Title in Progress

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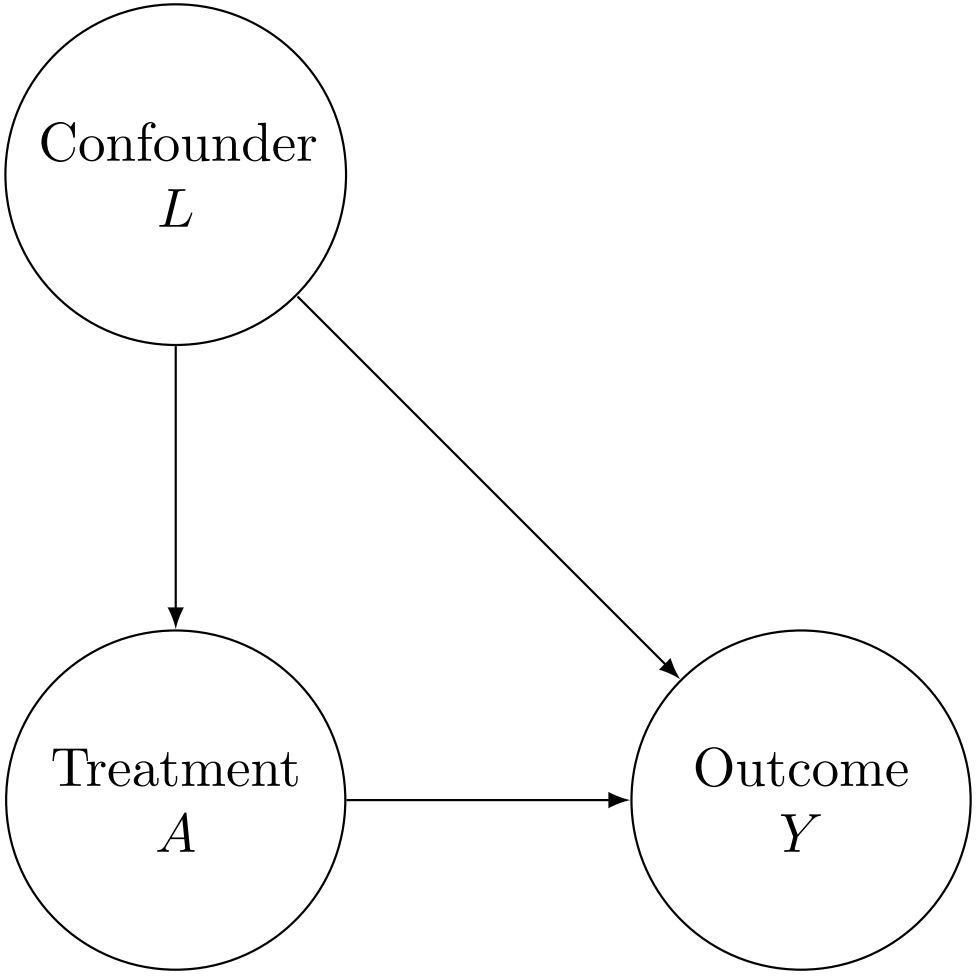
- Propensity score matching (PSM) is a tool that can help us mitigate the effects of confounders...
- ... but there is no consensus on the best way to estimate standard errors when using the PSM algorithm.
- How can we assess which procedures reliably estimate standard errors?

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.

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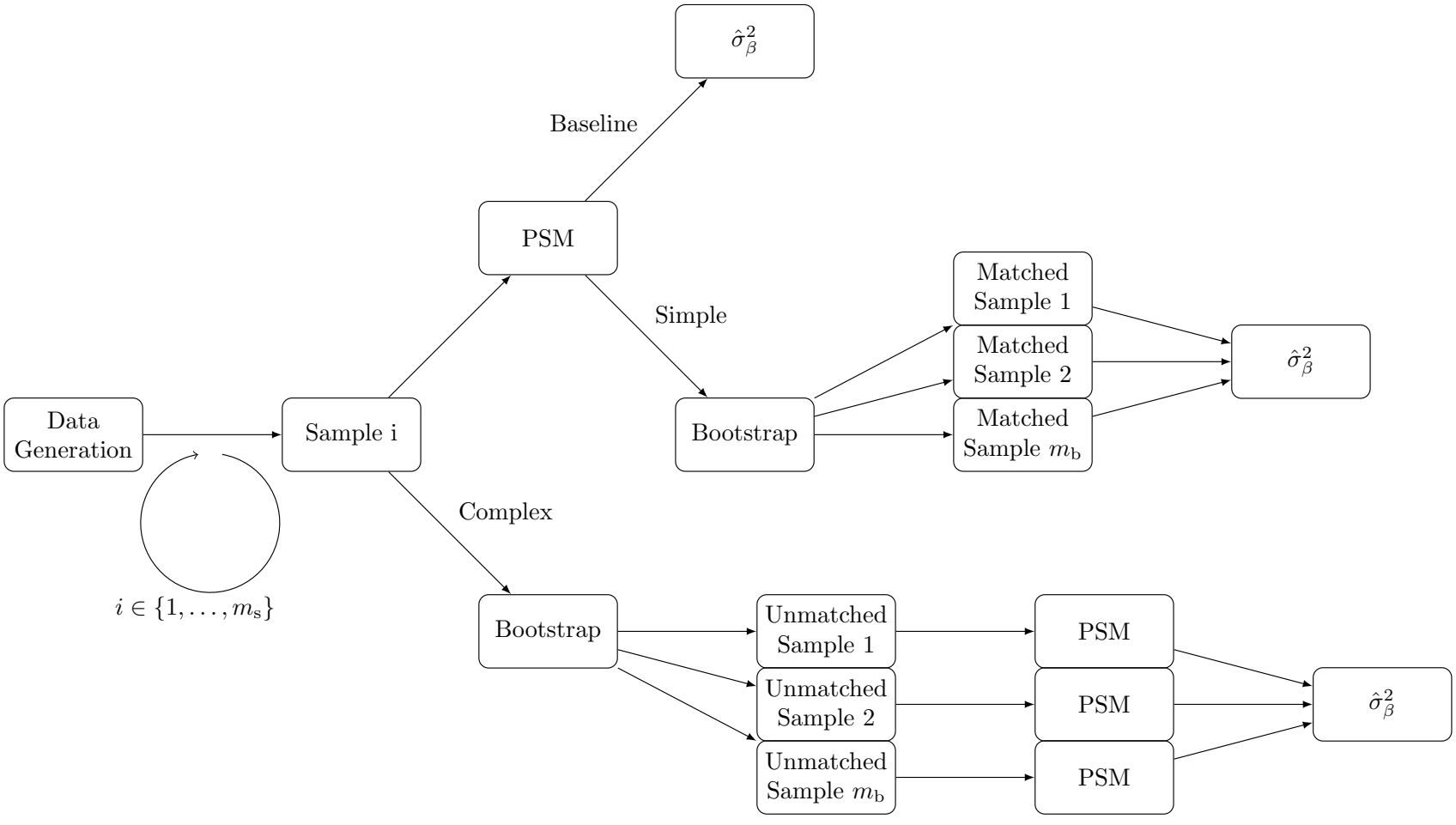
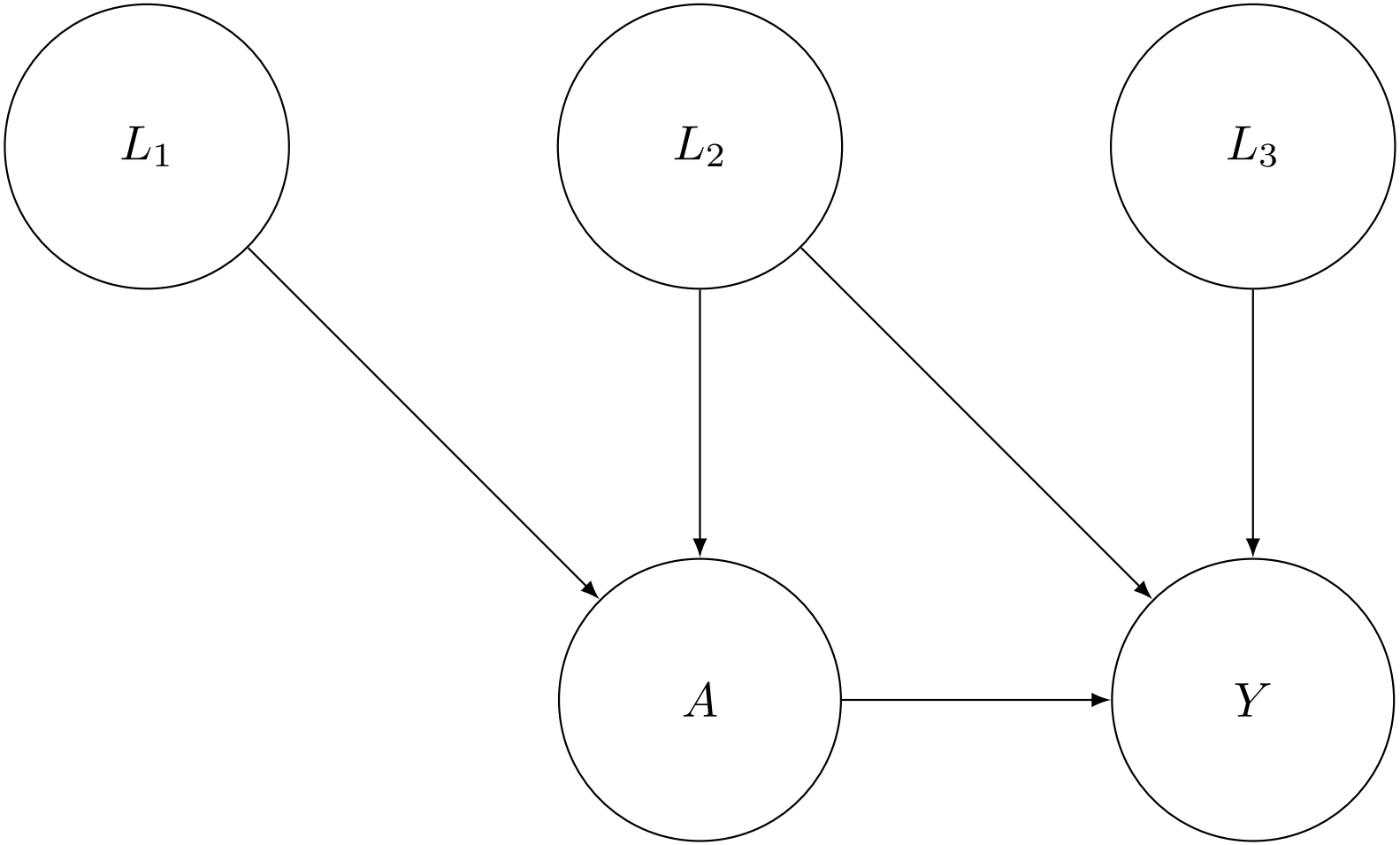
- The PSM algorithm intakes an unmatched dataset and outputs a matched one.
- When do we execute the bootstrap - before the match or after it?
- Let's try both!

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 $\pi \in \{0.113, 0.216, 0.313\}$
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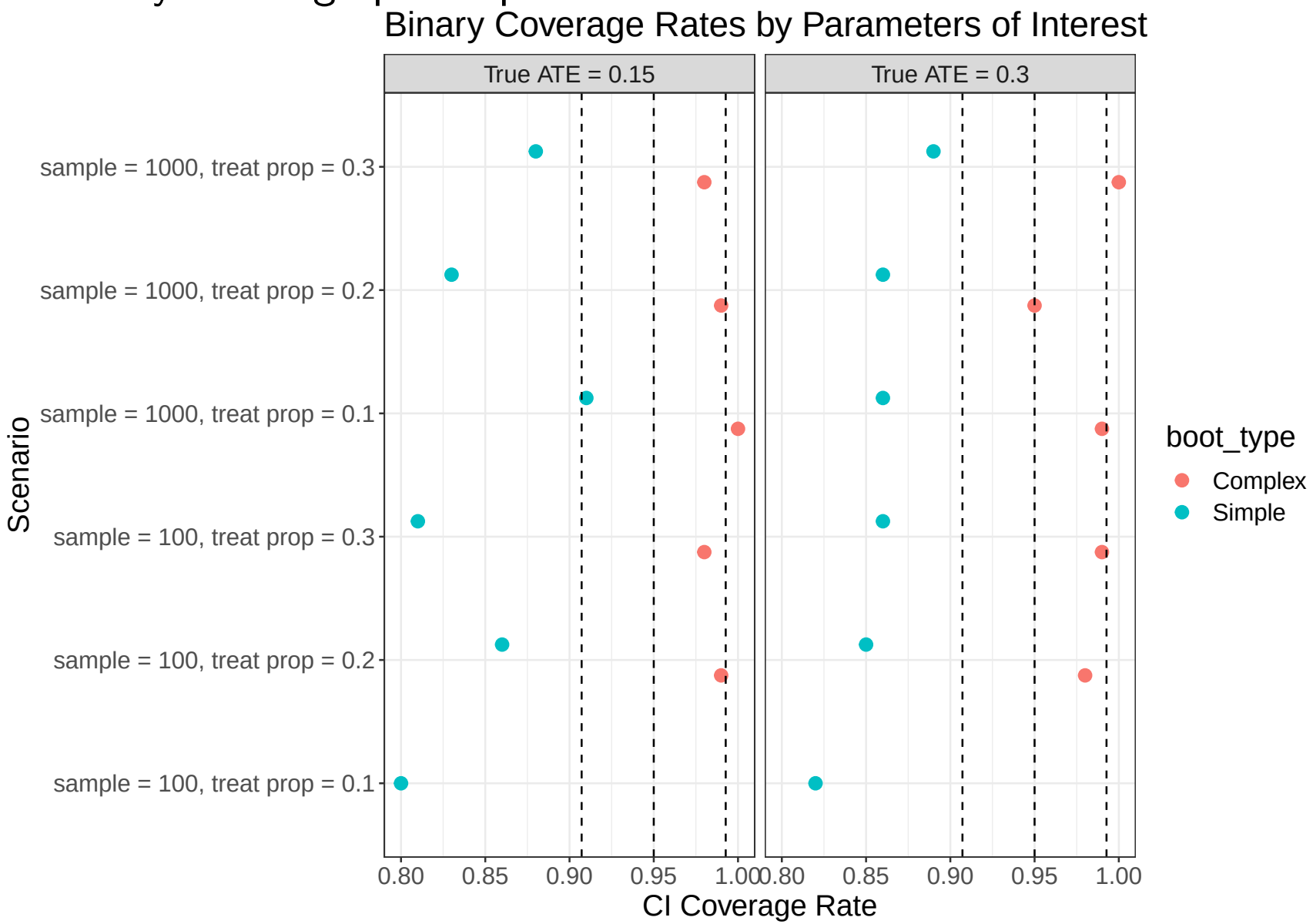
Other Parameters

- The number of datasets $m_{\text{sample}} = 100$

Measures of Interest

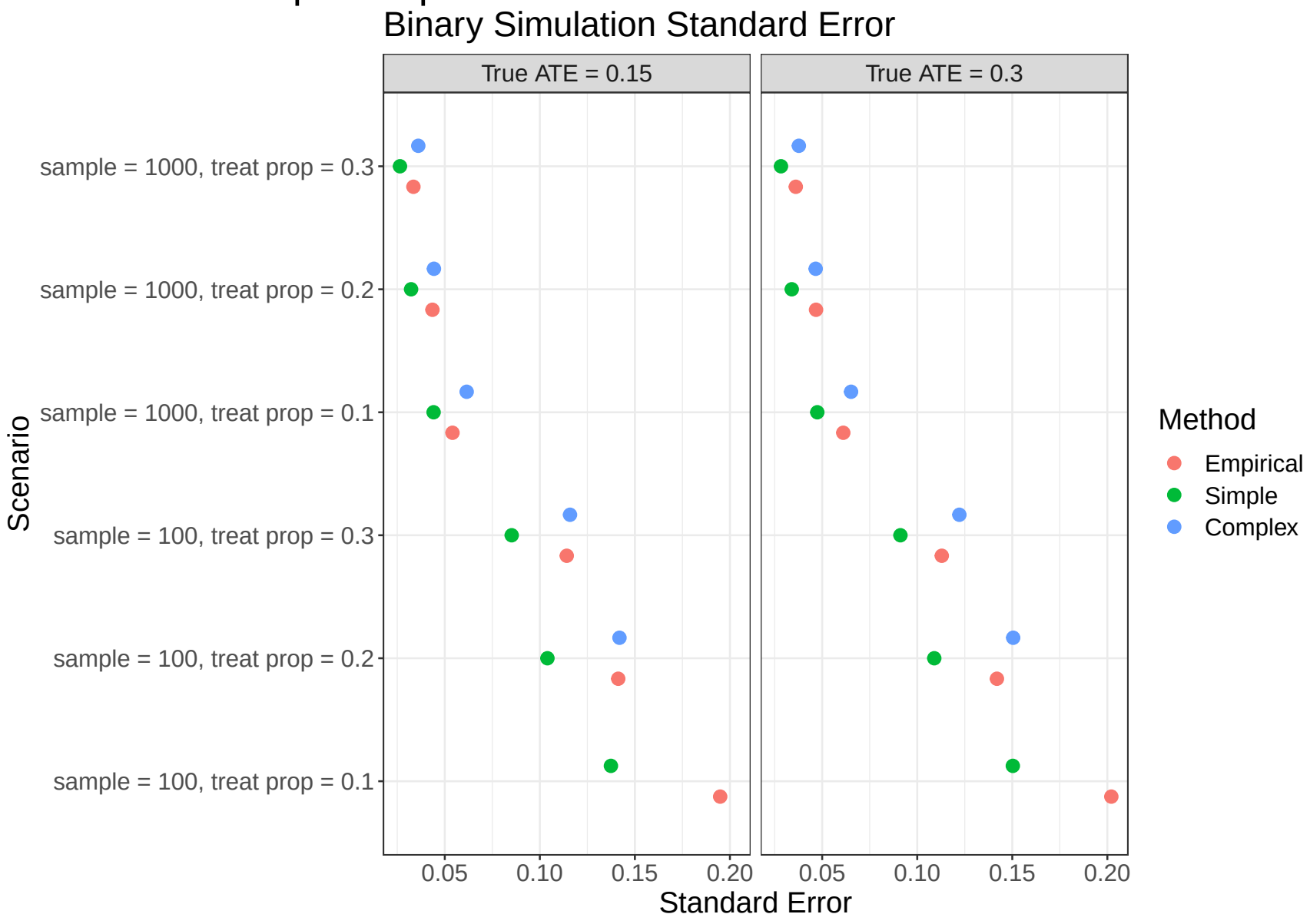
Results

in binary coverage plot-1.pdf



Results

standard error plot-1.pdf



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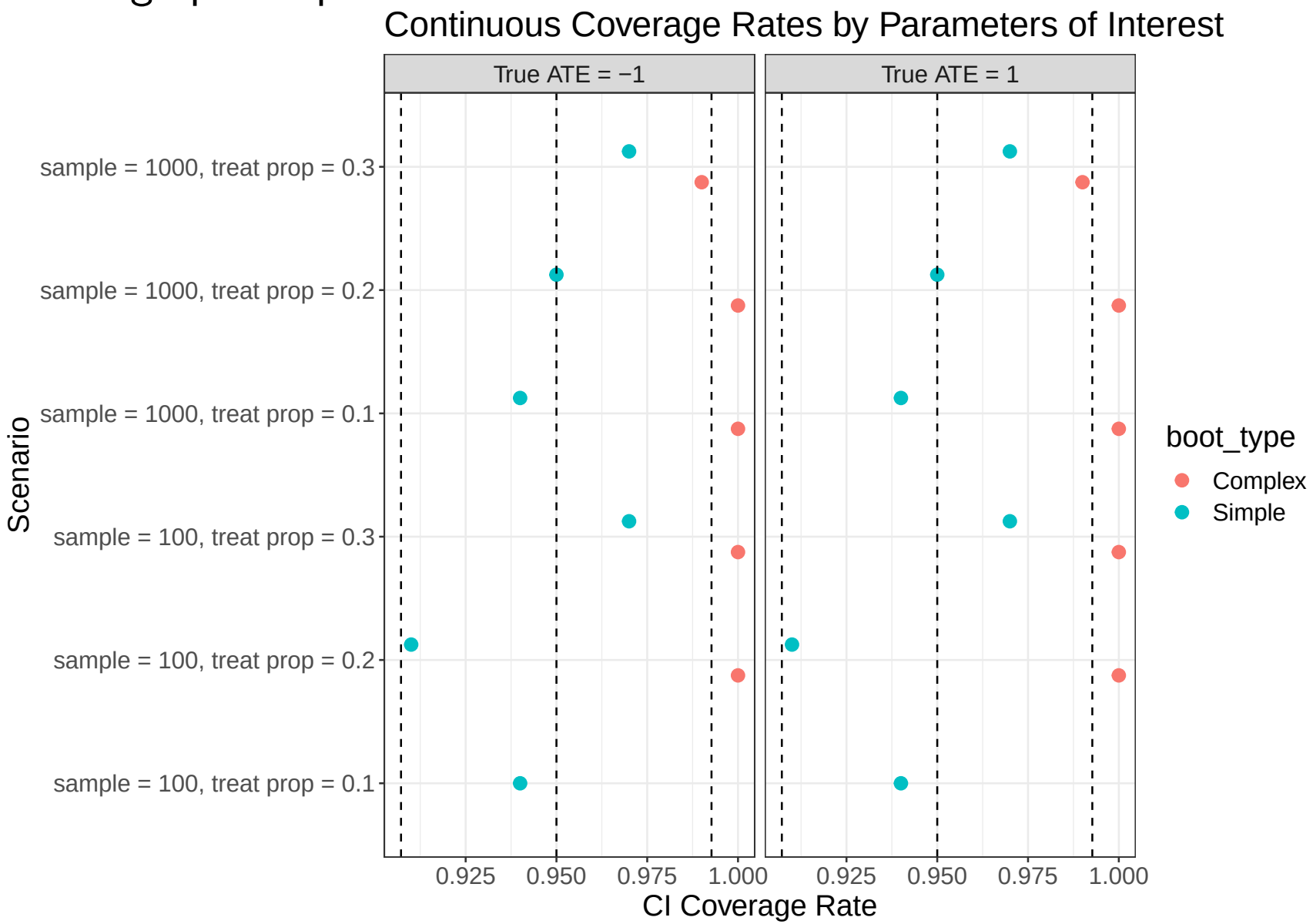
coverage plot-1.pdf



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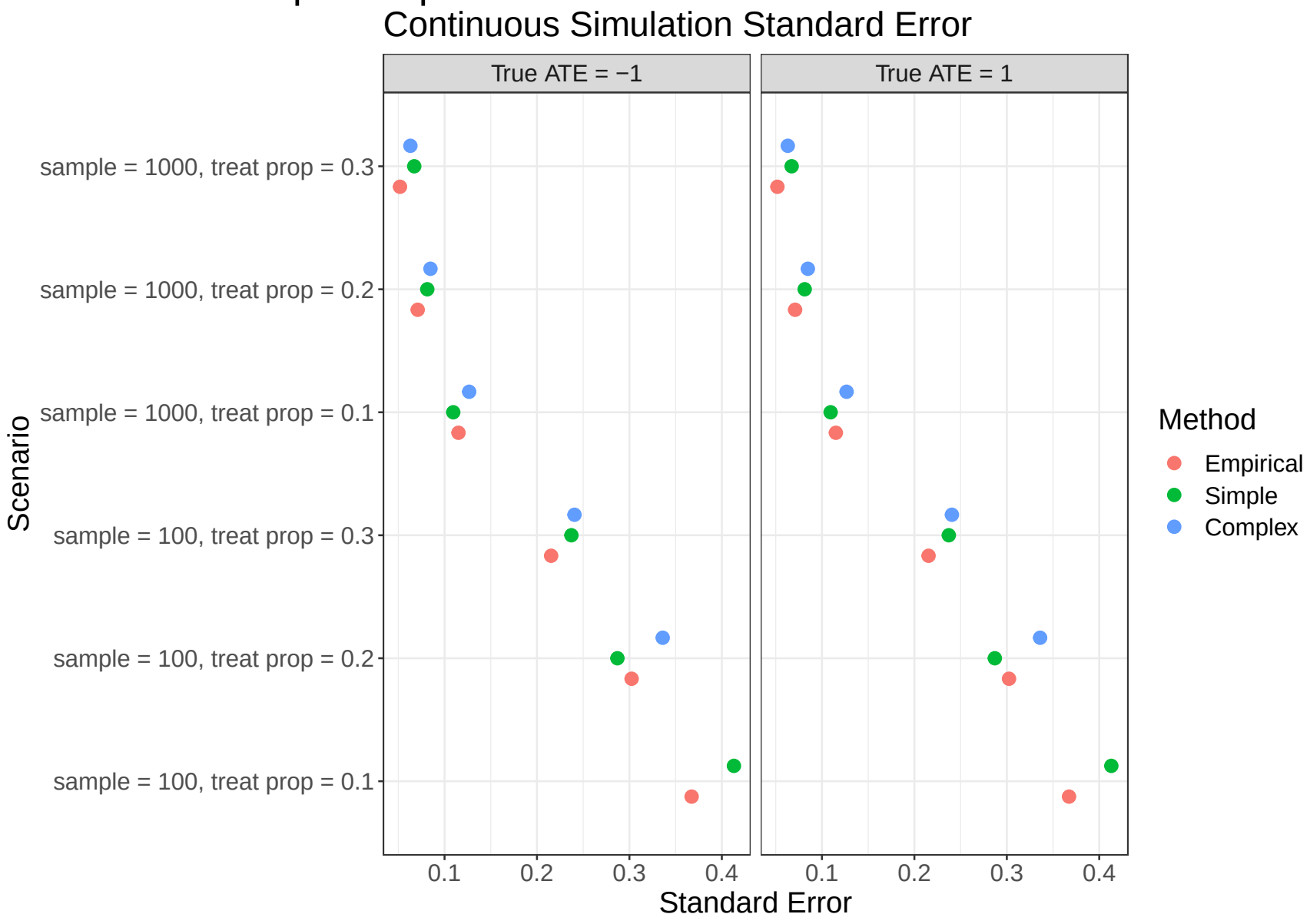

Summary of Results

Limitations

- Sample size / treatment (or exposure) prevalence

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- Increased sample size, changes in bootstrap performance?
- Changes in treatment propensity model
- Non-normal distributions of covariates