A latent variable exponential family modeling approach to estimate suppressed demand effects for increasing car travel costs

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A latent variable exponential family modeling approach to estimate suppressed demand effects for increasing car travel costs

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IVT
ETH Zurich

6th hEART Symposium
Haifa, September 14, 2017
Post-Car World: A multi-stage travel survey

- Motivation: Understanding travel behavior in a hypothetical world where privately owned cars are substituted by various forms of shared mobility
- Investigation of pricing mechanisms as a driving force to achieve behavioral reactions
  → Main focus: Transition towards (and not actual state of) such a (Pre-)Post-Car World
- One week travel diary and mobility tool data (stage I) as empirical basis for behavioral experiments (stage II & III)
  - Data collection: Canton of Zurich, 2015 - 2016
  - Average response rate: 55%, N = 220 households
Adaptations in daily scheduling

- How would respondents change their daily travel in the **short-run**, given the increase in travel costs?
- Personalized stated adaptation interviews with mode-specific total RP travel cost $R_{tc,n}$

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<td>$R_{tc,n} \cdot 4 + 1.4$</td>
<td>$R_{tc,n} \cdot 8 + 2$</td>
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<td>$R_{tc,n} \cdot 2$</td>
<td>$R_{tc,n} \cdot 4$</td>
<td>$R_{tc,n} \cdot 8$</td>
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</table>

- Experimental framing:
  - Road tolls, fuel and congestion taxes
  - Future policy developments to reduce MIV usage
  - Promotion of shared mobility (PT, CS, CP)
Adaptations in daily scheduling

Durchschnittlicher OEV-Takt: 3 min.
Zeit zum nächsten Carsharing Fahrzeug: 3 min
Zeit zum nächsten Carpooling Fahrzeug: 3 min

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<th>Arbeit/Ausbildung</th>
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**Summe Reisekosten (in CHF):** 79.04
Adaptations in daily scheduling

Focus of today:
- Suppressed demand effects for MIV (car driver, car passenger, motorbike) usage: What is the effect on daily mileage driven, given the increase in travel costs?
- "Aggregate" response function (given low sample size) using highly disaggregate data (activity-based perspective)
- Assumption: Cost minimizing behavior, given underlying (unobserved) preferences for daily plan
- "Two-step approach" for modeling (unobserved) heterogeneity
Environmental sensitivity / car loving traits ... 

envi1: Higher fuel prices should subsidize public transport  
envi2: Daily life without car is impossible  
envi3: Car driving is bad for the environment  
envi4: I could imagine to give up car usage completely  
envi5: Zurich without cars is inconceivable  
envi6: Environmental problems get too much attention  
envi7: The never-ending discussions about the greenhouse effect is exaggerated  
envi8: Fuel prices should increase to reduce pollution of the environment
... and socio-demographic characteristics
Data

- N = 162 respondents, 810 initial choice scenarios
- Dependent variable: Distance traveled by MIV $y_{n,t} \equiv km_{n,t}$ after adaptation in current scenario
  - Highly right-skewed data with some zeros (respondents might choose not to use MIV anymore)
  - Pseudo-balanced panel: After drop-out, respondents are excluded ($\rightarrow$ 735 actual choice observations)
- Main explanatory variable: Average MIV travel cost per km $x_{n,t} \equiv \log(CHF_{n,t-1})$ after adaptation in previous scenario
Adaptation patterns in distance traveled
Change in MIV travel cost
Modeling framework: GLM

- Log-linear OLS model is **inconsistent**
  - $\mathbb{E}[\log(\eta_{n,t}|X_{n,t})] \neq 0$ if CEF is exponential ($\eta_{n,t}$ is LN) and presence of heteroscedasticity (*Jensen’s inequality*)
  - Incompatible with mass point at zero
- Exponential family modeling approach using *pseudo* maximum likelihood techniques ([Gourieroux et al., 1984](#))

$$f(Y_{n,t}|X_{n,t}, z_n, \Lambda) = \exp \left( \frac{Y_{n,t} f(X_{n,t}, z_n, \Lambda) - b(f(X_{n,t}, z_n, \Lambda))}{a(\phi)} + c(\phi, Y_{n,t}) \right)$$

→ FOC score vector: GLM **consistent** as long as CEF is correctly specified ([Santos-Silva and Tenreyro, 2006](#))
- Poisson: $\mathbb{E}[Y_{n,t}|X_{n,t}, z_n] = \exp(f(X_{n,t}, z_n, \Lambda))$
- Heterosced.: $\mathbb{E}[Y_{n,t}|X_{n,t}, z_n] = \text{Var}[Y_{n,t}|X_{n,t}, z_n] = \lambda_{n,t}$
- Globally concave, simple and fast in convergence
Modeling framework: Panel structure

- Large variety in respondents’ characteristics and their daily plans (unobserved heterogeneity)
- Starting point: Poisson regression for a continuous, non-negative dependent variable with mixed effects (Hausman test: $H_0$ plausible $\rightarrow$ RE more efficient)
- Hausman et al. (1984): Equidispersion assumption further relaxed by the RE specification $\text{Var}[Y_{n,t}|X_{n,t}] = \lambda_{n,t} + \theta \lambda_{n,t}^2$
- Huber/White sandwich estimator for SEs (Arellano, 1987)
Modeling framework: Log-linear index

\[
\lambda_{1,n,t} = \epsilon_n \cdot \exp \left( \alpha + \beta_{COST} \cdot \log(CHF_{n,t-1}) \cdot \left( \frac{\text{dist}_{n,0}}{\text{dist}} \right)^{\omega_{DIST}} \right)
\]

\[
\lambda_{2,n,t} = \epsilon_n \cdot \exp \left( \alpha + \alpha_{INC} \cdot \text{inc}_n + \alpha_{ENVI} \cdot \text{envi}_n + \right.

\left( \beta_{COST} + \beta_{INC} \cdot \text{inc}_n + \beta_{ENVI} \cdot \text{envi}_n \right) \cdot \log(CHF_{n,t-1}) \cdot \left( \frac{\text{dist}_{n,0}}{\text{dist}} \right)^{\omega_{DIST}}
\]

\[
\lambda_{3,n,t} = \epsilon_n \cdot \exp \left( \alpha - \exp(\beta_{COST} + \psi_n) \cdot \log(CHF_{n,t-1}) \cdot \left( \frac{\text{dist}_{n,0}}{\text{dist}} \right)^{\omega_{DIST}} \right)
\]

\[
\lambda_{4,n,t} = \epsilon_n \cdot \exp \left( \alpha + \alpha_{INC} \cdot \text{inc}_n + \alpha_{ENVI} \cdot \text{envi}_n

- \exp(\beta_{COST} + \beta_{INC} \cdot \text{inc}_n + \beta_{ENVI} \cdot \text{envi}_n + \psi_n) \cdot

\log(CHF_{n,t-1}) \cdot \left( \frac{\text{dist}_{n,0}}{\text{dist}} \right)^{\omega_{DIST}} \right)
\]
Modeling framework: Estimation (1)

- **Analytical solution (random intercept):** Assuming that $\epsilon_n \sim \Gamma(1, \theta)$ and $y_{n,t}$ is distributed Poisson with mean $\lambda_{s,n,t} \equiv \lambda_{s,n,t}/\epsilon_n$, the likelihood of observing the sequence $Y_{n,t}$ given $X_{n,t}$ and $z_n$ of respondent $n$ is given by

$$\mathcal{L}_n(Y_{n,t}|X_{n,t}, z_n, \Lambda) = \log \Gamma \left( \frac{1}{\theta} + \sum_{t=1}^{T_n} y_{n,t} \right) - \sum_{t=1}^{T_n} \log \Gamma \left( 1 + y_{n,t} \right) - \log \Gamma \left( \frac{1}{\theta} \right) + \frac{1}{\theta} \cdot \log(u_n) + \log(1 - u_n) \sum_{t=1}^{T_n} y_{n,t} +$$

$$\sum_{t=1}^{T_n} y_{n,t} \cdot \log \left( \lambda_{s,n,t} \right) - \left( \sum_{t=1}^{T_n} y_{n,t} \right) \log \left( \sum_{t=1}^{T_n} \lambda_{s,n,t} \right)$$
Modeling framework: Estimation (2)

- Simulation (random coefficient or LV): The expected likelihood $\mathcal{L}_n^*(.)$ over all possible values of $\psi_n$ or $LV_n$ is given by the integral of the exponent of the log-likelihood function over the distribution of $\psi_n$ or $LV_n$

$$\mathcal{L}_n^*(Y_{n,t}, l_{w,n}|X_{n,t}, z_n, \Omega) = \int_{\psi_n, LV_n} \exp (\mathcal{L}_n(Y_{n,t}|X_{n,t}, z_n, \Lambda, \psi_n)) \, u(l_{w,n}|LV_n, \tau_{l_w}, \sigma_{l_w})$$

$$\times h(\psi_n|R) \, g(LV_n|z_n, \rho_z, \eta_{LV_z}) \, d\psi_n \, dLV_n$$

$$\tilde{\mathcal{L}}_n^*(Y_{n,t}, l_{w,n}|X_{n,t}, z_n, \Omega) = \frac{1}{R} \sum_{r=1}^{R} \exp (\mathcal{L}_n(Y_{n,t}|X_{n,t}, z_n, \Lambda, \psi_n)) \, u(l_{w,n}|LV_n, \tau_{l_w}, \sigma_{l_w})$$

$$\max \tilde{\mathcal{L}}(\Omega) = \sum_{n=1}^{N} \log \left( \tilde{\mathcal{L}}_n^*(Y_{n,t}|X_{n,t}, z_n, \Omega) \right)$$

→ Posterior analysis of cost elasticity
# Estimation results

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<th>LVREP</th>
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<td>−0.28**</td>
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Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

Note: LV model coefficients not reported in the table.
Results: Distribution of cost elasticities

![Box plot showing posterior distribution of cost elasticities for different groups (REP, REPS, MEP, MEPS, LVREP). The x-axis represents the cost elasticities ranging from -2.5 to 0%, with each group having a distinct distribution. The box plots illustrate the interquartile range, median, and outliers for each group.](image-url)
Results: Distance dependency

![Graph showing distance dependency]
Conclusions

- Median elasticity: If MIV travel costs increase by 1%, distance decreases by $\approx 0.3$ to 0.4% (re-weighted by MZMV distances)
- Remaining issues: Potential endogeneity of $dist_{n,0}$
- Strong, positive distance dependency
- Relatively high elasticities compared to related literature; usually between $-0.1$ (SR) and $-0.4$ (LR)
  - Sampling bias / low sample size
  - Survey design (daily travel, activity-based approach, etc.)
  - Very high variation in travel cost
- Respondents with pro-environmental traits travel less and show a stronger adaptation behavior
Questions?