Title in Progress

Amy Pitts, Hun Lee, Jimmy Kelliher,
Tucker Morgan, and Waveley Qiu

2022-02-21

Motivation

- Identifying the effect of a treatment or intervention is one of the most fundamental tasks we encounter as biostatisticians. . .

Motivation

- Identifying the effect of a treatment or intervention is one of the most fundamental tasks we encounter as biostatisticians. . .
- . . . but outside of a randomized control trial (RCT), confounding variables can bias our estimates of treatment effects.

Motivation

- Identifying the effect of a treatment or intervention is one of the most fundamental tasks we encounter as biostatisticians...
- ... but outside of a randomized control trial (RCT), confounding variables can bias our estimates of treatment effects.
- Propensity score matching (PSM) is a tool that can help us mitigate the effects of confounders...

Motivation

- Identifying the effect of a treatment or intervention is one of the most fundamental tasks we encounter as biostatisticians...
- ... but outside of a randomized control trial (RCT), confounding variables can bias our estimates of treatment effects.
- Propensity score matching (PSM) is a tool that can help us mitigate the effects of confounders...
- ... but there is no consensus on the best way to estimate standard errors when using the PSM algorithm.

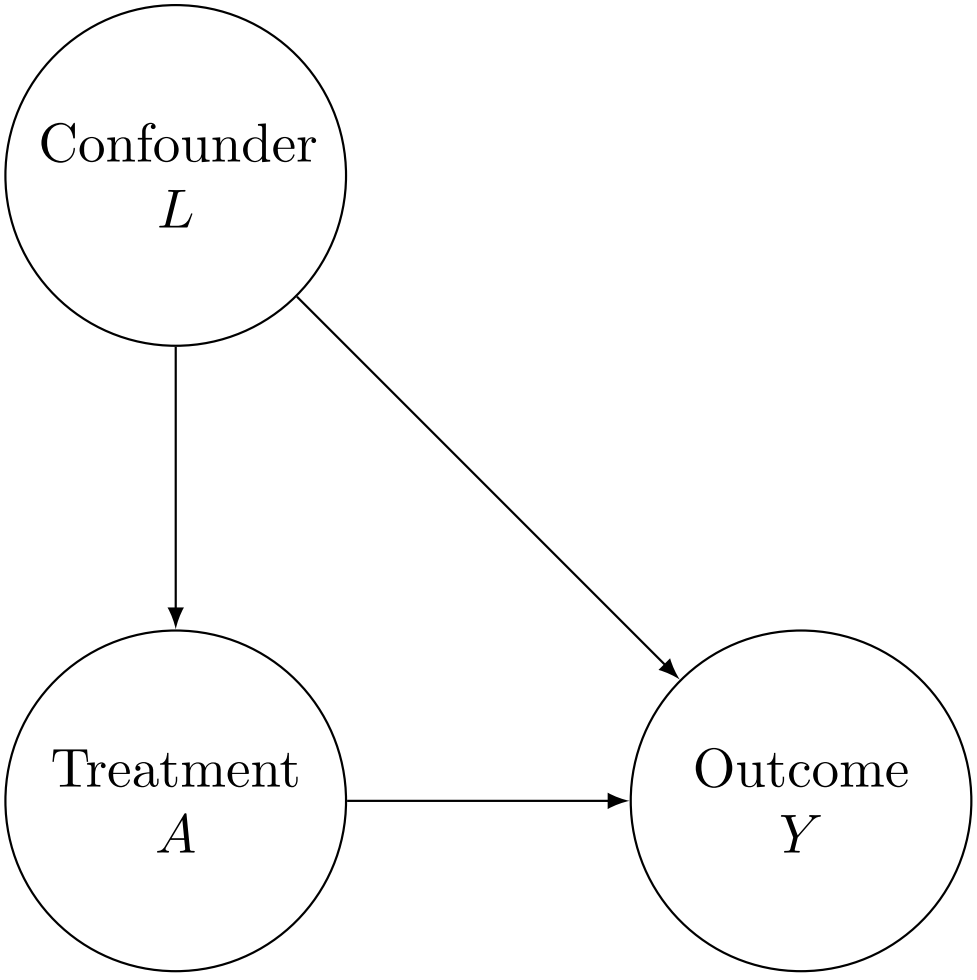
Motivation

- Identifying the effect of a treatment or intervention is one of the most fundamental tasks we encounter as biostatisticians...
- ... but outside of a randomized control trial (RCT), confounding variables can bias our estimates of treatment effects.
- Propensity score matching (PSM) is a tool that can help us mitigate the effects of confounders...
- ... but there is no consensus on the best way to estimate standard errors when using the PSM algorithm.
- How can we assess which procedures reliably estimate standard errors?

Motivation

A simulation study!

A Quick Foray into Confounding



Taking a Step Back, What is Propensity Score Matching?

- A *propensity score* is the probability that an individual receives a treatment A; that is, $P(A = 1)$. In an RCT, treatments are randomized, and hence outcomes Y are independent of treatment A.

Enter the Bootstrap

- Bootstrapping is one of the most common procedures for estimating standard errors.

Enter the Bootstrap

- Bootstrapping is one of the most common procedures for estimating standard errors.
- The PSM algorithm intakes an unmatched dataset and outputs a matched one.

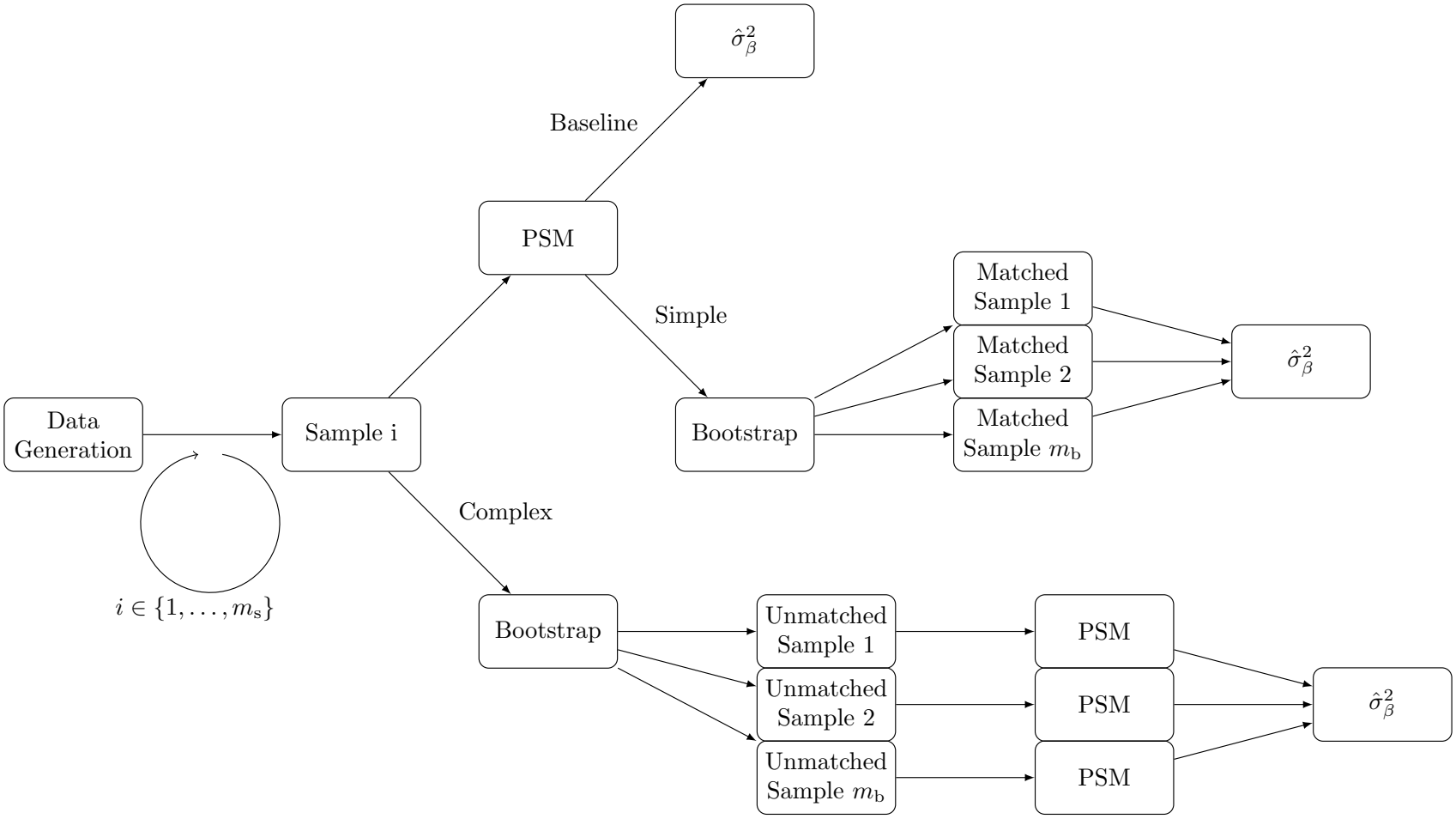
Enter the Bootstrap

- Bootstrapping is one of the most common procedures for estimating standard errors.
- The PSM algorithm intakes an unmatched dataset and outputs a matched one.
- When do we execute the bootstrap - before the match or after it?

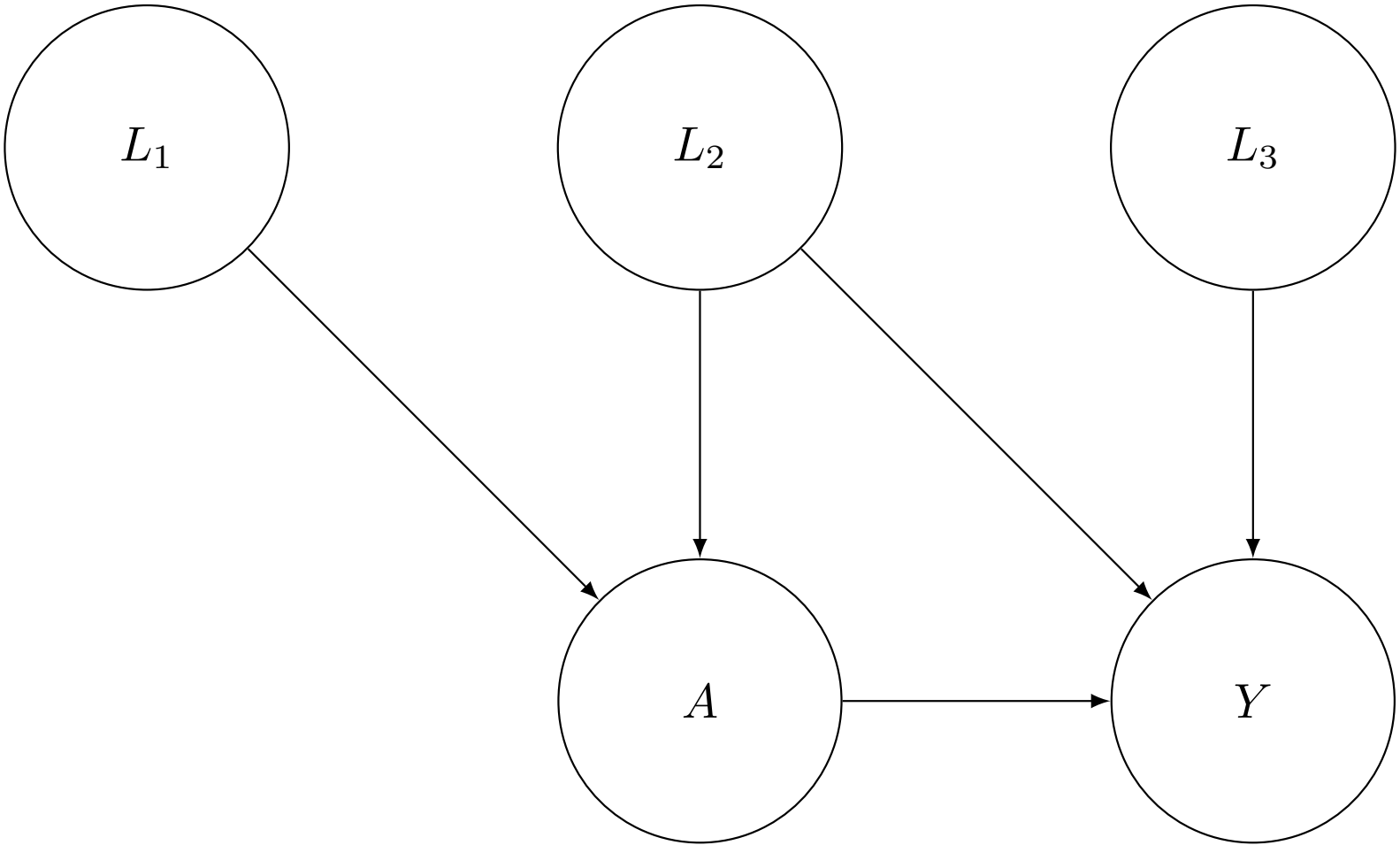
Enter the Bootstrap

- Bootstrapping is one of the most common procedures for estimating standard errors.
- The PSM algorithm intakes an unmatched dataset and outputs a matched one.
- When do we execute the bootstrap - before the match or after it?
- Let's try both!

Roadmap of the Simulation Study



Data Generation



Data Generation - Continuous Outcome

For each individual $i \in \{1, \ldots, n\}$, we consider covariates $L_{1i}, L_{2i}, L_{3i} \sim N(0, 1)$. Treatments are distributed according to law $A_i \sim B(\pi_i)$, where π_i - the true propensity to be treated - is subject to the data-generating process

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha_0 + \alpha_1 L_{1i} + \alpha_2 L_{2i}.$$

Given this, we further define the data-generating process of our continuous outcome via

$$Y_i = \beta_1 A_i + \beta_2 L_{2i} + \beta_3 L_{3i} + \varepsilon_i,$$

where ε_i denotes random error. Because L_{2i} effects both A_i and Y_i, it acts as a confounder in estimating the treatment effect.

Data Generation - Binary Outcome

For each individual $i \in \{1, \ldots, n\}$, we consider covariates $L_{1i}, L_{2i}, L_{3i} \sim N(0, 1)$. Treatments are distributed according to law $A_i \sim B(\pi_i)$, where π_i - the true propensity to be treated - is subject to the data-generating process

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha_0 + \alpha_1 L_{1i} + \alpha_2 L_{2i}.$$

Given this, we further define the data-generating process of our binary outcome via $Y_i \sim B(\tau_i)$ where

$$\log\left(\frac{\tau_i}{1-\tau_i}\right) = \beta_1 A_i + \beta_2 L_{2i} + \beta_3 L_{3i}.$$

Observe that we have omitted a random error term, as realizations of Y_i are innately subject to noise.

Parameters of Interest

- The sample size of each dataset $n_{\text{sample}} \in \{100, 1000\}$
- The population proportion of treated individuals $\pi \in \{0.113, 0.216, 0.313\}$
- The true average treatment effect $\beta_1 \in \{0.15, 0.30\}$

Other Parameters

- The number of datasets $m_{\text{sample}} = 100$
- The number of bootstrap re-sample $m_{\text{boot}} = 500$
- The sample size of bootstrap re-samples $n_{\text{simple}} = n_{\text{complex}} = n_{\text{sample}} \times \pi$
- Strength of Covariate Correlation on Treatment Status α_1, α_2 (continuous data (1,2), binary data $(\log(1.25), \log(1.75))$)
- Strength of Covariate Correlation on Outcome Variable β_2, β_3 (continuous data (2,1), binary data $(\log(1.75), \log(1.25))$)

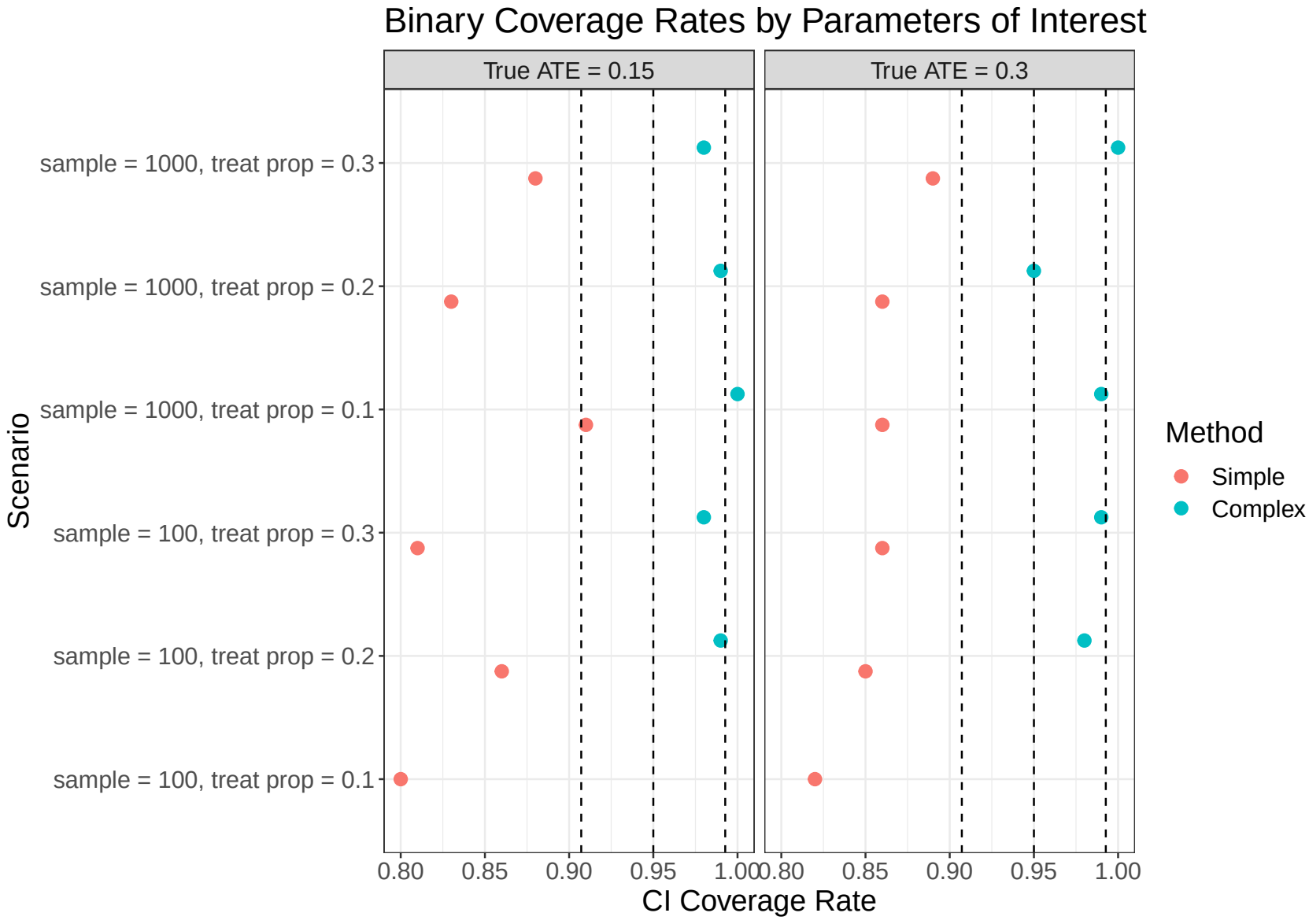
Measures of Interest

- **Coverage Rate:** Looks at the rate of the true avergae treatment effect falling in the 95% confidence intervals. $\hat{\text{ATE}} \pm 1.96 \times \text{SE}$
- **Standard Error:** the variability of the average estimate.

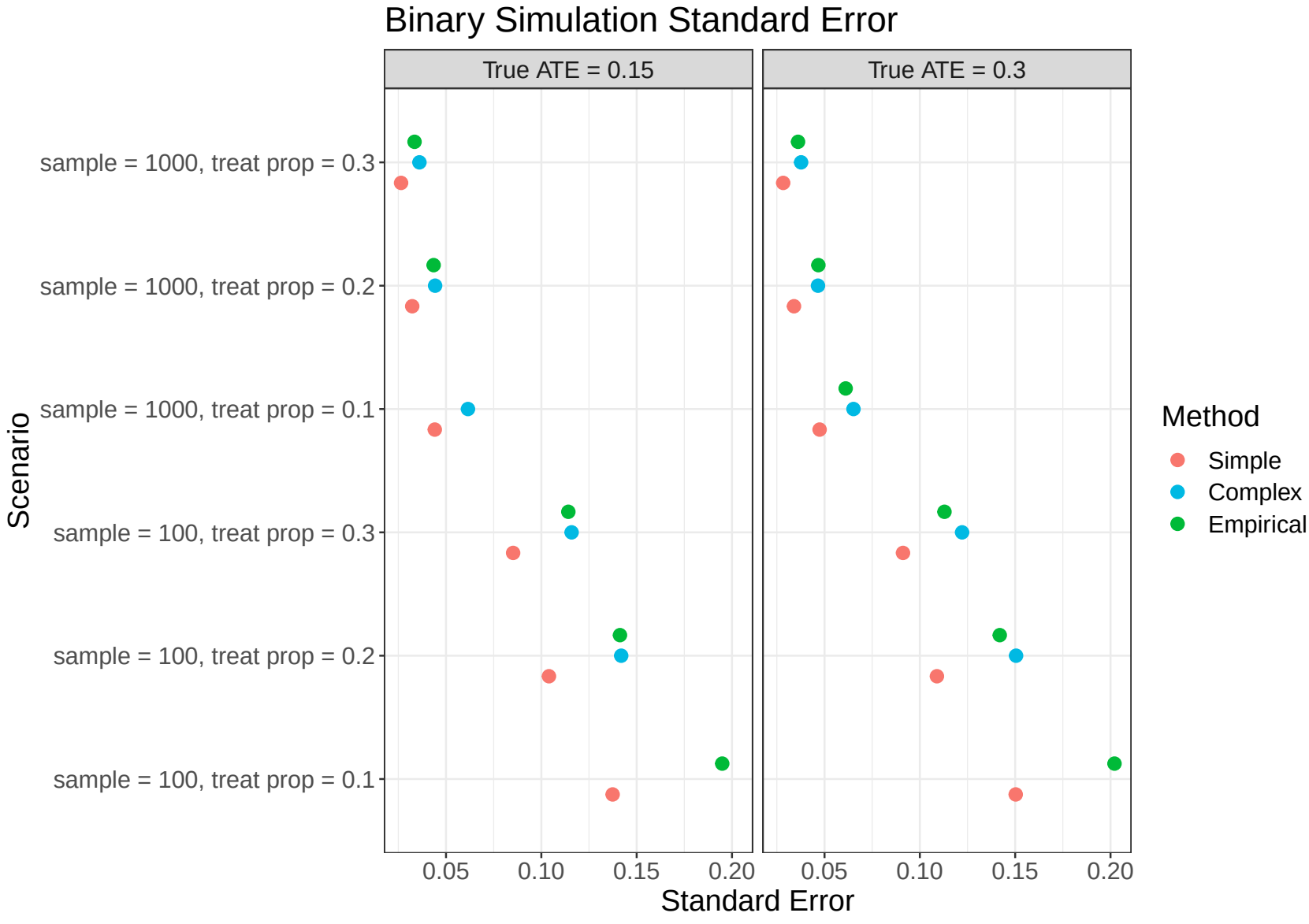
Other Measures

- **Bias:** This is mean of the average estimate subtract the true ATE
- **95% Confidence Intervals:**

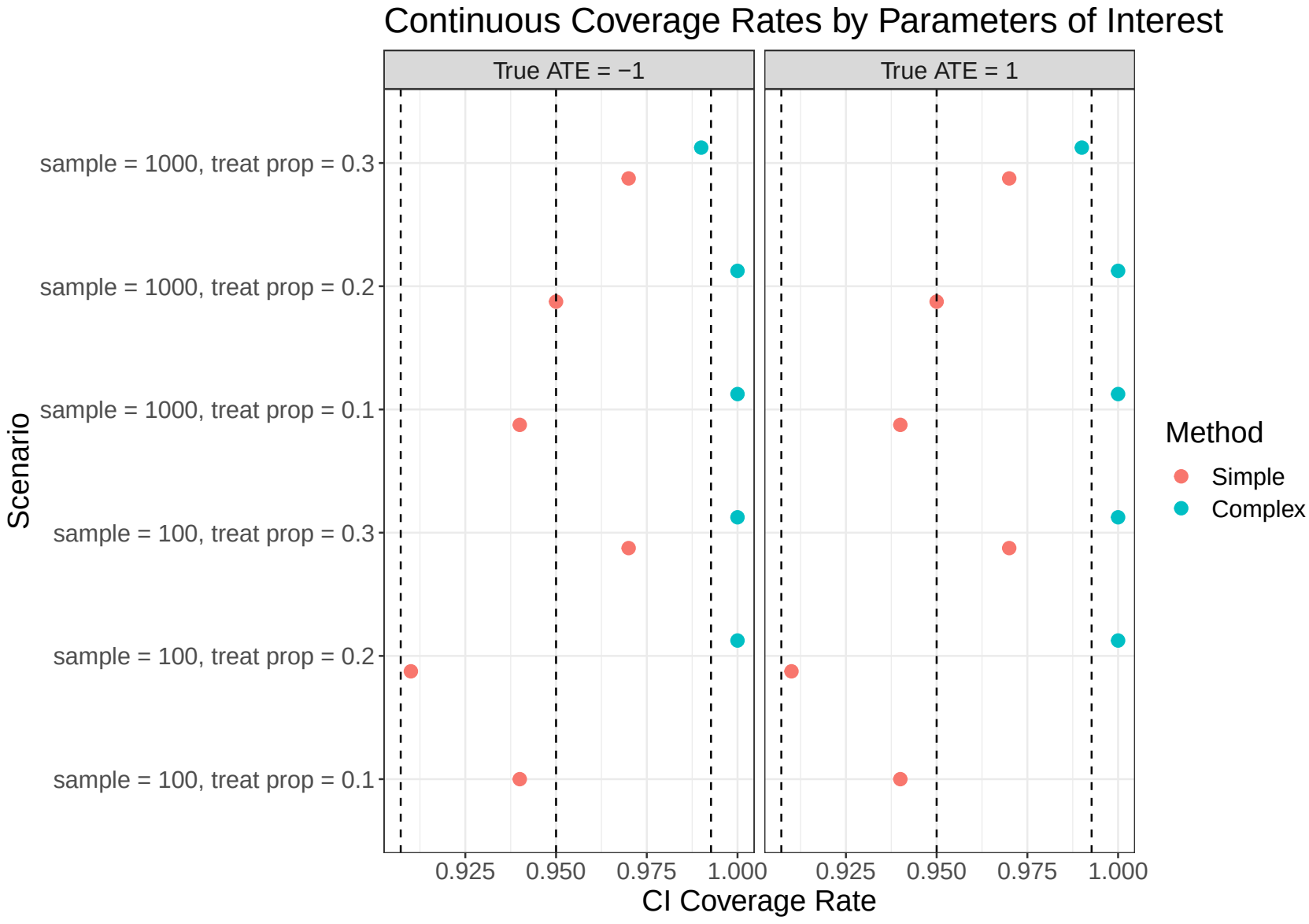
Results


Binary Coverage Rates by Parameters of Interest
True ATE = 0.15
True ATE = 0.3
sample = 1000, treat prop = 0.3
sample = 1000, treat prop = 0.2
sample = 1000, treat prop = 0.1
sample = 100, treat prop = 0.3
sample = 100, treat prop = 0.2
sample = 100, treat prop = 0.1
Scenario
0.80
0.85
0.90
0.95
1.00
CI Coverage Rate
Method
Simple
Complex

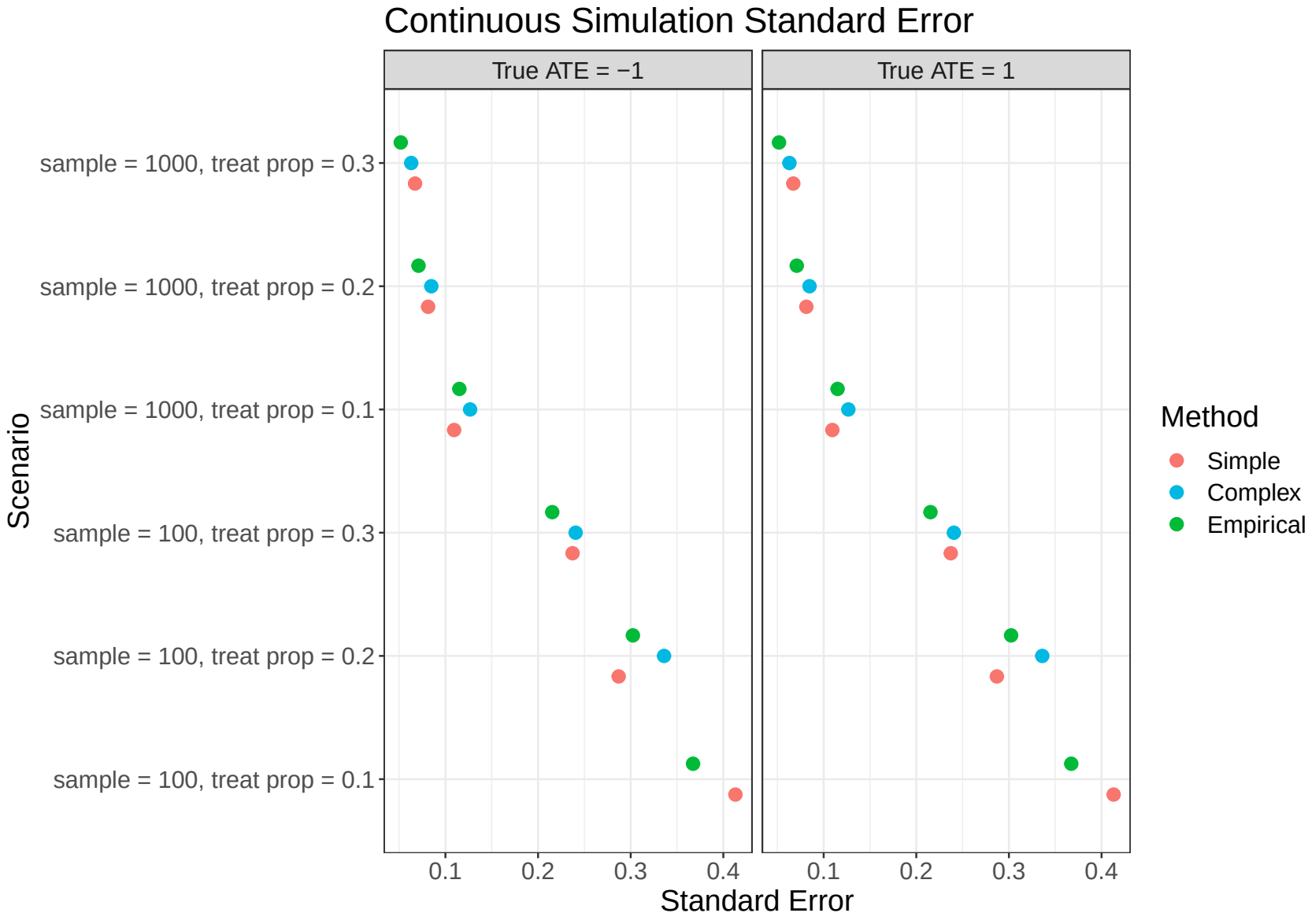
Results


Binary Simulation Standard Error
True ATE = 0.15
True ATE = 0.3
sample = 1000, treat prop = 0.3
sample = 1000, treat prop = 0.2
sample = 1000, treat prop = 0.1
sample = 100, treat prop = 0.3
sample = 100, treat prop = 0.2
sample = 100, treat prop = 0.1
Scenario
0.05
0.10
0.15
0.20
Standard Error
Method
Simple
Complex
Empirical

Results


Continuous Coverage Rates by Parameters of Interest
True ATE = −1
True ATE = 1
Scenario
sample = 1000, treat prop = 0.3
sample = 1000, treat prop = 0.2
sample = 1000, treat prop = 0.1
sample = 100, treat prop = 0.3
sample = 100, treat prop = 0.2
sample = 100, treat prop = 0.1
0.925
0.950
0.975
1.000
CI Coverage Rate
Method
Simple
Complex

Results


Continuous Simulation Standard Error
True ATE = −1
True ATE = 1
sample = 1000, treat prop = 0.3
sample = 1000, treat prop = 0.2
sample = 1000, treat prop = 0.1
sample = 100, treat prop = 0.3
sample = 100, treat prop = 0.2
sample = 100, treat prop = 0.1
Scenario
0.1
0.2
0.3
0.4
Standard Error
Method
Simple
Complex
Empirical

Summary of Results

- For binary outcomes, the simple bootstrap tended to underestimate the standard error
- Larger standard error estimates from complex bootstrap in binary and continuous settings
- Differences between simple and complex bootstrap were smaller for larger sample sizes
- Complex bootstrap not as reliable in small sample sizes

Limitations

- Sample size / treatment (or exposure) prevalence
- Small number of initial samples, limited in detecting significant differences in coverage rate
-
-

Future Work

- Larger number of initial samples, narrower coverage window
- Increased sample size, changes in bootstrap performance?
- Changes in treatment propensity model
- Non-normal distributions of covariates