

# Models for Examining Selective Reporting in Meta-Analysis with Dependent Effects

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SREE | September 2024

# Acknowledgement

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The research reported here was supported, in whole or in part, by the Institute of Education Sciences, U.S. Department of Education, through grant R305D220026 to the American Institutes for Research. The opinions expressed are those of the authors and do not represent the views of the Institute or the U.S. Department of Education.

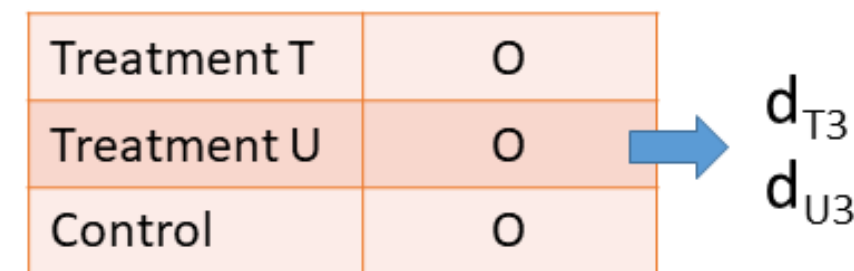
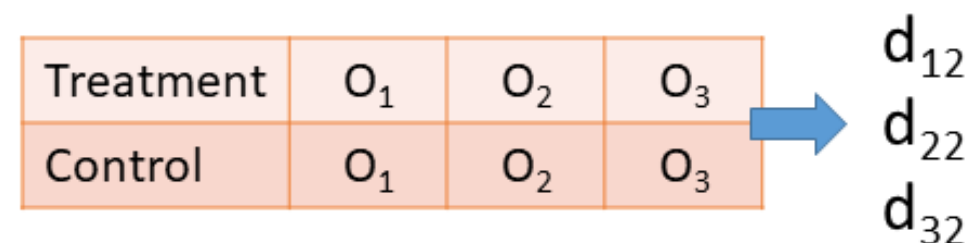
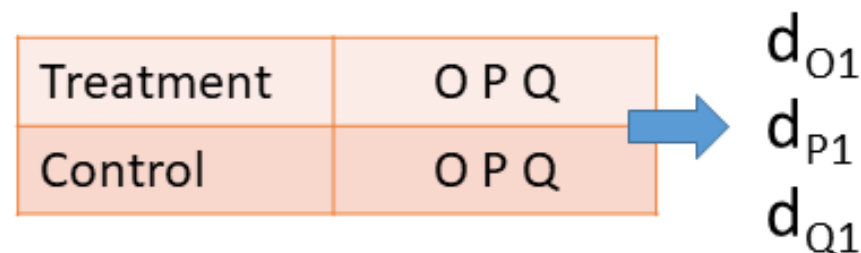
# Selective Reporting

- **Selective reporting** occurs if *affirmative* findings are **more likely to be reported** and available for inclusion in meta-analysis
- Selective reporting can **distort the evidence base** available for systematic review/meta-analysis
  - Inflate average effect size estimates from meta-analysis
  - Bias estimates of heterogeneity (Augusteijn et al., 2019)



# Dependent Effect Sizes

- Dependent effect sizes are **ubiquitous** in education and social science meta-analyses
- But most methods to examine selective outcome reporting bias do not account for **effect size dependency**
- Failing to account for dependency can result in **misleading conclusions** like too-narrow confidence intervals, and inflated Type 1 error rates



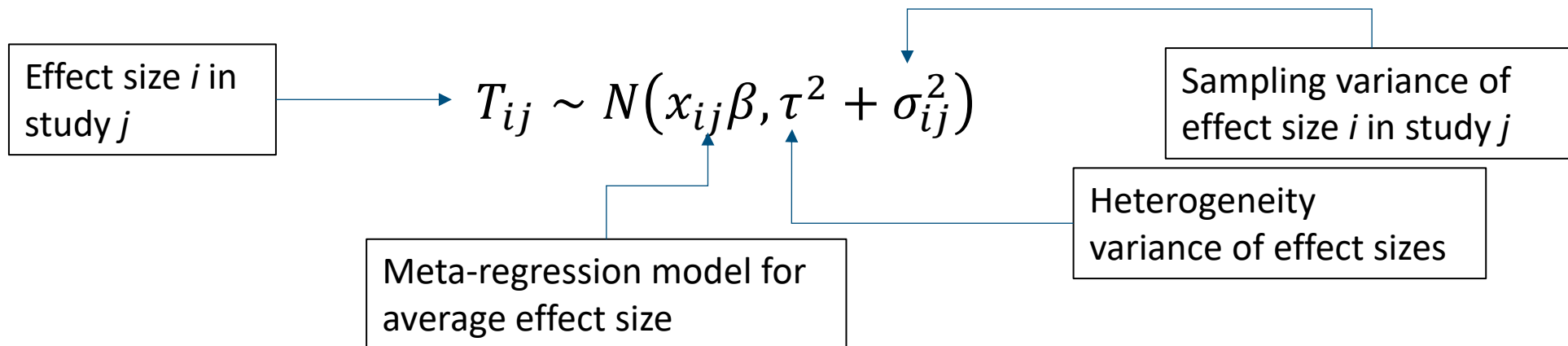
# Our Project

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- Develop methods for investigating selective reporting in meta-analysis that **account for dependent effect sizes**
- P-value selection models (Hedges, 1992; Vevea & Hedges, 1995)
  - Estimate the model ignoring dependence structure  
Use robust variance estimation or clustered bootstrapping to account for dependence

# P-value selection models

- The model for the evidence-generating process (prior to selective reporting):



- A step-function model for the selective reporting process:

$$\Pr(T_{ij} \text{ is observed}) \propto \begin{cases} 1 & \text{if } p_{ij} < \alpha_1 \\ \lambda_1 & \text{if } \alpha_1 \leq p_{ij} < \alpha_2 \\ \lambda_2 & \text{if } \alpha_2 \leq p_{ij} \end{cases}$$

- <https://jepusto.com/posts/step-function-selection-models/>

# Estimation strategies

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- Estimate selection models while *ignoring the dependency structure*
  - Maximum Likelihood (ML) estimation for all parameters.
  - A hybrid approach: Estimate selection parameters with ML score equation, estimate evidence-generating process using inverse-probability of selection weighting.
  
- Account for dependent effect sizes
  - Robust variance estimation (“independent effects” working model)
  - Cluster-wise bootstrapping (multinomial or fractional weighted bootstrap)
    - » Percentile, “basic”, or studentized confidence intervals

# Simulation Study

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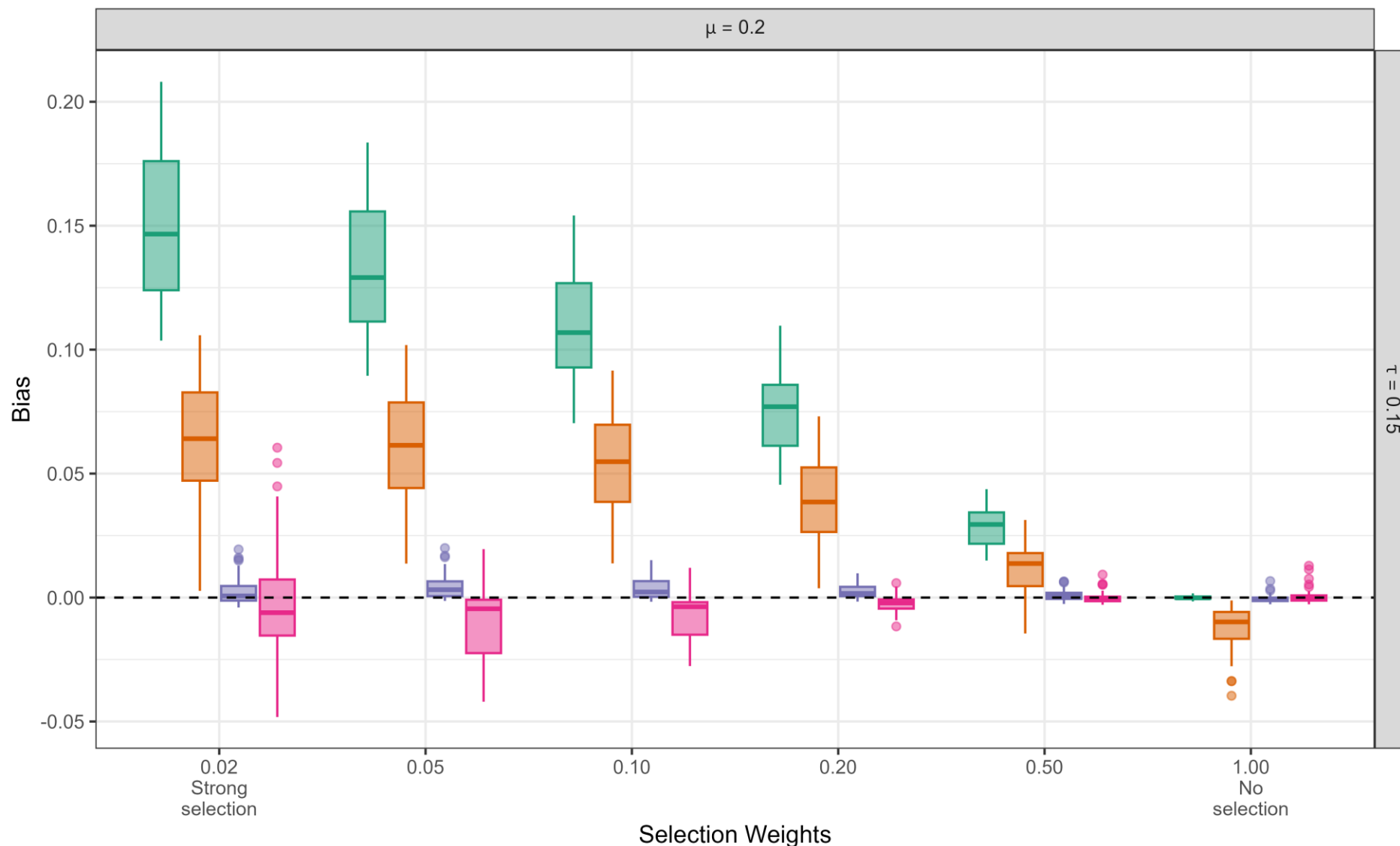


# Data Generation

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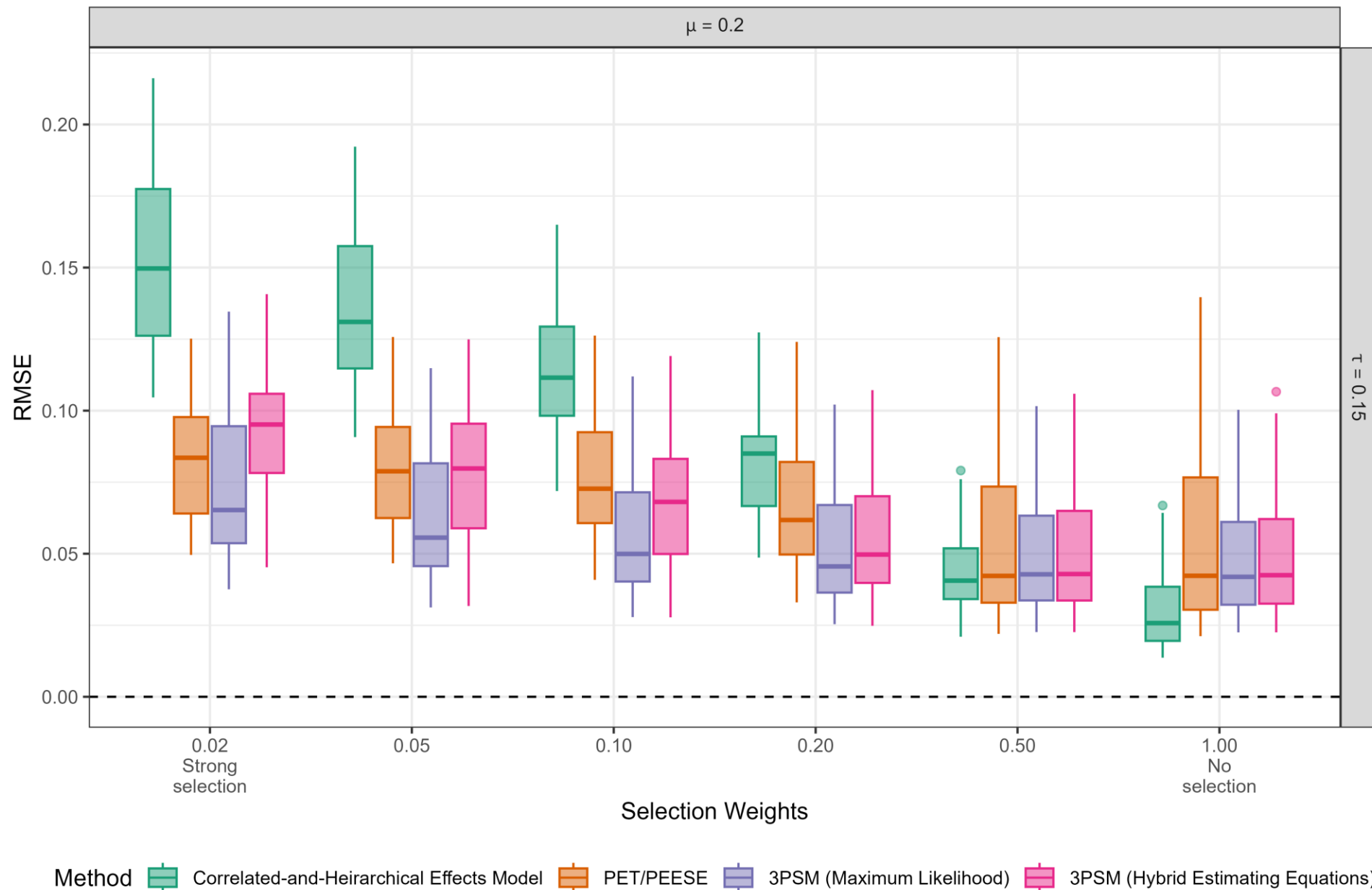
- Generated summary statistics for **correlated outcomes** for two-group comparison designs (equal sample size)
- Generated meta-analytic data
- Censored one-sided p-values  $> 0.025$  with **specified probability of selection**
- Continued sampling until dataset included effect sizes from  $m$  studies.

# Bias



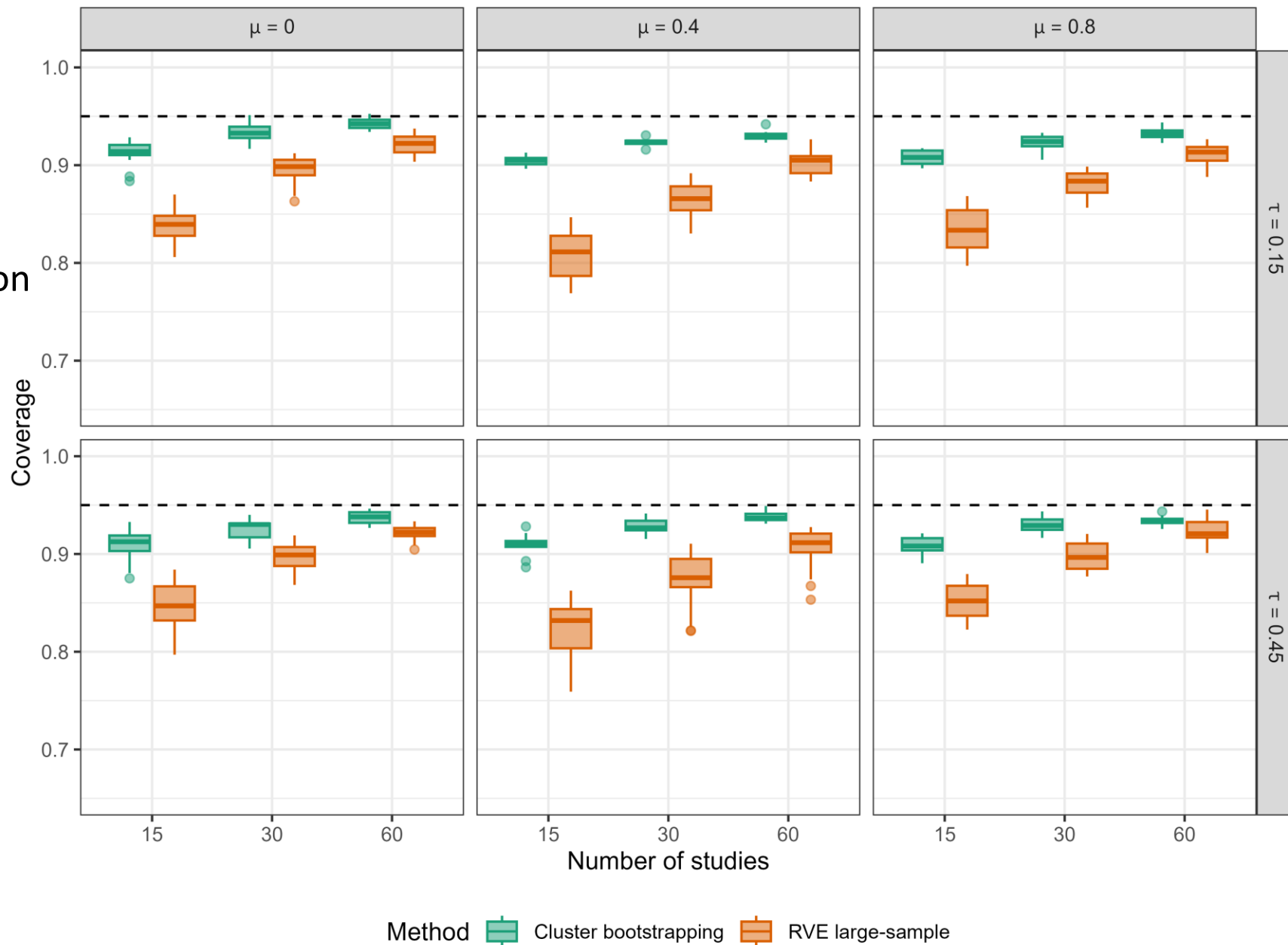
Method  Correlated-and-Heirarchical Effects Model  PET/PEESE  3PSM (Maximum Likelihood)  3PSM (Hybrid Estimating Equations)

# Root Mean Squared Error



# Coverage

- 3-parameter selection model
- Maximum likelihood estimation



# Empirical application

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# Meta-Analysis of Randomized Trials with Follow-Up

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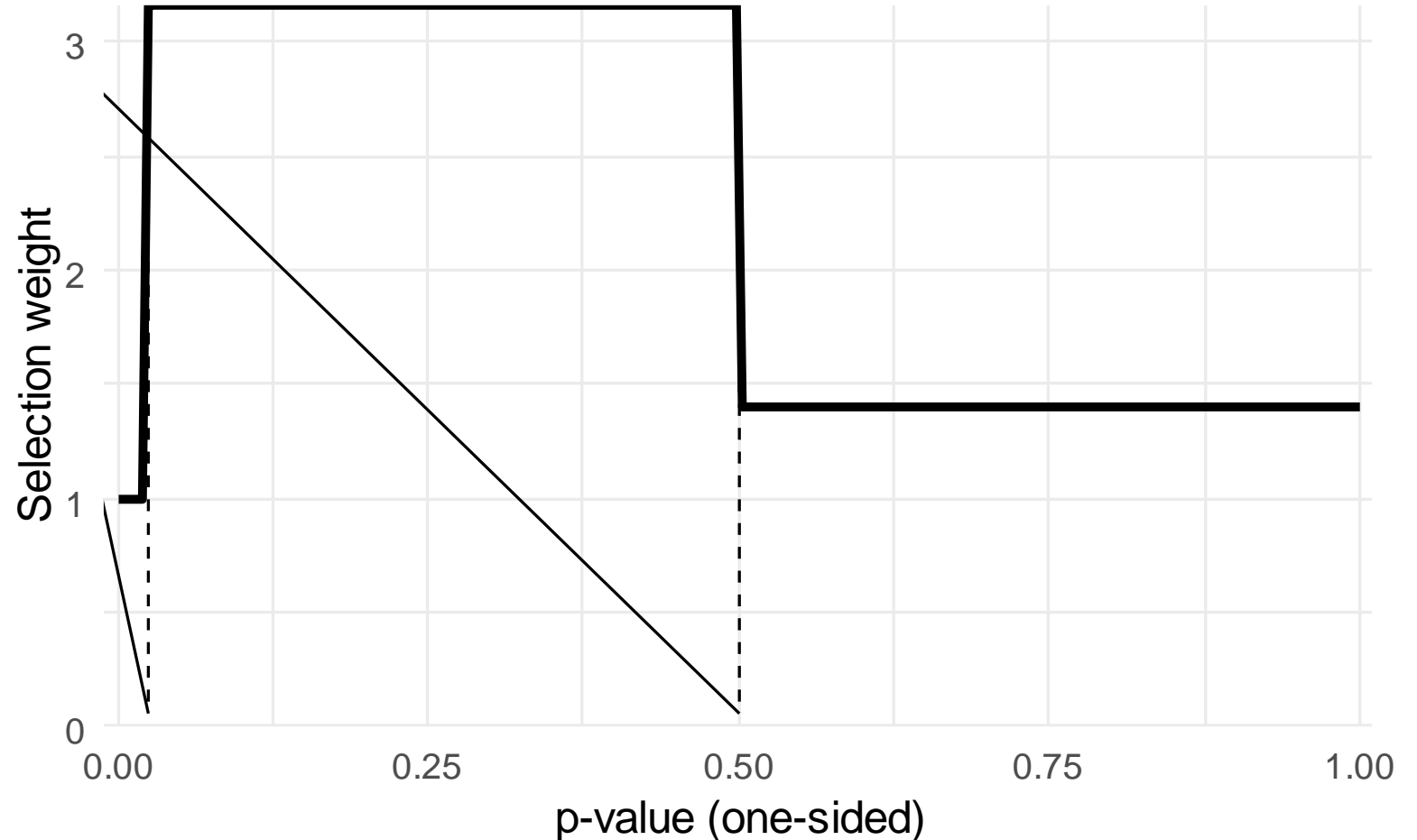
- Meta-analysis of Randomized Control Trials with Follow-up (MERF; Hart et al., 2023)
  - Educational RCTs that include both immediate post-intervention assessments and longer-term follow-up assessments of cognitive or socio-emotional outcomes
  - A total 68 studies with 450 outcomes assessed at multiple time points
- Ran two models and compared the estimates to the original analysis
  - Original model: Correlated and hierarchical effects; no adjustment for selective reporting
  - Random effects model: Independent effects with clustered SEs; no adjustment for selective reporting
  - P-value selection model: Independent effects with clustered SEs; adjusts for selective reporting using a step-function selection model with thresholds at  $\alpha = .025$  and  $\alpha = .500$

# Post-Intervention Effects

Parameter	Original Analysis Est [95%CI]	Random Effects Model Est [95%CI]	P-value Selection Model Est [95%CI]
Average ES: Cognitive	0.341 [0.241, 0.440]	0.360 [0.253, 0.468]	0.479 [0.264, 0.714]
Average ES: Social-Emotional	0.163 [0.085, 0.240]	0.157 [0.071, 0.242]	0.215 [0.022, 0.421]
Heterogeneity SD	0.367 [0.328, 0.412]	0.358 [0.325, 0.395]	0.455 [0.237, 0.610]
Selection weight $.025 < \alpha < .500$			3.164 [1.475, 5.997]
Selection weight $.500 < \alpha < 1.00$			1.395 [0.506, 3.822]

# Relative Likelihood of Being Published for Post-Intervention Effects

- Studies with  $0.025 < p\text{-value} < 0.500$  are 3 times as likely to be published than studies with  $p\text{-values} < 0.025$
- Studies with  $p\text{-value} > 0.500$  are nearly 1.4 times as likely to be published than studies with  $p\text{-values} < 0.025$



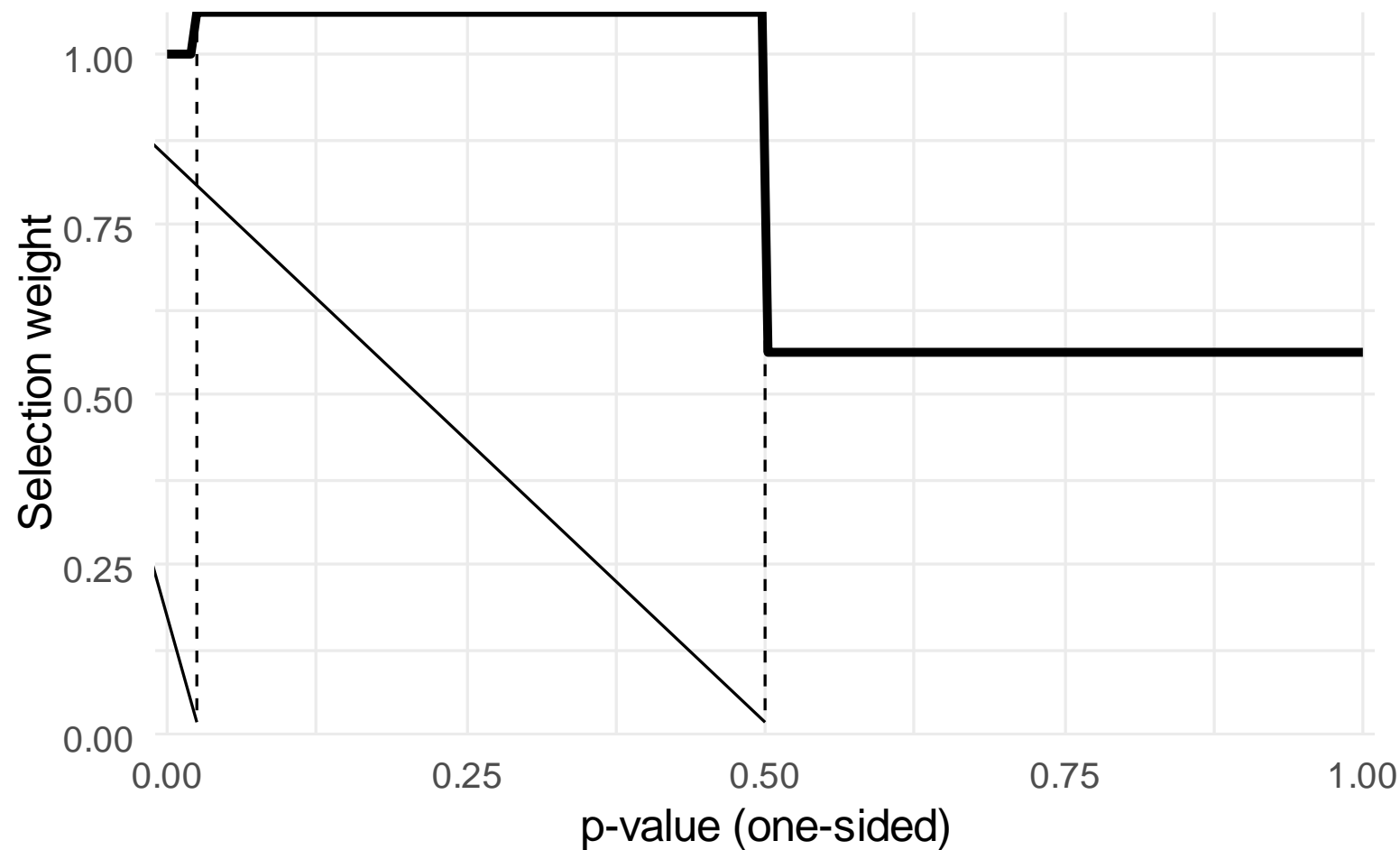


# Follow-Up Effects Conditional on Post-Intervention Effects

Parameter	Original Analysis Est [95%CI]	Random Effects Model Est [95%CI]	P-value Selection Model Est [95%CI]
Intercept: Cognitive	-0.003 [-0.059, 0.052]	0.019 [-0.043, 0.081]	-0.012 [-0.056, 0.105]
Intercept: Social-Emotional	0.054 [ 0.018, 0.090]	0.042 [ 0.011, 0.072]	0.014 [-0.030, 0.093]
Slope: Cognitive	0.462 [ 0.333, 0.592]	0.456 [ 0.383, 0.528]	0.476 [ 0.385, 0.606]
Slope: Social-Emotional	0.429 [ 0.258, 0.600]	0.563 [ 0.298, 0.827]	0.590 [ 0.302, 0.876]
Heterogeneity SD	0.095 [ 0.000, 0.123]	0.067 [ 0.044, 0.093]	0.071 [ 0.000, 0.200]
Selection weight $.025 < \alpha < .500$			1.064 [ 0.622, 2.562]
Selection weight $.500 < \alpha < 1.00$			0.563 [ 0.260, 1.630]

# Relative Likelihood of Being Published for Follow-Up Effects

- Studies with  $0.025 < p\text{-value} < 0.500$  are 1.1 times as likely to be published than studies with  $p\text{-values} < 0.025$
- Studies with  $p\text{-value} > 0.500$  are about half as likely to be published than studies with  $p\text{-values} < 0.025$



# Conclusion

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# Conclusions & Limitations

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- Cluster-bootstrapped selection model
  - Low bias compared to other selective reporting adjustment methods
  - Bias variance trade-off relative to a regular meta-analytic model
  - Tolerable coverage (between 90% to 95%)
- Results are specific to the **selection mechanism** we studied.

# Further Directions

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- Examining the consequences of selective reporting in education
  - Stratified sample of ~100 published meta-analyses of education research
  - Meta-analytic effects are frequently adjusted upwards
- Developing a second p-value selection model using the beta density
  - Extending the work of Citkowicz and Vevea (2017)

# R package metaselection

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- Currently available on Github at <https://github.com/jepusto/metaselection>
- Install using  

```
remotes::install_github("jepusto/metaselection")
```
- Under active development, feedback very welcome!

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# Supplement

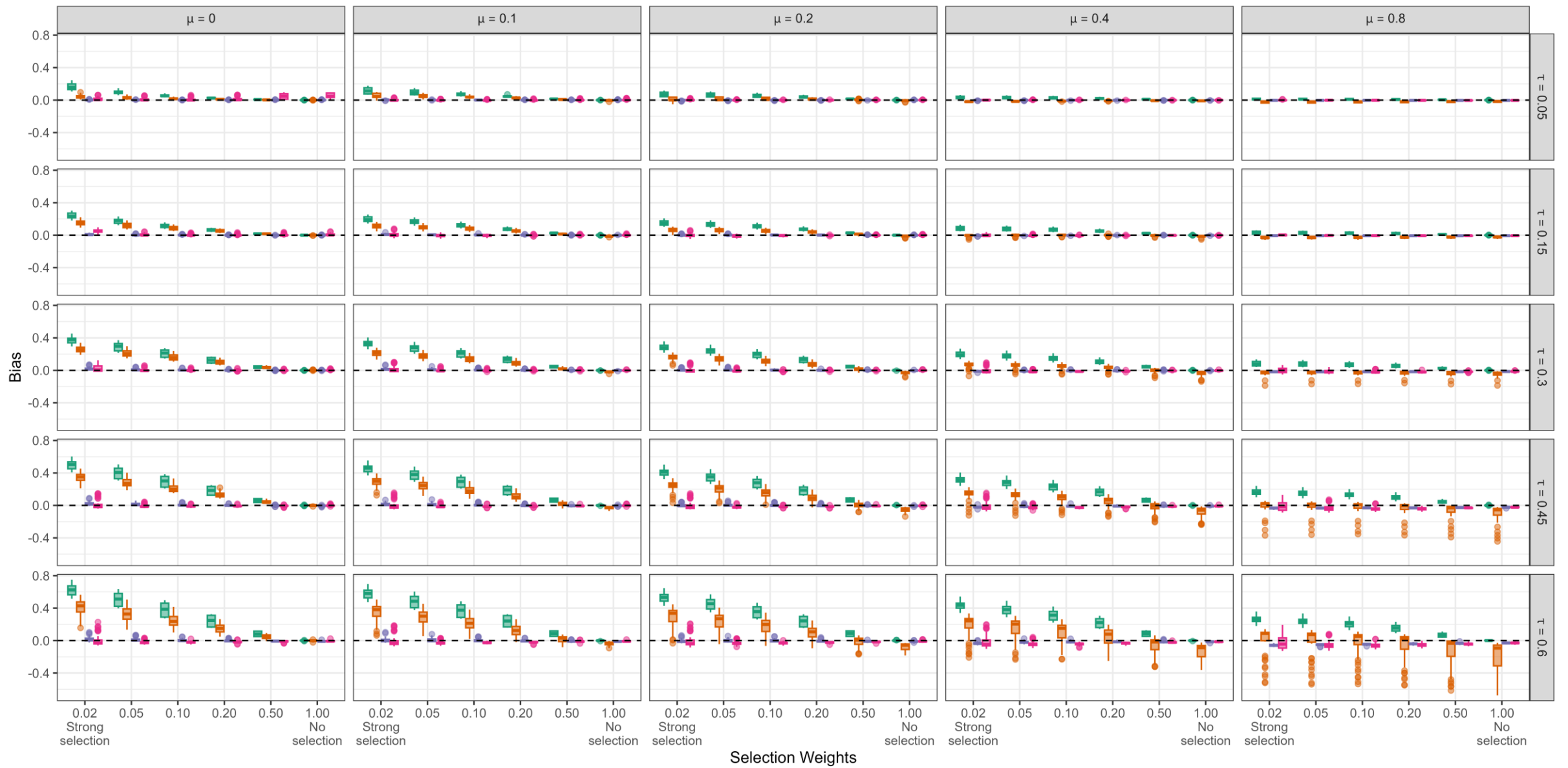
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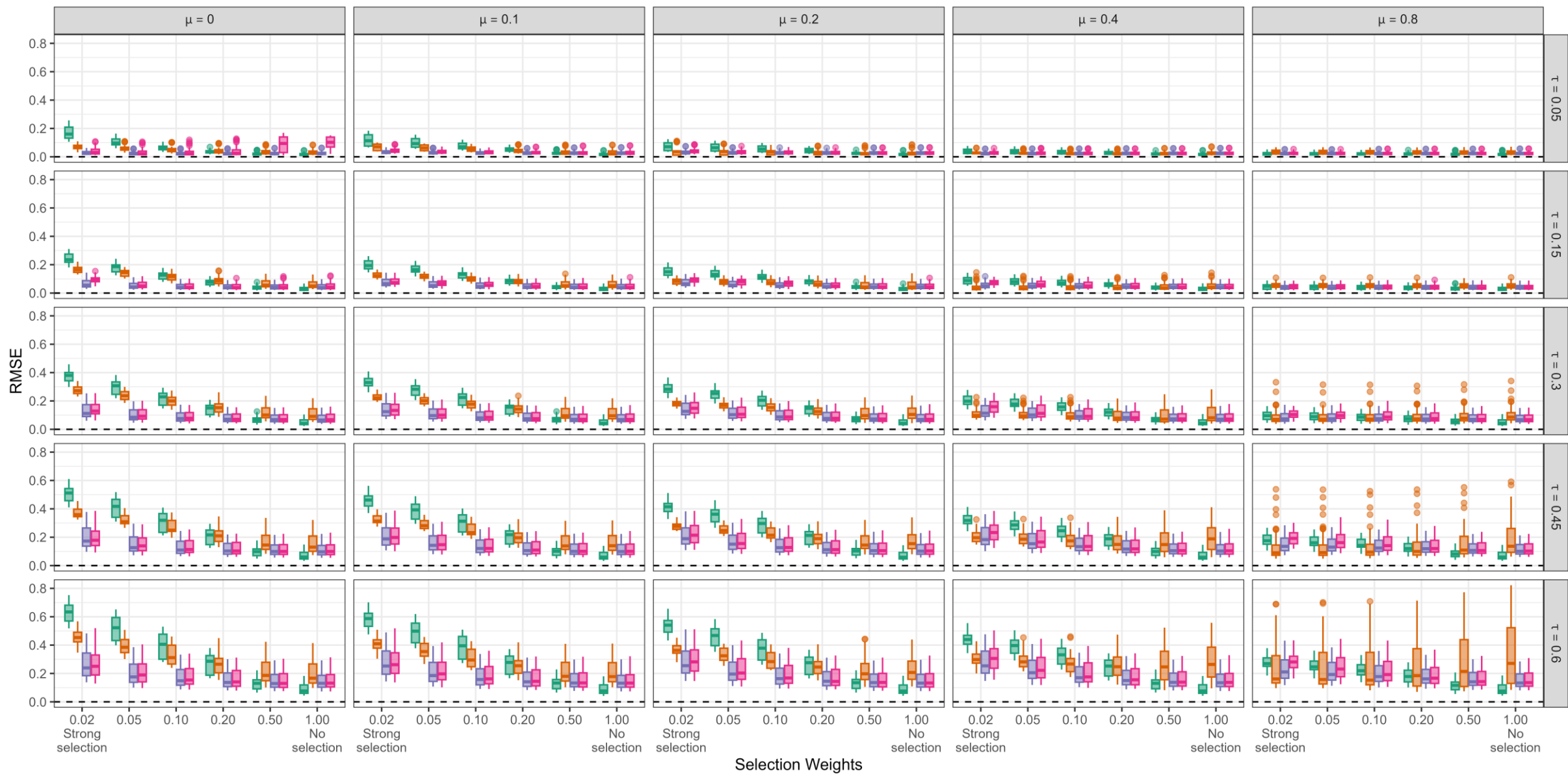
# Experimental Design

Conditions	Full simulation	Bootstrap CI simulation
Overall average SMD ( $\mu$ )	0.0, 0.1, 0.2, 0.4, 0.8	0.0, 0.4, 0.8
Between-study heterogeneity ( $\tau$ )	0.05, 0.15, 0.30, 0.45, 0.60	0.15, 0.45
Heterogeneity ratio ( $\omega^2/\tau^2$ )	0.0, 0.5	0.0, 0.5
Average correlation between outcomes ( $\rho$ )	0.4, 0.8	0.8
Weights for censoring (probability of selection for non-significant ES)	0.02, 0.05, 0.1, 0.2, 0.5, 1.0	0.05, 0.2, 1.0
Number of studies ( $m$ )	15, 30, 60, 90, 120, 200	15, 30, 60
Primary study sample size	Typical, small	Typical, small

Simulations used 2000 replications for each simulation condition, with 399 bootstraps for each replication.



Method  Correlated-and-Hierarchical Effects Model  PET/PEESE  3PSM (Maximum Likelihood)  3PSM (Hybrid Estimating Equations)



Method ■ Correlated-and-Heirarchical Effects Model ■ PET/PEESE ■ 3PSM (Maximum Likelihood) ■ 3PSM (Hybrid Estimating Equations)

# Coverage

- 3-parameter selection model
- Hybrid estimating equations

