On internal validity in multiple baseline designs

James E. Pustejovsky
The University of Texas at Austin
pusto@austin.utexas.edu

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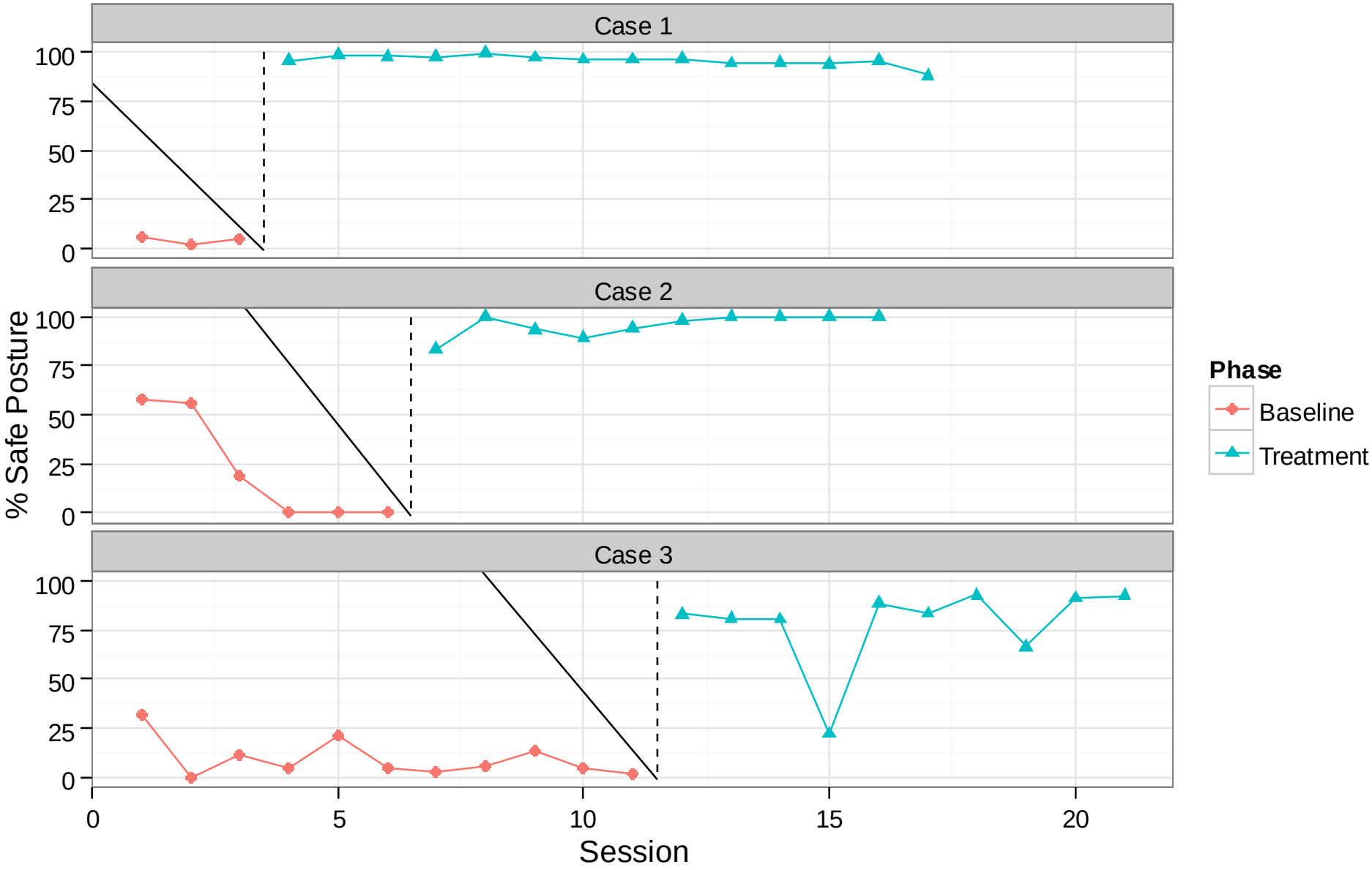
Single-case designs

- Core features:
  - Repeated measurements on a small number of individual cases.
  - Within-case comparisons of outcomes under different treatment conditions.

- Growing interest in statistical analysis, effect size measures, meta-analytic methods for single-case studies.

- Multiple baseline is most common single-case design (Shadish & Sullivan, 2011)

Sigurdsson & Austin (2008). Using real-time visual feedback to improve posture at computer workstations



Multiple baseline design (MBD)

- Key features for internal validity:
  - Deliberate introduction of treatment to cases
  - Staggered treatment introduction across cases

- My argument:
  - Appropriate analytic method depends on the specific treatment assignment mechanism.
  - Statistical analysis should account for staggered treatment introduction to maintain internal validity.

Notation and model

Structural model:

$$Y_{ij}\left(T_i\right) = \beta_{0i} + \beta_{1i} X_{ij}\left(T_i\right) + e_{ij}$$

$$\beta_{0i} = \gamma_0 + u_{0i}$$

$$\beta_{1i} = \gamma_1 + u_{1i}$$

Average treatment effect

- m cases
- n measurement occasions
- Y_{ij} outcome for case i at time j, i = 1,…,m, j = 1,…,n
- T_i length of baseline phase for case i
- X_{ij} = 0 if case i is in baseline at time j ($j \leq T_i$)
- X_{ij} = 1 if case i is in treatment at time j ($j > T_i$)

Random assignment of treatment times

- Uncommon in practice.
- Understood to improve internal validity (Kratochwill & Levin, 2010)

- Analytic model 1 (cf. Van den Noortgate & Onghena, 2003):

$$\left(Y_{ij} \mid X_{i1}, \ldots, X_{in}\right) = \beta_{0i} + \beta_{1i} X_{ij} + e_{ij}$$

$$\beta_{0i} = \gamma_0 + u_{0i}$$

$$\beta_{1i} = \gamma_1 + u_{1i}$$

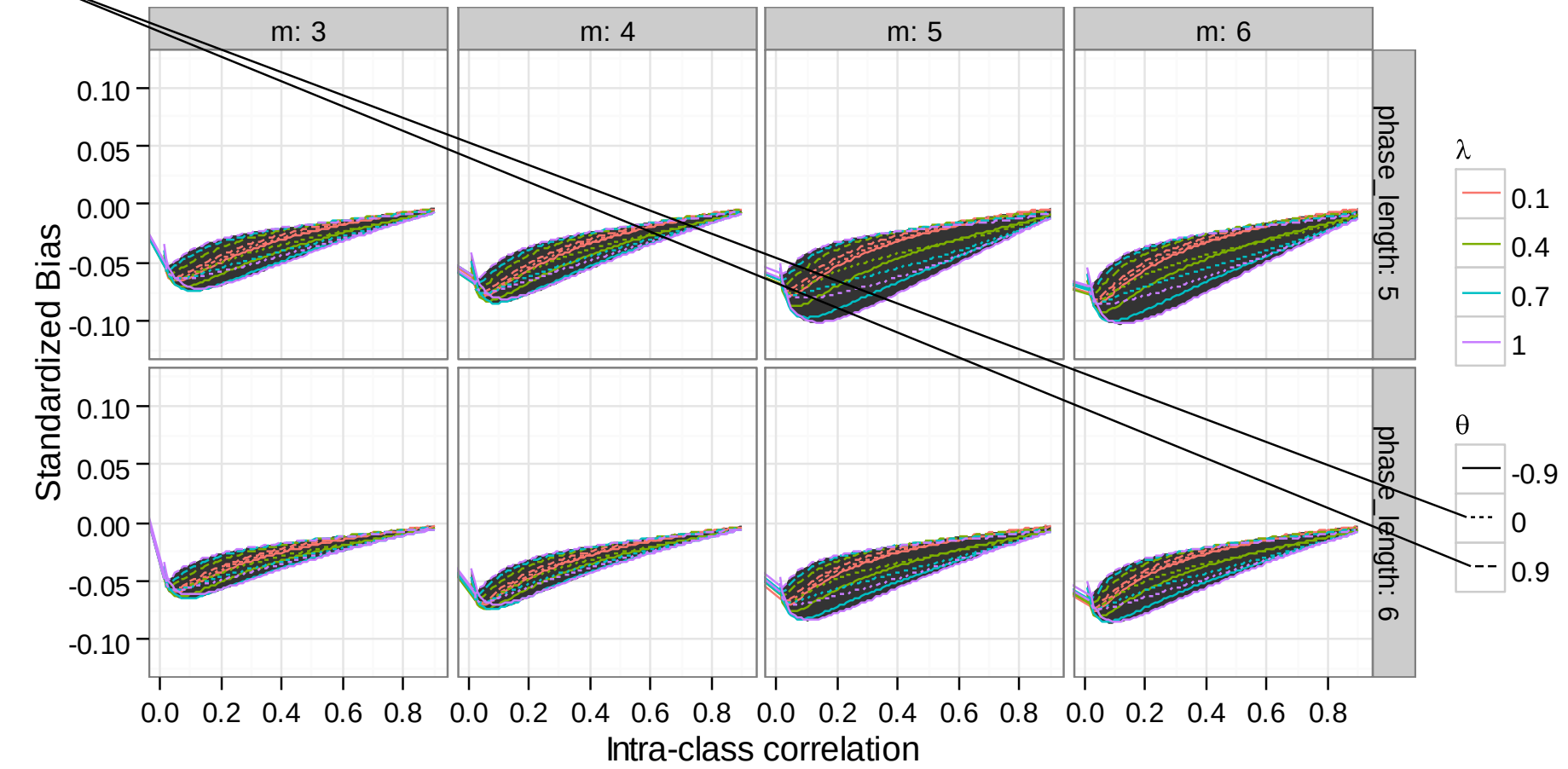
Triage on known baseline ranks

- Suppose that…
  - Fixed set of baseline lengths t_1, t_2, …, t_m.
  - Baseline lengths are assigned prior to start of study.
  - Investigator can accurately predict baseline outcome levels β_{01}, β_{02},…, β_{0m}.

- Triage on known baseline ranks:
  - Case with lowest baseline starts treatment first.
  - Case with 2nd lowest baseline starts treatment second.
  - Etc.

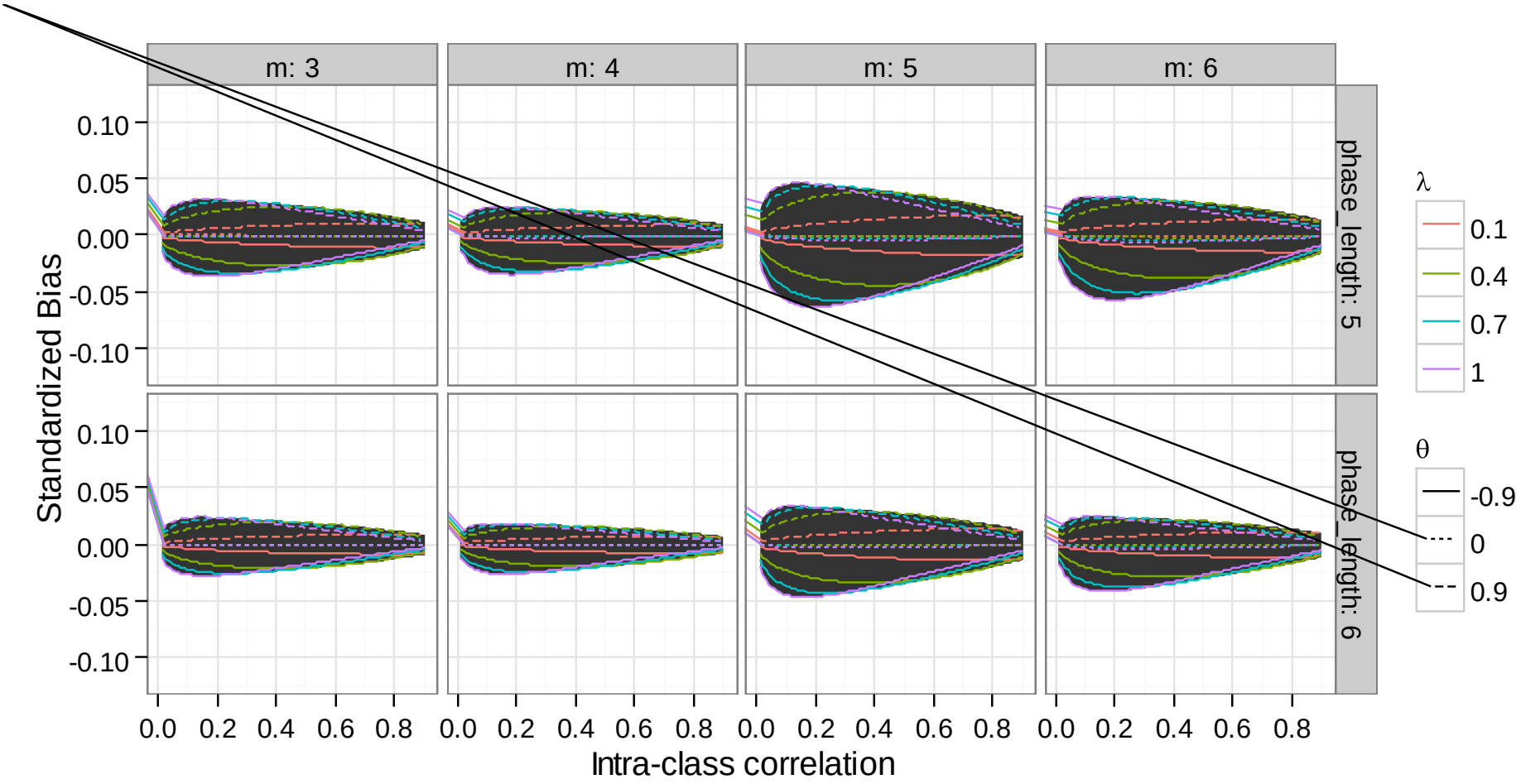
Triage on known baseline ranks

- Treatment effect estimator from Analytic Model 1 has negative bias.



Triage on known baseline ranks

- Centering the treatment indicator by case mitigates the bias.

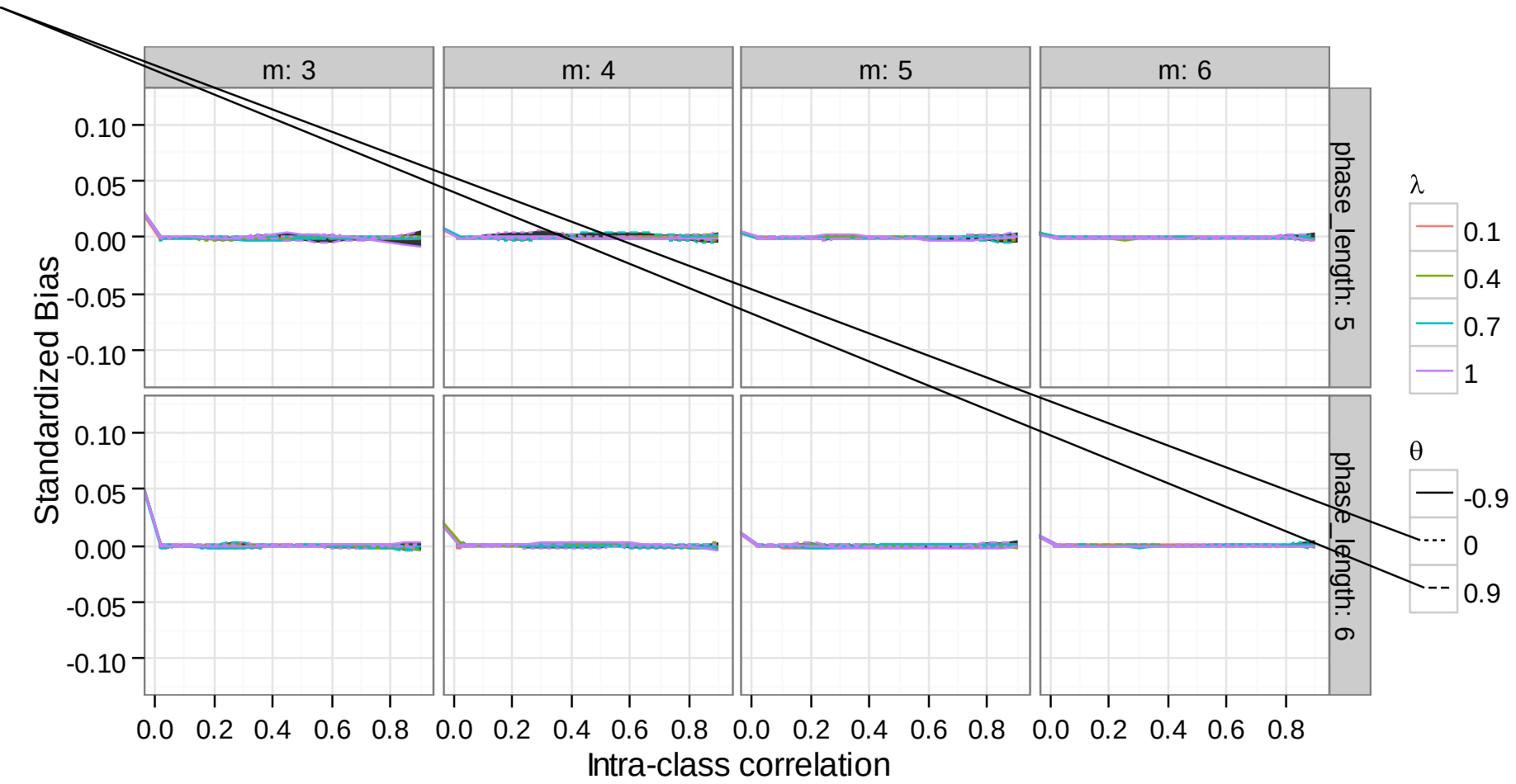


Triage on measured baseline ranks

- Triage based on running mean outcomes as of each possible treatment assignment time.
- Case with lowest measured baseline as of time t_1 receives treatment first.
- Of the remaining cases, case with lowest measured baseline as of time t_2 receives treatment second.
- Etc.

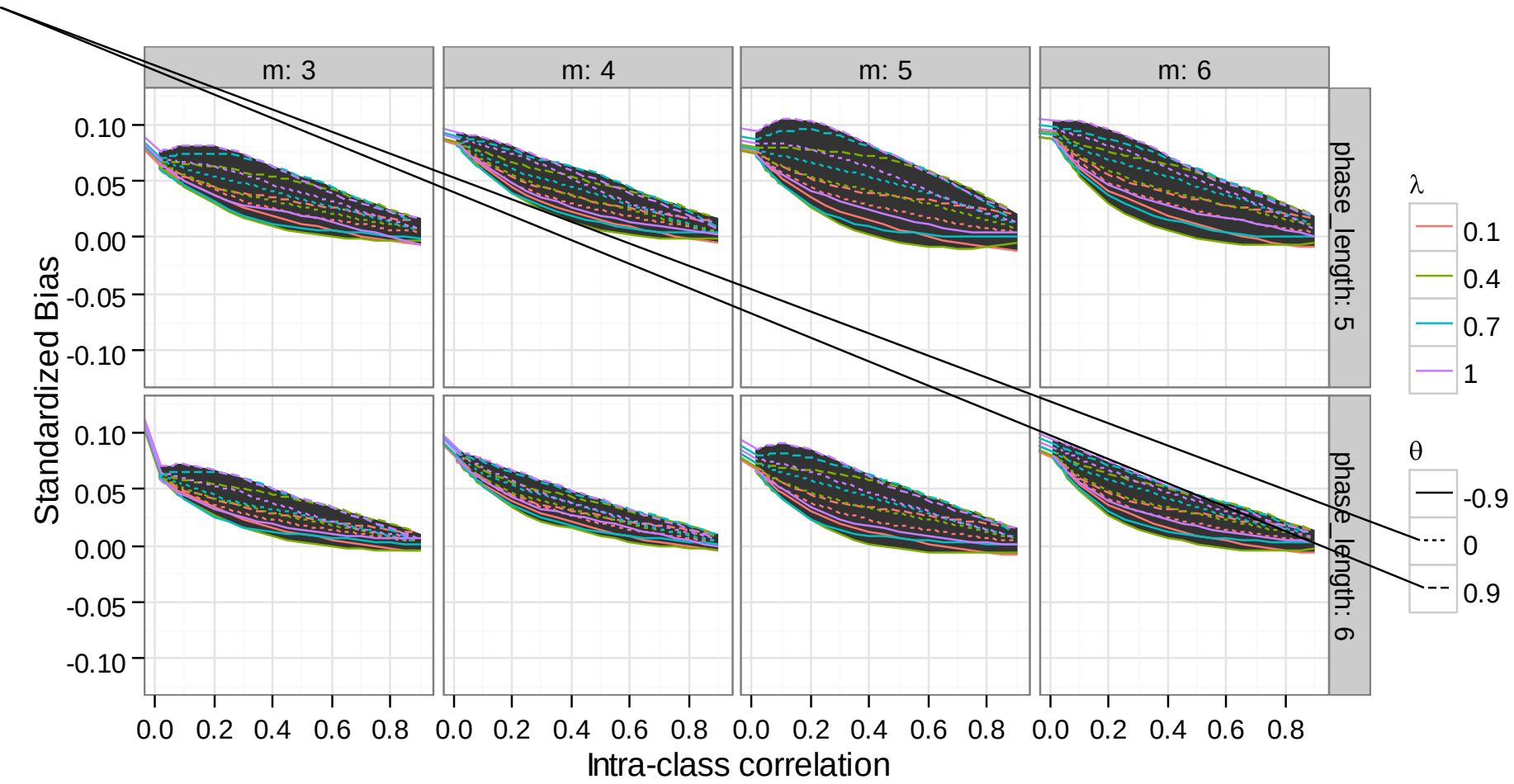
Triage on measured baseline ranks

- Treatment effect estimator based on Analytic Model 1 has negligible biases.



Triage on measured baseline ranks

- Treatment effect estimator based on Analytic Model 2 has larger, positive biases.



Implications

- Empirical researchers using MBDs should explain how they assign treatment times to cases.
- Methodologists should specify treatment assignment mechanisms for which a proposed analytic method is valid.
- Other assignment mechanisms used in practice?