**Title:** Supplement for Accurate confidence and Bayesian interval estimation for non-centrality parameters and effect size indices

### Wild Bootstraps

In addition to the non-parametric and Bayesian bootstrap we discussed in the main paper, we also considered several variants of the wild bootstrap, which was originally proposed by (Wu, 1986). The wild bootstrap is a kind of residual bootstrap which leaves the covariates at the sample value but resamples the outcome values based on the residual values. That is, in each replicate, the resampled outcome value of the i-th observation is

$$y_i^* = \hat{y}_i + \hat{\epsilon}_i \times w_i, \tag{1}$$

where  $\hat{y}_i$  and  $\hat{\epsilon}_i$  are the expected value and estimated residual of the *i*-th observation from the analysis model, respectively.  $w_i$  is a random number, called multiplier, drawn from a distribution W such that  $\mathbb{E}(W)=0$  and Var(W)=1. There are several different distributions from which  $w_i$  can be drawn, such as the Rademacher and standard Normal distributions.

The original wild bootstrap doesn't resample the data. We propose several variants of the original wild bootstrap: (1) resampling covariates along with residuals with replacement; (2) fixing covariates and only resampling residuals with replacement; (3) independently resampling covariates and residuals with replacement. We also considered 3 types of multipliers: (1) no multipliers, i.e.,  $w_i = 1$ ,  $\forall i$ ; (2) multipliers drawn from the Rademacher distribution; (3) multipliers drawn from standard Normal distribution. Table 1 below summarizes the original and variant wild bootstraps considered in this paper. The original wild bootstrap without using multipliers is excluded because no resampling happens within this combination. Therefore, there are 11 combinations of the wild bootstrapping evaluated in the simulations.

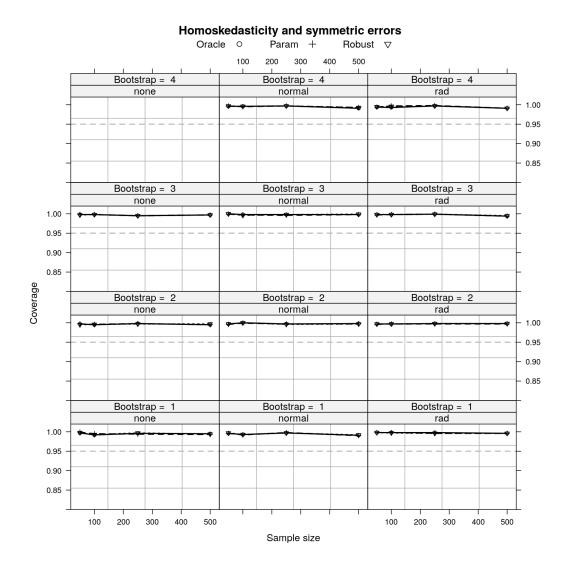
Wild bootstrap type	Multiplier	Bootstrap model	Assumption(s)
Original	None	$Y^{(b)} = X\hat{\beta} + \hat{\epsilon} \times 1 = Y$	Excluded b/c no sampling happens here
	Rademacher	$Y^{(b)} = X\hat{\beta} + \hat{\epsilon} \times W, w_i \sim Rad$	Symmetric errors
	N(0, 1)	$Y^{(b)} = X\hat{\beta} + \hat{\epsilon} \times W, w_i \sim N(0, 1)$	Symmetric errors
(1) Resampling covariates along with residuals	None	$Y^{(b)} = R^{(b)}X\hat{\beta} + R^{(b)}\hat{\epsilon} \times 1$	Non-parametric bootstrap. not assuming homo- /hetero-skedasticity or symmetric errors
	Rademacher	$Y^{(b)} = R^{(b)}X\hat{\beta} + R^{(b)}\hat{\epsilon} \times W, w_i \sim Rad$	Symmetric errors
	N(0, 1)	$Y^{(b)} = R^{(b)} X \hat{\beta} + R^{(b)} \hat{\epsilon} \times W, w_i \sim N(0, 1)$	Symmetric errors
(2) Fixing covariates and only resampling residuals	None	$Y^{(b)} = X\hat{\beta} + R^{(b)}\hat{\epsilon} \times 1$	Homoskedasticity
	Rademacher	$Y^{(b)} = X\hat{\beta} + R^{(b)}\hat{\epsilon} \times W, w_i \sim Rad$	Homoskedasticity and symmetric errors
	N(0, 1)	$Y^{(b)} = X\hat{\beta} + R^{(b)}\hat{\epsilon} \times W, w_i \sim N(0, 1)$	Homoskedasticity and symmetric errors
(3) independently resampling covariates and residuals	None	$Y^{(b)} = R_1^{(b)} X \hat{\beta} + R_2^{(b)} \hat{\epsilon} \times 1$	Homoskedasticity
	Rademacher	$Y^{(b)} = R_{1}^{(b)} X \hat{\beta} + R_{2}^{(b)} \hat{\epsilon} \times W, w_i \sim Rad$	Homoskedasticity and symmetric errors
	N(0, 1)	$Y^{(b)} = R_1^{(b)} X \hat{\beta} + R_2^{(b)} \hat{\epsilon} \times W, w_i \sim N(0, 1)$	Homoskedasticity and symmetric errors

Table 1: Eleven bootstrap procedures considered in this paper. The original wild bootstrap with constant multiplier is excluded since it performs no resampling.  $R^{(b)}$  denotes the bootstrap matrix for the b-th replicate;  $Y^{(b)}$  is the bootstrapped outcome values; X is the covariate(s);  $\hat{\beta}$  is the estimated parameters;  $\hat{\epsilon}$  is the estimated residuals; W is the randomly drawn values for the multiplier.

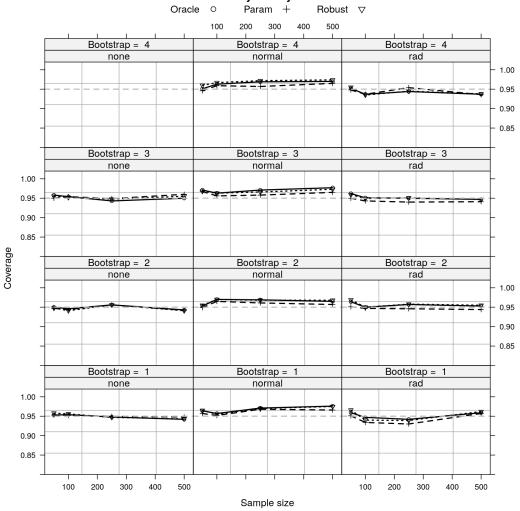
### **Simulation Results**

In this section, we show the coverage performance for the confidence intervals constructed using different wild bootstraps under different scenarios (homo-/hetero-skedasticity and symmetric skewed errors) given *random* covariate and different true RESI value.

## Homoskedasticity & Symmetric Errors



## Homoskedasticity and symmetric errors



100

200

300

400

500

#### Homoskedasticity and symmetric errors Param + Oracle O 200 100 300 500 400 Bootstrap = 4 Bootstrap = 4 Bootstrap = 4 none normal rad 1.00 0.95 0.90 0.85 Bootstrap = 3 Bootstrap = 3 Bootstrap = 3 normal 1.00 0.95 0.90 0.85 Coverage Bootstrap = 2 none Bootstrap = 2 normal Bootstrap = 2 rad 1.00 \$ - I + +---0.95 0.90 0.85 Bootstrap = 1 Bootstrap = 1 Bootstrap = 1 normal rad 1.00 0.95 0.90 0.85

Sample size

100

200

300

400

500

0.95 0.90 0.85

100

200

300

400

### Homoskedasticity and symmetric errors Param + Robust ▽ 200 300 400 100 500 Bootstrap = 4 Bootstrap = 4 Bootstrap = 4 none normal rad 1.00 0.95 0.90 0.85 Bootstrap = 3 Bootstrap = 3 Bootstrap = 3 normal 1.00 0.95 0.90 0.85 Coverage Bootstrap = 2 normal Bootstrap = 2 Bootstrap = 2 1.00 0.95 0.90 0.85 Bootstrap = 1 normal Bootstrap = 1 Bootstrap = 1 rad 1.00

Sample size

100

200

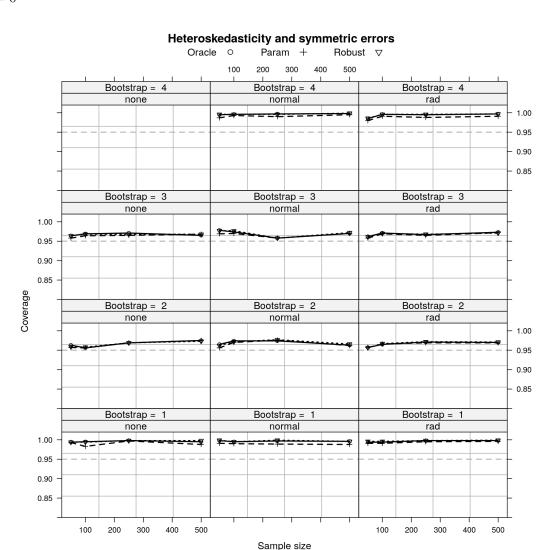
300

400

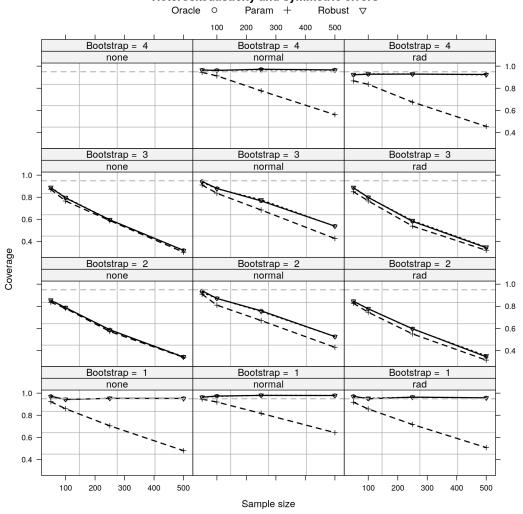
500

500

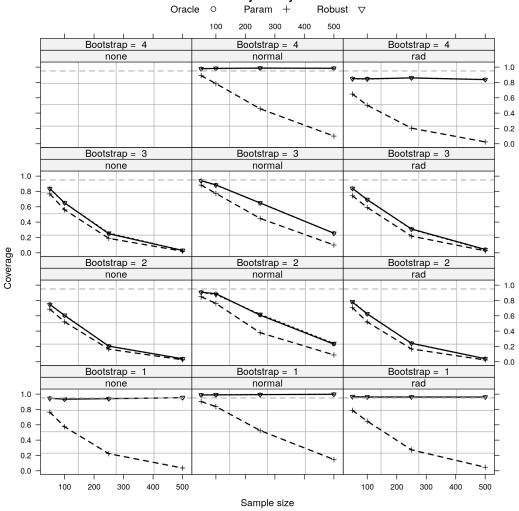
## Heteroskedasticity & Symmetric Errors



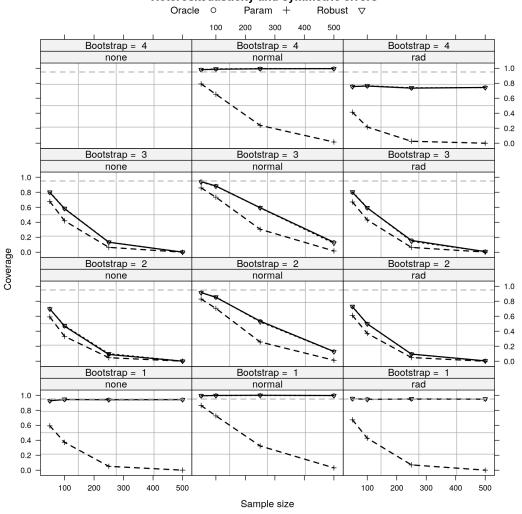
### Heteroskedasticity and symmetric errors



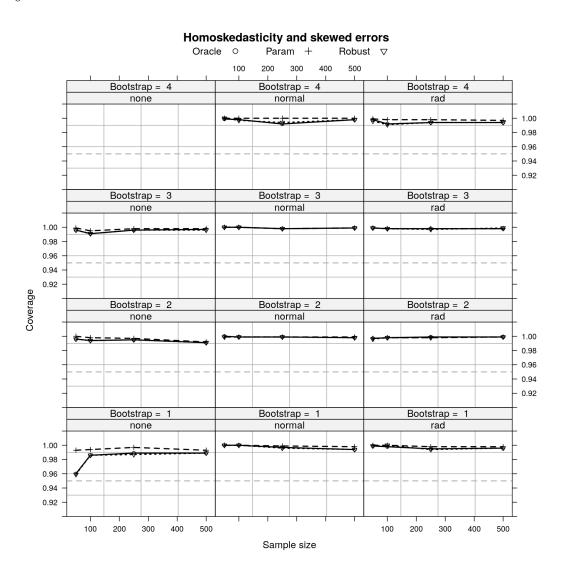
### Heteroskedasticity and symmetric errors



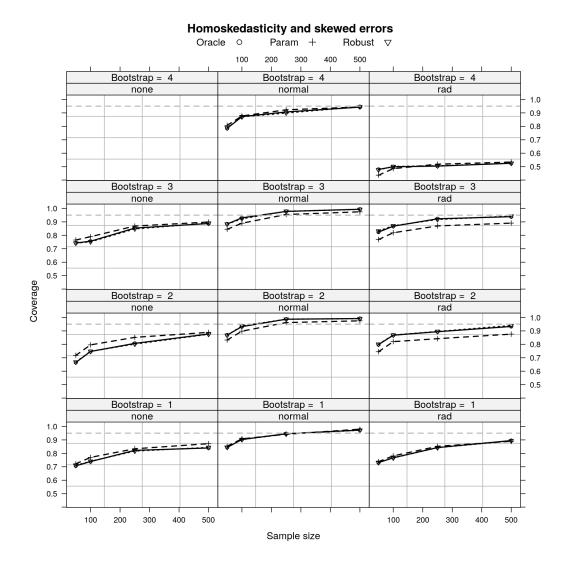
### Heteroskedasticity and symmetric errors

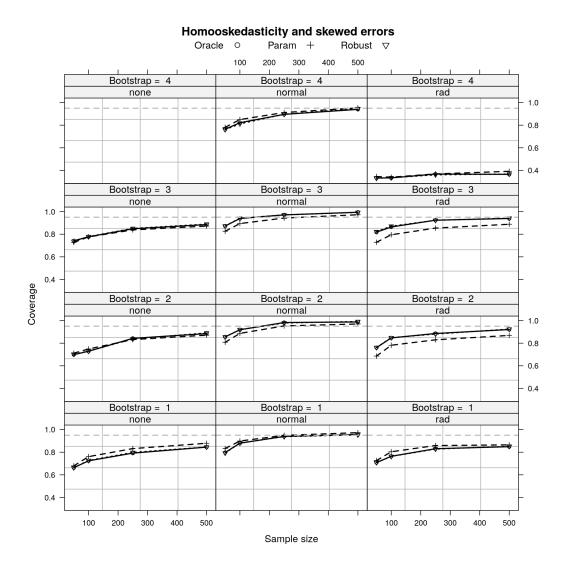


# Homoskedasticity & Skewed Errors

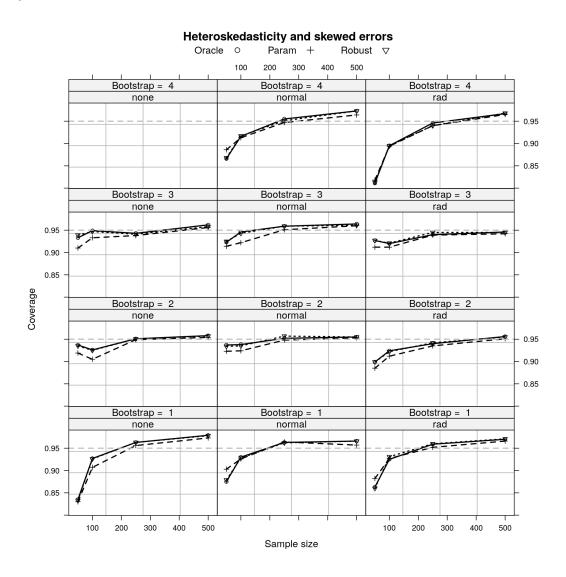


#### Homoskedasticity and skewed errors Oracle 0 Param + Robust ▽ 200 300 100 400 Bootstrap = 4 Bootstrap = 4 Bootstrap = 4 none normal rad 1.0 0.9 0.8 0.7 Bootstrap = 3 none Bootstrap = 3 normal Bootstrap = 3 1.0 0.9 8.0 0.7 Coverage Bootstrap = 2 normal Bootstrap = 2 Bootstrap = 2 1.0 0.9 8.0 0.7 Bootstrap = 1 normal Bootstrap = 1 none Bootstrap = 1 1.0 0.9 8.0 0.7 100 500 100 200 400 500 200 300 400 300 Sample size





## **Heteroskedasticity & Skewed Errors**



#### Heteroskedasticity and skewed errors Param + Robust ▽ 300 200 100 500 400 Bootstrap = 4 Bootstrap = 4 Bootstrap = 4 none normal rad 1.0 0.8 0.6 0.4 0.2 Bootstrap = 3 normal Bootstrap = 3 Bootstrap = 3 none rad 1.0 8.0 0.4 0.2 Coverage Bootstrap = 2 normal Bootstrap = 2 Bootstrap = 2 none rad 1.0 0.8 0.6 0.4 0.2 Bootstrap = 1 Bootstrap = 1 Bootstrap = 1 none normal rad 1.0 8.0 0.6 0.4 0.2 100 200 200 400 100 300 400 500 300 500

Sample size

#### Heteroskedasticity and skewed errors Param + Robust ▽ 300 200 100 500 400 Bootstrap = 4 Bootstrap = 4 Bootstrap = 4 none normal rad 1.0 0.8 0.6 0.4 0.2 Bootstrap = 3 normal Bootstrap = 3 Bootstrap = 3 none rad 1.0 0.8 0.6 0.4 0.2 Coverage Bootstrap = 2 normal Bootstrap = 2 Bootstrap = 2 none rad 1.0 0.8 0.6 0.4 0.2 Bootstrap = 1 normal Bootstrap = 1 Bootstrap = 1 none rad 1.0 8.0 0.6 0.4 0.2 100 200 200 300 500 100 300 400 500 400 Sample size

#### Heteroskedasticity and skewed errors Param + Robust ▽ 300 200 500 100 400 Bootstrap = 4 Bootstrap = 4 Bootstrap = 4 none normal rad 8.0 0.6 0.4 0.2 Bootstrap = 3 normal Bootstrap = 3 Bootstrap = 3 none rad 8.0 0.6 0.4 0.2 Coverage Bootstrap = 2 normal Bootstrap = 2 Bootstrap = 2 none rad 0.8 0.6 0.4 0.2 Bootstrap = 1 Bootstrap = 1 Bootstrap = 1 none normal rad 0.8 0.6 0.4 0.2 100 200 200 300 400 500 300 400 500 100

Sample size

# References

Wu, C. F. J. (1986). Jackknife, Bootstrap and Other Resampling Methods in Regression Analysis. *The Annals of Statistics*, 14(4):1261–1295. Publisher: Institute of Mathematical Statistics.