(How) Can We Improve the Behavioral Realism of Large-Scale Land Use/ Transportation Models?

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Motivation

- We're in a period of unprecedented change in the transportation "landscape", of
  - technologies
  - societal shifts
  - policy/planning instruments
- Accordingly, it has never been more vital to understand/predict the behavioral impacts of these changes
- However, our ability to do so is severely hampered…

Motivation (cont'd)

- … by the absence from our models of a major class of variables…
- Namely, ***attitudes***, including
  - opinions,
  - feelings,
  - preferences,
  - perceptions,
  - lifestyle orientation, and
  - personality

Motivation (cont'd)

- E.g., attitudes toward
  - sharing
  - multitasking
  - time pressure
  - privacy
  - materialism
  - physical activity
  - the environment
  - residential location
  - transit
  - self-efficacy
  - peer influence
  - risk taking
  - technology

Motivation (cont'd)

- Ample evidence supports the explanatory power of attitudes
- Conversely, models without attitudes will be deficient in their ability to respond to changing conditions, as evidenced by the
  - typically-less-than-10% explanatory power of many such models,
  - need to judgmentally alter ("assert") numerous parameters during calibration, and
  - lack of sensitivity to changing societal values

e.g. Mokhtarian and Salomon (1997); Kuppam et al. (1999); Domarchi et al. (2008)

And yet…

- If attitudes are so great, where are they?
- (Alleged) barriers to inclusion:
  - They're difficult to measure/analyze
    - Additional burden on already difficult-to-recruit respondents
    - Require "atypical" skills to design/analyze
  - They're impossible to forecast

Our challenge

- Can we incorporate into large-scale regional models the valuable information carried by attitudes, *without* adding (many) new questions to travel/activity diary surveys?
- A couple of ideas:
  1. Use attitudes to "inform" coefficients in conventional models
  2. Impute attitudes into (travel) behavioral datasets

1. Use attitudes to inform coefficients of typical variables

- Falls under the research theme of transferability of model parameters, which has been extensively studied (Koppelman & Wilmot, 1982; Fox & Hess, 2010)
- Sanko (2014) used repeated cross-sectional data to model commute mode choice coefficients as a function of time
- Chingcuanco & Miller (2014) regressed time-varying constant and scale parameters of MNL VO models against employment rate, gas prices, etc.
- But to my knowledge, we haven't yet used *attitudes* to model parameters of regional models

although see Abou-Zeid et al. (2011)

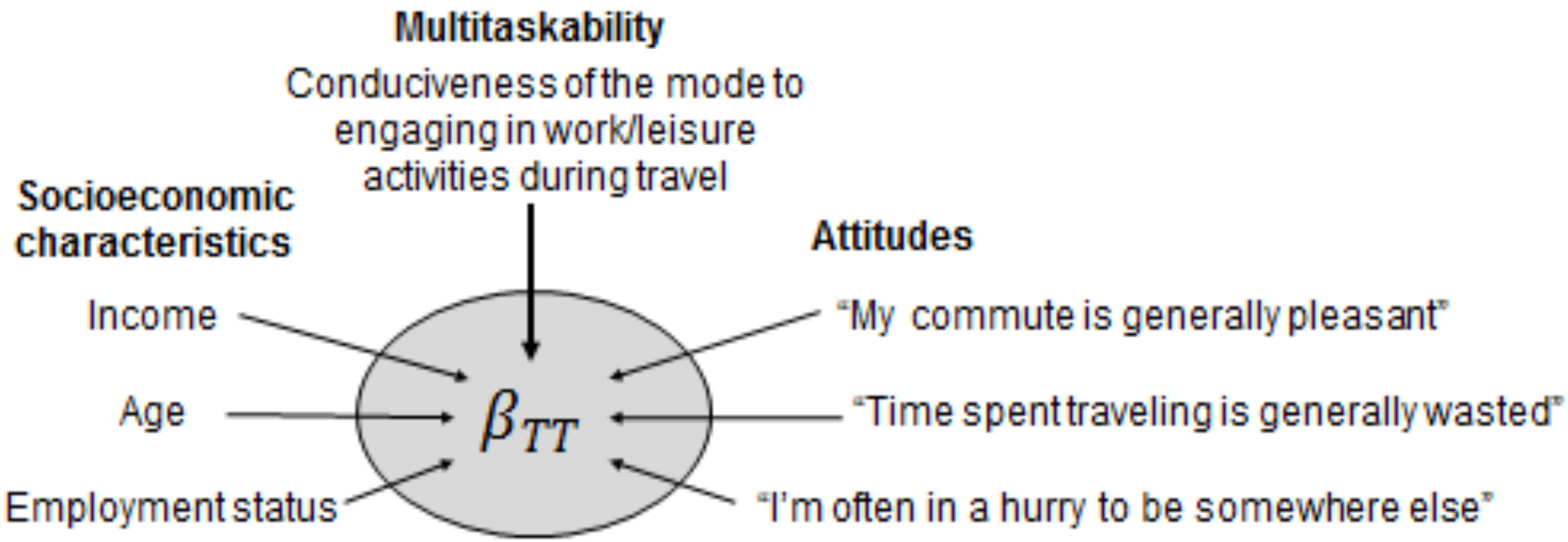
An example: AV impacts on β_{TT}

- For a dataset containing attitudes, model

$$V = \beta_0 + \beta_{TT}TT + \beta_{TC}TC + \sum_{k=1}^{K} \beta_k var_k \ ,$$

- where

$$\beta_{TT} = \gamma_0 + \sum_{z=1}^{Z} \gamma_z soc_z + \sum_{t=1}^{T} \gamma_t att_t + \sum_{m=1}^{M} \gamma_m MT_m.$$



Malokin et al. (under review; in process)

Ex: AV impacts on β_{TT} (cont'd)

- Once all parameters are estimated, we can, e.g.,
  - compute β_{TT} for everyone in the sample
  - examine the (weighted) distribution of β_{TT} across the full sample and by subgroup
  - analyze the factor by which multitasking discounts β_{TT}, namely $\sum_{m=1}^{M} \gamma_m MT_m / \beta_{TT}$.
- This provides an *empirical*, rather than purely *judgmental*, basis for discounting β_{TT} in a large-scale regional model, in order to simulate one impact of AVs

1. Use attitudes to inform coefficients of typical variables

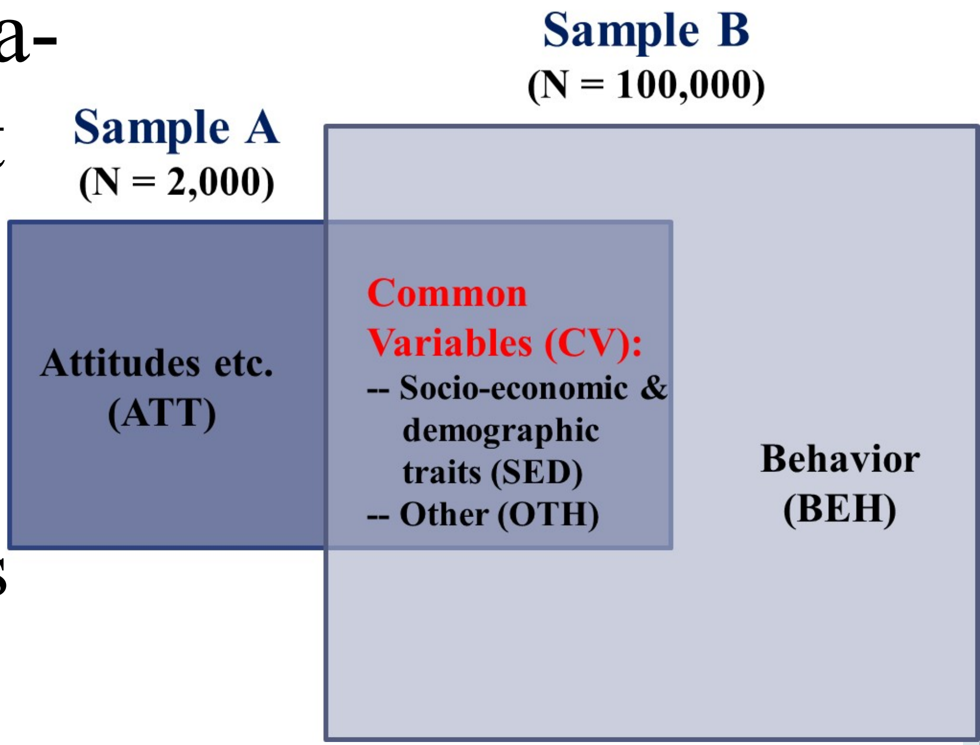
- In summary, to apply this method we can
  - collect attitudinal and behavioral data on a relatively small, but (weighted to be) representative, sample;
  - use that sample to estimate our "conventional" model;
  - analyze the influence of attitudes on the coefficients of the conventional model; and
  - transfer basic insights gained, over to simulations based on the large-scale model

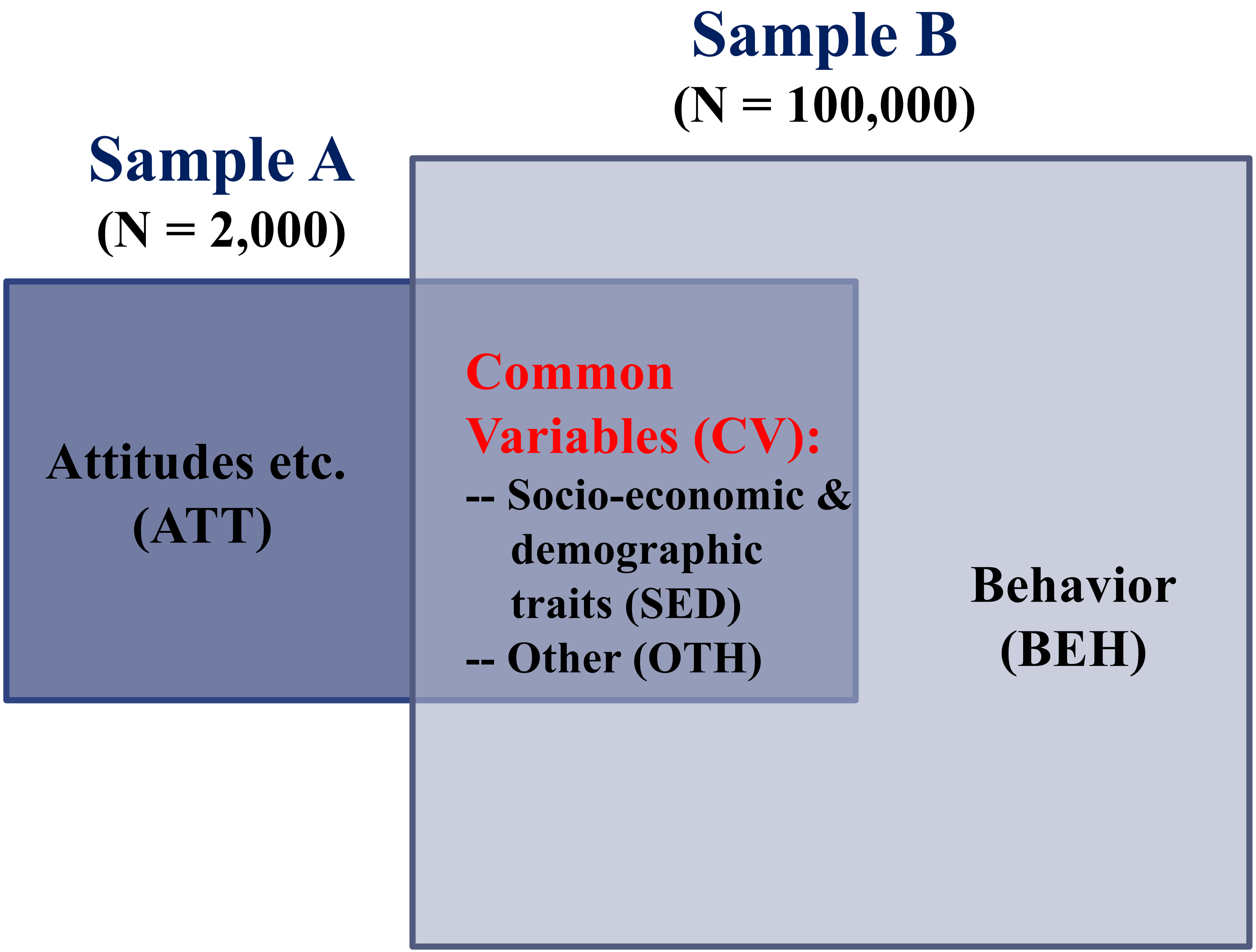
2. Impute attitudes into large behavioral dataset

- Think NHTS (US), NTS (UK etc.), but if this works, it can be applied to large-scale datasets measuring
  - time use (ATUS)
  - residential energy consumption (RECS)
  - consumer expenditure (CES)
  - physical activity (NHANES, BRFSS,…)
  - etc.…

2. Impute attitudes (cont'd)

- Using a set of explanatory variables present in (common to) both samples (CVs),
  - develop prediction functions for attitudes (ATTs) using "***Sample A***(tt)" and
  - apply those functions to predict ATTs for "***Sample B***(eh)"




Sample B
(N = 100,000)
Sample A
(N = 2,000)
Attitudes etc.
(ATT)
Common
Variables (CV):
-- Socio-economic &
demographic
traits (SED)
-- Other (OTH)
Behavior
(BEH)

2. Impute attitudes (cont'd)

- Uh… that's been tried… And such models are lousy at predicting attitudes (typical R^2s < 0.1)
- True! But that's when
  - only SED variables are used as predictors *(what if we add LU and other variables?)*; and
  - one-size-fits-all coefficients are estimated *(what if we get fancier with segmentation?)*

Two potential approaches

1. **Microsegmentation:**
   - Using the CVs as clustering variables, identify *K* microsegments for **Sample A** (e.g. N = 2000, K = 60)
   - Find a separate "best-fitting" distribution of attitudes for each **Sample A** microsegment
   - Match each **Sample B** case to the **Sample A** micro-segment to which it's most similar based on the CVs
   - Make a random draw from that segment's attitudinal distribution, and assign the resulting value to the associated **Sample B** case

Two potential approaches (cont'd)

2. **Machine learning:**
   - **decision trees & random forests** (*cluster specifically so as to maximize within-cluster homogeneity on the target attitude*)
   - **k-nearest neighbor**
   - least absolute shrinkage selection operator **(LASSO) regression**
   - **adaptive boosting**
   - **support vector machines**, etc…

- Both approaches result in imputing attitudes to Sample B

Wu & Kumar (2009)

Proof of the pudding

	Sam-ple	ATTs	Specifi-cation	Rationale
1	A	"Observed"	Best	Benchmark
2	A	None	Same as 1, exc. w/o ATTs	See how much explanatory power the "true" ATTs have
3	A	Predicted	Same as 1	Assess how much GOF of benchmark model degrades when only imputed ATTs are available
4	A	Predicted	Best new	Assess how different a model might be from the benchmark, when only imputed ATTs are available and the specification of the "true" model is unknown
5	B	Imputed	Same as 1	Assess how well imputed ATTs allow recovery of the "true" model
6	B	Imputed	Best new	Same as for 3
7	B	None	Same as 6, exc. w/o ATTs	See how much explanatory power even "noisily" estimated ATTs have

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Some quick initial results

- **Sample A** (N=2,352):
  - LASSO regression reduced MSE in prediction of (pro-transit, -active transp, -density) ATTs by 21-24% compared to using the mean
  - Adding "true" ATTs to regression model of VO

Variable	rhd	ave	lar
pro-transit	1.996	1	0.777
pro-active transp	2.094	1.004	0.787
pro-density	1.986	1.014	0.755

    » pro-transit + but insig; other 2 ATTs v. sig. w exp (-) signs

Some quick initial results

- **Sample A** (N=2,352):
  - LASSO regression reduced MSE in prediction of (pro-transit, -active transp, -density) ATTs by 21-24% compared to using the mean
  - Adding "true" ATTs to regression model of VO improved adj. R^2 from 0.385 to 0.437 (14%)
- **Sample B** (NHTS, N=91,362):
  - Adding imputed ATTs to regression model of VO improved adj. R^2 from 0.372 to 0.398 (7%)
  - Poisson regression:
    - ATTs reduced residual deviance by 5%
    - pro-transit + but insig; other 2 ATTs v. sig. w exp (-) signs

Some potential problems

- There may be mismatch between (imputed) ATTs and (reported) BEH for some (many) cases, in which case ATTs may not appear to explain BEH very well (an ex. of the attenuation of estimated effects caused by measurement error; e.g. Cameron and Trivedi, 2005)
- Will we induce circularity? (E.g., using mode choice to predict ATTs and then those ATTs to predict mode choice)

Looking to the future…

- Addition of just a few new CVs to Sample B might considerably improve our ability to impute ATTs
- And about forecasting ATTs…
  - We could start with ***monitoring*** them over time, via panels and repeated cross-sections…
  - … allowing us to ***identify patterns*** in how they change over time
  - … eventually leading to ***models of formation and change***
  - ***Big Data*** could help – e.g. social media postings

Conclusions

- Have suggested some ways to use attitudes obtained from smaller separate samples to inform models estimated on large-scale behavioral datasets
- Even this early, it looks like at least modest gains in
  - "goodness"
  - behavioral realism
  - responsiveness to important variables

  of our models can be achieved by incorporating attitudinal variables
- Seems like a path worth traveling a bit farther!

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