Cluster Wild Bootstrapping to Handle Dependent Effect Sizes

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Dependence

- Typical meta-analytic techniques involves the assumption that effect sizes are independent
- However, common for each primary study to yield more than one effect size or studies to be nested in some way creating dependence
- Example: Tanner-Smith and Lipsey (2015) meta-analysis of the effects of brief alcohol interventions
    - 185 studies, 1446 effect sizes
    - Multiple correlated outcome measures: e.g., alcohol consumption measured by frequency of consumption, quantity consumed, blood alcohol concentration
    - Repeated measures
    - Multiple comparison groups

Handling Dependence

- Ignore dependence
    - Incorrect standard errors, incorrect inference from hypothesis tests
- Ad-hoc methods
    - Loss of information
- Standard multivariate methods - ideal
    - Require info on covariance between effect sizes
    - Primary studies often don't report

Robust Variance Estimation

- Robust variance estimation (CR0-type CRVE) (Hedges, Tipton, and Johnson, 2010)
    - Rough approximate assumptions about dependence structure - sandwich estimators
    - Only works well when number of studies is large (> 40, Hedges Tipton, Johnson, 2010)
    - Meta-analysis in social science research typically have smaller number of studies
    - Small number of studies - CRVE - Type 1 error inflation - meta-analysts can conclude some effect is present when it is actually not

Small Sample Corrections

- Tipton (2015) for tests of single coefficients
- Tipton and Pustejovsky (2015) for multiple-contrast hypothesis tests
  - e.g., Do effects differ across outcome measurements?
- Both recommended a method - HTZ test
  - CR2 correction method and using the Satterthwaite degrees of freedom for single coefficient tests
  - Extension of CR2 + Satterthwaite for multiple-contrast hypothesis tests
- HTZ controls Type 1 error rates adequately
- But, low Type 1 error rates especially for multiple-contrast hypothesis tests (Tipton and Pustejovsky, 2015)
  - Indicating that the test may have low power

Cluster Wild Bootstrapping (CWB)

- Alternative method - examined in the econometrics literature - not in meta-analytic framework
- Bootstrapping - estimate unknown quantities by re-sampling from original data many times (Boos et al., 2013)
- CWB - re-sampling residuals by multiplying them by cluster-level random weights (Cameron, Gelbach, and Miller 2008)

CWB Algorithm

1. Fit a null model and a full model on the original data
2. Obtain residuals from the null model
3. Generate an auxiliary random variable that has mean of 0 and variance of 1 and multiply the residuals by the random variable (e.g., Rademacher weights) set to be constant within clusters (CWB)
    - Can also multiply the residuals by CR2 matrices before multiplying by weights (CWB Adjusted)
4. Obtain new outcome scores by adding the transformed residuals to the predicted values from the null model fit on the original data
5. Re-estimate the full model with the new calculated outcome scores and obtain the test statistic
6. Repeat steps 3-5 R times. Calculate p-value:

$$p = \frac{1}{R}\sum_{r=1}^{R} I\left(F^{(r)} > F\right)$$

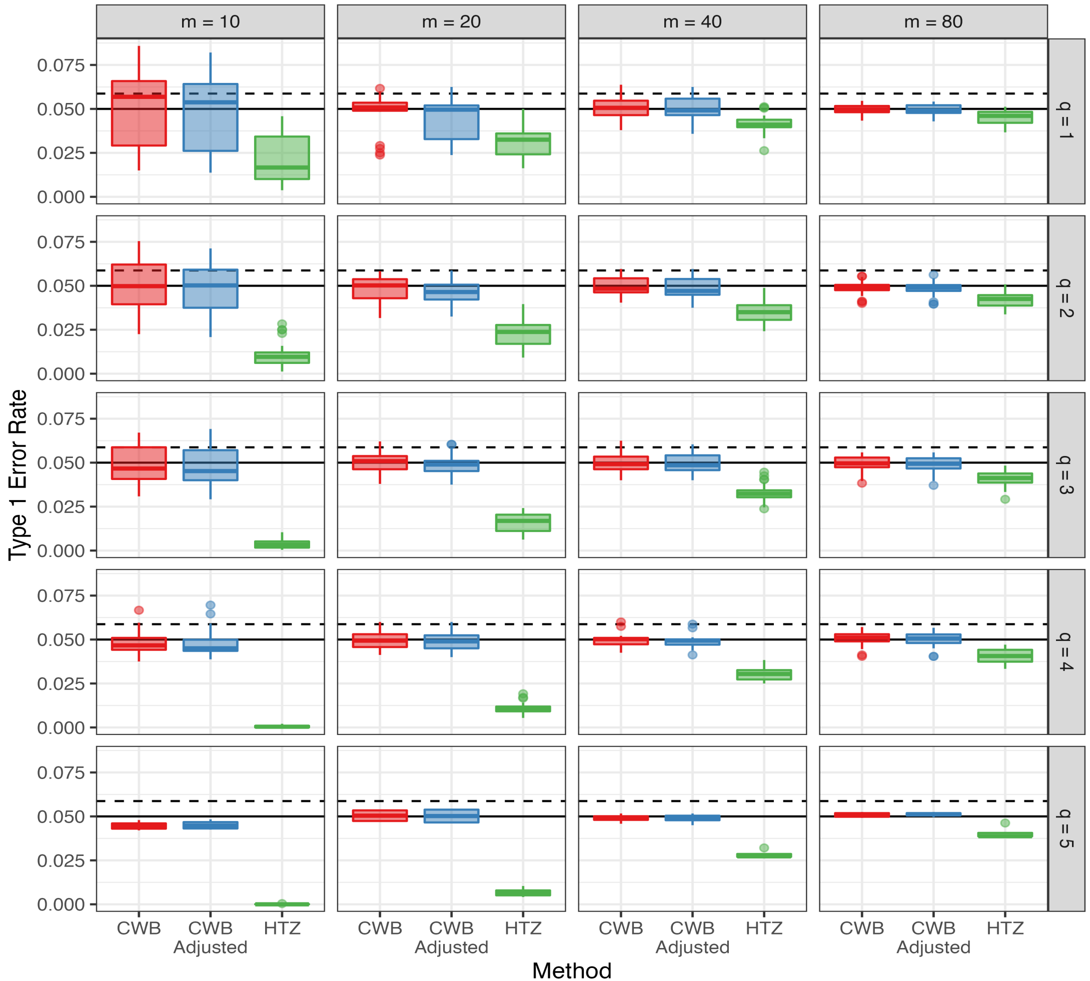
Research Question

To what extent does CWB improve upon the current standard test, the HTZ test, in terms of Type I error rates and power?

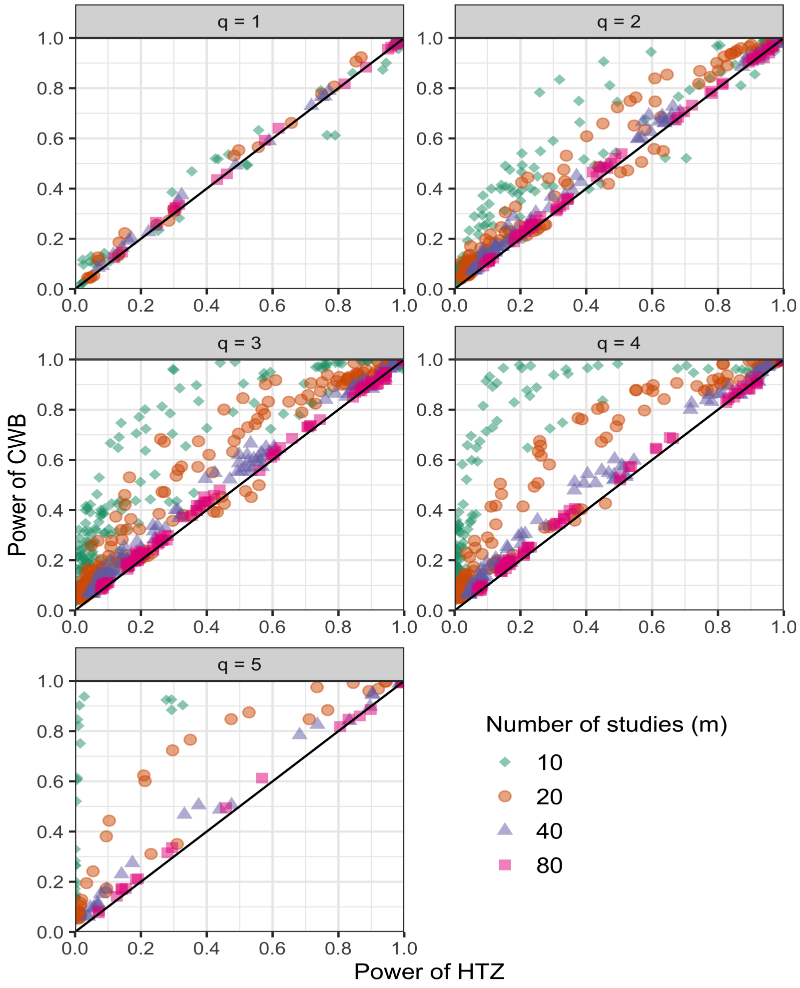
Simulation

- Ran two simulations - presenting on Study 1
- Compared CWB against the HTZ test in terms of Type 1 error rates and power
- Results
  - CWB maintained Type 1 error rates adequately
  - And, provided huge gains in power over the standard method, the HTZ test

Results: Type I Error



Results: Relative Power



Conclusion

- Dependent effect sizes - common
- Ignore them - incorrect standard errors and inferences
- Use RVE - Type 1 error inflation - false discovery rate high
- Use small sample correction HTZ test - may miss effects that are present
- Use CWB - balances Type 1 error rates and also provides more power than existing corrections

R Package

https://meghapsimatrix.github.io/wildmeta/

THANK YOU!

Questions?

References

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