Calibrating Big Data for Population Inference: Applying Quasi-randomization Approach to Naturalistic Driving Data using Bayesian Additive Regression Trees

Ali Rafei[1] Carol A. C. Flannagan[3] Michael R. Elliott[2]

[1]Program in Survey Methodology, University of Michigan

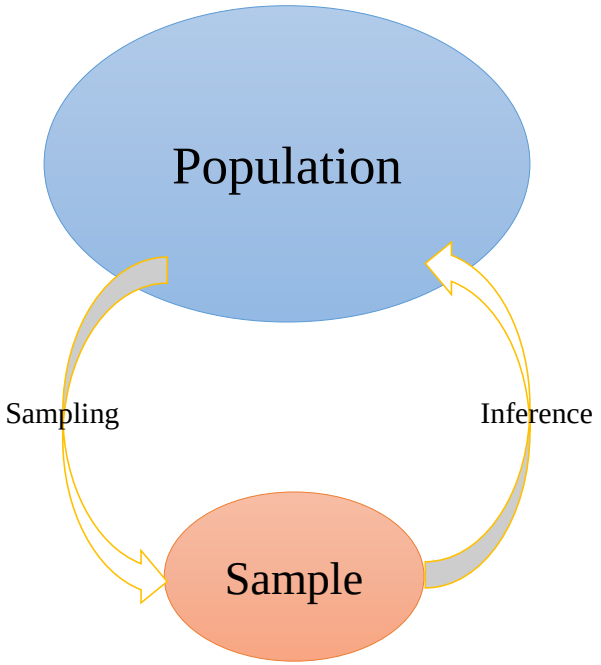
[2]Department of Biostatistics, University of Michigan

[3]University of Michigan Transportation Research Institute

BigSurv Meeting
October 2018

Big Data vs survey data

- Probability sampling is the "gold standard" for population inference (Neyman, 1934).
  1. The upward trends of non-response rate
  2. The rising cost and complexity



- Methods are developed to adjust for selection bias, where the "gold standard" is violated.
  1. Post-survey adjustment in probability samples e.g. GREG
  2. Calibration methods for nonprobability samples e.g. pseudo-weighting

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  1. Predictive analysis and small area estimation
  2. "Big challenge" for population inference

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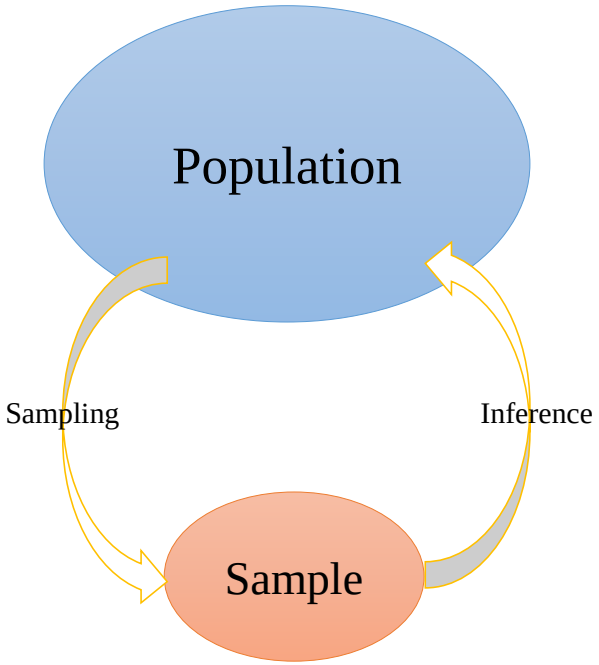

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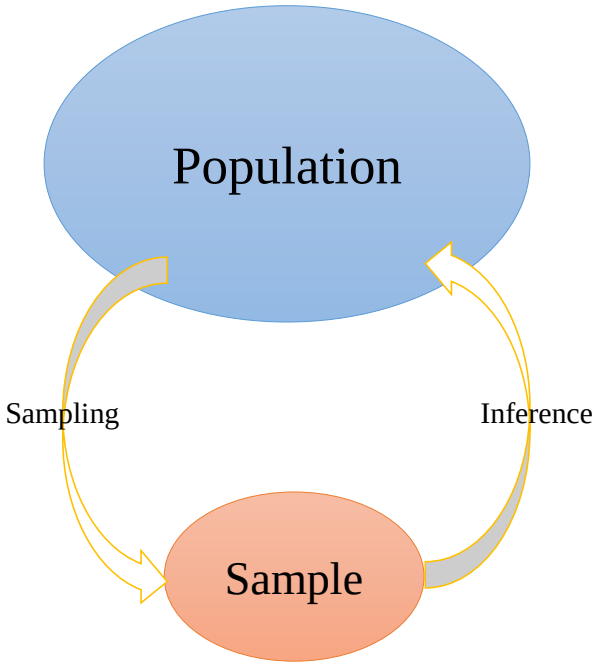

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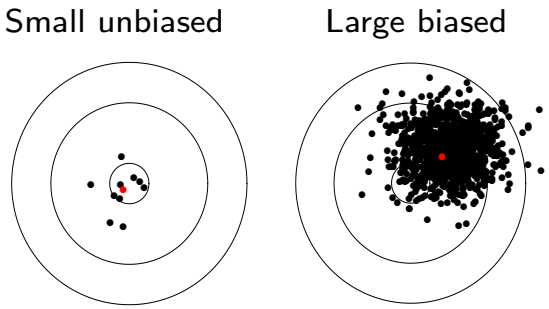
  1. Lack of a known random selection mechanism
  2. Lack of control over data collection process



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  2. CPS (c.r.=0.05%) vs LEHD (c.r.=90%)

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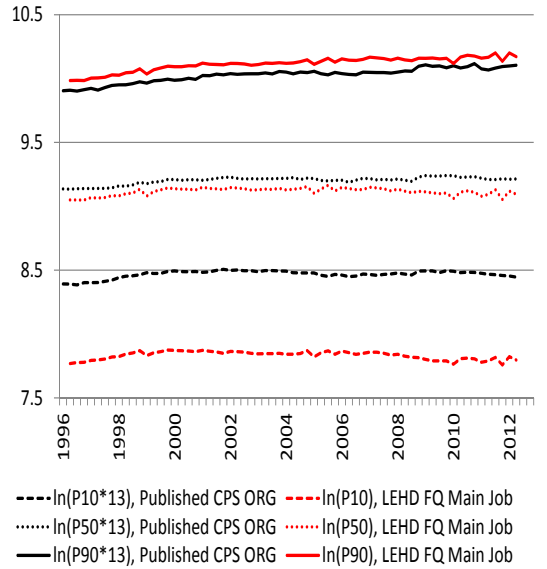
- **Objective**: To improve the representativeness of naturalistic driving data in SPMD based on the NHTS as benchmark using quasi-randomization approach.

CPS vs LEHD: earnings percentiles



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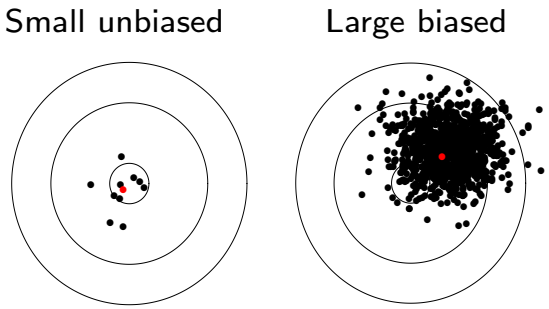

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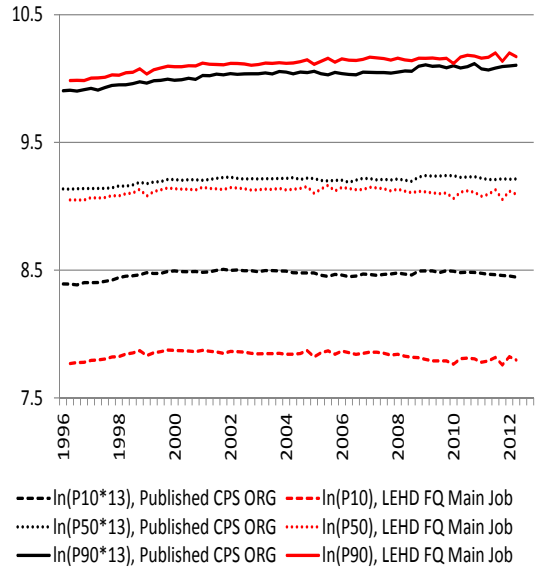

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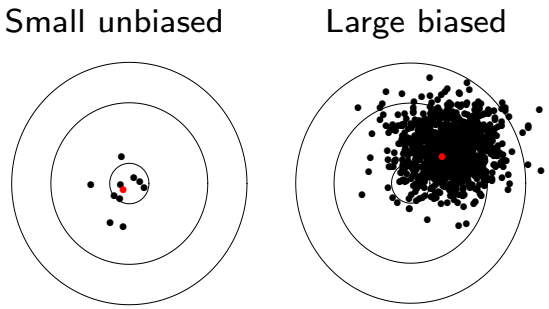

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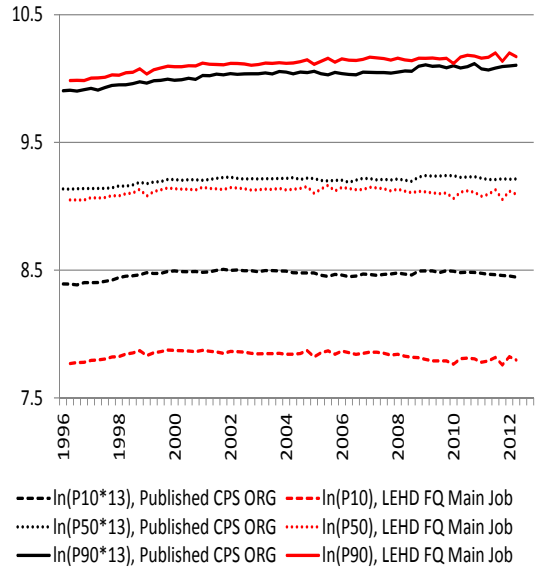

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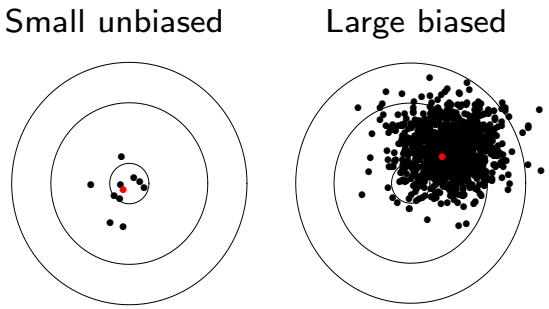

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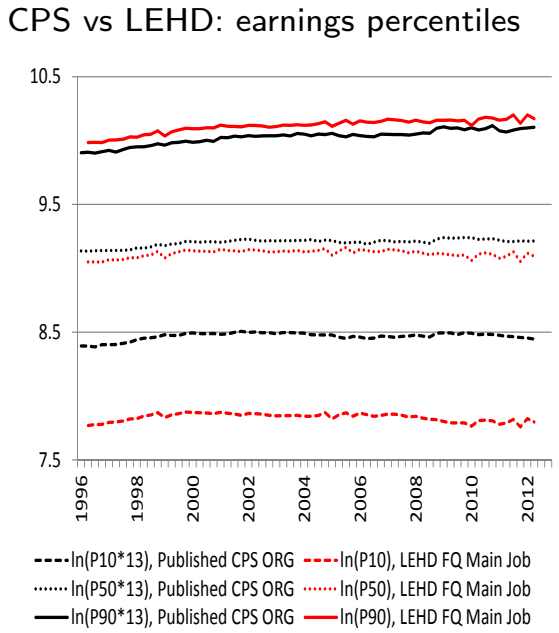

Naturalistic Driving Studies (NDS)

- Continuously monitoring of driving behaviors by instrumented vehicles
- A rich resource for testing novel transportation technologies, and exploring crash causality, traffic safety, and travel dynamics.
- Launched in Sep 2012 by UMTRI, SPMD is among the largest NDS, encompassing over 3,000 instrumented vehicles.
- SPMD characterizes real-world implementation of automated and connected vehicles, with the primary aim of testing DSRC-based connected vehicle communication technology.
- $\sim$6 million trips were captured within average participation time of $\sim$1 person-year.
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Review of existing approaches

- Elliott, M., and Valliant, R. (2017) provides an extensive review of methods used for calibrating non-probability samples.
- There are two general approaches:
  1. **Quasi-randomization:**
     The inclusion probabilities are modeled and predicted to construct pseudo-weights.
     - Pseudo-weighting
     - Predictive Mean Matching (PMM)
  2. **Super-population:**
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Quasi-randomization

- Let S_i and S_i^* denote the indicator for probability sample and non-probability sample, respectively. Then, combining the probability and non-probability samples, we define Z_i to be the indicator for non-probability cases, given $S_i^* + S_i = 1$.

Pseudo-weighting:

$$\tilde{\omega}_i = 1/\hat{P}(S_i^* = 1|x_i = x_0) \propto \omega_i \times \frac{\hat{P}(Z_i = 0|x_i = x_0)}{\hat{P}(Z_i = 1|x_i = x_0)}$$

where $\omega_i = 1/P(S_i = 1|x_i = x_0)$.

Predictive mean matching:

Let $p_0, p_1, ..., p_{100}$ to be the percentiles of probabilities of selection in the probability sample,

$$\tilde{\omega}_i = \frac{q_k / \sum_k q_k}{n_k / n}, i \in k$$

where $q_k = \sum_j \omega_j I(p_{k-1} < \omega_j^{-1} \leq p_k)$.

Generalized Linear Regression

- Need to compute $\hat{P}(S_i|x_i = x_0)$ and $\hat{P}(Z_i|x_i = x_0)$.
- Can compute $\hat{P}(S_i|x_i = x_0)$ without error if x contains all design variables and sampling mechanism is known; otherwise use logistic or beta regression.
- Compute $\hat{P}(Z_i|x_i = x_0)$ using logistic regression
- For variance estimation, use a jackknife estimator across both the non-probability and probability sample
  - Non-probability sample: single stratum with IID observations.
  - Probability sample: Follow the sample design.

Bayesian Additive Regression Trees (BART)

- To minimize model misspecification when estimating the probabilities of selection and sample membership, we use BART (Chipman et al. 2007).
- Provides a strong flexible predictive tool by capturing non-linear relationships as well as high-order interaction effects.
- The idea is based on the sum-of-trees model.

BART approximates the outcome Y_i as:

$$Y_i = \sum_{j=1}^{m} f(x_i, T_j, M_j) + \epsilon_i \quad \textit{where} \quad \epsilon_i \sim N(0, \sigma^2)$$

- BART is a Bayesian approach that assigns a prior distribution to T, M, and σ.
- For binary outcomes, a *probit* link is typically used.

Variance estimation in pseudo-weighting

- To incorporate variability in both outcome and pseudo-weights, we employ a conditional variance approach:

$$Var(\hat{y}) = E\{Var(\hat{y}|w)\} + Var\{E(\hat{y}|w)\}$$

where the first part can be obtained through the TSL method:

$$\widehat{E}\{Var(\hat{y}|w)\} = var_{TSL}(\hat{y}_w)$$

and the second part is estimated based on the MCMC of posterior in BART:

$$\widehat{Var}\{E(\hat{y}|w)\} = \frac{1}{K-1}\sum_{j=1}^{K}(\hat{y}_{w_j} - \hat{y}_w)^2$$

$$w_{ij} = 1/\hat{P}_j(S_i = 1|x_i)\frac{\hat{P}_j(Z_i = 0|x_i)}{\hat{P}_j(Z_i = 1|x_i)}, \quad \forall j = 1, 2, ..., K$$

Construction of pseudo-weights

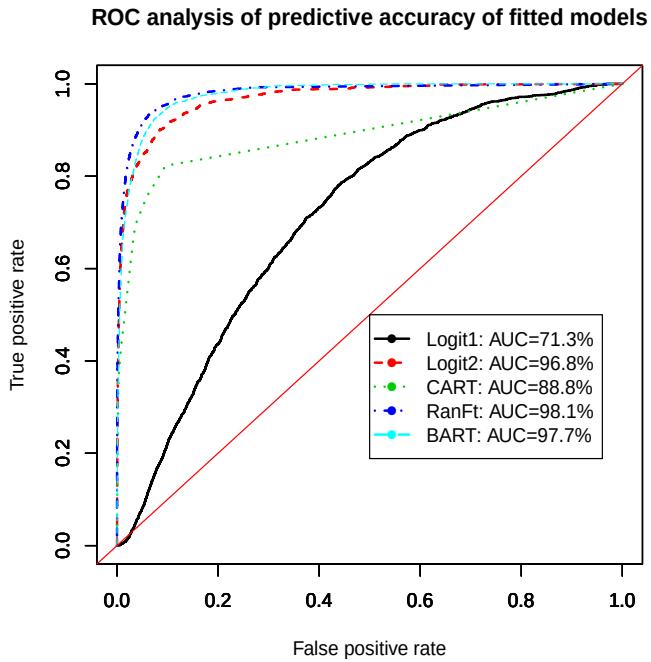
Comparing BART with alternative models in two steps of pseudo-weighting:

(1) $\hat{P}(S_i^* = 1 | x_i = x_0)$:

Model	RMSE	R^2
Original scale of response		
Linear Reg I	0.0190	5.95
Linear Reg II	0.0190	6.51
Poisson Reg I	0.0190	5.95
Poisson Reg II	0.0190	6.53
Beta Reg I	0.0191	5.02
Beta Reg II	0.0191	5.32
BART	0.0189	**7.43**
Log Scale of response		
Linear Reg I	1.350	14.99
Linear Reg II	1.346	15.56
BART	1.329	**17.66**

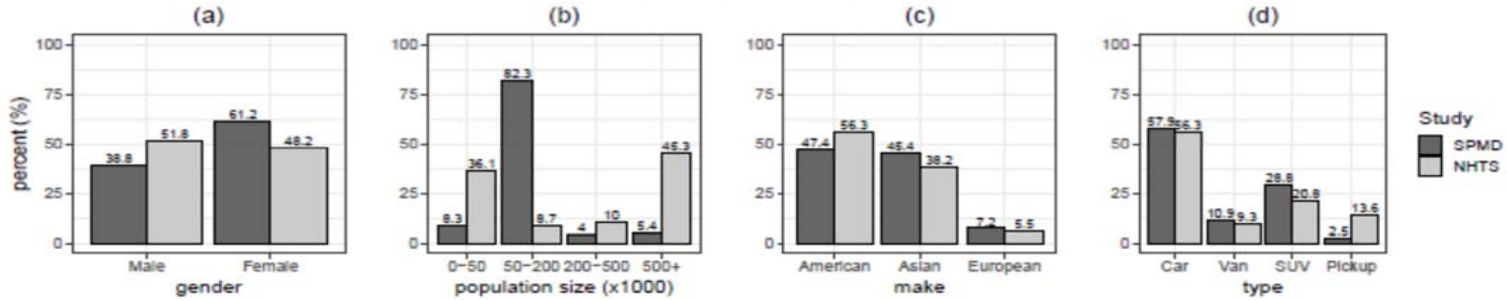
I: main effects in the model
II: two-way interaction effects were included

(2) $\hat{P}(Z_i = 1 | x_i = x_0)$:

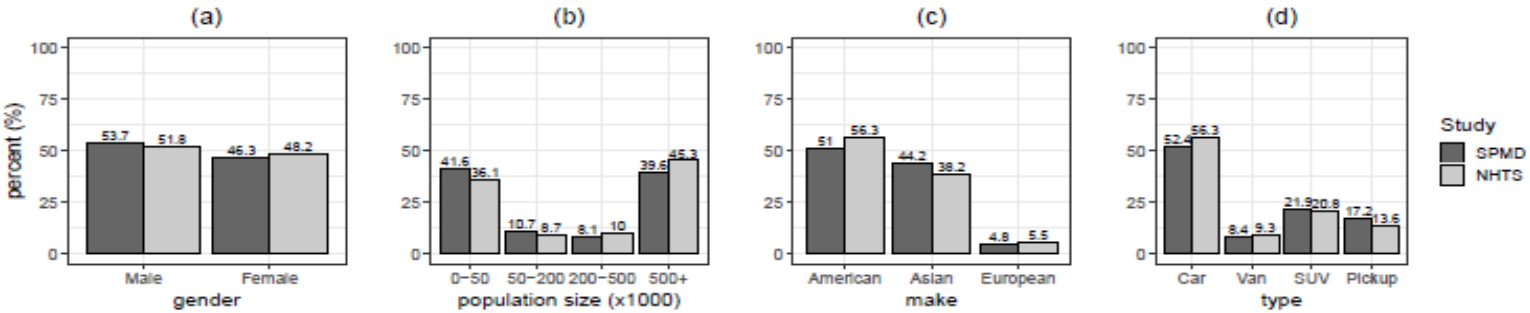


Distribution of common categorical auxiliary variables

Distribution of unweighted categorical covariates in SPMD vs NHTS:

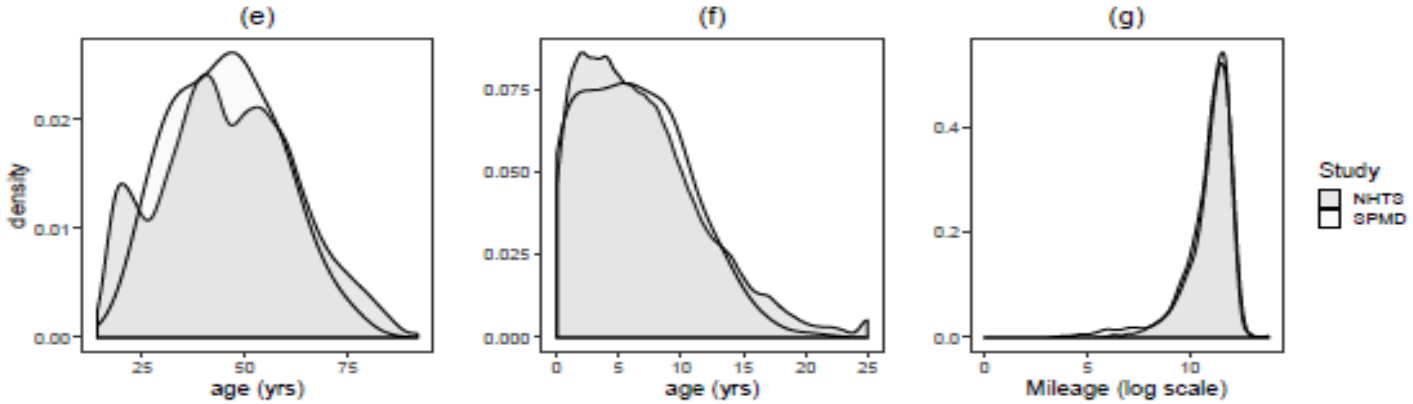


Distribution of categorical covariates using pseudo-weights:



Distribution of common continuous auxiliary variables

Kernel density of unweighted continuous covariates in SPMD vs NHTS:



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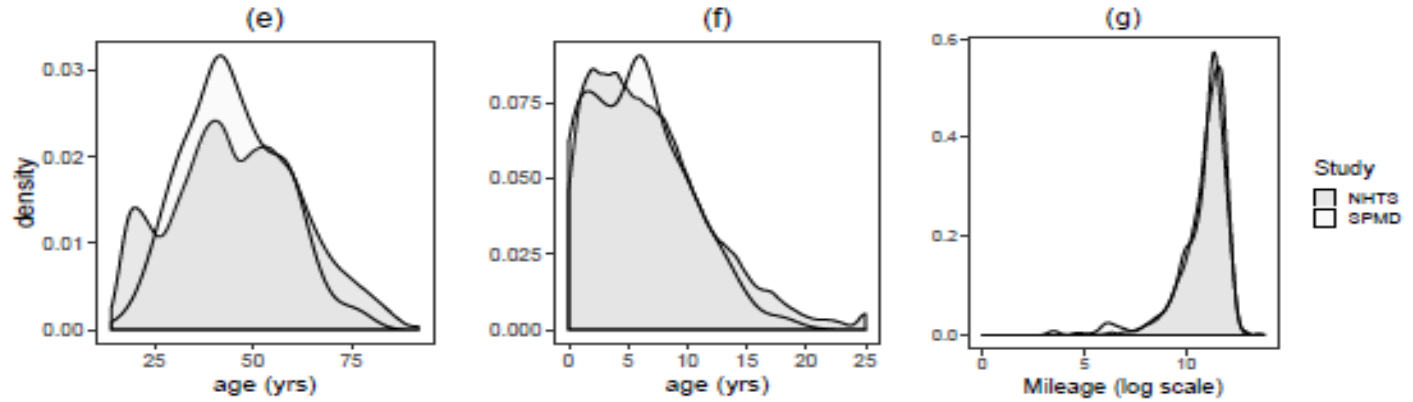
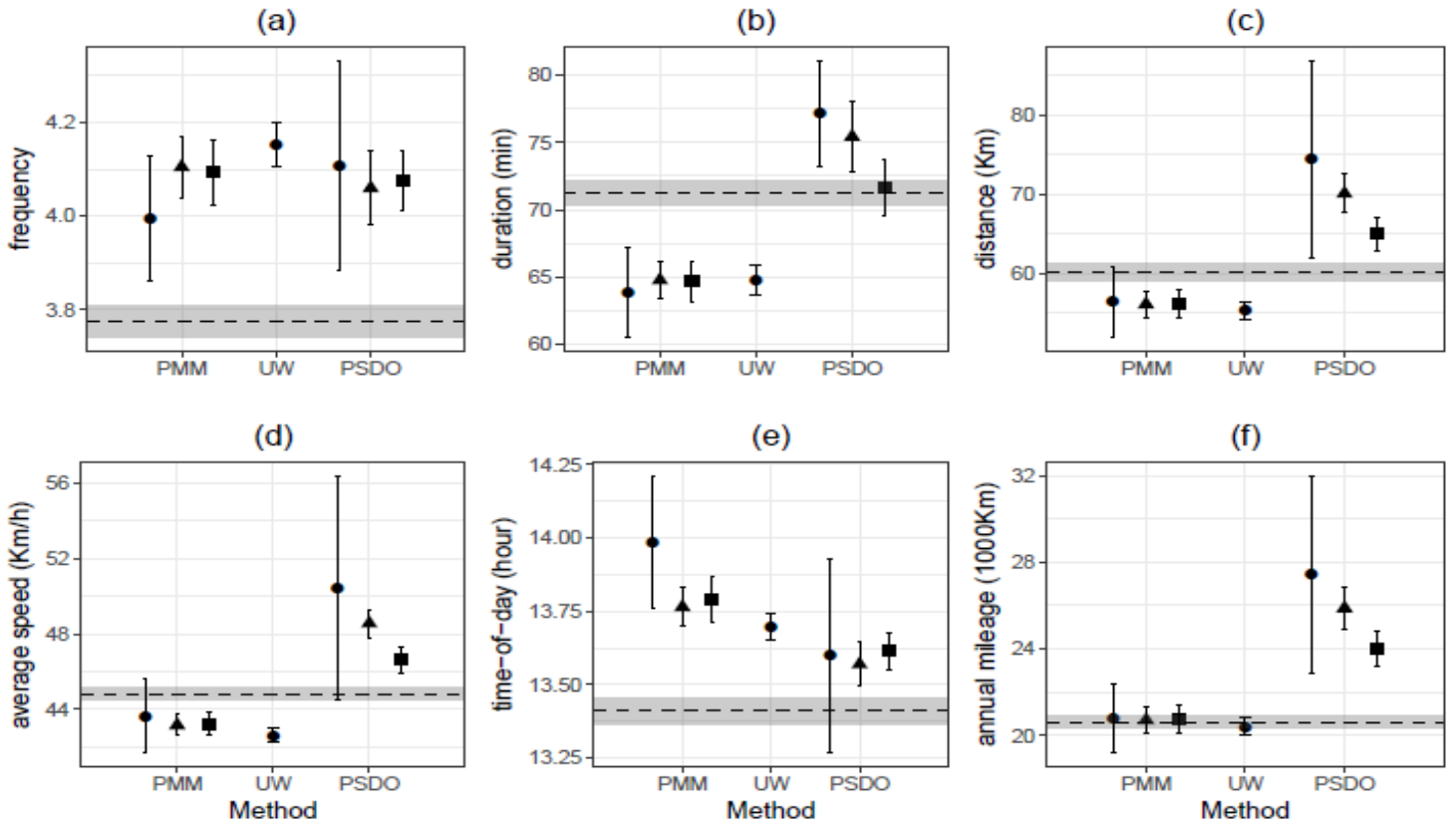


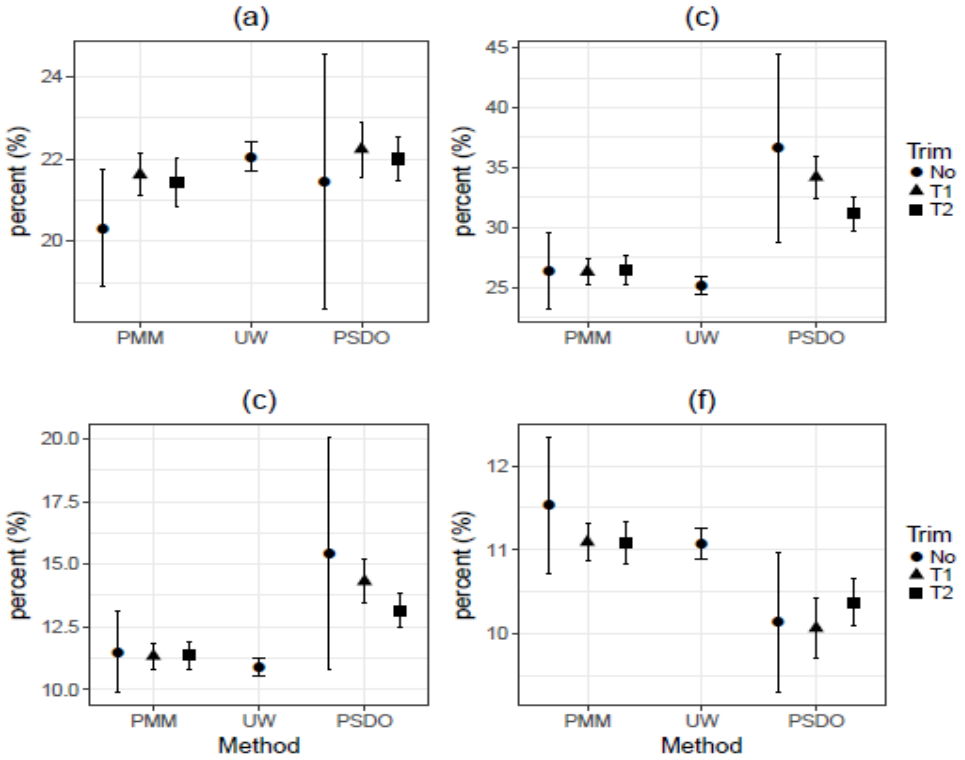
Weighted estimates of some trip-related outcomes

We compare weighted estimates of some trip-related outcomes with NHTS using pseudo-weights and PMM: Mean daily (a) frequency, (b) total duration, (c) total distance, (d) average speed, (e) start time; (f) annual mileage.



Weighted estimates of some SPMD-specific outcomes

We also estimated some SPMD-specific outcomes: Mean percent (a) trips using interstate, (b) of total trip spent on interstate, (c) time spent stopped during trip, (d) trip started between 6 and 10 am.



Simulation

- Two correlated sets of covariates were generated: W associated with probabilities of selection, and X associated with the outcome of interest.

$$\begin{pmatrix} W_1 \\ W_2 \\ X_1 \\ X_2 \end{pmatrix} \sim MVN\left(\begin{pmatrix} 0 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 & -\rho/2 & \rho & -\rho/2 \\ -\rho/2 & 1 & -\rho/2 & \rho \\ \rho & -\rho/2 & 1 & -\rho/2 \\ -\rho/2 & \rho & -\rho/2 & 1 \end{pmatrix} \right)$$

- Let Y_c and Y_b are two continuous and binary outcome variables as below:

$$Y_c|X = x \sim N(-2 + x_1 - 2x_2 + 3x_1x_2, 1)$$

$$Y_b|X = x \sim b\left(\frac{e^{-2+x_1-2x_2+3x_1x_2}}{1 + e^{-2+x_1-2x_2+3x_1x_2}}\right)$$

- Each units in the population were assigned two sets of unequal probabilities of selection, which were correlated with W through a *logistic* link as below:

$$P(S_i = 1|W) = \frac{e^{-2-2w_1+w_2+0.5w_1w_2}}{2(1 + e^{-2-2w_1+w_2+0.5w_1w_2})}$$

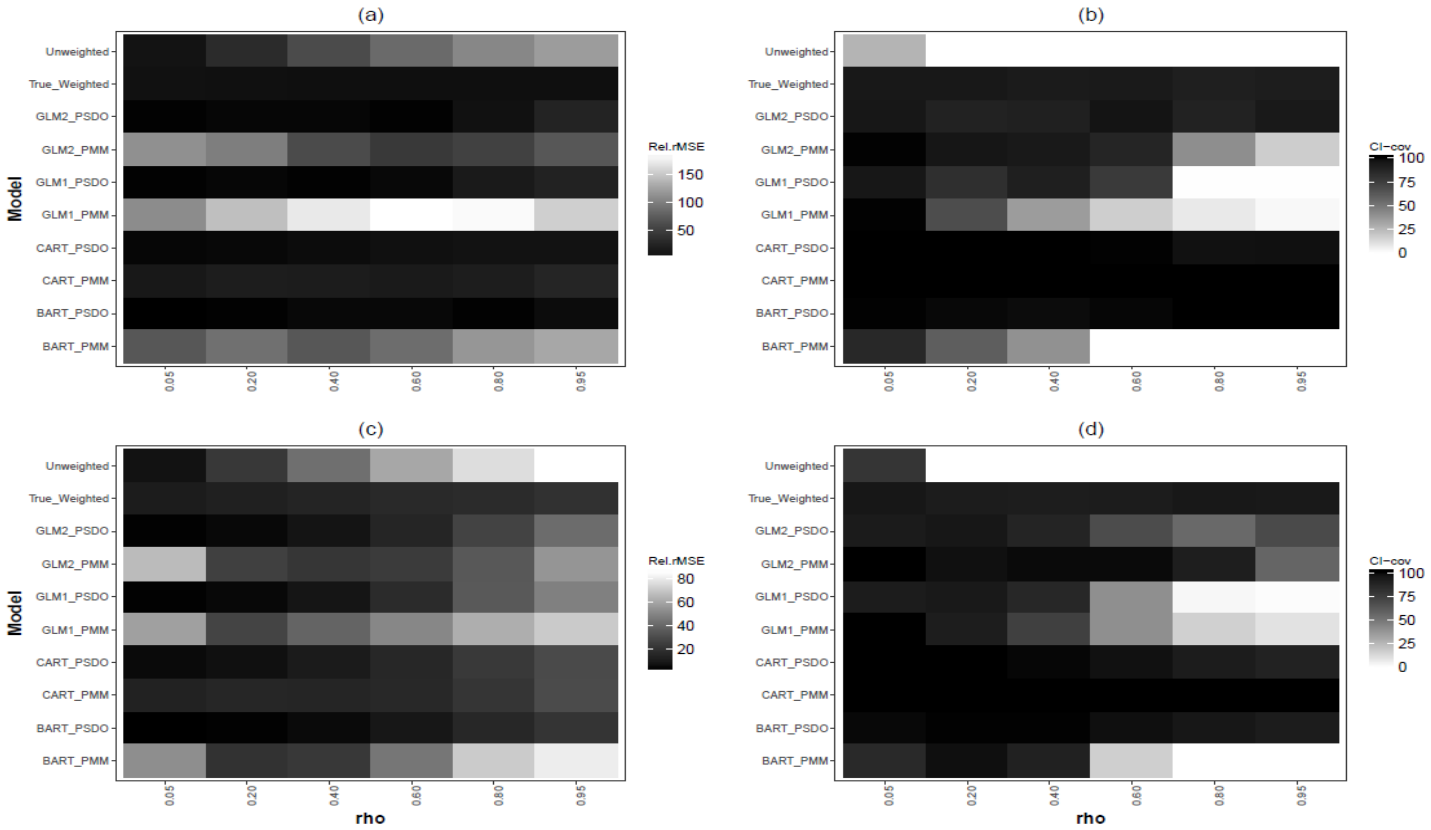
$$P(S_i^* = 1|W) = \frac{e^{-1+0.5w_1^2-w_2}}{4(1 + e^{-1+0.5w_1^2-w_2})}$$

Simulation

- The simulation was iterated 500 times, and relRMSE (standardized by mean) and nominal coverage rate of 95%CI were computed.
- Four models were utilized: (1) GLM1 (without interactions), (2) (1) GLM2 (with interactions), (3) BART, (4) CART, crossed with (a) pseudo-weight and (b) PMM construction.
- ρ=(0.05, 0.25, 0.50, 0.75, 0.95).

Simulation

- (a) and (c): relMSE for continuous and binary; (b) and (d) coverage rate for continuous and binary.



Discussion

Conclusion:

- Model specification seems to play a key role in the calibration process.
- BART works considerably better than alternative models in terms of bias reduction.
- Pseudo-weighting outperforms PMM, especially when bias is large.
- However, it may result in outliers, which need to be detected and trimmed properly.

Suggestions:

- Particular attention should be paid to identify and collect adequate predictive covariates.
- Pseudo-weighting with BART is recommended to be used for selection bias adjustment.

Next Steps

- Model based weight trimming might be helpful because of the unstable weights (Elliott and Little 2000; Elliott 2007, 2008)
- Data harmonization and measurement error: potentially differing definitions of "trips" in NHTS and SPMD
- Super-population modeling: generating synthetic populations from survey data for combination with non-probability data
- Sensitivity to failures of ignorability.

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Questions?

Email: mrelliot@umich.edu