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 $t = 0, 1$
  - S = study assignment: S=1 for RCT, S=0 for population/observational study
  - T = treatment assignment: T = 1 for treatment, T = 0 for control
  - D = treatment received
- Other variables
  - W = observed covariates
  - C = compliance to treatment
  - Y = response

Estimating treatment effects

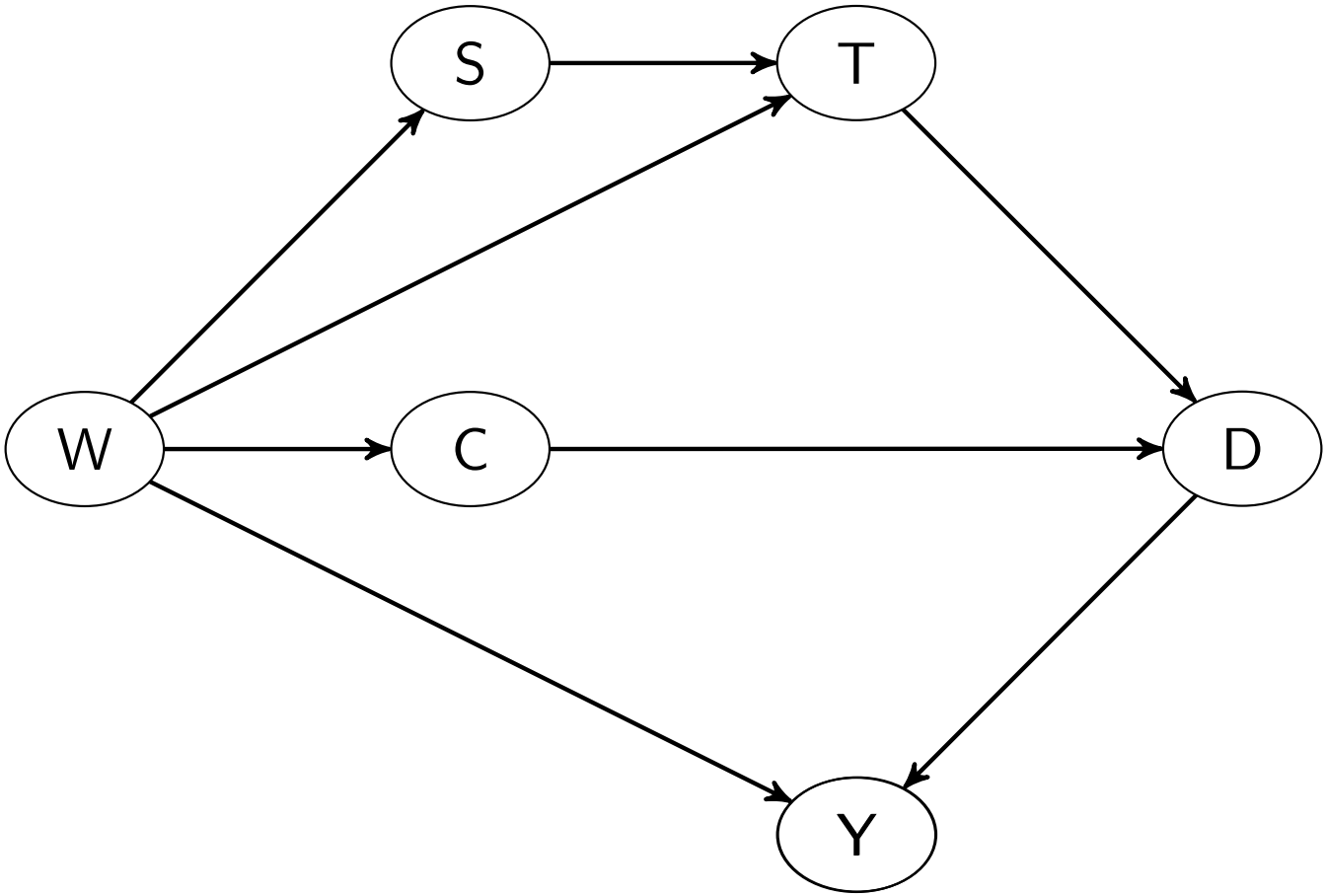


Figure: Causal diagram indicating the conditional independence assumptions needed to estimate the PATT.

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

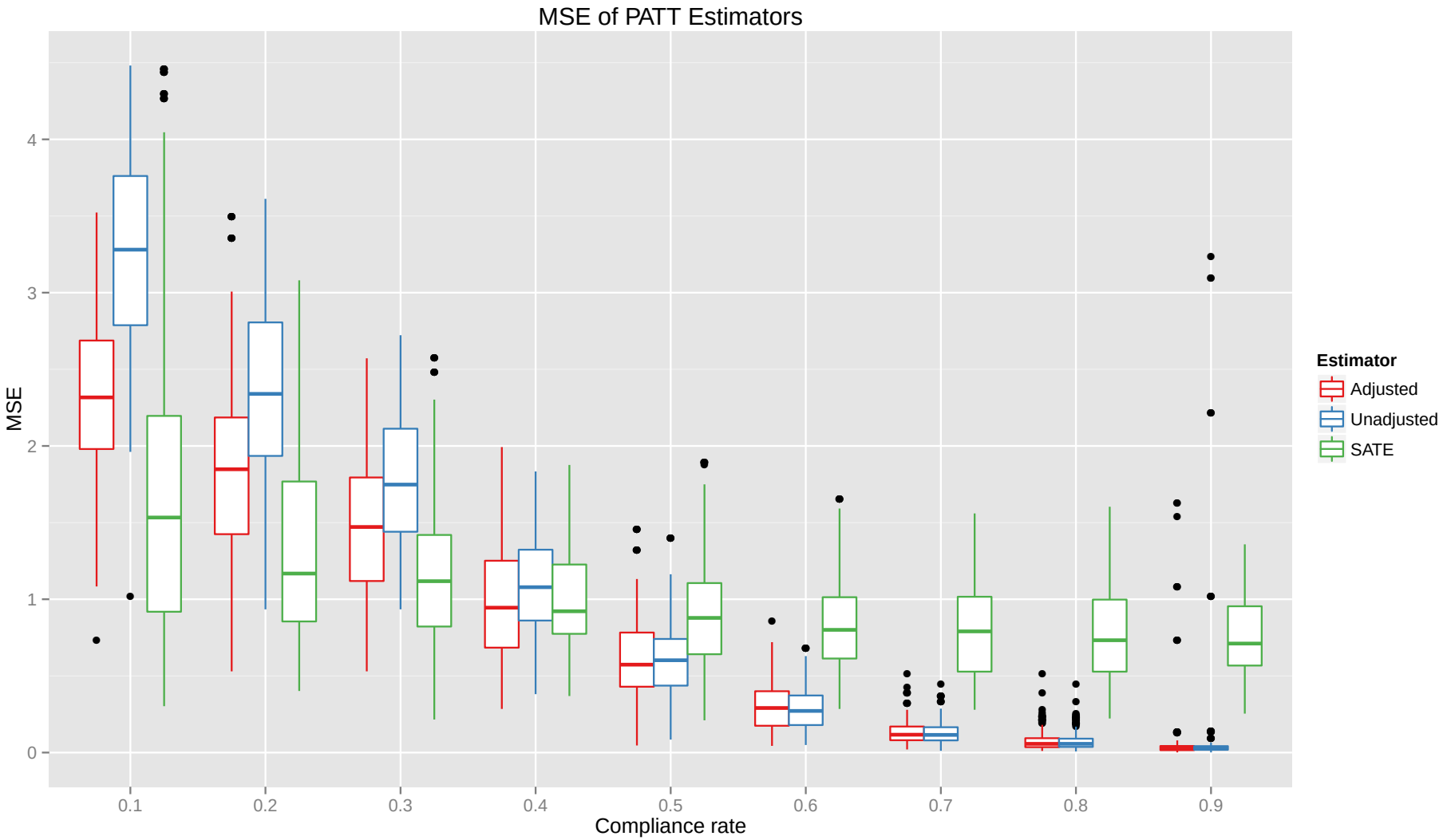
Under assumptions (1) - (7),

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

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 Design

- Generate a population of 30,000 with 3 observable covariates W
- Set S, T, C, Y to be linear functions of W, with some Gaussian noise
- Heterogeneous treatment effect: magnitude of effect depends on one of the covariates
- Sample 5,000 "randomizables" for RCT and 5,000 "observables" for observational study. Enroll individuals according to S
- Predict would-be compliers in the RCT control group using logistic regression
- Estimate response curve in RCT compliers using a random forest
- Use model to estimate potential outcomes in the observational study to estimate τ_{PATT}


MSE of PATT Estimators
MSE
0
1
2
3
4
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

Checking Assumptions

- Monotonicity is violated. There is some 2-way cross-over
- Key assumption is strong ignorability: model of response given covariates is the same in the RCT and in the population
  - No way to check that we've included all possible confounders
  - We have included all the confounders we have data on

Checking Assumptions (cont.)

table of covariates, in OHIE and NHIS

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.

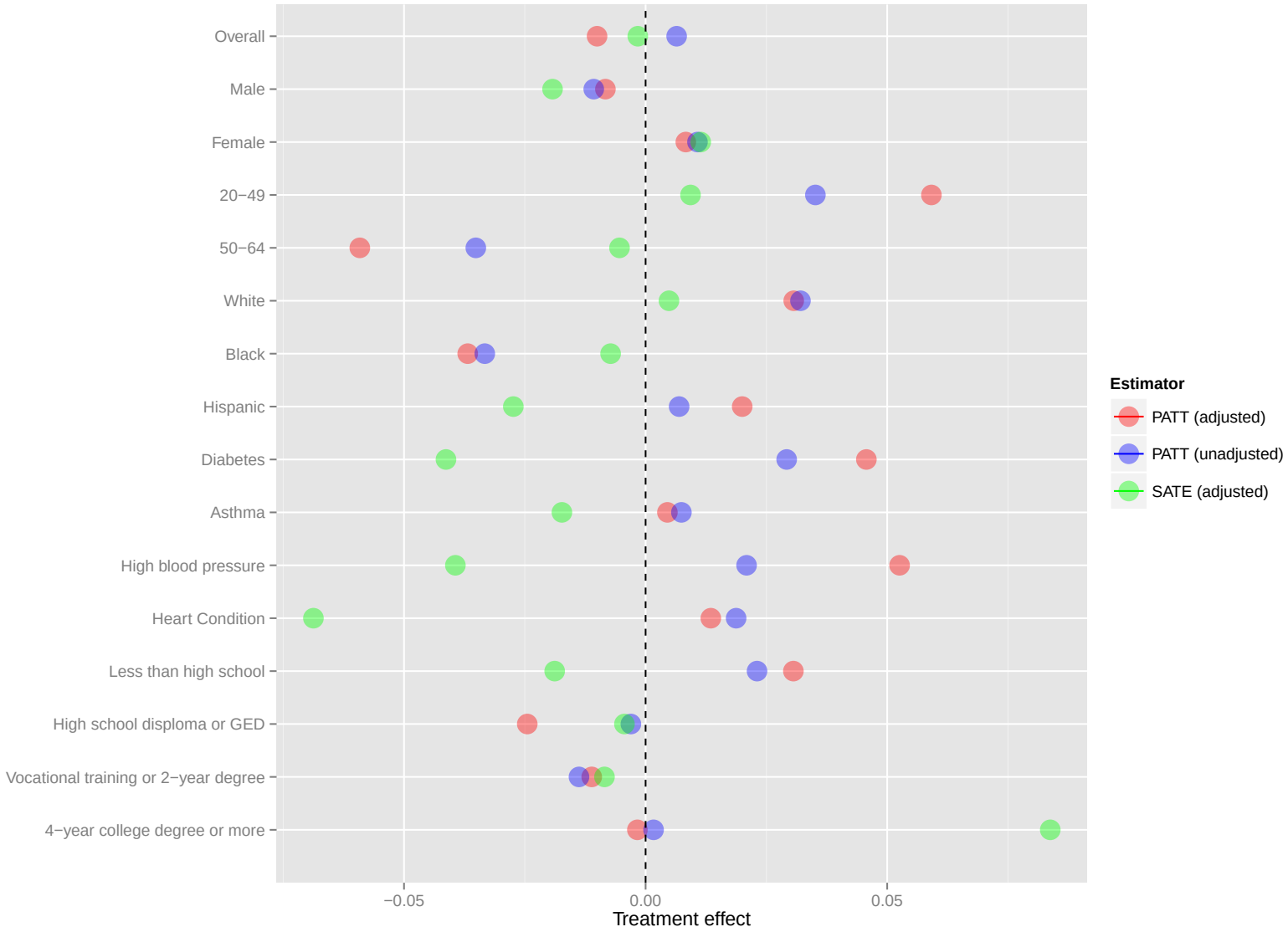
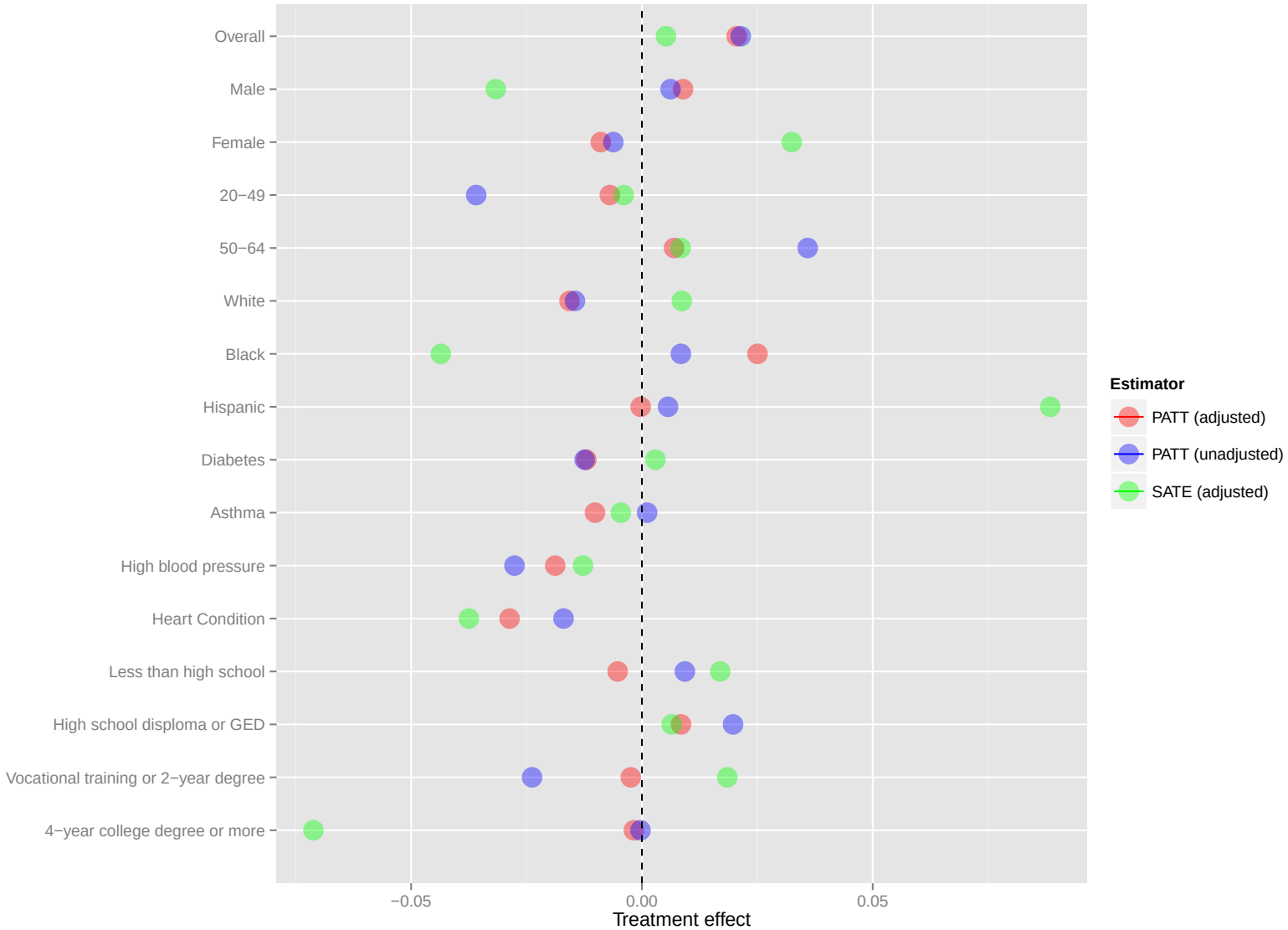


Figure: Heterogeneous effects of Medicaid enrollment on outpatient visits.



Conclusions

- If the compliance rate is moderate and compliance is predictable by observed covariates, then it makes sense to use the proposed estimator
- statement or two about the OHIE/NHIS conclusions

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.