

Simulated Treatment Comparisons Using Jackknife Pseudo Values for Population-Adjusted Marginal Effect Estimation

[MSR186]

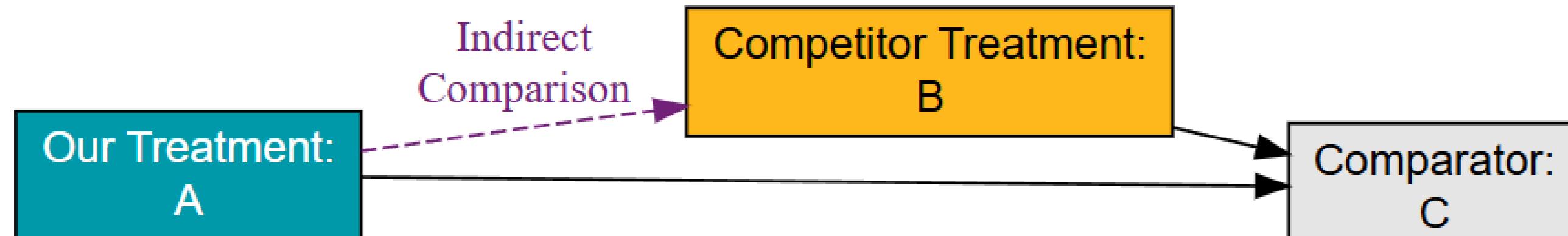
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Why did we perform this research?

Setting:

An anchored cross-trial ITC, with IPD available for our trial of treatment A vs C but only aggregate data available for a competitor's trial of treatment B vs C.



Rationale:

Existing population adjustment methods have limitations.

- MAIC: Targets marginal effects but can be inefficient or infeasible when covariate overlap is limited.
- STC (conventional): Applicable under poor overlap but targets conditional effects, which for non-linear outcome models differ from marginal effects due to non-collapsibility.
- Recent STC extensions: Target marginal effects but require the full joint covariate distribution and/or simulation of patient-level data, adding computational complexity.

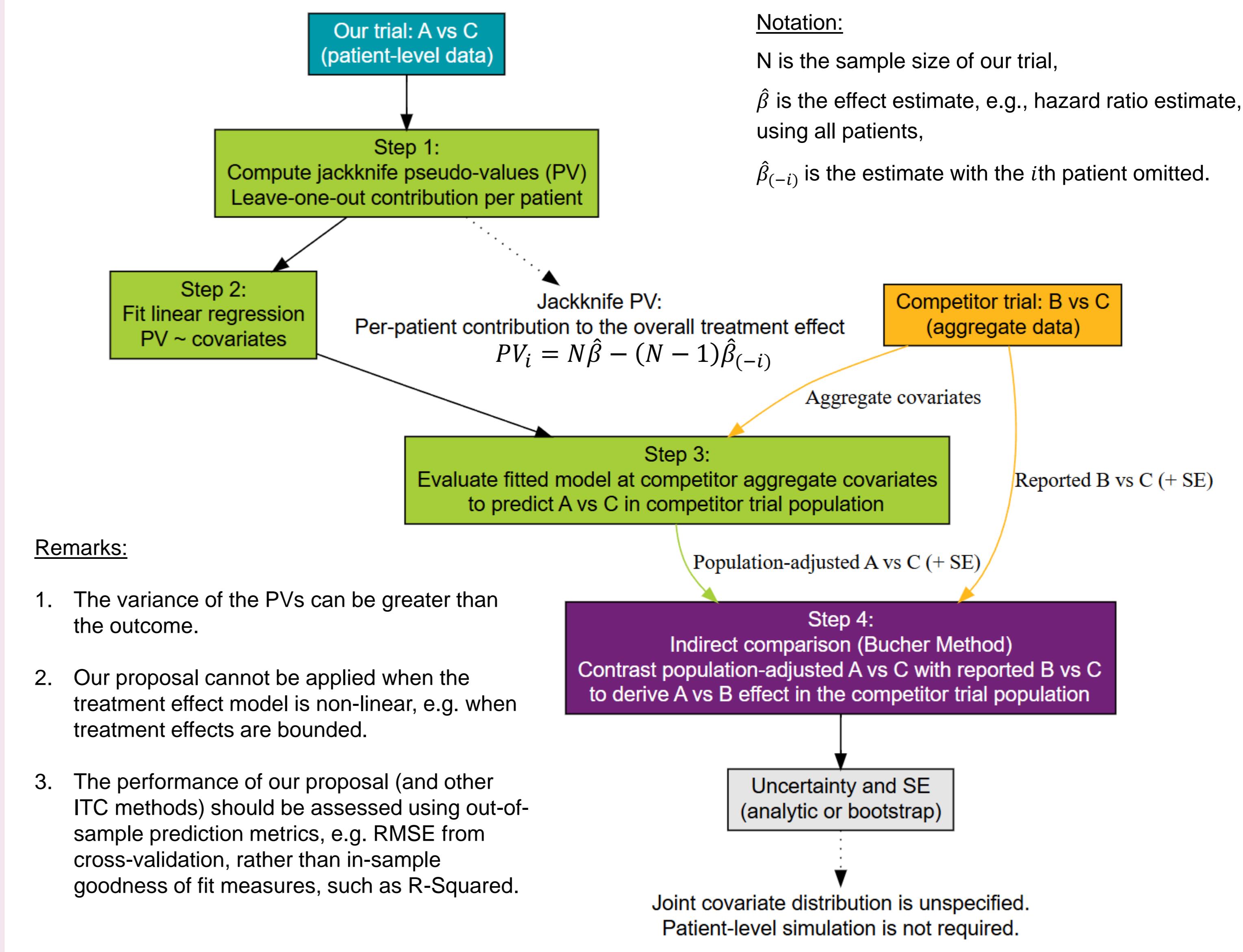
Aim:

Develop a practical ITC method to estimate marginal treatment effects for non-linear outcome models without specifying the full joint covariate distribution.

How did we perform this research?

Proposed approach:

Applicable when the treatment effect model is linear on the predictor scale (commonly assumed for log OR and log HR in meta-regression). Our proposal is to apply STC to jackknife pseudo values of the marginal treatment effect on that scale.



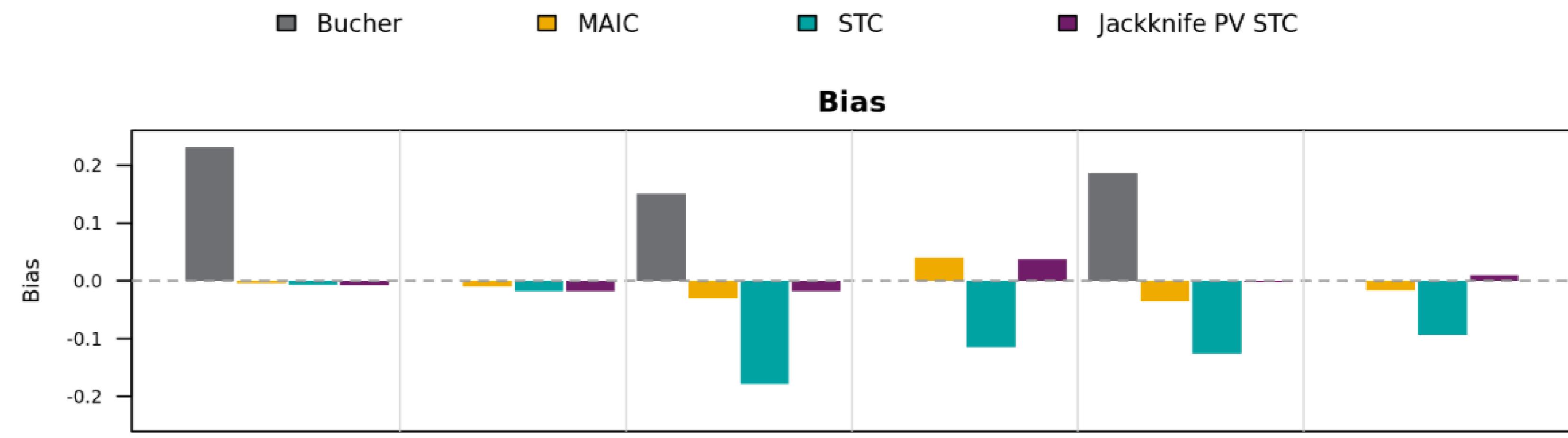
Performance was contrasted with standard MAIC and STC approaches in simulation settings with continuous, binary and time-to-event outcomes.

What did we find?

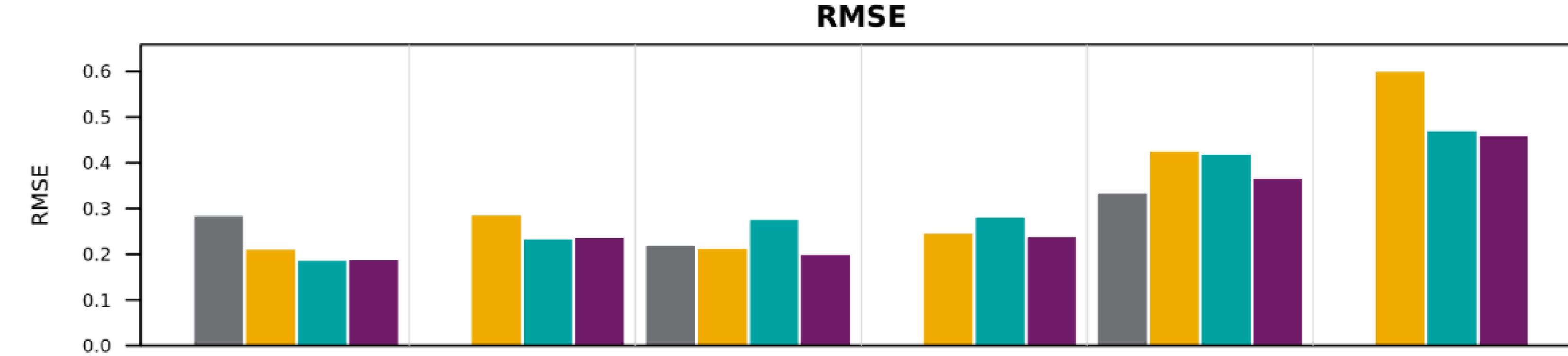
Simulation setup

- Two anchored RCTs (A vs C; B vs C); 500 patients per trial.
- Covariates (cross-trial imbalance):
 - Our trial (A vs C):
 $X_1 \sim N(0,1)$; $X_2 \sim N(1,1)$; $X_3 \sim \text{Bernoulli}(0.5)$
 - Competitor (B vs C):
 $X_1 \sim N(1,1)$; $X_2 \sim N(2,1)$; $X_3 \sim \text{Bernoulli}(0.7)$
- Outcomes:
 - Continuous: normal distribution with linear mean model
 - Binary: logistic mean model
 - Time-to-event: exponential distribution with log-linear hazard model; right-censored at 1.5 years
- Effect size of A vs B in competitor trial population:
 - Linear settings: MD -0.855 (continuous), log HR -0.659 (time to event), log OR -0.6724 (binary)
- Simulations: 1,000 per outcome scenario.
- Robustness to model misspecification with population adjustment on:
 - Untransformed effect modifiers: X_1 and X_3
 - Transformed effect modifiers ($X_1 \cdot X_2$), and ($X_1 + 2X_3$)

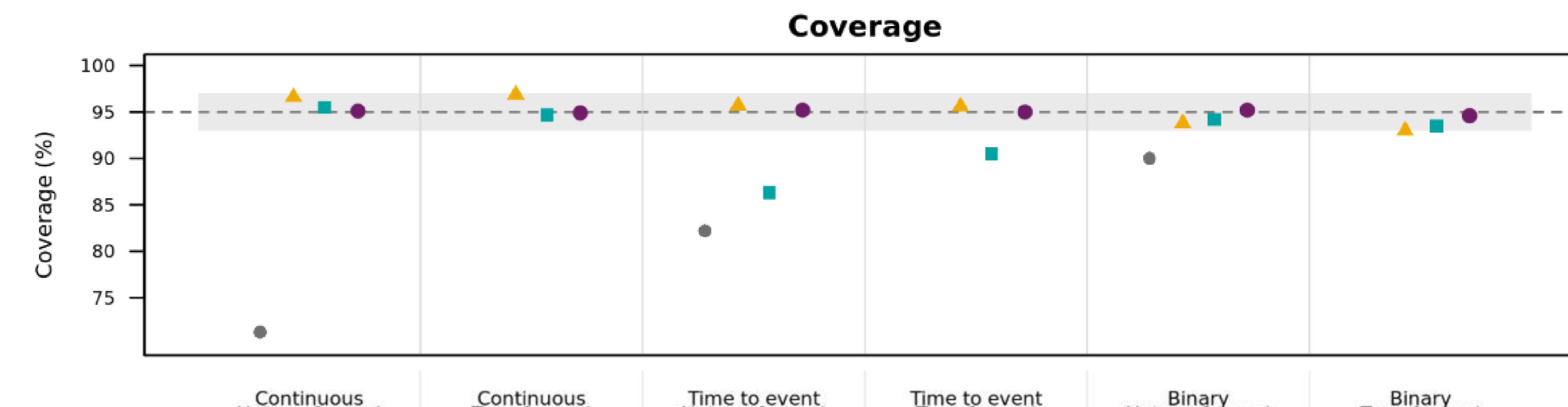
Findings were similar at n=200 (results not shown).



Bias: Jackknife PV STC reduced bias vs conventional STC for non-linear outcome models by targeting marginal effects (addressing non-collapsibility). It showed the least bias under model misspecification.



Accuracy: RMSE for Jackknife PV STC was lower or comparable to MAIC and conventional STC for binary and time-to-event outcomes, and similar to STC for continuous outcomes. The (unadjusted) Bucher method sometimes had lower RMSE but remained biased.



Coverage: Under Jackknife PV STC, the 95% CI coverage was close to nominal based on the analytical variance, with some reduction under model misspecification (e.g., transformed modifiers in binary settings).

How might this impact current clinical practice?

- Jackknife PV STC estimates marginal treatment effects without the need to specify the full joint covariate distribution or conduct complex modelling.
- The implementation is straightforward and practical, using standard regression software.
- The proposed method resulted in lower bias and improved accuracy compared with conventional MAIC and STC methods.
- Jackknife PV STC can serve as complementary to alternative population adjustment methods, strengthening confidence in comparative effectiveness evaluations.

Abbreviations
HR: Hazard ratio; IPD: Individual patient data; ITC: Indirect treatment comparison; MAIC: Matching Adjusted Indirect Comparison; MD: Mean difference; OR: Odds ratio; PV: Pseudo value; RMSE: Root mean squared error; SE: Standard error; STC: Simulated Treatment Comparison

References
Signorovitch JE, et al. Matching-adjusted indirect comparisons. *Value Health*. 2012;15:940–947.

Ishak KJ, Proskorovsky I, Benedict A. Simulation and matching-based approaches for indirect comparisons. *Pharmacoeconomics*. 2015;33:537–549.

Phillippo DM, et al. Population-adjusted indirect comparisons in HTA. *Med Decis Making*. 2018;38:200–211.

Miller RG. The jackknife: a review. *Biometrika*. 1974;61:1–15.

Thorburn DT. Some asymptotic properties of jackknife statistics. *Biometrika*. 1976;63:305–313.