

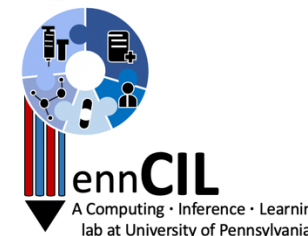
Department of Biostatistics, Epidemiology and Informatics

The Fine Art of Tolerance: Robustify P-value Calibration in Observational Studies with Partially Valid Negative Control Outcomes

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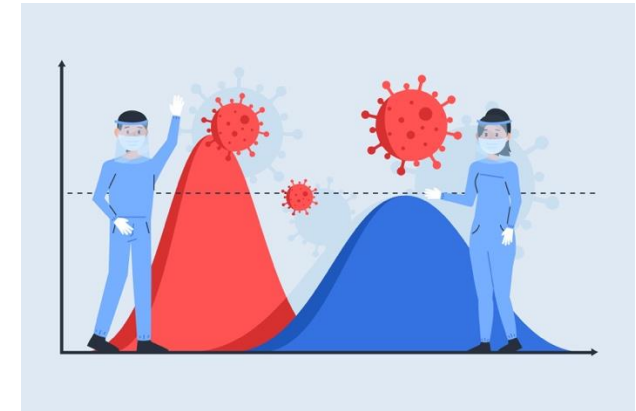
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Joint work with Drs. Dazheng Zhang, Huiyuan Wang, Wenjie Hu, Qiong Wu, Chongliang Luo, Lu Li, Tsai Hor Chan, Yudong Wang, Yuru Zhu, Martijn Schuemie, Patrick Ryan, George Hripcsak, Marc Suchard, and Yong Chen

Motivation: Bias in Real-World Data

- ▶ Vaccine effectiveness
- ▶ SARS-CoV-2 infection and Long COVID
- ▶ Cancer therapies
- ▶ ...
- ▶ Residual Bias in Observational Research
 - Unmeasured confounding
 - Measurement error
 - Selection bias
 - Missing data
 - ...



Negative Controls: Current Frameworks

- ▶ Negative control outcome (NCO)
 - A clinical outcome that should not be causally affected by the treatment of interest
 - share similar sources of bias as the primary outcome
- ▶ Bias detection
- ▶ Bias correction

Research Article

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Interpreting observational studies: why empirical calibration is needed to correct p -values

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William DuMouchel^{b,d} Marc A. Suchard^{b,e} and David Madigan^{b,f}

Empirical confidence interval calibration for population-level effect estimation studies in observational healthcare data

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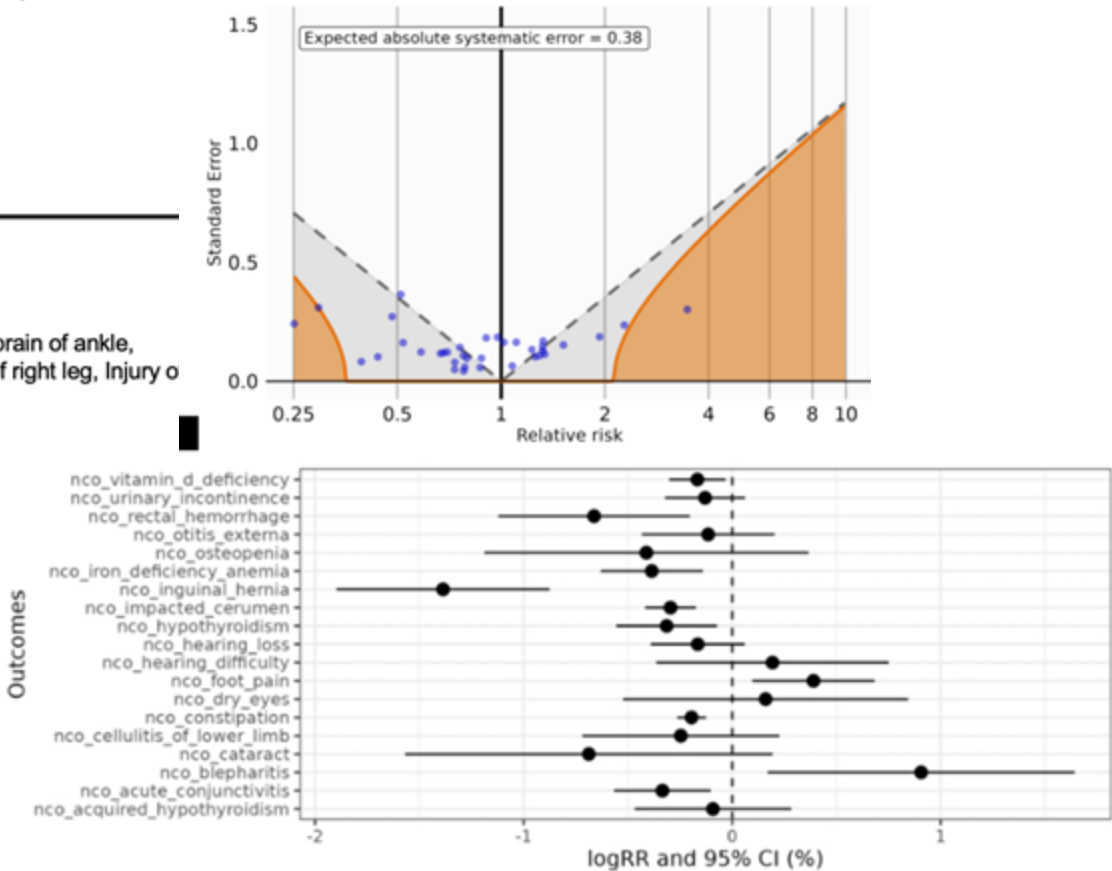
Example of Implementation

- ▶ Exposure: COVID-19 vaccination
- ▶ Outcome: SARS-CoV-2 infection

Categories	Examples
Infectious and parasitic diseases	Impetigo, Tinea capitis, Tinea corporis, Insect bite
Diseases of the skin and subcutaneous tissue	Contact dermatitis, Diaper rash, Acne
Diseases of the musculoskeletal system and connective tissue	Dislocations (Displacements - bone), Closed fracture of distal end of radius, Sprain of ankle, Scoliosis, Foot pain, Injury of free lower limb, Injury of upper extremity, Injury of right leg, Injury of left leg, Injury of right foot
Diseases of the nervous system	Seizure, Epilepsy, Concussion, Closed injury of head
Diseases of the eye and adnexa	Visual testing abnormal, Myopia, Astigmatism
Diseases of the ear and mastoid process	Wax in ear/impacted cerumen, Foreign body in ear
Diseases of the respiratory system	Snoring/Obstructive sleep apnea
Diseases of the digestive system	Umbilical hernia, Inguinal hernia
Endocrine, nutritional, and metabolic diseases	Obesity
Diseases of the speech and voice	Speech delay, Speech dysfunction, Tongue tie

Real-World Effectiveness of BNT162b2 Against Infection and Severe Diseases in Children and Adolescents

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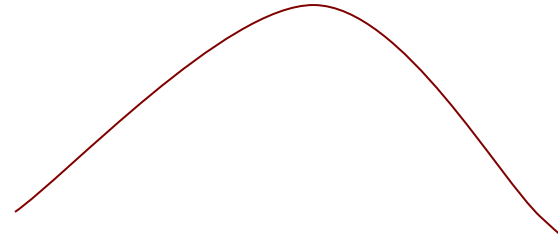


But... NCOs May Be Invalid

- ▶ Current frameworks assume all NCOs are valid
 - Normal-normal (N-N) model

$$y_i \sim N(\theta_i, s_i^2)$$

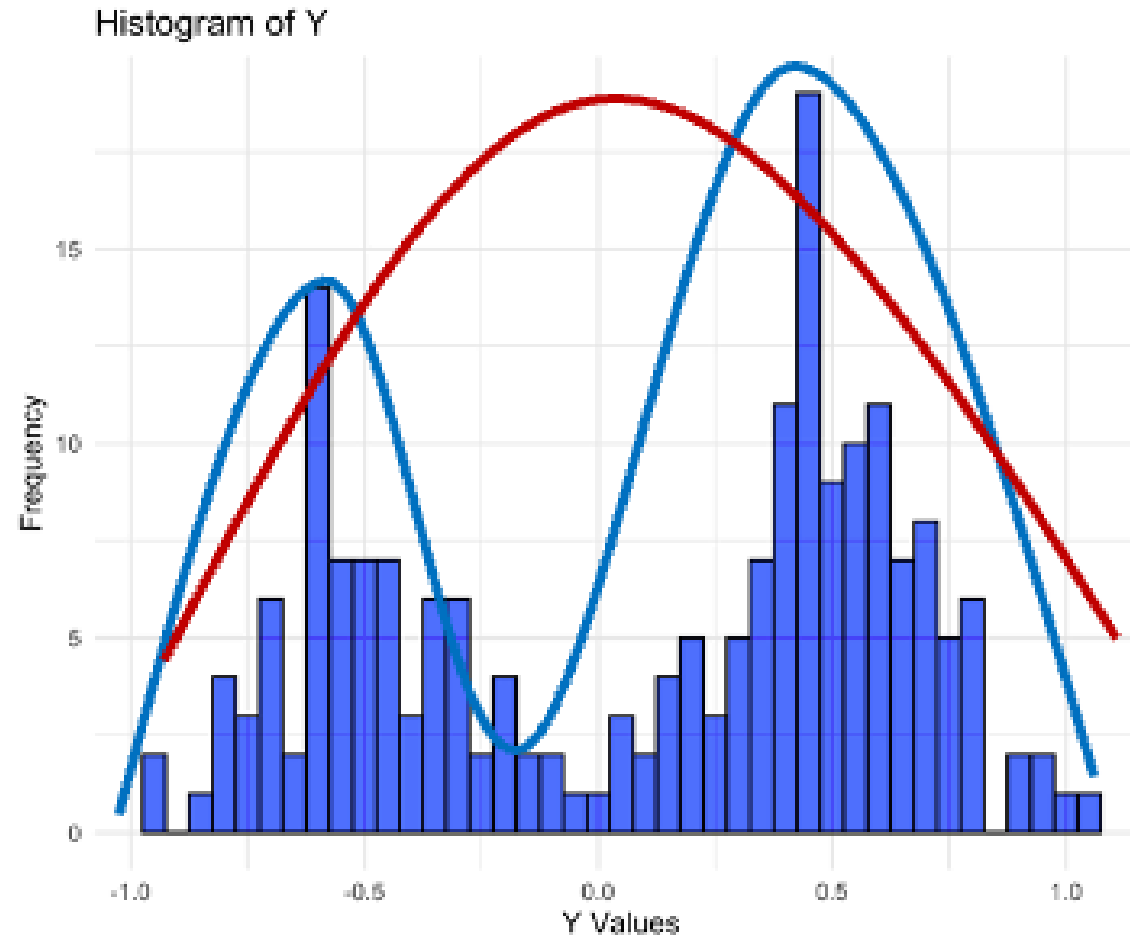
$$\theta_i \sim N(\mu, \sigma^2)$$



- ▶ In real-world scenarios, some NCOs may actually be invalid
 - Different confounding structures, data quality issues, coding practices, ...
- ▶ This can bias bias-correction!

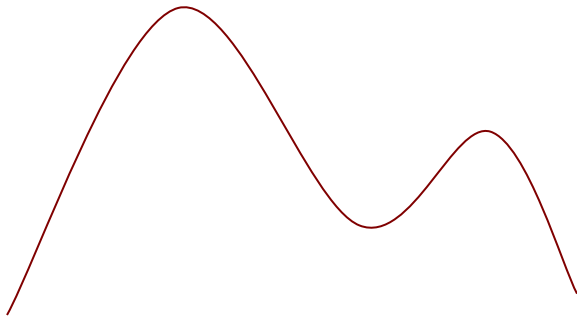
Why a Single Normal Fails

- ▶ Biased mean
- ▶ Larger variance



Proposed Method: Robustify P-value Calibration

- ▶ (A1) Two cluster mixture model
 - Relax the normality assumption
 - Mixture normal-normal (MN-N) model
- ▶ (A2) Majority rule
 - >50% NCOs are valid



$$y_i \sim N(\theta_i, s_i^2)$$

$$\theta_i \sim N(\mu, \sigma^2)$$



$$y_i \sim N(\theta_i, s_i^2)$$

$$\theta_i \sim \pi \cdot N(\mu_1, \sigma_1^2) + (1 - \pi) \cdot N(\mu_2, \sigma_2^2)$$

$$\pi > 0.5$$

Mixture Model Framework

- ▶ For each NCO, observe estimated treatment effect y_i with standard error s_i
- ▶ Assume each NCO comes from one of the following two distributions:

- Valid NCOs (true nulls)

$$y_i \sim N(\mu_1, \sigma_1^2 + s_i^2)$$

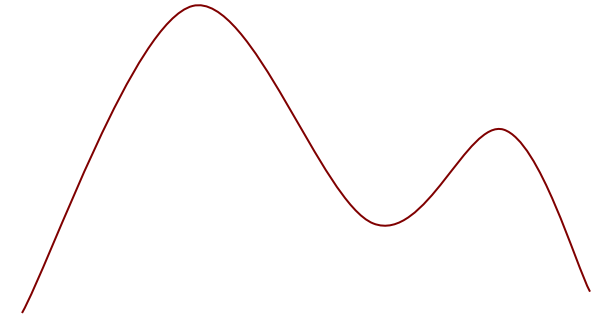
- Invalid NCOs

$$y_i \sim N(\mu_2, \sigma_2^2 + s_i^2)$$

- ▶ Model the observed NCO distribution as a mixture:

$$\begin{cases} f(y_i) = \pi \cdot N(y_i | \mu_1, \sigma_1^2 + s_i^2) + (1 - \pi) \cdot N(y_i | \mu_2, \sigma_2^2 + s_i^2) \\ \pi > 0.5 \end{cases}$$

- ▶ Estimate parameters $(\pi, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2)$ using EM algorithm



Calibrated p-value

- ▶ Using the estimated valid null distribution, for an effect estimate from a new drug-outcome pair, the two-sided p-value is then

$$p_{cal} = 2 \cdot \Phi \left(- \frac{|y_{n+1} - \hat{\mu}_1|}{\sqrt{\hat{\sigma}_1^2 + s_{n+1}^2}} \right)$$

Estimated mean of majority NCOs (valid)

Estimated sd of majority NCOs (valid)

- ▶ Φ is the cumulative distribution function of the standard normal distribution

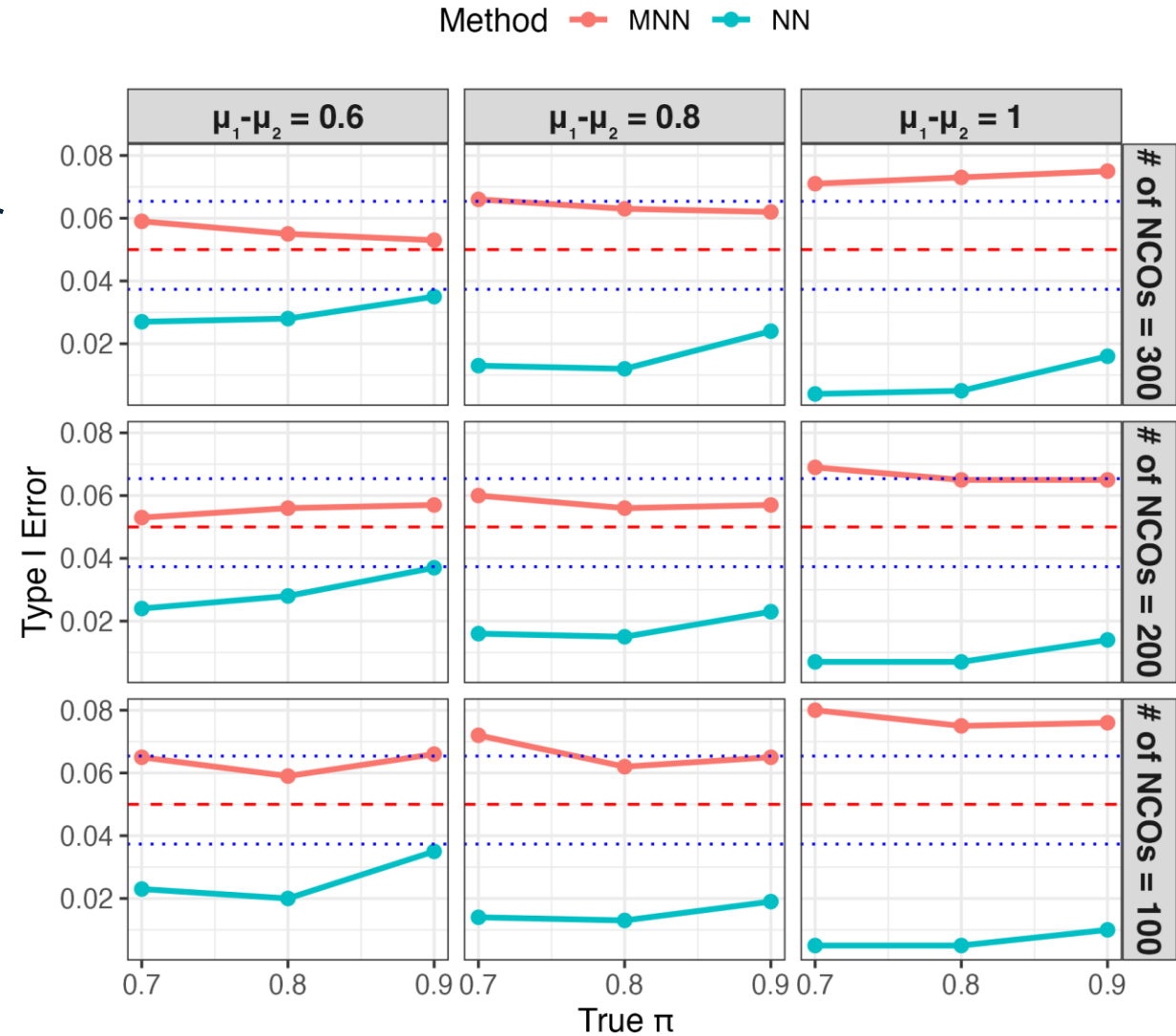
Simulation

- ▶ Proportion of valid NCO π : 0.7, 0.8, 0.9
- ▶ Number of NCOs n : 100, 200, 300
- ▶ Separation between valid and invalid means $\mu_1 - \mu_2$: 0.6, 0.8, 1.0



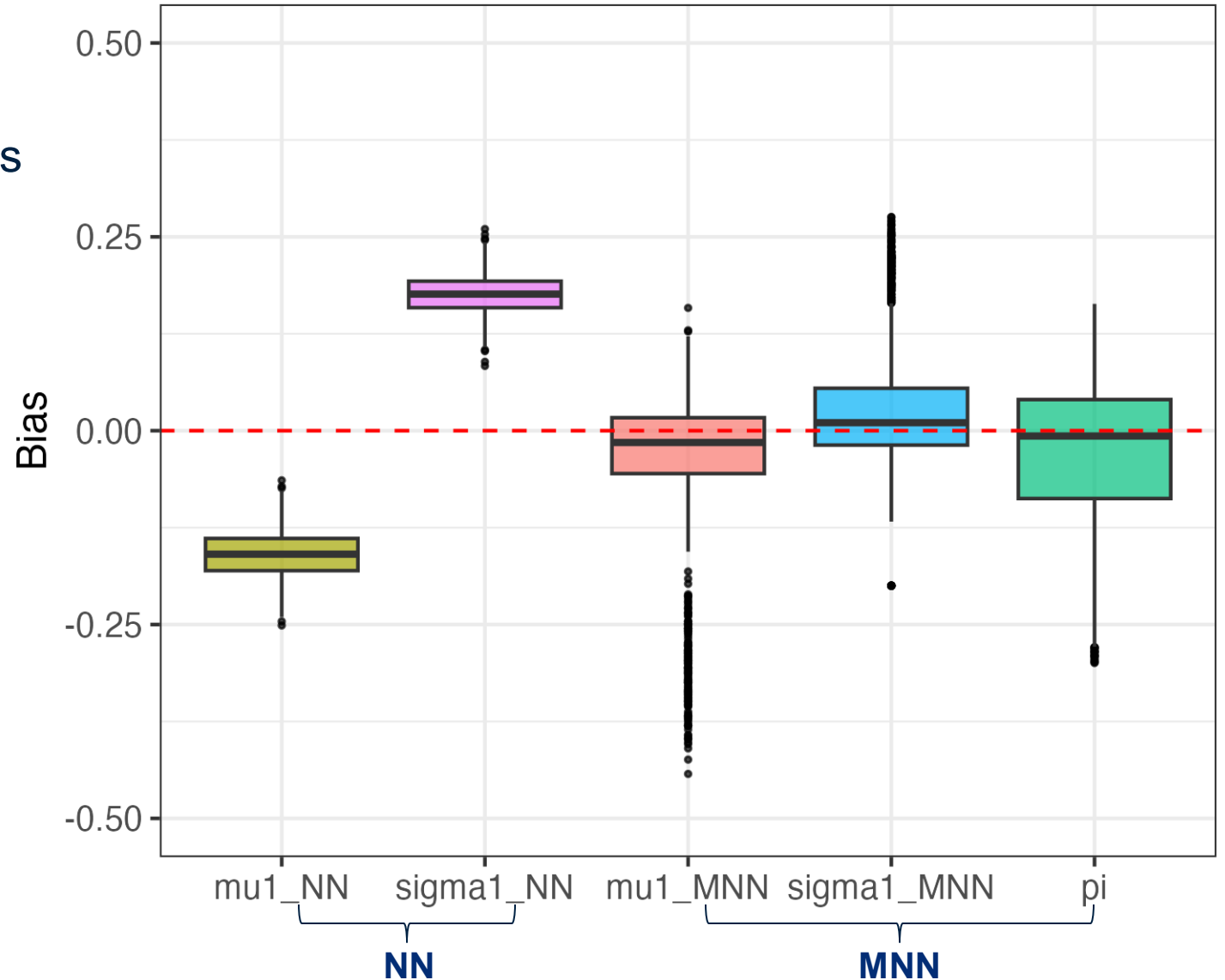
Simulation: Type I Error

- MNN achieved the nominal type I error



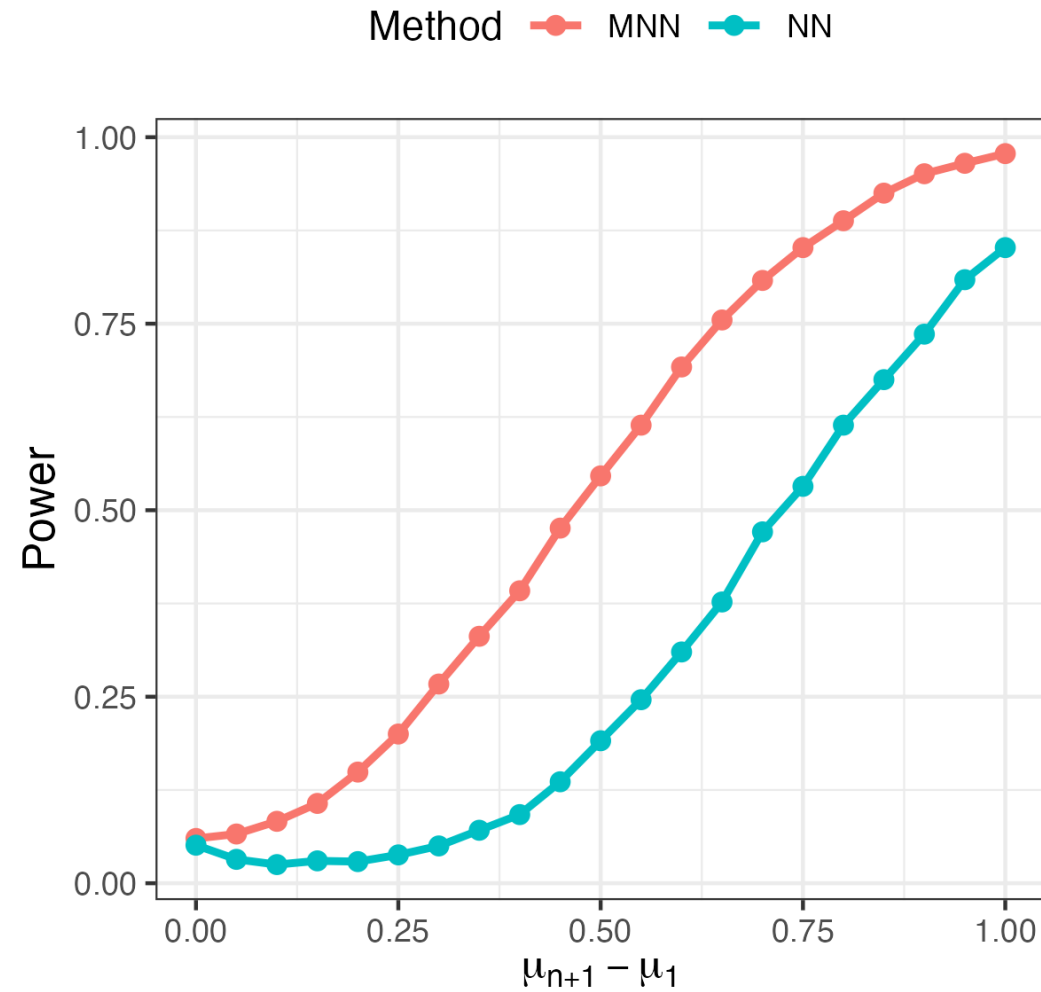
Simulation: Parameter Estimation

- MNN produced less biased estimates



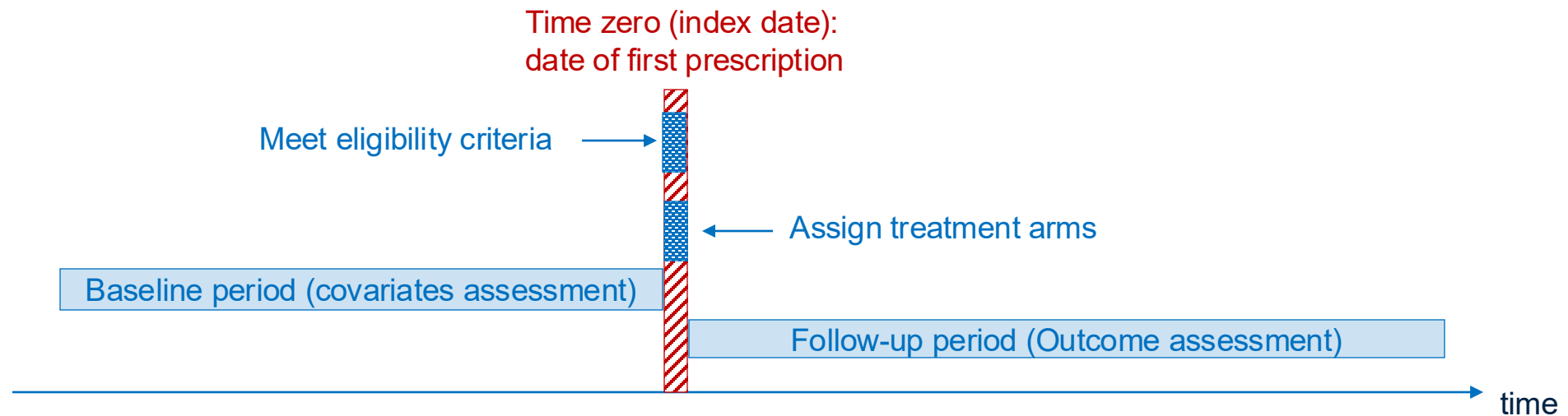
Simulation: Power

- MNN had higher power

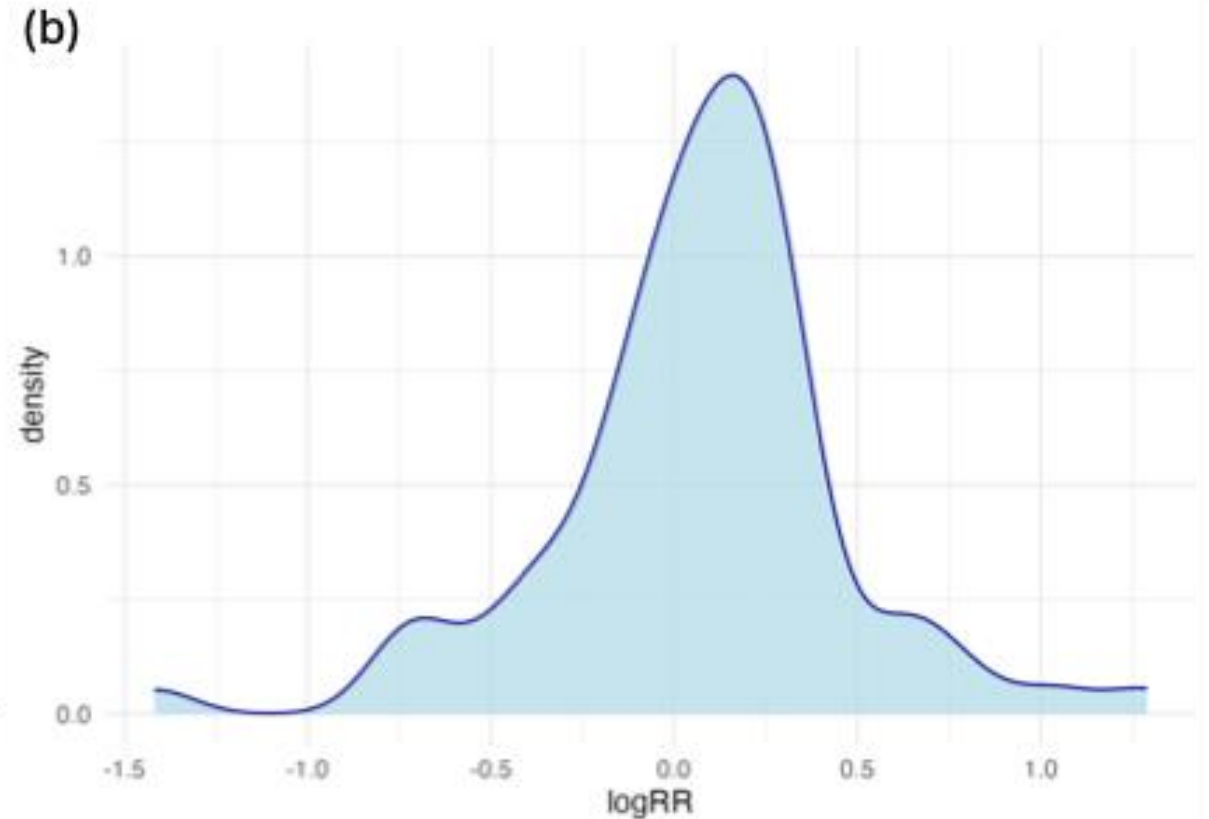
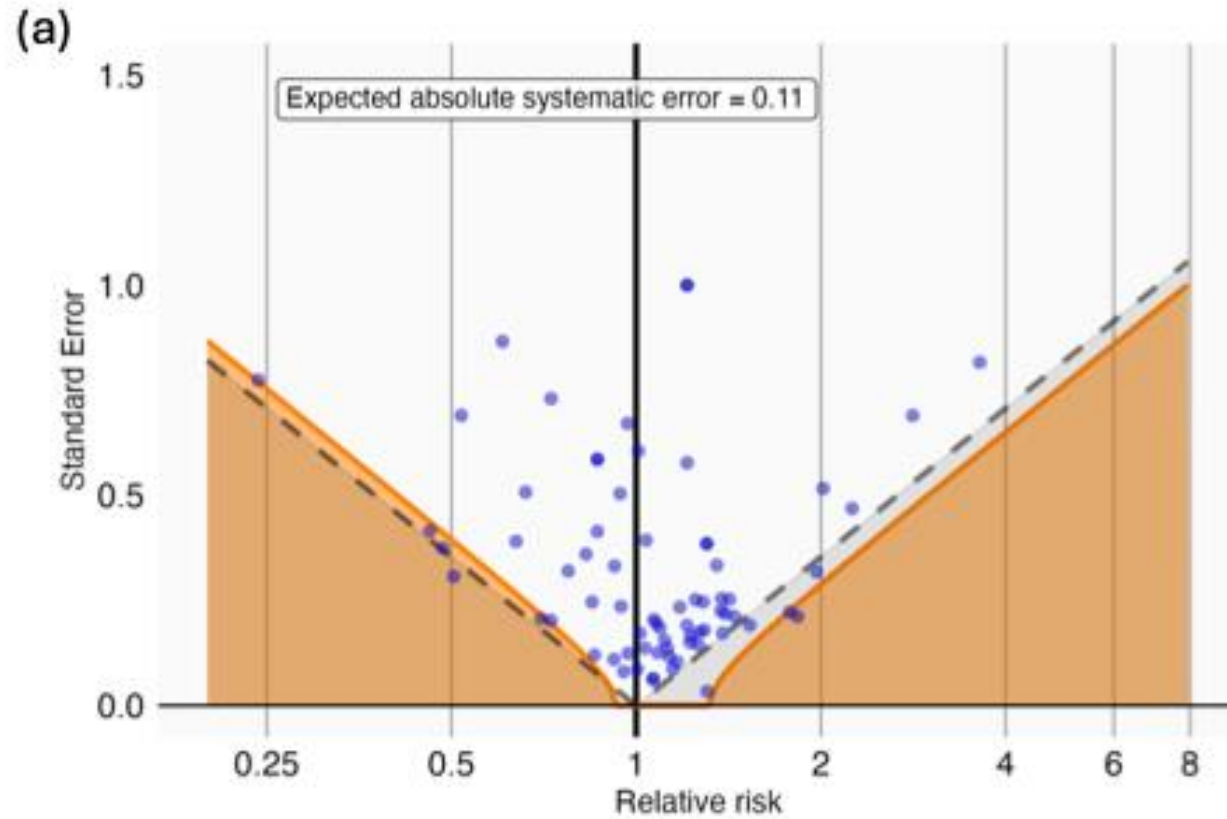


Real-World Use Case

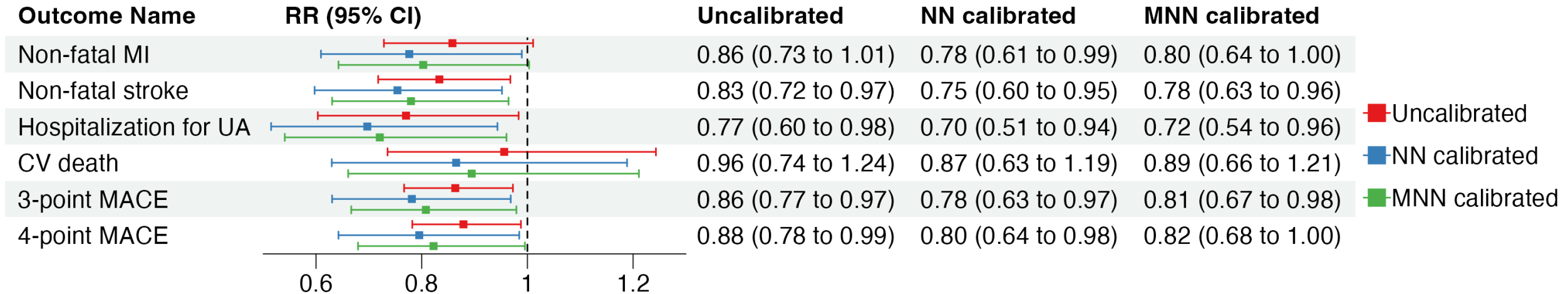
- ▶ Data source: Penn Medicine EHR data
- ▶ Population: Patients with type 2 diabetes
- ▶ Treatment: GLP-1 receptor agonists
- ▶ Comparison: DPP4 inhibitors
- ▶ Outcomes: six cardiovascular outcomes
- ▶ Statistical analysis: large-scale propensity score matching + modified Poisson regression model



Distribution of NCOs



Treatment Effectiveness



- ▶ MNN: smaller bias correction, narrower CI
- ▶ GLP1RAs have protective cardiovascular effects compared to DPP4is

Conclusion

- ▶ RWD enables large-scale observational research but is vulnerable to residual bias
- ▶ NCOs are essential tools but their validity cannot be guaranteed
- ▶ We propose a robust two-cluster model that:
 - Distinguishes valid from invalid NCOs
 - Enables bias correction even with partially invalid controls
 - Improves the reliability of p-values and confidence intervals

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