Improving the spatial transferability of travel demand forecasting models: An empirical assessment of the impact of incorporating attitudes on model transferability

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Teaching Old Models New Tricks

Introduction

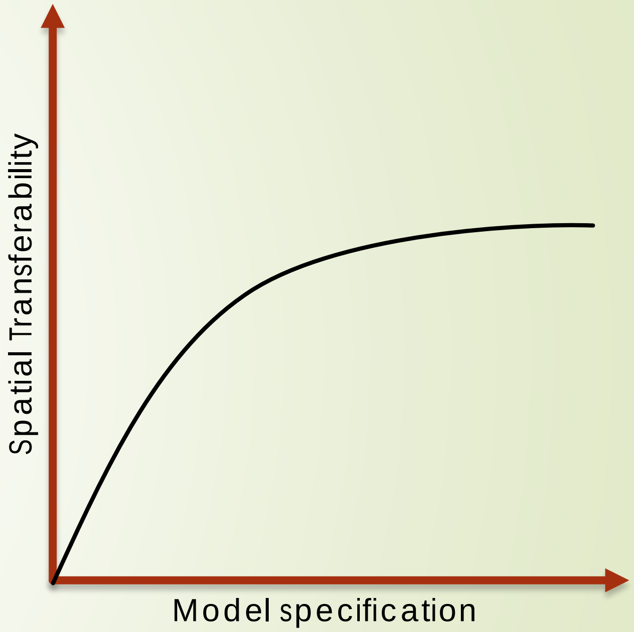
What is spatial transferability?

- *Spatial Transferability:* Ability to use travel demand forecasting models developed in one region for demand forecasting in another region.
- It is of interest as this can save a lot of time and cost for regions that cannot afford to build a model from scratch. (Atherton and Ben-Akiva, 1976; Sikder et al., 2014, 2013)
- It is also of interest for developing nations, which generally have meagre budget for Transportation Planning all together (Santoso and Tsunokawa, 2005).

- Atherton, T., Ben-Akiva, M., 1976. Transferability and updating of disaggregate travel demand models. Transportation Research Record 610, 12–18.
- Sikder, S., Augustin, B., Pinjari, A., Eluru, N., 2014. Spatial Transferability of Tour-Based Time-of-Day Choice Models. Transportation Research Record: Journal of the Transportation Research Board 2429, 99–109. https://doi.org/10.3141/2429-11
- Sikder, S., Pinjari, A.R., Srinivasan, S., Nowrouzian, R., 2013. Spatial transferability of travel forecasting models: a review and synthesis. International Journal of Advances in Engineering Sciences and Applied Mathematics 5, 104–128. https://doi.org/10.1007/s12572-013-0090-6
- Santoso, D.S., Tsunokawa, K., 2005. Spatial transferability and updating analysis of mode choice models in developing countries. Transportation Planning and Technology 28, 341–358. https://doi.org/10.1080/03081060500319694

Spatial transferability and model specification

- A positive relationship (need not be linear) between model specification and model transferability has always been argued (Atherton and Ben-Akiva, 1976; Koppelman and Wilmot, 1986; Lerman, 1981; Tardiff, 1979).
- Well specified models (e.g. models that better capture observed and unobserved heterogeneity) are expected to be better transferable than basic models.
- It has been speculated that the models which capture "*soft factors*" (attitudes, perception, norms, and beliefs) are better transferable than standard models with only observable explanatory variables (age, gender, income etc.).
- However, there is no empirical evidence in the literature that the hypothesis is true.



- Atherton, T., Ben-Akiva, M., 1976. Transferability and updating of disaggregate travel demand models. Transportation Research Record 610, 12–18.
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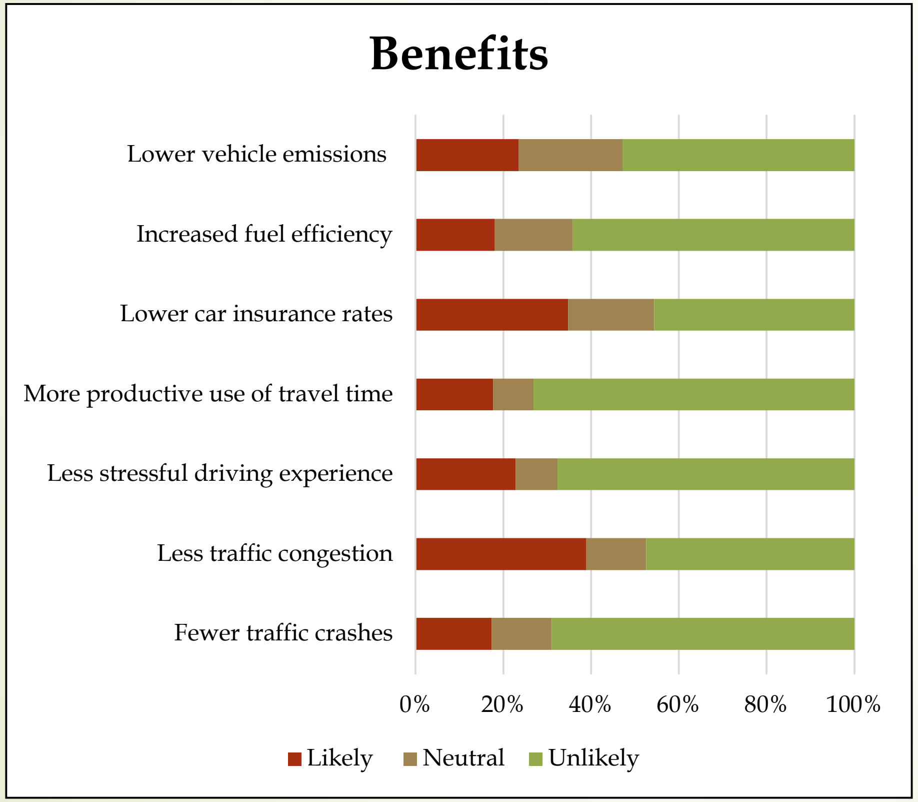
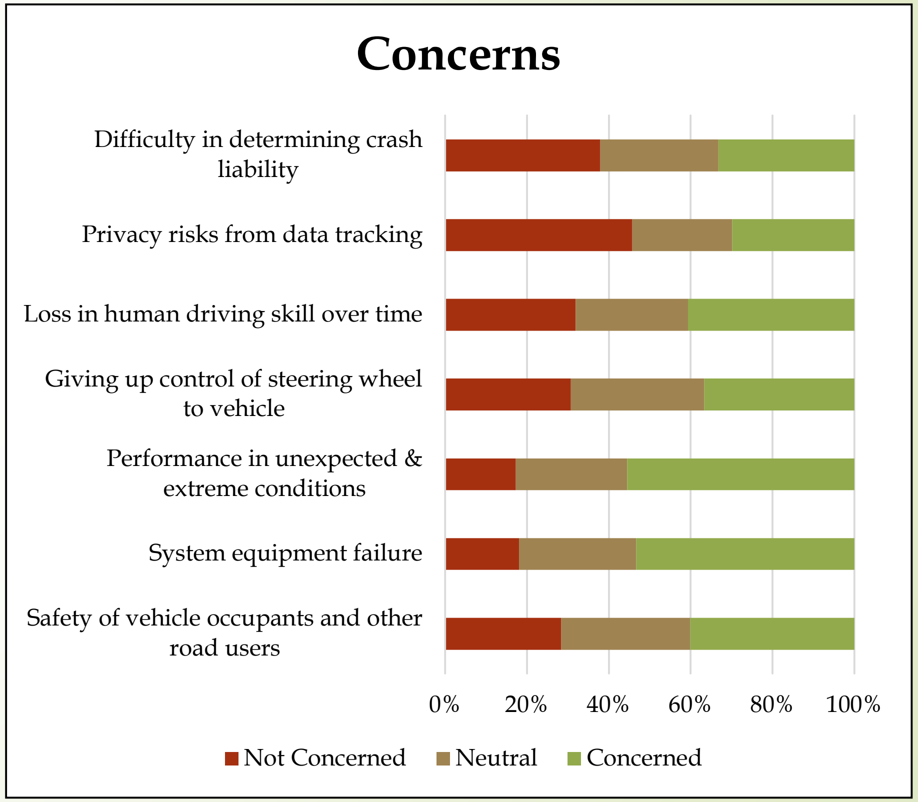
- Lerman, S., 1981. A Comment on Interspatial, Intraspatial, and Temporal Transferability, in: New Horizons in Travel-Behavior Research. pp. 628–632.
- Tardiff, T.J., 1979. Specification analysis for quantal choice models. Transportation Science 13, 179–190. https://doi.org/10.1287/trsc.13.3.179

Present study

- Comparison of spatial transferability of widely used Multinomial Logit (MNL) model and Integrated Choice and Latent Variable (ICLV) model.
- Empirical setting includes a discrete choice model of preferred way (own, share, not use AVs at all) of using autonomous vehicles (AVs), when available.
- Data from survey conducted among 811 respondents in Florida (414 observations) and Michigan (397 observations).
- MNL model includes just observable explanatory variables, while ICLV model also includes latent variables (perception of benefits of AVs and perception of concerns regarding AVs).

Distribution of Responses for AV Benefit and Concern Likert Scale Questions





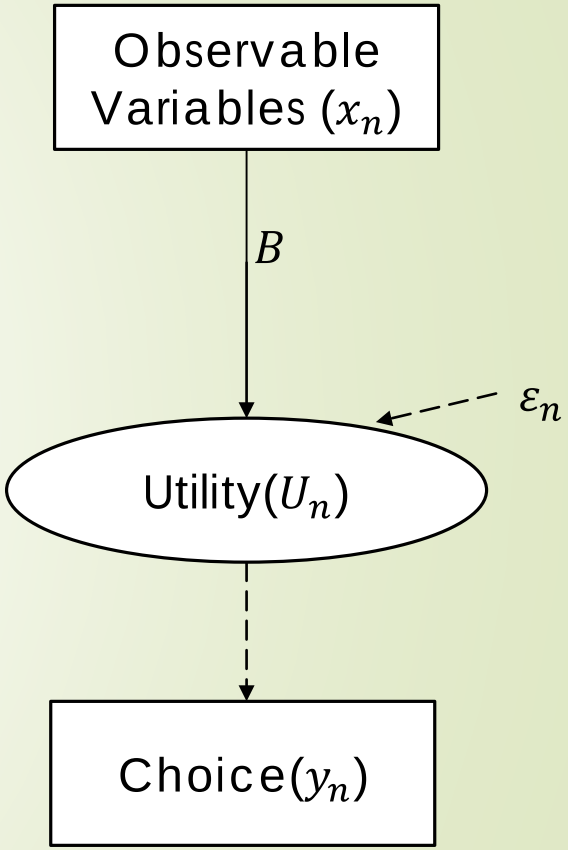
Econometric Model Structures

Multinomial Logit Model

$$U_n = Bx_n + \varepsilon_n$$

$$y_{nj} = \begin{cases} 1 \; if \; U_{nj} > U_{nj'} \; \forall j' \in \{1, \ldots, \ldots, \ldots J\} \\ 0 \; otherwise \end{cases}$$

$$P\left(y_{nj} = 1 \middle| x_n; B\right) = \frac{\exp(\beta_j * x_n)}{\sum_{j'=1}^{J} \exp(\beta_{j'} * x_n)}$$



$U_n \rightarrow (J \times 1)$ vector of utilities of each of J alternatives

$x_n \rightarrow (K \times 1)$ vector of observable explanatory variables

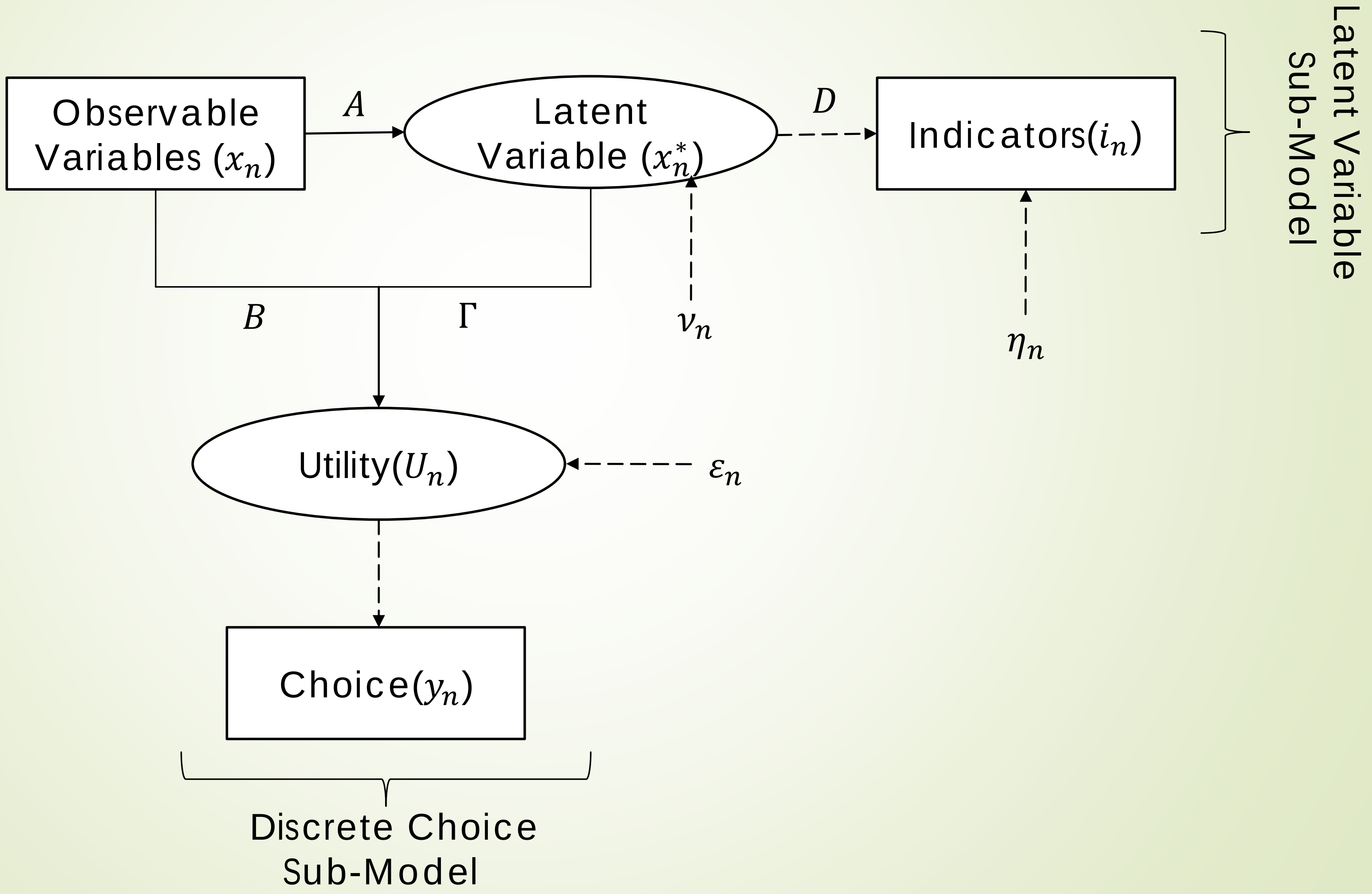
$B \rightarrow (J \times K)$ matrix of model parameters

$\varepsilon_n \rightarrow (J \times 1)$ vector of IID Gumbel error terms

$y_{nj} \rightarrow$ choice indicator, 1 if decision-maker chooses alternative j, zero otherwise

$P\left(y_{nj} = 1 \middle| x_n; B\right) \rightarrow$ choice probability

Integrated Choice and Latent Variable Model



Integrated Choice and Latent Variable Models

$U_n = Bx_n + \Gamma x_n^* + \varepsilon_n$ ⟶ Utility Equation

$x_n^* = Ax_n + \upsilon_n$ ⟶ Structural Equation

$i_n = Dx_n^* + \eta_n$ ⟶ Measurement Equation

$$y_{nj} = \begin{cases} 1 \; if \; u_{nj} > u_{nj'} \; \forall j' \in \{1, \dots, \dots, \dots J\} \\ 0 \; otherwise \end{cases}$$

$U_n \rightarrow (J \times 1)$ vector of utilities of each of J alternatives
$x_n \rightarrow (K \times 1)$ vector of observable explanatory variables
$x_n^* \rightarrow (M \times 1)$ vector of latent explanatory variables
$B, \Gamma \rightarrow (J \times K)$ and $(J \times M)$ matrices of model parameters
$\varepsilon_n \rightarrow (J \times 1)$ vector IID Gumbel error terms
$A \rightarrow (M \times K)$ matrix of parameters denoting the relationship between the latent & observable variables

Transferability Assessment

Transferability assessment techniques

To popular approaches available in the literature for transferability assessment:

- **Application-based approach:**
  - Here, model parameters are estimated in one region (base context) and applied to data in another region (application context).
  - A model's transferability assessment is done as a whole, without allowing for examination of which specific parameters are not transferable.
- **Estimation-based approach:**
  - Data from contexts are combined to estimate single model, while recognizing context specific differences via difference parameters.
  - Approach is advantageous especially when small data samples are available.

Transferability assessment metric

- **Transfer Index (TI):** TI uses local model as a yardstick for transferability assessment and is written as:

$$TI = \frac{\mathcal{L}_i(\beta_j) - \mathcal{L}_i(C_i)}{\mathcal{L}_i(\beta_i) - \mathcal{L}_i(C_i)}$$

where,

$\mathcal{L}_i(\beta_j)$ = log-likelihood of transferred model applied to application context data.

$\mathcal{L}_i(\beta_i)$ = log-likelihood of the local model applied to the application context data.

$\mathcal{L}_i(C_i)$ = log-likelihood of a constants only model for the application context data.

Hypothesis is that the models with latent variable models will have better choice model log-likelihood and hence will also have better transfer index than multinomial logit models.

How availability of indicators can help spatial transferability?

When no model is available at application context but simple **MNL is available at base** context

- Traditional case of transferability;
- Model specification and parameters from base context are transferred to the application context;
- Beneficial for regions with absolutely no model building capabilities.

When no model is available at application context but **ICLV is available at base** context

- Transfer model specification and parameters from base context to application context;
- Model includes parameters of structural equation corresponding to soft factors, along with parameter of observation variables;
- Availability of indicators not required at the application context;
- Likely, this transfer is better than the traditional transfer. However, this hypothesis needs to be tested.

When only simple **MNL is available at application context but ICLV is available at base** context

- Transfer specification and parameters of structural equation from the base context and re-estimate the model with application context specification;
- New estimation is like estimation of a mixed logit model but still does not require availability of indicators at application context;
- Beneficial for regions with some model building capabilities but no availability of latent variable indicators.

Results

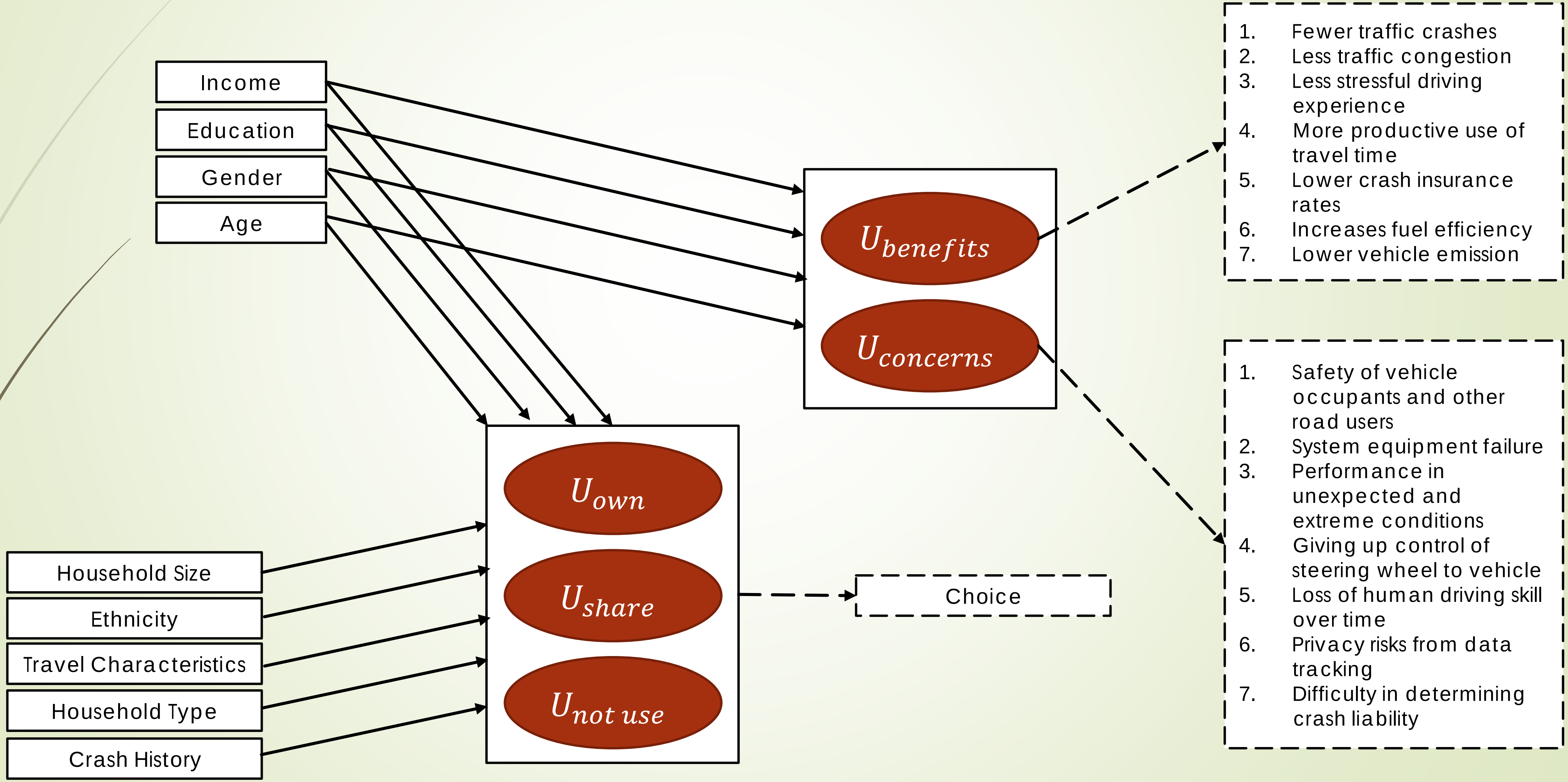
Multinomial Logit Model – Florida Dataset

Variable Name	Parameter Estimate (t-stat)	
	Own an AV for personal use	Share an AV
Constant	-0.0109 (-0.030)	0.0198 (0.080)
Old age indicator (1 if the respondent is more than 60 years old, 0 otherwise)	-0.5285 (-2.091)	-0.7701 (-2.361)
Male indicator (1 if the respondent is male, 0 otherwise)	0.3121 (1.448)	--
White ethnicity indicator (1 if the respondent's ethnicity is white, 0 otherwise)	--	-1.0005 (-2.912)
High household income indicator (1 if the respondent's household income is more than $100,000, 0 otherwise)	0.4545 (1.929)	0.5324 (1.698)
Single person household indicator (1 if the respondent lives in a single person household, 0 otherwise)	--	0.5711 (1.771)
Short commute indicator (1 if the respondent's typical one way commute distance is less than 5 miles, 0 otherwise)	--	0.5354 (1.874)
Household with child indicator (1 if the household has at least one child with age less than 16 years, 0 otherwise)	-1.0576 (-2.707)	-0.6218 (-1.368)
No. of observations	414	
Log-likelihood at convergence	-412.05	
Log-likelihood for constants only model	-429.823	

Multinomial Logit Model – Michigan Dataset

Variable Name	Parameter Estimate (t-stat)	
	Own an AV for personal use	Share an AV
Constant	-1.2691 (-5.805)	-0.2623 (-1.686)
High household income indicator (1 if the respondent's household income is more than $100,000, 0 otherwise)	0.7208 (3.104)	0.8844 (2.905)
Household with child indicator (1 if the household has at least one child with age less than 16 years, 0 otherwise)	-1.1576 (-3.399)	-0.9100 (-2.098)
No. of observations	397	
Log-likelihood at convergence	-395.277	
Log-likelihood for constants only model	-406.722	

Integrated Choice and Latent Variable Model



ICLV Model – Florida Dataset

Choice Model

Variables	Estimated Parameters: Parameter Estimate	Estimated Parameters: t-stat
Own AVs		
Constant	-0.129	-0.25
Child indicator (household has children, 0 otherwise)	-1.56	-1.39
Benefit latent variable	2.03	4.23
Concern latent variable	-0.808	-1.48
Share AVs		
Constant	0.986	1.25
Age indicator (1 if age more than 60yrs, 0 otherwise)	-0.504	-1.49
Male indicator (1 if respondent is male, 0 otherwise)	-0.569	-1.80
Less commute distance	0.549	1.88
White ethnicity indicator (1 if white; 0 otherwise)	-0.798	-1.84
Benefit latent variable	1.23	2.00
Concern latent variable	-1.24	-1.55

Structural Equation

Latent Variable model (Structural model: 2 equations)	Estimate (t-stat)
Benefit	
Education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)	0.117 (2.18)
Crash indicator (1 if the respondent has ever been involved in a traffic crash, 0 otherwise)	0.265 (4.69)
Age indicator (1 if age less than 40yrs, 0 otherwise)	0.375 (3.22)
Worker indicator (1 if the respondent is a worker; 0 otherwise)	0.303 (4.77)
Child indicator (1 if r1 if household has children, 0 otherwise)	-0.667 (-3.24)
Indicator for household with people with physical or cognitive constraints	-0.188 (-1.88)
Concern	
Female indicator (1 if respondent is a female, 0 otherwise)	0.232 (4.40)
White Ethnicity (1 if ethnicity is white; 0 otherwise)	0.359 (6.37)
Type of Household indicator (1 if family, 0 otherwise)	0.293 (5.45)

ICLV Model – Florida Dataset

Measurement Equation - Benefits

Variable	Parameter Estimate (t-stat)	Scale Parameter (t-stat)
Fewer traffic crashes	1.46 (12.22)	0.675 (13.14)
Less traffic congestion	1 (--)	1 (--)
Less stressful driving experience	1.59 (12.53)	0.620 (12.50)
more productive (than driving) use of travel time	1.38 (12.05)	0.711 (13.73)
Lower car insurance rates	1.01 (10.78)	0.910 (15.36)
Increased fuel efficiency	1.10 (11.74)	0.713 (14.630)
Lower vehicle emissions	0.925 (11.30)	0.727 (15.16)

Measurement Equation - Concerns

Variable	Parameter Estimate (t-stat)	Scale Parameter (t-stat)
Safety of the vehicle occupants and other road users such as pedestrians, bicyclists	0.856 (10.14)	1.02 (15.36)
System/equipment failure or AV system hacking	1 (--)	1 (--)
Performance in (or response to) unexpected traffic situations	0.911 (10.79)	0.952 (15.42)
Motion sickness	-0.418 (0.0849)	1.28 (15.10)
Giving up my control of the steering wheel to the vehicle	0.965 (10.05)	1.12 (14.96)
Loss in human driving skill over time	0.804 (8.91)	1.12 (14.96)
Privacy risks from data tracking on my travel locations and speed	0.915 (9.19)	1.12 (14.96)
Difficulty in determining who is liable in the event of a crash	0.779 (9.22)	1.007 (15.24)

ICLV Model – Michigan Dataset

Choice Model

Variable	Parameter Estimate	t-stat
Own AVs		
Constant	0.388	0.72
Male indicator (1 if Male; 0 otherwise)	-0.471	-1.68
Child indicator (household has children, 0 otherwise)	0.586	1.38
Benefit latent variable	2.23	6.59
Concern latent variable	-1.23	-4.74
Share AVs		
Constant	-0.310	0.91
Shared mode indicator (if the person is using shared mode for commute)	-1.40	-1.33
Benefit latent variable	1.99	5.76
Concern latent variable	-0.848	-3.38

Structural Equation

Variable	Parameter Estimate (t-stat)
Benefit	
Education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)	0.264 (4.03)
Age indicator (1 if age less than 40yrs, 0 otherwise)	0.588 (2.37)
Worker indicator (1 if the respondent is a worker; 0 otherwise)	-0.198 (-2.95)
Concern	
Female indicator (1 if respondent is a female, 0 otherwise)	0.491 (5.18)
Age indicator (1 if age more than 60yrs, 0 otherwise)	0.171 (1.92)
White Ethnicity (1 if ethnicity is white; 0 otherwise)	0.767 (7.06)

ICLV Model – Michigan Dataset

Measurement Equation - Benefits

Variable	Parameter Estimate (t-stat)	Scale Parameter (t-stat)
Fewer traffic crashes	1.53 (1254)	0.789 (12.74)
Less traffic congestion	1 (--)	1 (--)
Less stressful driving experience	1.54 (12.92)	0.724 (12.97)
more productive (than driving) use of travel time	1.42 (12.37)	0.834 (13.55)
Lower car insurance rates	0.954 (9.30)	1.30 (14.84)
Increased fuel efficiency	1.16 (12.59)	0.711 (13.86)
Lower vehicle emissions	0.894 (11.67)	0.770 (14.85)

Measurement Equation - Concerns

Variable	Parameter Estimate (t-stat)	Scale Parameter (t-stat)
Safety of the vehicle occupants and other road users such as pedestrians, bicyclists	0.892 (13.67)	0.983 (12.75)
System/equipment failure or AV system hacking	1 (--)	1 (--)
Performance in (or response to) unexpected traffic situations	0.981 (14.31)	0.966 (12.97)
Motion sickness	-0.108 (-1.79)	1.46 (13.82)
Loss in human driving skill over time	0.931 (11.78)	1.31 (12.61)
Privacy risks from data tracking on my travel locations and speed	0.893 (11.31)	1.37 (12.98)
Difficulty in determining who is liable in the event of a crash	0.742 (11.44)	1.17 (13.47)

Spatial Transferability Assessment Results

Multinomial Logit Model

Measure	Value
$LL_{Florida}$	-412.05
$LL_{Michigan}$	-395.28
$LL_{Florida}^{constants\ only}$	-429.82
$LL_{Michigan}^{constants\ only}$	-406.72
$LL_{Florida \rightarrow Michigan}$	-412.29
$LL_{Michigan \rightarrow Florida}$	-430.30
$TI_{Florida \rightarrow Michigan}$	-0.487
$TI_{Michigan \rightarrow Florida}$	-0.027

Integrated Choice and Latent Variable Model

Measure	Value
$LL_{Florida}$	-419.39
$LL_{Michigan}$	-410.72
$LL_{Florida}^{constants\ only}$	-429.82
$LL_{Michigan}^{constants\ only}$	-406.72
$LL_{Florida \rightarrow Michigan}$	-422.46
$LL_{Michigan \rightarrow Florida}$	-449.68
$TI_{Florida \rightarrow Michigan}$	3.94
$TI_{Michigan \rightarrow Florida}$	-1.90

Conclusions

- Contrary to expectation (early effort), ICLV choice model log-likelihood not as good as the MNL.
- The hypothesis that ICLV will give better spatial transferability than MNL could not be established. However, this just might be due the data being used in this empirical analysis.
- Further efforts are already underway to utilize NHTS 2017 data (which has bigger sample size) to establish the hypothesis.
- Expectation is that choice models with latent variable will have better log-likelihood and hence will transfer better.

Thank You