Representation of heterogeneity and consumer behavior in the transport sector

Stylized or Explicit?

O. Y. Edelenbosch, D. McCollum
Non cost barriers in consumer choice

- Adoption of new vehicle technologies rely on consumer purchases
- Energy efficiency research shows that consumers do not purchase energy-efficient technologies based solely on a cost-effectiveness criterion (Mundaca et al. 2010)
- And that choices are heterogeneous as considerations are different for consumers

→ Non Cost Barriers for different types of consumers are captured in the MA³T disutility dataset
Key question

- Most Integrated Assessment Models (IAMs) represent investment decisions in technology as done by a homogeneous and ‘unboundedly rational’ end user.
- How to represent in our models influences on vehicle choices beyond costs and prices.
  - Can we use a simple model to represent this complex issue? (given scope of IAMs, data quality)
Outline Research

1. Implement non monetary factors (disutility costs) disaggregated over consumer 27 groups implemented in IMAGE

Does adding the consumer groups lead to more heterogeneity?

2. Parameterize the multinominal equation in IMAGE vehicle choice model

Can this heterogeneity be approximated or parameterized in a simpler, more stylized way?
**IMAGE transport**

- Transport activity is related to **population, income, mode costs, speed**
- Techno-economic parameter for each technology are **exogenously assumed**.
- **Technologies compete** with each other based cost per passenger km
- Technologies modelled are **ICE, HEV, PHEV, Fuel Cell, EV**

**Focus Research:**
- Vehicle choice in passenger road transport (cars)
Vehicle choice model

Energy cost
- Efficiency
- Energy price
- Energy use correction
- NPV

Technology cost
- Non energy cost
- Subsidy
- Load correction

Cost per pkm

λ = high \rightarrow full optimisation
λ = 0 \rightarrow indifferent
λ = low \rightarrow heterogeneity

\begin{equation}
Share_{i,t} = \frac{\exp(\lambda \times \text{Cost}_{i,t})}{\sum_i \exp(\lambda \times \text{Cost}_{i,t})}
\end{equation}
Scenario results US - baseline

27 consumers

Without disutility cost

With disutility cost
Scenario results US - mitigation

27 consumers

Without disutility cost

With disutility cost

Slower phase out of oil
More cars on biofuel
More heterogeneity
Parameterizing the MNL

27 groups

1 group
\( \lambda = 100 \)
Parameterizing the MNL

27 groups

1 group
\( \lambda = 50 \)
Parameterizing the MNL

27 groups

Decreasing $\lambda$ leads to more heterogeneity in choices but does not reflect the spread in attitude towards a technology

1 group
$\lambda = 10$
Vehicle choice model in IMAGE

\[ Share_{i,t} = \frac{\exp(\lambda_i \times Cost_{i,t})}{\sum_i \exp(\lambda_i \times Cost_{i,t})} \]
Differentiating in the 27 groups

Resembles 27 groups better than original
Conclusions and ways forward:

• Logit parameterization can reflect explicit representation of heterogeneity.

→ Results improve when $\lambda$ is technology specific

• Current disutility cost are static which is a barrier for vehicle transition

→ Endogenise disutility cost assumptions on refuelling stations, model availability
  • Subsidies for early adopters
Thanks for your attention.
Questions?
MA³T Model disutility costs

Lin, 2009. Oakland Ridge National Laboratory

- Limited EV Range “anxiety”
- Refueling Station Availability
- Model Availability
- New Technology Risk Premium

So, this data set only includes additional barriers for electric vehicles

Cost per km driven (USD ¢ / km)

- Non cost barrier
- Fuel cost
- Vehicle cost

Internal Combustion Engine (ICE)
Fuel Cell Vehicle (FCV)
Electric Vehicle (EV)

Late technology adopter
Early technology adopter
27 Consumer groups

- **Light-Duty Vehicle Consumers/Drivers**
  - Early Adopter
    - Urban
    - Suburban
    - Rural
    - Frequent Driver
    - Average Driver
    - Modest Driver
  - Early Majority
    - Urban
    - Suburban
    - Rural
  - Late Majority
    - Urban
    - Suburban
    - Rural

<= structure repeated =>
Differentiating in the 27 groups
Differentiating in the 27 groups
Differentiating in the 27 groups
Differentiating in the 27 groups
Differentiating in the 27 groups

Does not resemble 27 groups better than original
## Comparison model results

<table>
<thead>
<tr>
<th></th>
<th>Mitigation No disutility cost</th>
<th>Mitigation Disutility cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electric car deployment</td>
<td>2020-2045</td>
<td>2040-2050</td>
</tr>
<tr>
<td>Phase out of fossil ICE</td>
<td>30 – 40 yr</td>
<td>60 – 80 yr</td>
</tr>
<tr>
<td>Max % ICE Bio deployment</td>
<td>0 - 8.5 %</td>
<td>57 – 81 %</td>
</tr>
<tr>
<td>Cumulative CO$_2$ emissions</td>
<td>14 - 15 GtC</td>
<td>17 - 21 GtC</td>
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<tr>
<td>(1990-2100)</td>
<td></td>
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