Estimating population average treatment effects from experiments with noncompliance

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Stat 215B

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Motivation

- RCTs are the “gold standard” for estimating the causal effect of a treatment
  - External validity is an issue when RCT participants don’t reflect the target population
  - Non-compliance to treatment assignment biases estimates of the sample average treatment effect (SATE) towards 0
- Idea: reweight responses in the treatment group of RCT compliers to estimate population average treatment effect on the treated (PATT)
  - Hartman et al. [to appear] develop a nonparametric reweighting method to extend SATE to PATT
  - We extend this method to the case of one-way crossover

Overview of experiment

- Oregon Health Insurance Experiment

Estimating treatment effects

- Neyman-Rubin framework: each $i = \{1, ..., N\}$ participants have four potential outcomes, Y_{ist} for $s = 0, 1$ and $t = 0, 1$
- Define W, S, T, C, D, Y

Estimating treatment effects

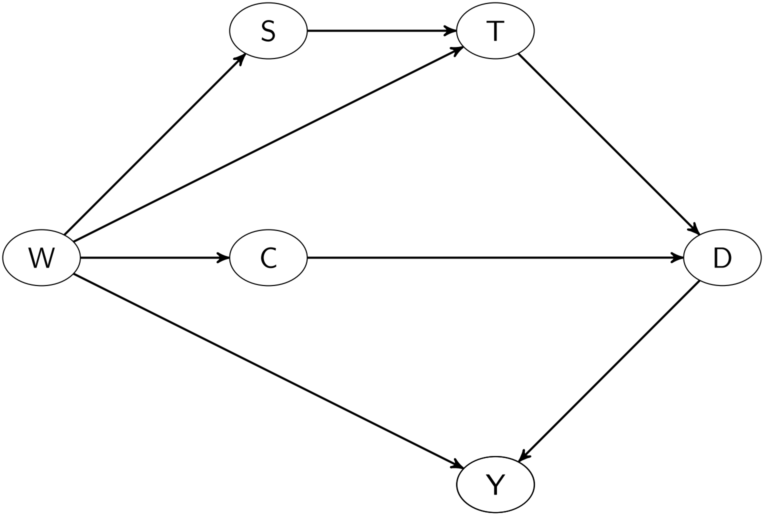


Figure: Causal diagram indicating the conditional independence assumptions needed to estimate the PATT.

Estimating treatment effects (cont.)

Assumption 1

Consistency under parallel studies: for all i and for $t = 0, 1$,

$$Y_{i0t} = Y_{i1t}$$

Estimating treatment effects (cont.)

Assumption 2

Strong ignorability of sample assignment for treated:

$$(Y_{01}, Y_{11}) \perp\!\!\!\perp S \mid (W, T = 1, C = 1), 0 < \mathbb{P}(S = 1 \mid W, T = 1, C = 1) < 1$$

Potential outcomes for treatment are independent of sample assignment for individuals with the same covariates W and assignment to treatment.

Assumption 3

Strong ignorability of sample assignment for controls:

$$(Y_{00}, Y_{10}) \perp\!\!\!\perp S \mid (W, T = 1, C = 1), 0 < \mathbb{P}(S = 1 \mid W, T = 1, C = 1) < 1$$

Potential outcomes for control are independent of sample assignment for individuals with the same covariates W and assignment to treatment.

Estimating treatment effects (cont.)

Assumption 4

Stable unit treatment value assumption (SUTVA):

$$Y_{ist}^{L_i} = Y_{ist}^{L_j}, \forall i \neq j$$

where L_j is the treatment and sample assignment vector for unit j.

Assumption 5

Conditional independence of compliance and assignment:

$$C \perp\!\!\!\perp T = 1 \mid W, 0 < \mathbb{P}(C = 1 \mid W) < 1$$

Estimating treatment effects (cont.)

Assumption 6

Monotonicity:

$$T_i \geq D_i, \forall i$$

This assumption implies that there are no defiers and that crossover is only possible from treatment to control.

Assumption 7

Exclusion restriction: For non-compliers

$$Y_{11} = Y_{10}$$

The treatment assignment affects the response only through the treatment received. In particular, the treatment effect may only be non-zero for compliers.

Estimating treatment effects (cont.)

Theorem

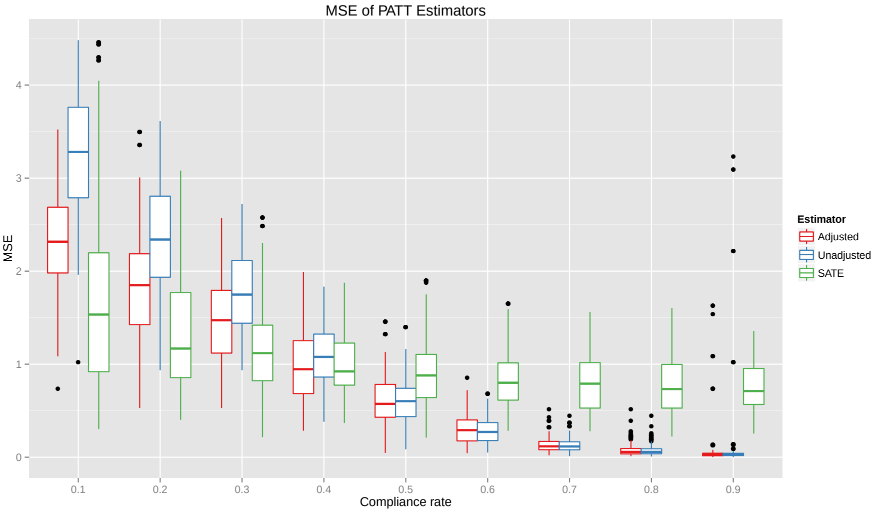
Under assumptions (1) - (7),

$$\tau_{PATT} = \mathbb{E}_{01}\left[\mathbb{E}\left(Y_{11} \mid S=1, D=1, W\right)\right] - \mathbb{E}_{01}\left[\mathbb{E}\left(Y_{10} \mid S=1, T=0, C=1,\right.\right.$$

where $\mathbb{E}_{01}\left[\mathbb{E}(\cdot \mid \ldots, W)\right]$ *denotes the expectation with respect to the distribution of* W *in the treated individuals in the target population.*

Simulation

- describe simulation design?


MSE of PATT Estimators
MSE
4
3
2
1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Compliance rate
Estimator
Adjusted
Unadjusted
SATE

Data

- OHIE data
- NHIS data

Estimation Procedure

1. Using the Medicaid lottery winners in the OHIE ($S = 1$, $T = 1$), train a model to predict complier status using observed covariates.
2. Predict which lottery losers in the OHIE *would have* signed up for Medicaid had they been eligible.
3. For the group of observed compliers to treatment and predicted compliers in the control group, train a model to predict hospital use using the covariates and Medicaid enrollment as features.
4. For all individuals who enrolled in Medicaid in the NHIS, estimate their potential outcomes Y_{10} and Y_{11} using the model from step 3. The mean counterfactual Y_{11} minus the mean counterfactual Y_{10} is the estimate of τ_{PATT}.

Figure: Heterogeneous effects of Medicaid enrollment on hospital visits.

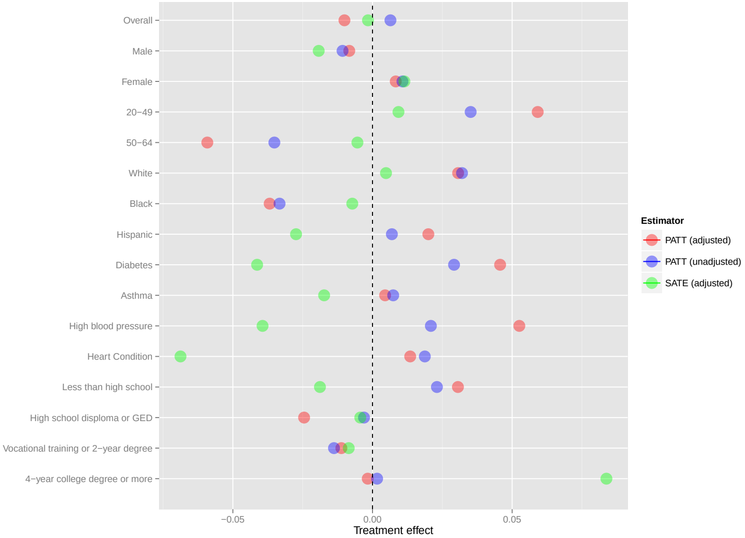
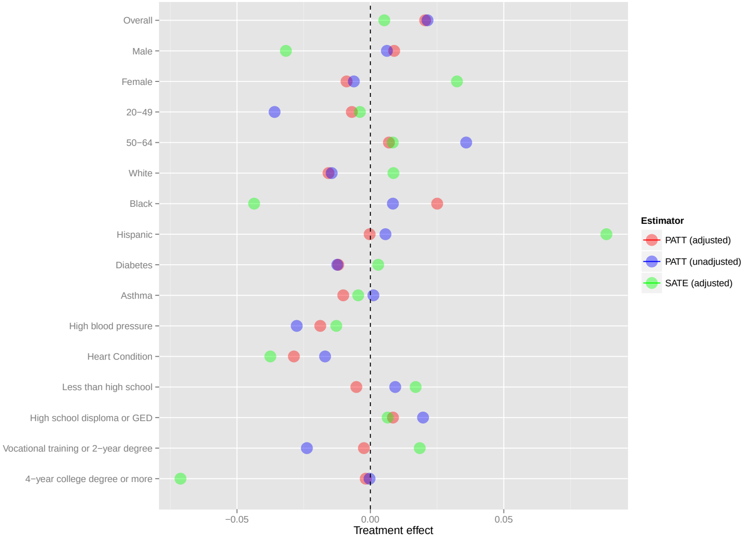


Figure: Heterogeneous effects of Medicaid enrollment on outpatient visits.



Discussion

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Erin Hartman, Richard Grieve, Roland Ramsahai, and Jasjeet S. Sekhon. From sate to patt: Combining experimental with observational studies to estimate population treatment effects. *Journal of the Royal Statistical Society, Series A*, to appear.