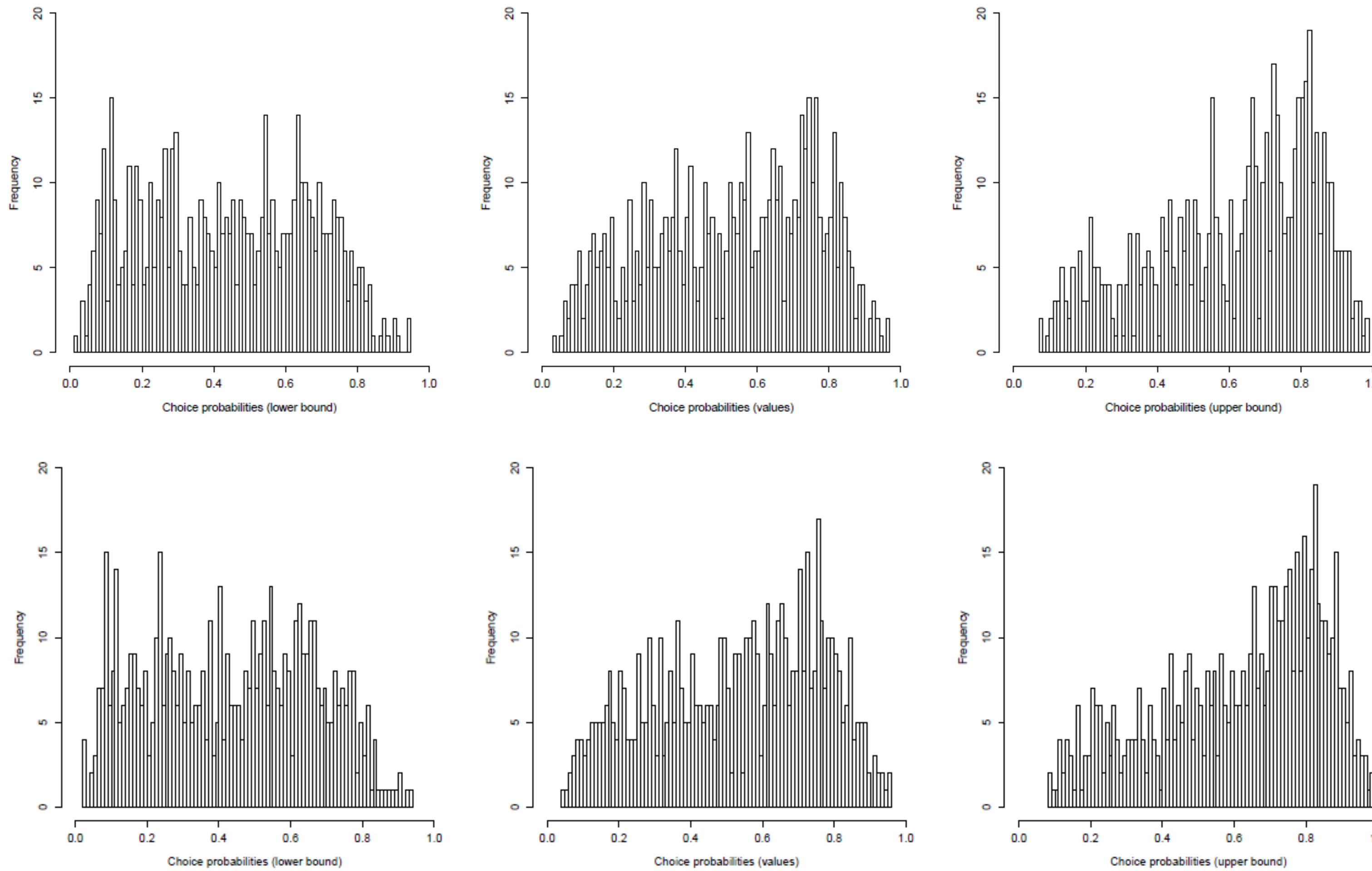

Lower bound

Value

Upper bound

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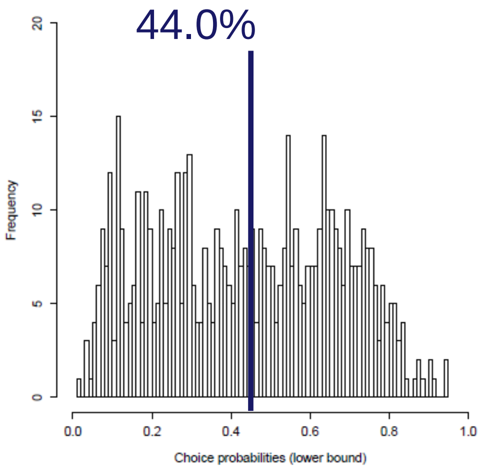
SP MODEL

VALIDATION

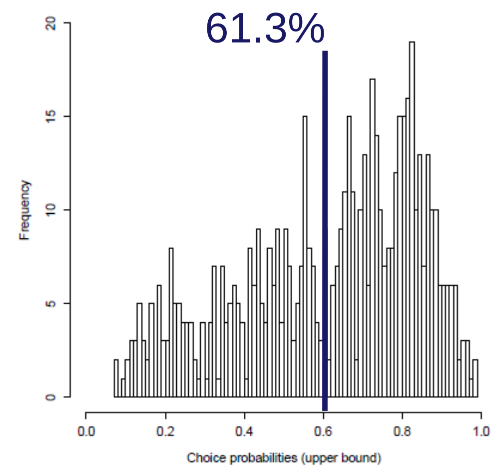
Histogram of **choice probabilities** predicted by MNL and ICLV (80%/20%)

ICLV



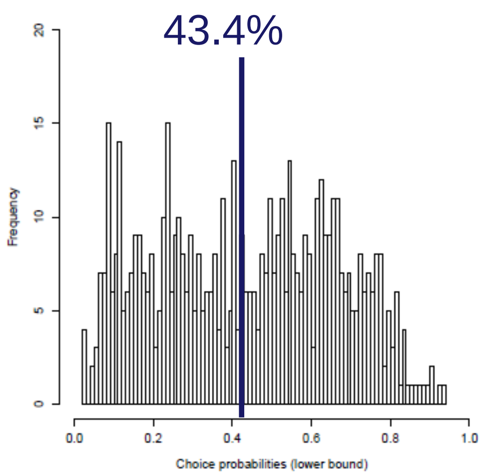
Difference between average confidence bounds

17.3%

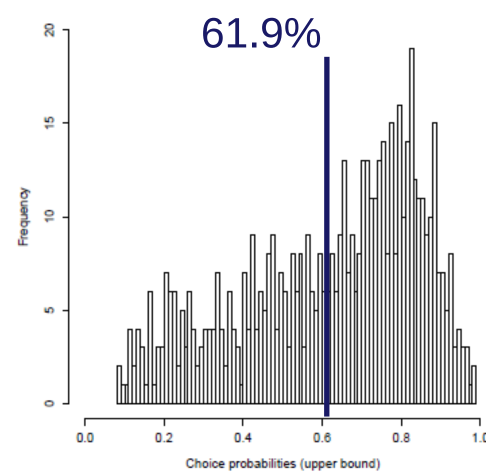


^

MNL



18.5%



Lower bound

Upper bound

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CHOICE MODEL FOR FORECASTING

Several corrections to the SP model are needed before the model can be applied for scenario forecasting:

1. **Introduction of an aggregate alternative** for car models from competitors (using logsum)

2. **Correction of constants**:

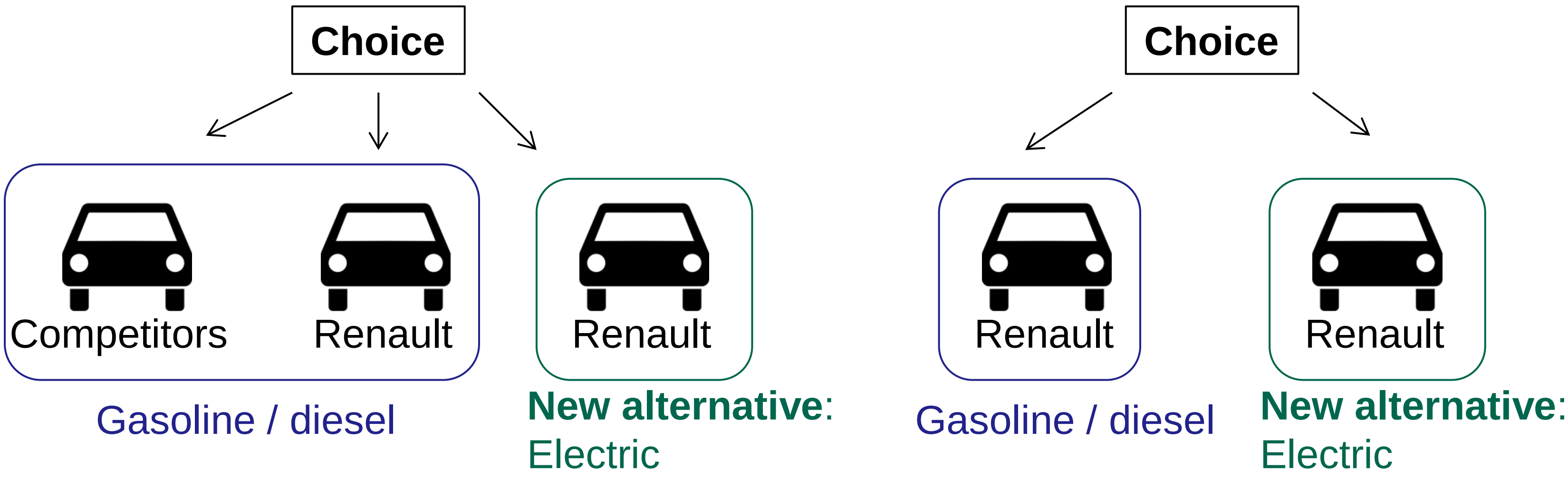
    - Current ratio of market shares between Renault and competitors is preserved.

    - Estimate potential market share of EV using acceptance rate and Swiss market data.

CHOICE MODEL FOR FORECASTING

1. AGGREGATE ALTERNATIVE

Two possible choice situations



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

CHOICE MODEL FOR FORECASTING

1. AGGREGATE ALTERNATIVE

Aggregate alternative imputed for Competitors – Gasoline (CG)

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

$$U_{\mathrm{ln}} = ASC_{CG} + \sum_{s \in S_n} \beta_s \cdot x_s - \exp(\beta_{price_{CG}} + \beta_{AttC} \cdot AttC_n) \cdot price_l$$
$$+ \beta_{UseCostGasoline} \cdot Cost100_l \cdot (Cost100_l \leq 12) + \varepsilon_{\mathrm{ln}}$$

Generated from **prices** & **operating costs** of new cars on market (matching segment of 2 other alternatives in choice situation)

CHOICE MODEL FOR FORECASTING

2. CORRECTIONS OF CONSTANTS

Idea:

Use:

- Market data of current alternatives
- SP survey data

To estimate possible share for new alternative

CHOICE MODEL FOR FORECASTING

2. CORRECTIONS OF CONSTANTS

Idea:

Use:

- Market data of current alternatives
- SP survey data

To estimate possible share for new alternative

Evaluation of potential market share (MS) for EV

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

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

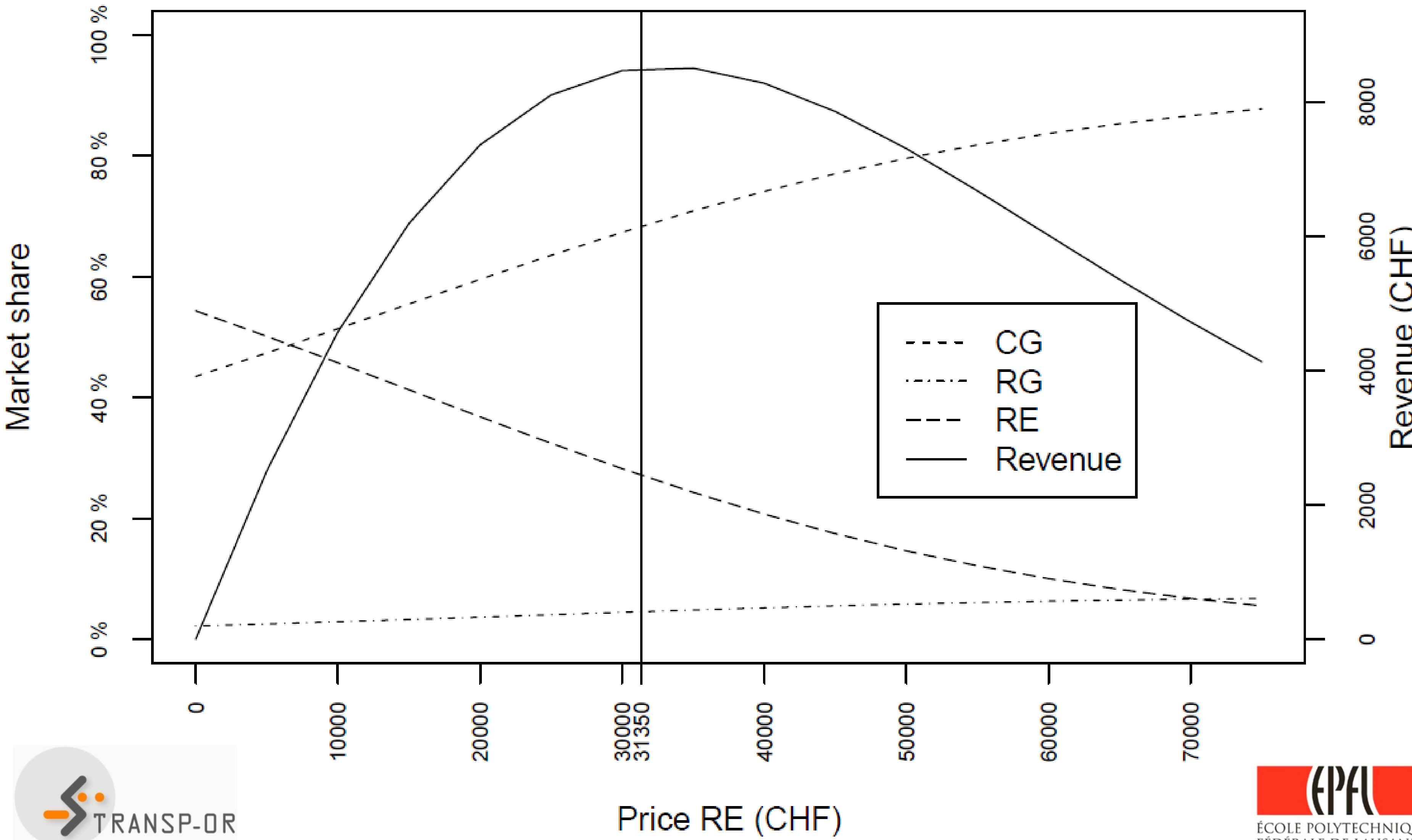
$$
\begin{aligned}
MS(\mathrm{RE}) &= \boxed{\%(\text{Choice RE} \mid \text{Owns CG})} \cdot \boxed{94\%} + \boxed{\%(\text{Choice RE} \mid \text{Owns RG})} \cdot \boxed{6\%} \\
&= 27\%
\end{aligned}
$$

Market share of competitors

Market share of Renault

FORECASTING ANALYSIS

Example of scenario



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CONCLUSION

Conclusions

- Operational model obtained by the presented procedure: from data collection to model application
- Important to include market data when forecast for a new alternative

Future analyses

- Analyzed the demand for EV for private use, but alternative uses exist (e.g. car sharing)
- Now that EVs are more present on the market, revealed preferences (RP) data can be collected and the model can integrate both.

USING ADJECTIVES TO MEASURE PERCEPTIONS IN HYBRID CHOICE MODELS

Aurélie Glerum
Bilge Atasoy
Michel Bierlaire

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OUTLINE

Introduction & motivation

The data

Model specification

Estimation results

Validation

Conclusion

INTRODUCTION & MOTIVATION

Issues related to the integration of latent variables into choice models:

1. **Measurement of latent variable**

   ⟹ How to obtain the most realistic and accurate measure of a perception?

2. **Integration of the measurement into the choice model**

   ⟹ How to incorporate this information in the choice modeling framework?

INTRODUCTION & MOTIVATION

1. **Measurement of latent variable:**

- Use of **opinion statements**
  Five-point Likert scale

  Usual way in literature
  (Likert, 1932; Bearden and Netemeyer, 1999)

- **Recent technique** developed in **social sciences:**

  Respondents report **adjectives** characterizing a variable of interest (Kaufmann et al., 2001; Kaufmann et al., 2010)

  Reflects **spontaneous** perceptions of individuals
  (≠ survey designer's conception of the perception)

INTRODUCTION & MOTIVATION

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  (≠ survey designer's conception of the perception)

⇒ **1ST AIM OF THIS RESEARCH: USE THE ADJECTIVES TO MEASURE PERCEPTIONS**

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INTRODUCTION & MOTIVATION

2. Integration of the measurement into the choice model:

- Structural equation model (SEM) framework used to characterize latent variable and relate it to its measurement indicators (e.g. Bollen, 1989).

- Latent variable model embedded into DCM $\Longrightarrow$ HCM framework

- Integration of measurements into HCM framework:
  - Well-established for models with opinion statements

  - **Adjectives need to be quantified**

INTRODUCTION & MOTIVATION

2. **Integration of the measurement into the choice model:**

- Structural equation model (SEM) framework used to characterize latent variable and relate it to its measurement indicators (e.g. Bollen, 1989).
- Latent variable model embedded into DCM ⟹ HCM framework
- Integration of measurements into HCM framework:
  - Well-established for models with opinion statements
  - **Adjectives need to be quantified**

⟹ **2ND AIM OF THIS RESEARCH: QUANTIFY THE ADJECTIVES TO INTEGRATE THEM IN AN HCM**

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THE DATA

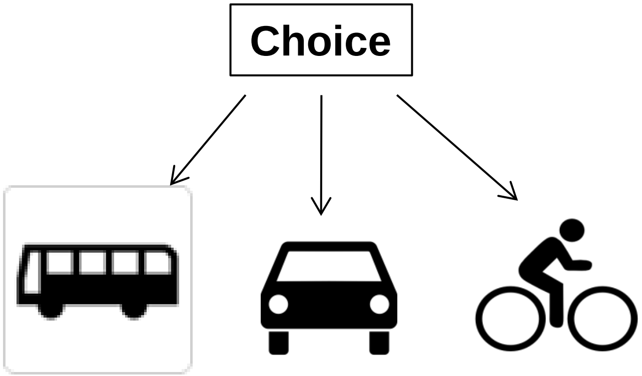
Two surveys:

- Revealed preferences (RP) survey
- Survey with evaluators (adjective quantification survey)

THE DATA

RP survey

- Mode choice study
- Conducted between 2009-2010 in low-density areas of Switzerland
- Conducted with PostBus (major bus company in Switzerland, operates in low-density areas)
- Info on all trips performed by inhabitants in one day:
    - Transport mode
    - Trip duration
    - Cost of trip
    - Activity at destination
    - Etc.
- **1763 valid questionnaires** collected



THE DATA

RP SURVEY

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:			
2	The train is:			
3	The bus, the metro and the tram are:			
4	The post bus is:			
5	The bicycle is:			
6	The walk is:			

THE DATA

RP SURVEY

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**

Extraction of information on perceptions

1. Classification into themes:

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

2. Focused on adjectives related to one theme only and one mode only:

Comfort in public transportation (PT)

Comfort
hardly full
packed
bumpy
comfortable
hard
irritating
tiring
unsuitable with bags
uncomfortable
bad air
…

THE DATA

RP SURVEY

Extraction of information on perceptions

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- Difficulty of access
- Flexibility
- Comfort, etc.

2. Focused on adjectives related to one theme only and one mode only:

Comfort in public transportation (PT)

⇒ **LATENT VARIABLE WE STUDY**

Comfort
hardly full
packed
bumpy
comfortable
hard
irritating
tiring
unsuitable with bags
uncomfortable
bad air
…

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THE DATA

ADJECTIVE QUANTIFICATION SURVEY

SURVEY ON ADJECTIVES

Email address (optional):	
Age:	
Gender:	--
Nationality:	(please select a country)
Native language:	--
Language at work:	--
Language used at home:	--
Highest educational degree:	--
Professional occupation:	--

For each adjective below, we ask you to rate how strongly it characterizes the concept of *comfort* of a transportation mode (car, bus, train, etc.) Please select an integer **between -2 and 2** on the corresponding slider, where a positive number corresponds to adjectives associated with comfort, and a negative number with discomfort. If you do not associate an adjective with the concept of *comfort*, rate it with 0.

Hard	-2	2	
Relaxing	-2	2	
Stressful	-2	2	
Without stress	-2	2	

- Asked 25 external evaluators to rate the adjectives on scale of comfort.
- Discrete scale: ratings from -2 to 2.

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THE DATA

ADJECTIVE QUANTIFICATION SURVEY

Aims:

- Use adjectives to measure perceptions
- Quantify them to integrate them into the HCM framework

Now:

Ratings from 25 different evaluators

$\Longrightarrow$ How reliable is each set of ratings?

Next step:

- Estimate an HCM for each set of ratings (i.e. for each evaluator)
  - LV is perception of comfort in PT
  - LV measured by ratings of one evaluator
- Compare the fit & prediction capabilities of each model

THE DATA

ADJECTIVE QUANTIFICATION SURVEY

Adjectives	Mean	Median	Standard deviation	Central evaluator	Outlying evaluator
bad air	-1.52	-2	0.714	-1	1
bumpy	-1.08	-1	0.862	-1	1
comfortable	1.72	2	0.542	1	2
difficult	-1.00	-1	0.707	-1	-2
empty	0.880	1	0.726	1	1
expensive	-0.680	0	0.988	-2	-1
fast	1.04	1	0.735	2	1
full	-1.00	-1	1.00	-2	2
hard	-0.920	-1	0.640	-1	-1
hardly full	-0.280	0	1.28	1	2
irritating	-1.44	-2	0.870	-1	1
packed	-0.880	-1	1.20	-2	1
relaxing	1.72	2	0.737	1	1
	...	...	...	...	...

THE DATA

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	...	...	...	...	...

Smallest Euclidean distance to other evaluators

THE DATA

ADJECTIVE QUANTIFICATION SURVEY

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	...	...	...	...	...

Furthest away from central evaluator

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MODEL SPECIFICATION

Hybrid choice model

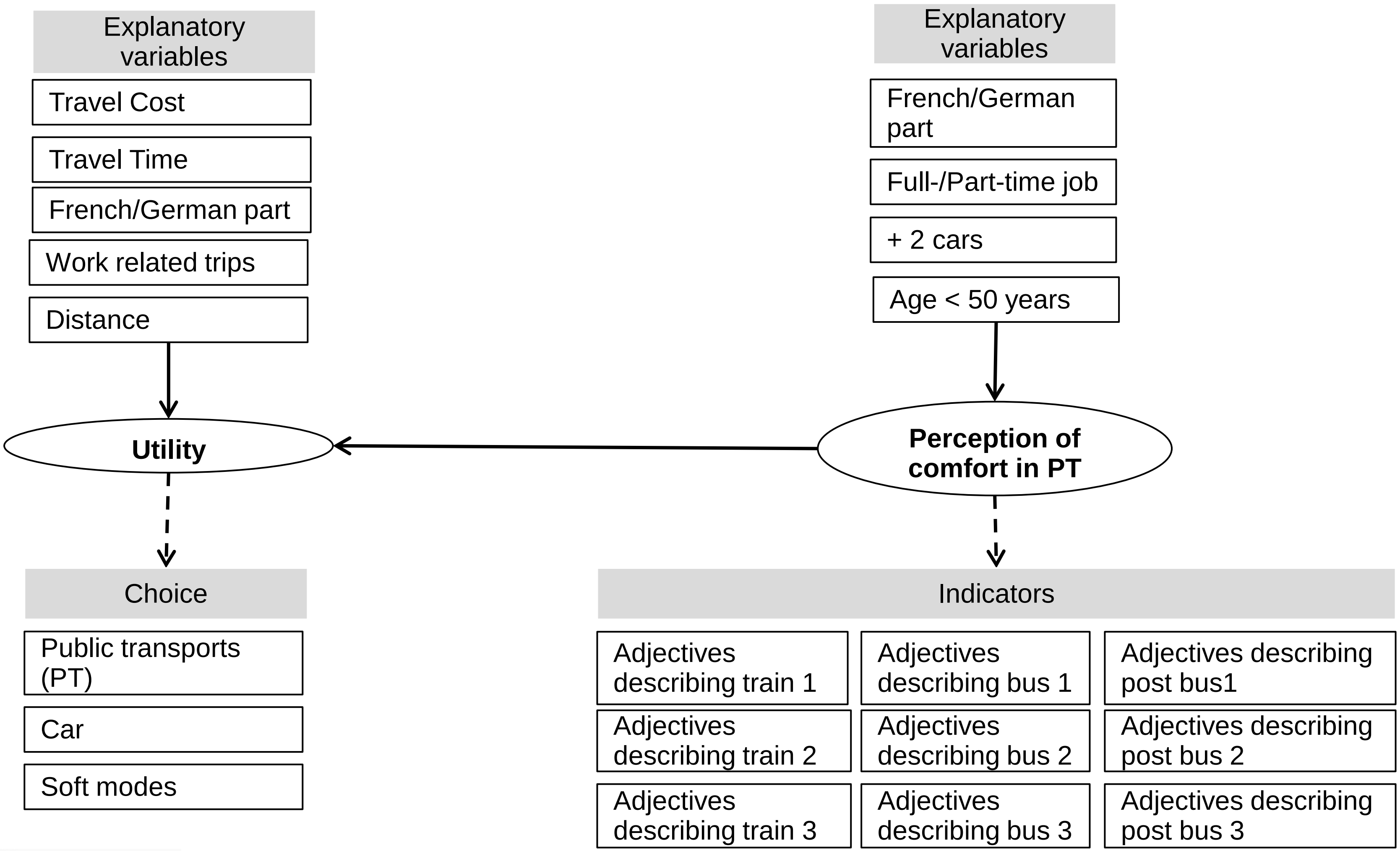

Figure based on Walker and Ben-Akiva, 2002.

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MODEL SPECIFICATION

Hybrid choice model

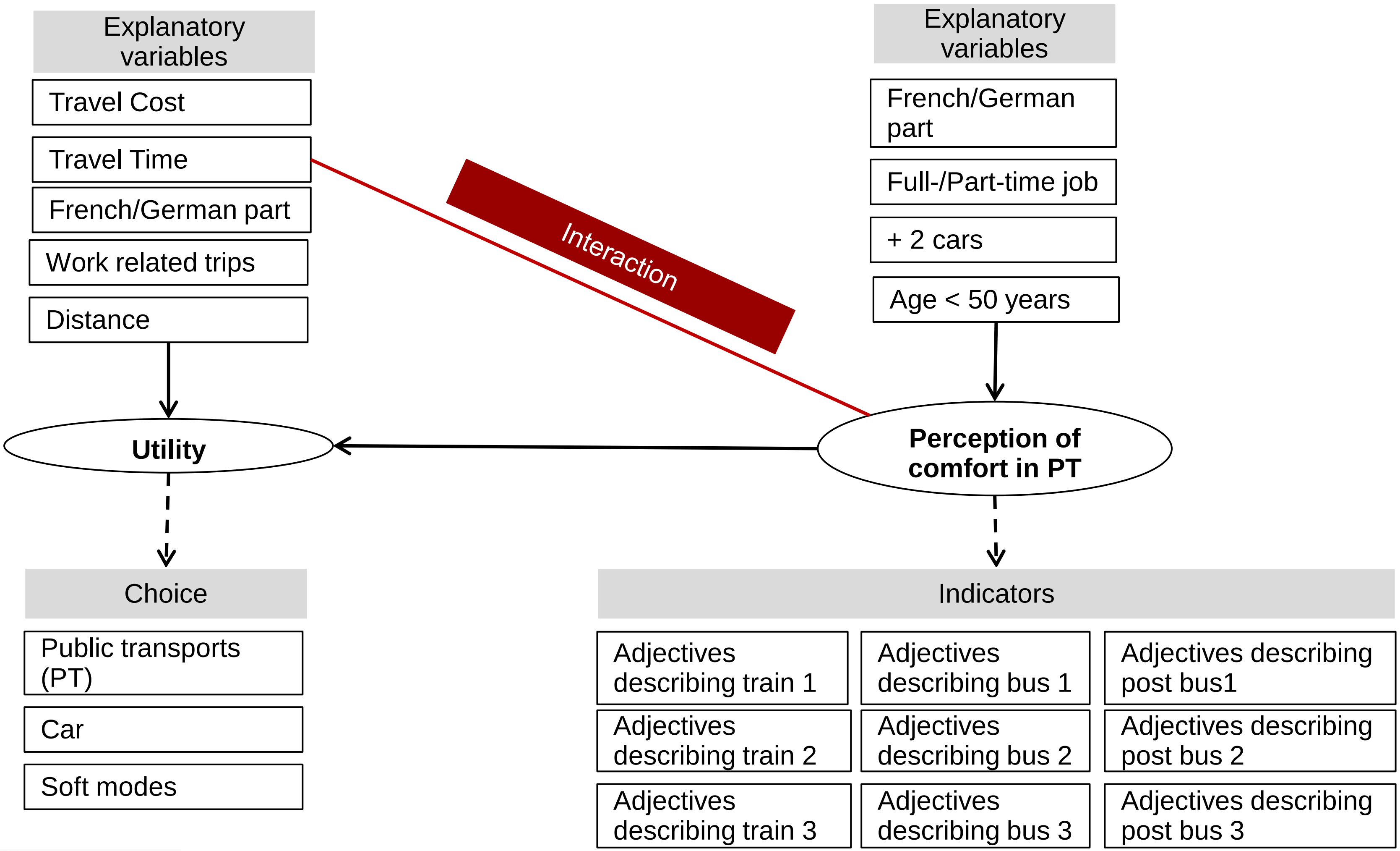

Figure based on Walker and Ben-Akiva, 2002.

ESTIMATION RESULTS

- **Model estimated for each evaluator** (→ 25 models estimated)

- **Fit indices (for the choice model):**

Indicator	Logit	Central evaluator	Outlying evaluator	Median ratings
Loglikelihood	−1153	−1192	−1199	−1190
J	14	11	11	11
$\bar{\rho}^2$	0.443	0.425	0.422	0.427

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ESTIMATION RESULTS

	Logit			Central evaluator			Outlying evaluator			Median ratings		
Name	Value	t-test		Value	t-test		Value	t-test		Value	t-test	
$\mathrm{ASC}_{\mathrm{PT}}$	-0.178	-0.88	*	-0.155	-0.77	*	-0.132	-0.66	*	-0.155	-0.77	*
$\mathrm{ASC}_{\mathrm{PMM}}$	0.423	2.30		0.416	2.26		0.410	2.22		0.419	2.27	
β_{cost}	-0.0658	-8.67		-0.0637	-8.11		-0.0628	-8.02		-0.0653	-8.08	
β_{timePT}	-0.00600	-3.34		-0.0143	-7.71		-0.0293	-4.17		-0.0208	-7.06	
β_{timePMM}	-0.0330	-10.27		-0.0313	-9.53		-0.0312	-9.55		-0.0323	-9.43	
$\beta_{\mathrm{distance}}$	-0.236	-11.51		-0.233	-11.4		-0.233	-11.38		-0.235	-11.45	
β_{workPT}	0.0987	0.42	*	-0.0602	-0.26	*	-0.0928	-0.40	*	-0.0474	-0.20	*
β_{workPMM}	-0.613	-2.77		-0.572	-2.58		-0.560	-2.53		-0.575	-2.60	
$\beta_{\mathrm{FrenchPT}}$	-0.228	-0.61	*	-0.073	-0.24	*	-0.113	-0.37	*	-0.0808	-0.26	*
$\beta_{\mathrm{FrenchPMM}}$	0.990	3.64		0.966	3.56		0.969	3.57		0.967	3.56	
β_{comfort}	-	-		1.06	3.46		1.09	2.65		1.33	4.34	
λ_{mean}	-	-		3.33	9.40		15.7	11.46		7.47	9.98	
$\lambda_{\mathrm{French}}$	1.11	0.44	*	-0.559	-1.80		-0.139	-0.48	*	-0.456	-1.58	*
λ_{age50}	1.42	1.25	*	-1.30	-5.53		0.0643	0.30	*	-1.04	-4.62	
$\lambda_{\mathrm{active}}$	-8.34	-6.77		-1.10	-4.37		-0.582	-2.68		-1.12	-4.62	
λ_{cars}	-7.81	-6.59		-0.730	-3.06		-0.362	-1.58	*	-0.688	-3.04	

$\beta_{comfort} > 0$: A high perception of comfort of PT increases its utility.

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ESTIMATION RESULTS

	Logit			Central evaluator			Outlying evaluator			Median ratings		
Name	Value	t-test		Value	t-test		Value	t-test		Value	t-test	
ASC_{PT}	-0.178	-0.88	*	-0.155	-0.77	*	-0.132	-0.66	*	-0.155	-0.77	*
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$\beta_{time_{PT}}$	-0.00600	-3.34		-0.0143	-7.71		-0.0293	-4.17		-0.0208	-7.06	
$\beta_{time_{PMM}}$	-0.0330	-10.27		-0.0313	-9.53		-0.0312	-9.55		-0.0323	-9.43	
$\beta_{distance}$	-0.236	-11.51		-0.233	-11.4		-0.233	-11.38		-0.235	-11.45	
$\beta_{work_{PT}}$	0.0987	0.42	*	-0.0602	-0.26	*	-0.0928	-0.40	*	-0.0474	-0.20	*
$\beta_{work_{PMM}}$	-0.613	-2.77		-0.572	-2.58		-0.560	-2.53		-0.575	-2.60	
$\beta_{French_{PT}}$	-0.228	-0.61	*	-0.073	-0.24	*	-0.113	-0.37	*	-0.0808	-0.26	*
$\beta_{French_{PMM}}$	0.990	3.64		0.966	3.56		0.969	3.57		0.967	3.56	
$\beta_{comfort}$	-	-		1.06	3.46		1.09	2.65		1.33	4.34	
λ_{mean}	-	-		3.33	9.40		15.7	11.46		7.47	9.98	
λ_{French}	1.11	0.44	*	-0.559	-1.80		-0.139	-0.48	*	-0.456	-1.58	*
$\lambda_{age_{50}}$	1.42	1.25	*	-1.30	-5.53		0.0643	0.30	*	-1.04	-4.62	
λ_{active}	-8.34	-6.77		-1.10	-4.37		-0.582	-2.68		-1.12	-4.62	
λ_{cars}	-7.81	-6.59		-0.730	-3.06		-0.362	-1.58	*	-0.688	-3.04	

$\beta_{comfort} > 0$ and $\beta_{time_{PT}} < 0$: Travel time sensitivity decrease with an increased perception of comfort of PT.

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VALIDATION

Estimation on 80% data / Application on 20 % data

Fit indices:

Indicator	Logit	Central evaluator	Outlying evaluator	Median ratings
Loglikelihood	-220	-227	-229	-226
J	14	11	11	11
$\bar{\rho}^2$	0.459	0.449	0.444	0.452
Percentage choice probabilities > 0.5	70.5%	69.7%	70.0%	70.5%

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- Fit similar across evaluators
- Slightly lower for outlying evaluator

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VALIDATION

Analysis of demand indicators across evaluators

Example: computation of market shares

		Example of respondents with different probabilities for the chosen alternative						All observations	
Indicator	Mode	Low		Medium		High			
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Probability of choice / Market share	PT	0.047	0.008	0.543	0.013	0.067	0.005	0.278	0.001
	PMM	0.953	0.008	0.457	0.013	0.933	0.005	0.659	0.001
	SM	0.000	0.000	0.000	0.000	0.000	0.000	0.063	0.000

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Disaggregate indicators → Probabilities to choose each mode.

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Aggregate indicators → market shares for each mode.

VALIDATION

Analysis of demand indicators across evaluators

Example: computation of market shares

		Example of respondents with different probabilities for the chosen alternative						All observations	
		Low		Medium		High			
Indicator	Mode	Mean	SD	Mean	SD	Mean	SD	Mean	SD
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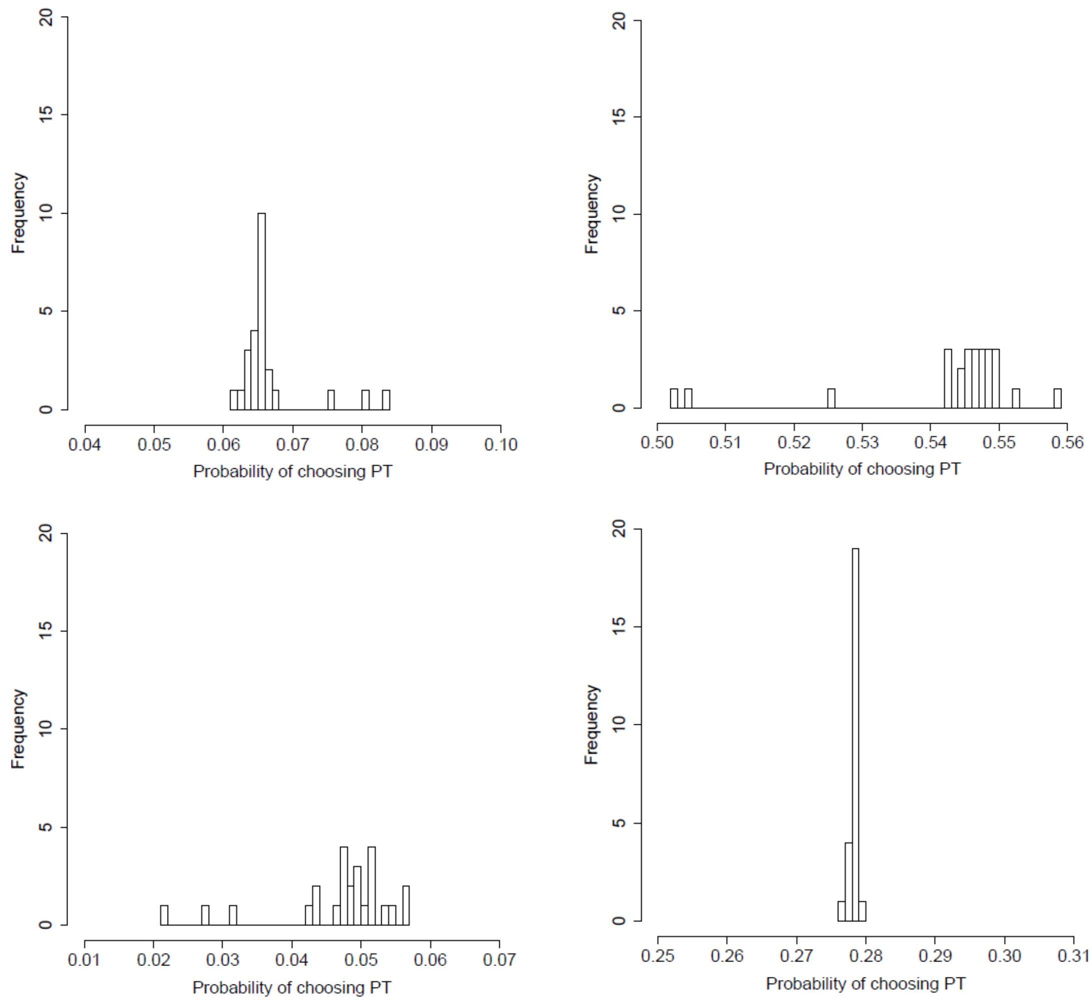
	SM	0.000	0.000	0.000	0.000	0.000	0.000	0.063	0.000

Aggregate indicators have lower standard deviations than disaggregate indicators ➔ more consistency at aggregate level.

Analysis of demand indicators across evaluators

High

Medium



Low

All observations

CONCLUSION

Conclusions:

- Adjectives: alternative way to measure perceptions
- Propose a methodology to rate adjectives in order to minimize subjectivity
- Method is robust with respect to poor evaluators

Further improvements:

- Two surveys in one step
- Comparative approach between classical opinion questions and adjectives
- Comparison between adjective rating on a discrete (-2 to 2) and continuous scale (-1000 and 1000)
- Investigate the effect of other themes (than comfort in PT)

Thank you!