DEMAND MODELS FOR TRANSPORTATION MODES
A FOCUS ON THE MEASUREMENT OF LATENT CONSTRUCTS AFFECTING DECISIONS

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KTH Royal Institute of Technology

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Introduction & motivation

Methodology

The data
- Vehicle choice case study
- Mode choice case study

Incorporation of measurements into HCM
- Vehicle choice case study (ICLV example)
- Mode choice case study (ICLC example)

Conclusion
Recent developments in demand modeling for transportation

- **Hybrid choice model (HCM) framework** (Walker, 2001; Ben-Akiva et al., 2002)
  Comprehensive framework that allows to incorporate unobservable factors as explanatory variables of choice.

- Choice of transportation mode, car, etc.
  - Influenced by economic factors:
    - Price
    - Trip duration
    - Etc.
  - Often also involve more subjective factors:
    - Attitudes
    - Perceptions
    - Lifestyles
    - Habits

- HCM framework incorporates these subjective factors.
Hybrid choice model (HCM): DCM with latent constructs.
Hybrid choice model (HCM): DCM with latent constructs. Latent construct can be… either a latent class model
- Unobservable construct is discrete
- Useful for segmentation according to lifestyle

Figure extracted from Walker and Ben-Akiva, 2002.
Hybrid choice model (HCM): DCM with latent constructs. Latent construct can be… or a latent variable model
• Unobservable construct is continuous
• Useful to analyze the impact of changes in prices across individuals → pricing

Figure extracted from Walker and Ben-Akiva, 2002.
Important issues in the use of HCMs:

1. **Measurement of latent variable / latent class**

   How to obtain the most realistic and accurate measure of an attitude / perception / lifestyle?

   **Opinion statements:** usual way in the literature

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

   How to incorporate this information in the choice modeling framework?
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1. **Measurement of latent variable / latent class**
   
   How to obtain the most realistic and accurate measure of an attitude / perception / lifestyle?
   
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2. **Integration of the measurement into the choice model**
   
   How to incorporate this information in the choice modeling framework?
   
   **Focus of this research:** measurement model
Integration of the measurement into the choice model
Integration of the measurement into the choice model:

- **Structural equation model (SEM)** framework used to characterize latent construct and relate it to its measurement indicators
  (e.g. Bollen, 1989; Hancock and Mueller, 2006; Bartholomew et al., 2011).
Integration of the measurement into the choice model

- In transportation applications:
  - Heterogeneity of latent construct (e.g. attitude) captured among population
  - But: also need to capture heterogeneity in reporting indicators of latent construct
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Focus of this presentation
Model specification

Likelihood function given by: \[ L = \prod_{n=1}^{N} f(y_{in}, I_n | X_{in}; \alpha, \beta, \lambda, \sigma_\omega) \] with

**Integrated choice and latent variable model**

\[ f(y_{in}, I_n | X_{in}; \alpha, \beta, \lambda, \sigma_\omega) = \int_{X_n^*} P(y_{in} | X_{in}, X_n^*; \beta)^{y_{in}} \cdot f(I_n | X_{in}, X_n^*; \alpha) \cdot f(X_n^* | X_n; \lambda, \sigma_\omega) dX_n^* \]

\[ y_{in} = \begin{cases} 1 & \text{if } U_{in} = \max_j U_{jn} \\ 0 & \text{otherwise} \end{cases} \]  

**Integrated choice and latent class model**

\[ P(y_{in}, I_n | X_{in}; \alpha, \beta, \lambda, \sigma_\omega) = \left\{ \sum_{s \in S} P(y_{in} | X_{in}, s; \beta) \cdot P(I_n | X_{in}, s; \alpha) \cdot P(s | X_n; \lambda, \sigma_\omega) \right\}^{y_{in}} \]
METHODOLOGY

Model specification

Likelihood function given by: \[ L = \prod_{n=1}^{N} f(y_{in}, I_n \mid X_{in}; \alpha, \beta, \lambda, \sigma_\omega) \quad \text{with} \]

\[ f(y_{in}, I_n \mid X_{in}; \alpha, \beta, \lambda, \sigma_\omega) = \int_{X^*_n} P(y_{in} \mid X_{in}, X^*_n; \beta)^{y_{in}} \cdot f(I_n \mid X_{in}, X^*_n; \alpha) \cdot f(X^*_n \mid X_n; \lambda, \sigma_\omega) dX^*_n \]

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Few examples that incorporate socio-economic information into the measurement model
Two case studies:

1. **Integrated choice and latent variable model (ICLV):** analysis of the impact of pro-convenience attitude on choice of car.

   **Car purchase choice case study**

2. **Integrated choice and latent class model (ICLC):** analysis of the transportation mode choices for individuals segmented according to dependent / independent classes.

   **Mode choice case study**
Stated preferences (SP) survey:

- Car purchase choice study

- Conducted in Switzerland in 2011 among individuals who bought a new car recently or intend to buy one soon.

- Conducted with Renault Suisse SA.

- Customized choice situations

- **693 questionnaires** obtained
Opinion statements related to five themes

- 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)
Revealed preferences (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
Opinion statements related to four themes

- **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.

**Ratings**

- Total disagreement (1)
- Disagreement (2)
- Neutral opinion (3)
- Agreement (4)
- Total agreement (5)
- I don’t know (6)
Role of indicators of latent construct:
• Measure a latent variable
• Enhance a latent class model

Issue: biases in the measurement of indicators due to heterogeneity of response behavior

By introducing socio-economic information into the measurement component of the HCM, the bias is reduced.

Two examples:
• Car choice case study (ICLM): capture exaggeration effects in responses to indicators.
• Transportation mode choice case study (ICLC): capture bias in responses to indicators due to various socio-economic characteristics.
Motivation for integration of explanatory factors of measurement indicators:

- **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.

- **Socio-economic characteristics** might explain different response behaviors

  → Need to account for heterogeneity of response behavior
1. Integrated choice and latent variable model (ICLV): analysis of the impact of pro-convenience attitude on choice of car.

Vehicle choice case study

Choice

Competitors
Renault

Gasoline / diesel

Renault

New alternative:
Electric
INCORPORATION OF MEASUREMENTS INTO HCM

VEHICLE CHOICE CASE STUDY (ICLV EXAMPLE)

Discrete choice model

Explanatory variables
- Purchase price
- Gasoline / electricity costs
- Battery lease
- Incentive
- Electric car model
- Socio-economic characteristics

Utility

Choice
- Competitors gasoline, Renault gasoline, Renault electric

Latent variable model

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

Pro-convenience attitude

Indicators
- Design is secondary, a car is a practical transport mode.
- Spaciousness / capacity more important than look.
- New propulsion technology more important than look.

Explanatory variables
- Exaggeration effects
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
Definition of scale parameter:

- Measurement model:
  \[ I^*_n = m(X^*_n; \alpha) + \nu_n \]
  \[ \nu_n \sim \text{Logistic}(0, \sigma_{\nu_n}) \]

- Scale that captures heterogeneity in response behavior:
  \[ \sigma_{\nu_n} = I_{E_n<\theta} \cdot 1 + (1 - I_{E_n<\theta}) \cdot \sigma_{\nu_{\text{Ext}}}(E_n) \]
  \[ = I_{E_n<\theta} \cdot 1 + (1 - I_{E_n<\theta}) \cdot E_n \cdot \gamma \]
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Define **threshold** \( \theta \) above which individuals show extreme behavior.
Statistical analyses show that highest fit for \( \theta = 7 \).
Definition of scale parameter:

- Measurement model:
  \[ I_n^* = m(X_n^*; \alpha) + \nu_n \]
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Group-specific scale
Definition of scale parameter:

- **Measurement model:**
  \[ I_n^* = m(X_n^*; \alpha) + \nu_n \]
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- **Scale that captures heterogeneity in response behavior:**
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  \[ = I_{E_n < \theta} \cdot 1 + (1 - I_{E_n < \theta}) \cdot E_n \cdot \gamma \]

**Progressive scale:**
- The higher the degree of extremity, the higher the scale.
- \( \gamma \) parameter to estimate
Results for the latent variable model

<table>
<thead>
<tr>
<th>Structural equation</th>
<th>Measurement equation</th>
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</tr>
<tr>
<td>$\sigma_\omega$</td>
<td>3.21</td>
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Simultaneous estimation of the HCM using the extended version of Biogeme (Bierlaire and Fetiarison, 2009)
## Results from the latent variable model

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$$\sigma_{\nu_n} = I_{E_n<\theta} \cdot 1 + (1 - I_{E_n<\theta}) \cdot E_n \cdot \gamma$$
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\[ \sigma_{v_n} = I_{E_n<\theta} \cdot 1 + (1 - I_{E_n<\theta}) \cdot E_n \cdot \gamma \]

We observe dispersion effects, since for the ‘extreme’ group we have:

\[ \sigma_{v_n} = 7 \cdot \gamma = 1.42 \]
Results from the choice model

<table>
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<th>Parameters in linear terms</th>
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Pro-convenience attitude significantly affects car choice.
Improvement of fit over model without dispersion effects

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<th>Model</th>
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<td>-13'687</td>
<td>-18'083</td>
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2. Integrated choice and latent class model (ICLC): analysis of the transportation mode choices for individuals segmented according to dependent / independent classes.

Mode choice case study
INCORPORATION OF MEASUREMENTS INTO HCM

MODE CHOICE CASE STUDY (ICLC EXAMPLE)

Class-specific choice model

Explanatory variables
- Travel cost
- Travel time
- Distance
- Trip purpose
- Student
- Number of children
- Number of cars
- Number of bikes
- French part vs German part
- Urban vs rural

Utility

Choice
- Private motorized modes (PMM), Public transportation (PT), Soft modes (SM)

Latent class model

Latent classes
- Independent
- Dependent

Indicators
- Hard to take PT when I travel with my children.
- With my car, I can go where I want when I want.
- I would like to spend more time with my family and friends.

Explanatory variables
- High income
- Family
- Single
- Children
- Number of cars
- Full time job
- Couples + children
- Couples - children
- Single parents
Class-specific measurement equations:

\[ \tilde{I}^s_{k,n} = m(X_n; \lambda^s) + \xi^s_{k,n} \quad \text{with} \quad \xi^s_{k,n} \sim \text{Logistic}(0, 1) \]

\[ I^s_{k,n} = \begin{cases} 
1 & \text{if } -\infty < \tilde{I}^s_{k,n} \leq \tau^s_{1,k} \\
2 & \text{if } \tau^s_{1,k} < \tilde{I}^s_{k,n} \leq \tau^s_{2,k} \\
3 & \text{if } \tau^s_{2,k} < \tilde{I}^s_{k,n} \leq \tau^s_{3,k} \\
4 & \text{if } \tau^s_{3,k} < \tilde{I}^s_{k,n} \leq \tau^s_{4,k} \\
5 & \text{if } \tau^s_{4,k} < \tilde{I}^s_{k,n} \leq +\infty 
\end{cases} \]
Class-specific measurement equations:

Class-specific parameters

\[
\tilde{I}_{k,n}^s = m(X_n; \lambda^s) + \xi_{k,n}^s \text{ with } \xi_{k,n}^s \sim \text{Logistic}(0, 1)
\]

\[
I_{k,n}^s = \begin{cases} 
1 & \text{if } -\infty < \tilde{I}_{k,n}^s \leq \tau_{1,k}^s \\
2 & \text{if } \tau_{1,k}^s < \tilde{I}_{k,n}^s \leq \tau_{2,k}^s \\
3 & \text{if } \tau_{2,k}^s < \tilde{I}_{k,n}^s \leq \tau_{3,k}^s \\
4 & \text{if } \tau_{3,k}^s < \tilde{I}_{k,n}^s \leq \tau_{4,k}^s \\
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\end{cases}
\]
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\end{cases} \]

Socio-economic information as explanatory variables of response to indicators
Estimation results for ICLC

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<th>Parameters</th>
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<th>Atasoy et al., 2012</th>
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<td>-0.86**</td>
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<td>0.51**</td>
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- Increase of the significance of the parameters of the latent class model.
Estimation results for LCCM

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- Increase of the significance of the parameters of the latent class model.
- **Income** parameter has become more important.
Model application: computation of VOT

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<td>Overall</td>
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</table>

- VOTs comparable with literature on transport economics (Jara-Diaz, 2007), where VOT can be compared to wage rate.
- Individuals in the independent class have higher incomes (> 8000 CHF), hence a higher value of time.
Main findings:

- **Heterogeneity of response behavior** exists and can be captured by individual-specific information in measurement model.

- **Evidence for the importance of accounting for it:**
  
  - **ICLV model of car choice:**
    - Significant scale parameter
    - Increases as degree of extremity increases

  - **ICLC model of mode choice:**
    - Socio-economic characteristics affect response to opinion questions significantly
    - Parameters of the class membership utility increase in significance
    - VOT are comparable with existing studies
Thanks!