ACCOUNTING FOR RESPONSE BEHAVIOR HETEROGENEITY IN THE MEASUREMENT OF ATTITUDES:

AN APPLICATION TO DEMAND FOR ELECTRIC VEHICLES

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OUTLINE

Introduction & motivation

Methodology

- HCM with discrete measurements
- Integration of dispersion effects
- Individuals with extreme answers

Application to demand for electric cars

- Case study
- Model specification
- Model estimation

Conclusion

INTRODUCTION & MOTIVATION

Recent developments in discrete choice modeling (DCM)

- Choice cannot only be explained by economic indicators (travel duration, price or a trip, etc.)
- **Attitudes & perceptions play important role in choice behavior**: need to be integrated in an appropriate way into DCMs.
- Framework providing the solution to this issue: **hybrid choice models (HCM)** (Walker, 2001; Ben-Akiva et al., 2002)

INTRODUCTION & MOTIVATION

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

Allows to capture attitudes et perceptions

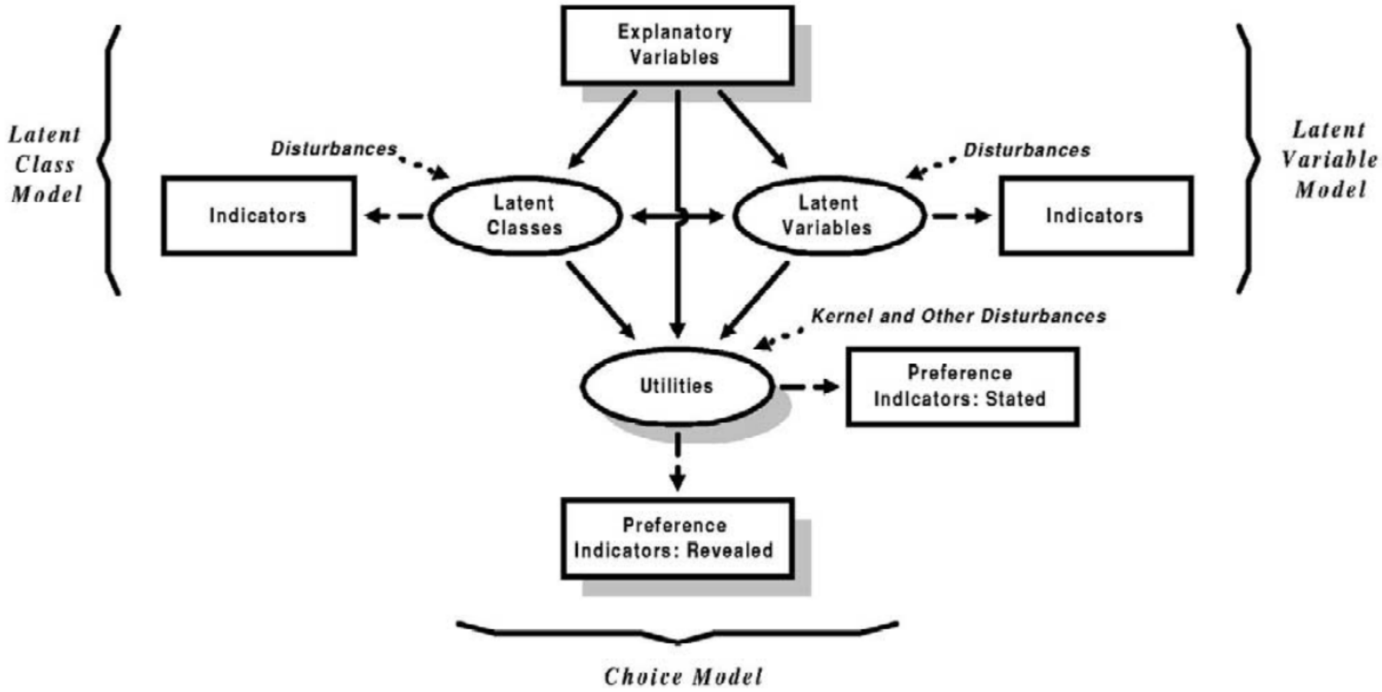

Figure extracted from Walker and Ben-Akiva, 2002.

INTRODUCTION & MOTIVATION

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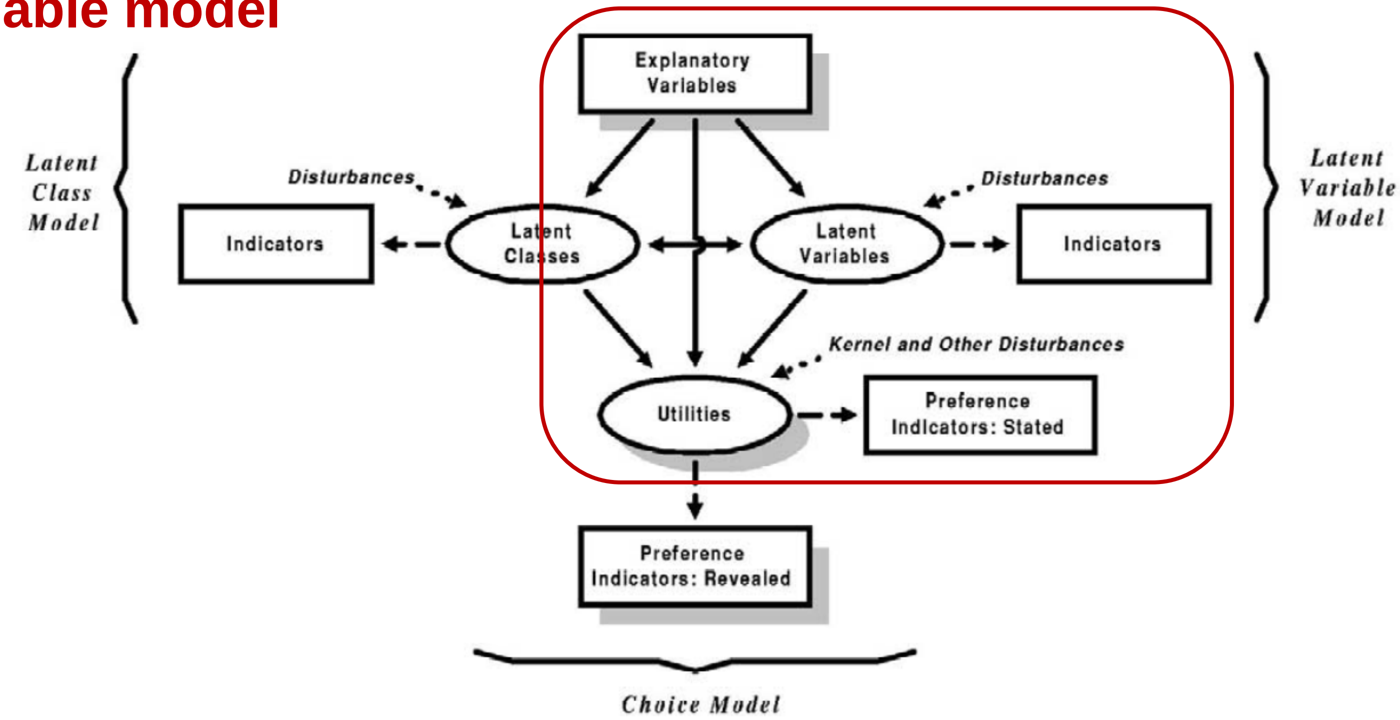
In this research: focus on the **integration of choice model and latent variable model**



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INTRODUCTION & MOTIVATION

Several issues linked to the integration of latent variables into choice models:

- Measurement of latent variable

- Integration of the measurement into the choice model

INTRODUCTION & MOTIVATION

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  - Use of **psychometric indicators**
  - **Five-point Likert scale**

Usual way in literature

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  - **Discrete versus continuous** measurements

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Focus of this presentation

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INTRODUCTION & MOTIVATION

Motivation for integration of dispersion effects:

- Exaggeration effects in experiments on survey design in social science literature (Schuman and Presser, 1996)
- Some individuals tend to report responses at extremities of scale of agreement though their commitment to the opinion statement is not strong.
- Need to account for **heterogeneity of response behavior**

METHODOLOGY

Hybrid choice model with discrete indicators

Structural equations:

Choice model:

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

Latent variable model:

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

Measurement equations:

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

$$\upsilon_n \sim Logistic(0, \sigma_{\upsilon_n})$$

$$I_n = \begin{cases} 1 \text{ if } -\infty < I_n^* \leq \tau_1 \\ 2 \text{ if } \tau_1 < I_n^* \leq \tau_2 \\ 3 \text{ if } \tau_2 < I_n^* \leq \tau_3 \\ 4 \text{ if } \tau_3 < I_n^* \leq \tau_4 \\ 5 \text{ if } \tau_4 < I_n^* \leq +\infty \end{cases}$$

METHODOLOGY

INTEGRATION OF DISPERSION EFFECTS

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Individual-specific scale

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METHODOLOGY

Steps:

1. Identify **individuals with extreme answers**, systematically stating:
   - Total disagreement (coded as 1)
   - Total agreement (coded as 5)

2. Specify scale σ_{υ_n} which depends on **response behavior** of subject *n*

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METHODOLOGY

INDIVIDUALS WITH EXTREME ANSWERS

Definition of index:

- Definition of *degree of extremity*

$$E_n = \sum_{r=1}^{R} J_{rn} \quad \text{with} \quad J_{rn} = \begin{cases} 1 & \text{if } I_{rn} = 1 \text{ or } I_{rn} = 5 \\ 0 & \text{otherwise} \end{cases}$$

- E_n : number of occurrences of ‘total disagreement’ and ‘total agreement’ for individual *n* over all *R* opinion questions of the survey

METHODOLOGY

Definition of scale parameter:

- Measurement model:

$$I_n^* = m(X_n^*;\alpha) + \upsilon_n$$
$$\upsilon_n \sim Logistic(0, \sigma_{\upsilon_n})$$

- Scale that captures heterogeneity in response behavior:

$$\begin{aligned}\sigma_{\nu_n} &= I_{E_n<\theta} \cdot 1 + (1 - I_{E_n<\theta}) \cdot \sigma_{\nu_{Ext}}(E_n) \\ &= I_{E_n<\theta} \cdot 1 + (1 - I_{E_n<\theta}) \cdot E_n \cdot \gamma\end{aligned}$$

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Define **threshold θ** above which individuals show extreme behavior

METHODOLOGY

INDIVIDUALS WITH EXTREME ANSWERS

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Group-specific scale

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METHODOLOGY

INDIVIDUALS WITH EXTREME ANSWERS

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Progressive scale:

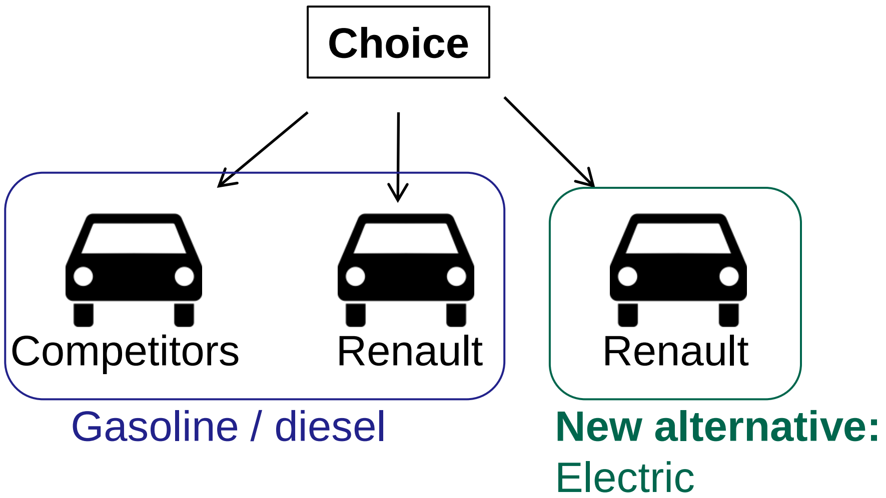
- The higher the degree of extremity, the higher the scale.
- **γ** parameter to estimate

APPLICATION TO DEMAND FOR ELECTRIC CARS

Models developed based on case study:

Stated preference survey to analyze **vehicle choice**

- Customized choice situations



- Collection of psychometric data

APPLICATION TO DEMAND FOR ELECTRIC CARS

Opinions on themes related to electric vehicles

- Environmental concern
  - *An electric car is a 100% ecological solution.*
- Attitude towards new technologies
  - *A control screen is essential in my use of a car.*
- Perception of the reliability of an electric vehicle
  - *Electric cars are not as secure as gasoline cars.*
- Perception of leasing
  - *Leasing is an optimal contract which allows me to change car frequently.*
- Attitude towards design
  - *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)

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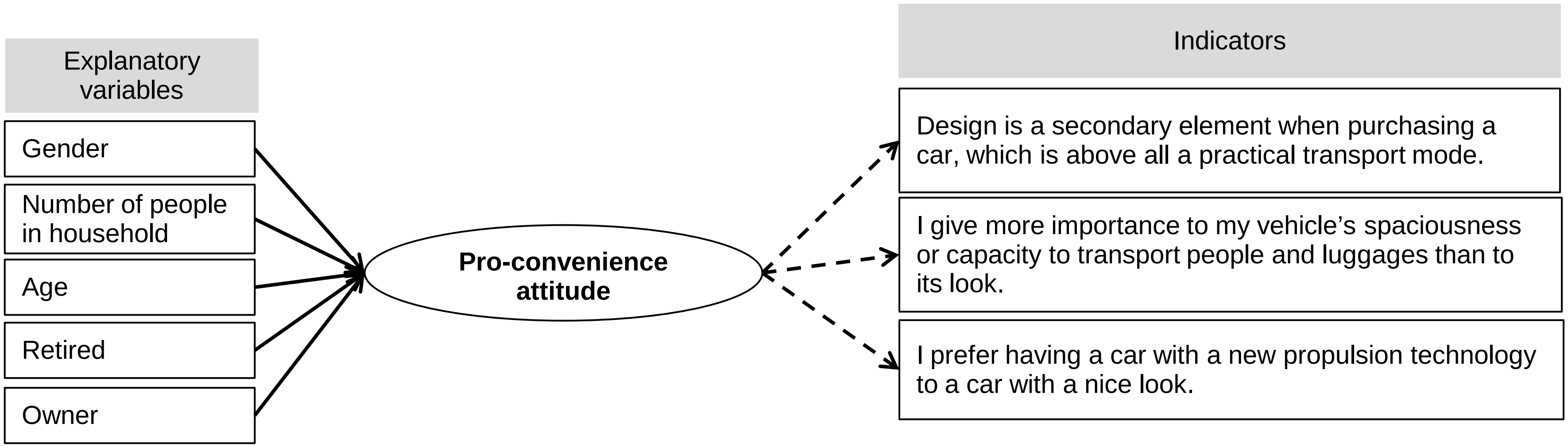
Latent variable model:



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Structural model

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Measurement model

APPLICATION TO DEMAND FOR ELECTRIC CARS

Latent variable model:

Explanatory variables

- Gender
- Number of people in household
- Age
- Retired
- Owner

Pro-convenience attitude

Indicators

- Design is a secondary element when purchasing a car, which is above all a practical transport mode.
- I give more importance to my vehicle's spaciousness or capacity to transport people and luggages than to its look.
- I prefer having a car with a new propulsion technology to a car with a nice look.

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Issue: how to select θ ?

APPLICATION TO DEMAND FOR ELECTRIC CARS

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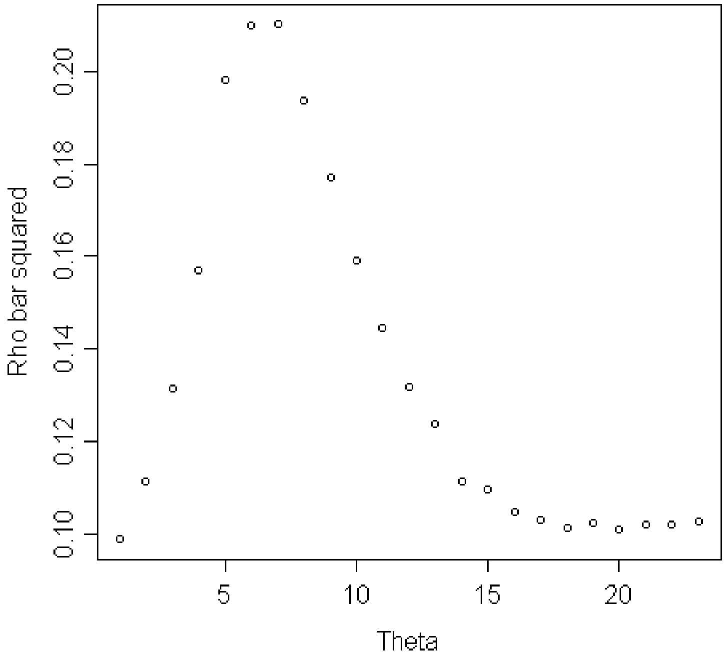
- Estimation of latent variable models for all thresholds between 1 and 25
- Computation of $\overline{\rho}^2 = 1 - \frac{L(\hat{\mu}) - Q}{L(0)}$
- $\overline{\rho}^2$ highest for θ = 7
- Latent variable model with θ = 7 selected to be integrated into HCM



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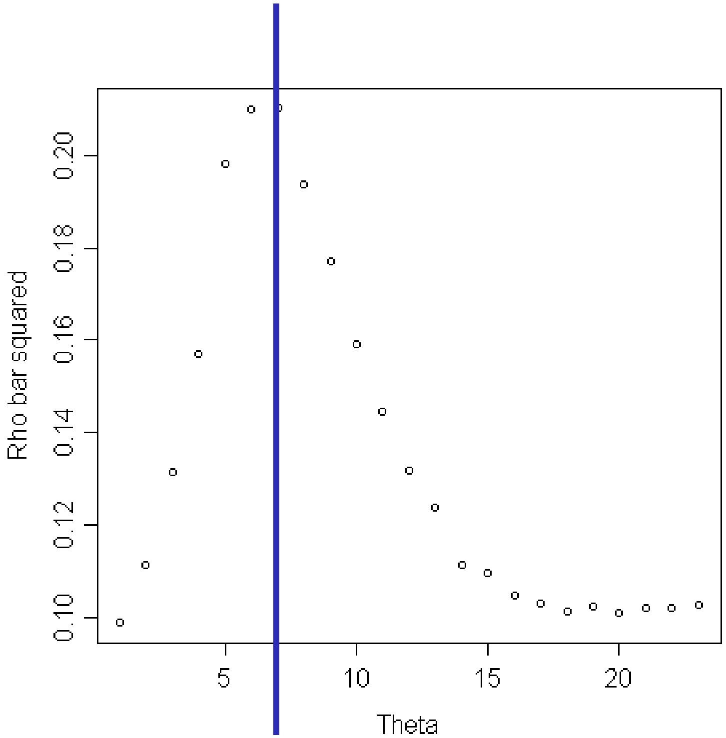

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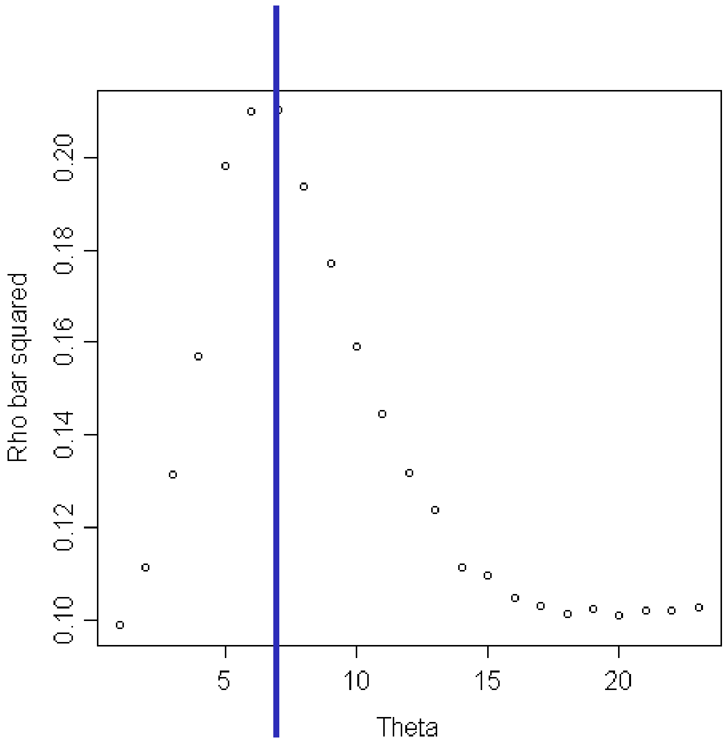

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MODEL SPECIFICATION

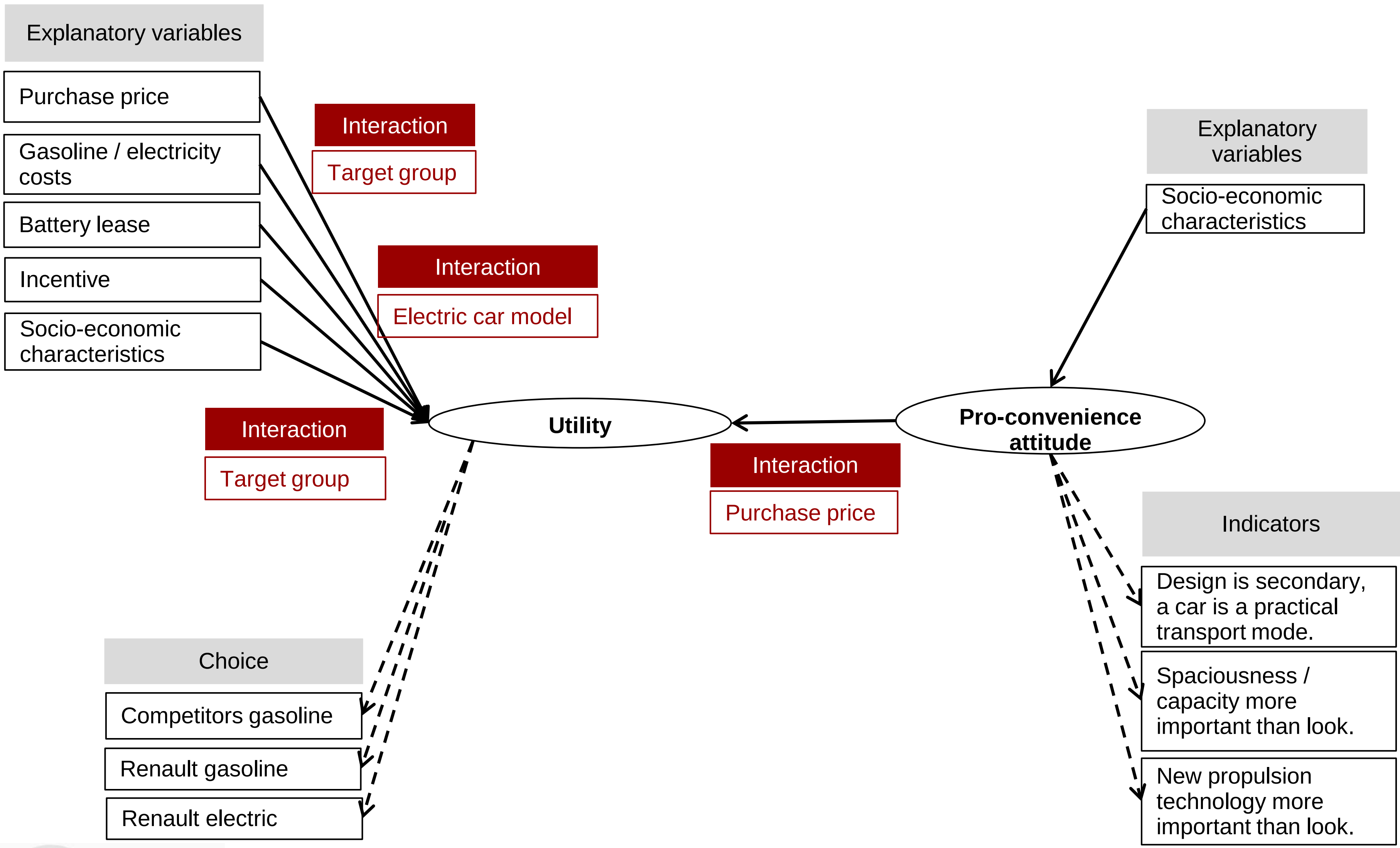

Figure based on Walker and Ben-Akiva, 2002.

Estimation of the model

- Simultaneous estimation
- Extended version of Biogeme (Bierlaire and Fetiarison, 2009)

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MODEL ESTIMATION

Results from the latent variable model

Structural equation			*Measurement equation*		
Name	Value	*t*-test	Name	Value	*t*-test
β_{Mean}	-6.03	-17.32	τ_1	-9.23	-33.72
β_{Male}	-0.256	-1.54**	γ	0.203	29.62
β_{NbPeople}	0.362	5.46	δ_1	4.76	32.36
β_{Age}	0.0166	5.55	δ_2	2.15	40.76
β_{Retired}	1.40	5.31	δ_3	3.45	41.46
$\beta_{\text{Homeowner}}$	0.673	4.31	α_2	0.552	31.53
σ_ω	3.21	28.04	α_3	0.574	22.61

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✓ since $\sigma_{\upsilon_n} = 7 \cdot \gamma = 1.42$

APPLICATION TO DEMAND FOR ELECTRIC CARS

MODEL ESTIMATION

Results from the choice model

Name	Value	t-test
Parameters in linear terms		
ASC_{CG}	-2.54	-4.23
ASC_{RG}	-1.78	-2.98
$\beta_{\text{UseCostGasoline}}$	-0.0706	-2.10
$\beta_{\text{UseCostElecHigh}_{\text{Fluence}}}$	-0.282	-2.35
$\beta_{\text{UseCostElecHigh}_{\text{Zoé}}}$	-0.818	-5.13
$\beta_{\text{UseCostElecMed}_{\text{Zoé}}}$	-0.483	-3.11
$\beta_{\text{IncentiveHigh}}$	0.748	5.80
$\beta_{\text{IncentiveMed}}$	0.0630	0.47**
$\beta_{\text{IncentiveLow}}$	-0.0150	-0.11**
$\beta_{\text{PT}_{\text{CG,TG1245}}}$	-0.251	-1.86*
$\beta_{\text{PT}_{\text{RG,TG1245}}}$	-0.596	-4.03
$\beta_{\text{PT}_{\text{CG,TG3}}}$	-2.10	-2.88
$\beta_{\text{PT}_{\text{RG,TG3}}}$	-1.01	-4.63
$\beta_{\text{NbCars}_{\text{CG}}}$	-0.269	-3.65
$\beta_{\text{NbCars}_{\text{RG}}}$	-0.361	-5.48
$\beta_{\text{Income}_{\text{CG}}}$	-0.272	-2.33
$\beta_{\text{Income}_{\text{RG}}}$	-0.281	-2.64

Name	Value	t-test
Parameters in linear terms (ctd)		
β_{Battery}	-4.73	-1.63**
$\beta_{\text{French}_{\text{CG}}}$	0.347	2.77
$\beta_{\text{French}_{\text{RG}}}$	0.109	0.91**
$\beta_{\text{Age}_{\text{CG}}}$	0.0206	4.37
$\beta_{\text{Age}_{\text{RG}}}$	0.00487	1.09**
$\beta_{\text{TG12}_{\text{CG}}}$	1.66	4.35
$\beta_{\text{TG12}_{\text{RG}}}$	0.681	1.80*
$\beta_{\text{TG3}_{\text{CG}}}$	-0.984	-1.33**
$\beta_{\text{TG3}_{\text{RG}}}$	1.29	3.10
Parameters in non-linear terms		
$\beta_{\text{price}_{\text{CG}}}$	-4.15	-6.05
$\beta_{\text{price}_{\text{RG,TG1245}}}$	-1.97	-6.36
$\beta_{\text{price}_{\text{RG,TG3}}}$	-0.843	-3.51
$\beta_{\text{price}_{\text{RE,TG12}}}$	-1.01	-7.05
$\beta_{\text{price}_{\text{RE,TG3}}}$	-0.843	-3.51
$\beta_{\text{price}_{\text{RE,TG45}}}$	-0.766	-4.62
β_{X^*}	-0.0527	-4.81

Pro-convenience attitude significantly affects car choice.

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MODEL ESTIMATION

Improvement of fit over model without dispersion effects

Model	Q	$\mathscr{L}(0)$	$\mathscr{L}(\hat{\mu})$	$\bar{\rho}^2$
Without dispersion	46	$-16'746$	$-14'030$	0.16
With dispersion	47	$-13'687$	$-18'083$	0.24

CONCLUSION

Main findings:

- **Heterogeneity of response behavior** exists and can be captured by individual-specific scale of measurement model
- **Scale increases** as degree of extremity increases

Further research:

- **Indicator-specific scales** instead of generic scale
- **Latent class model** to characterize individuals with extreme vs moderate scales (by socio-economic characteristics)

CONCLUSION

Perspectives:

- More **importance** should be given to **measurement model of HCM**
- In particular: measurement equation should reflect **more individual-specific information**, e.g. linked to response behavior

Thanks!