



SYNTHESIS OF DEPENDENT EFFECT SIZES: ROBUST VARIANCE ESTIMATION WITH CLUBSANDWICH

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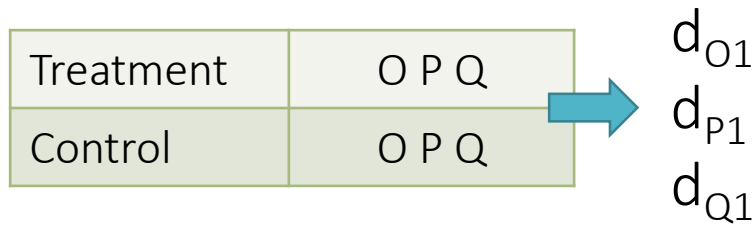
joint work with Elizabeth Tipton, Northwestern University

Paper: <https://doi.org/10.31222/osf.io/vyfcj>

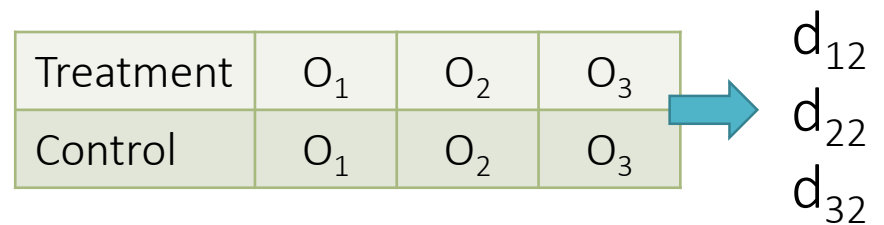
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Oslo R User Group Meetup

Dependent effect sizes are very common

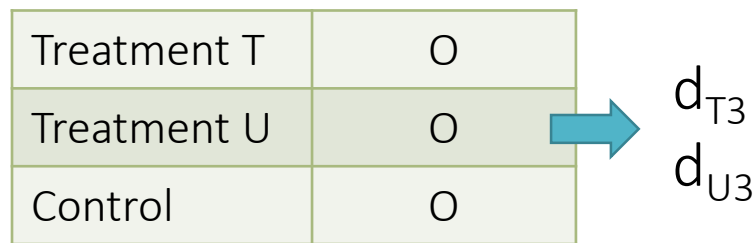
Multiple outcomes measured on common set of participants



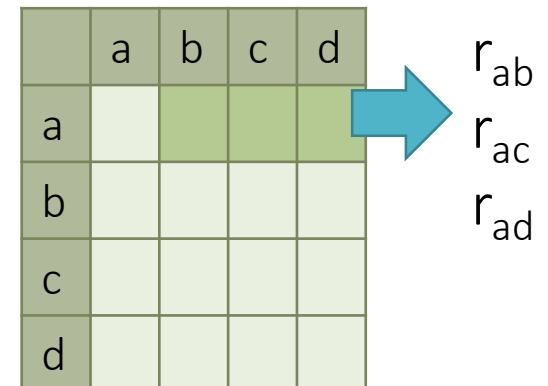
Outcome measured at multiple follow-up times



Multiple treatment conditions compared to a common control



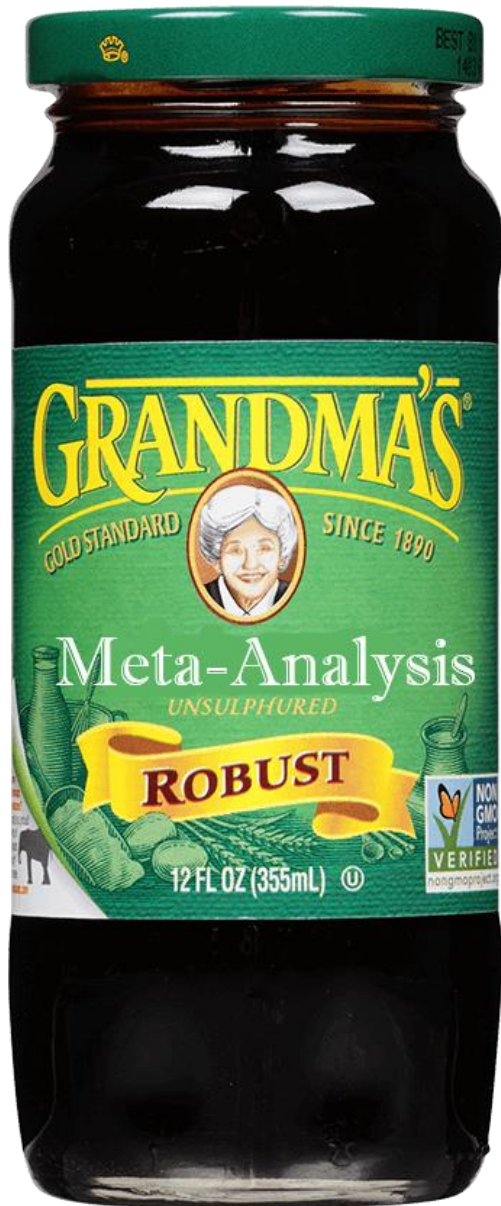
Multiple correlations from a common sample



Tanner-Smith & Lipsey (2015). Brief alcohol interventions for adolescents and young adults: A systematic review and meta-analysis.

185 studies, 1446 effect size estimates (standardized mean differences comparing alcohol consumption outcomes of intervention participants versus comparison participants).

- ✓ 1-108 effect size estimates per study (median = 6, IQR = 3-12)
- ✓ Multiple outcome measures
- ✓ Multiple follow-up times
- ✓ Multiple intervention conditions
- ✓ Multiple comparison groups



Robust Variance Estimation (RVE)

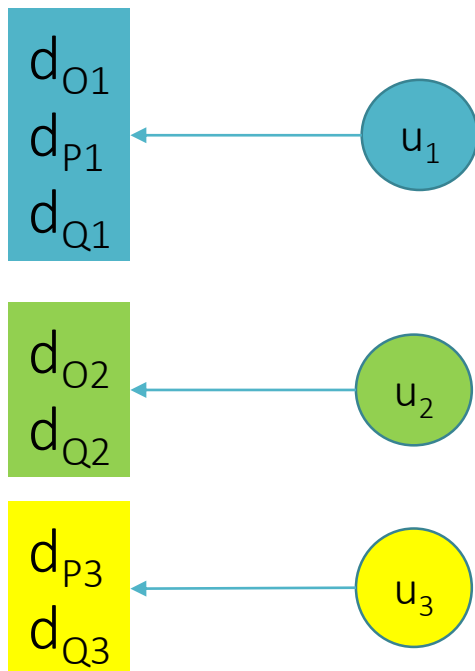
(Hedges, Tipton, & Johnson, 2010)

- Meta-analysis/meta-regression method using “sandwich” variance estimators.
- SEs, hypothesis tests, confidence intervals are robust to mistaken assumptions about the dependence structure of effect sizes within independent studies.
- RVE uses a “working model” to approximate the dependence structure.
 - It doesn't have to be correct.
 - But getting closer to the true dependence structure *improves precision*.

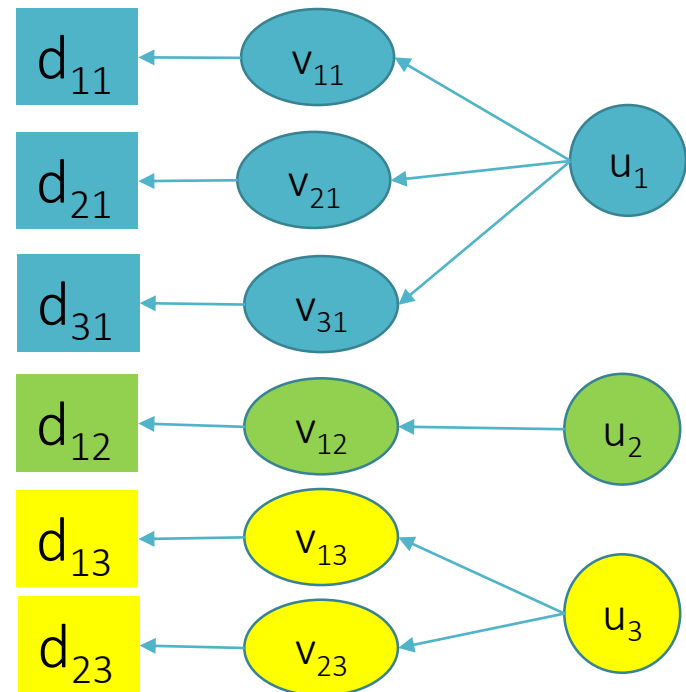
Working models in `robumeta`

- `robumeta` package (Fisher, Tipton, & Hou, 2017) is the most popular implementation of RVE.
- Two available working models.

Correlated Effects



Hierarchical Effects



Working models in metafor

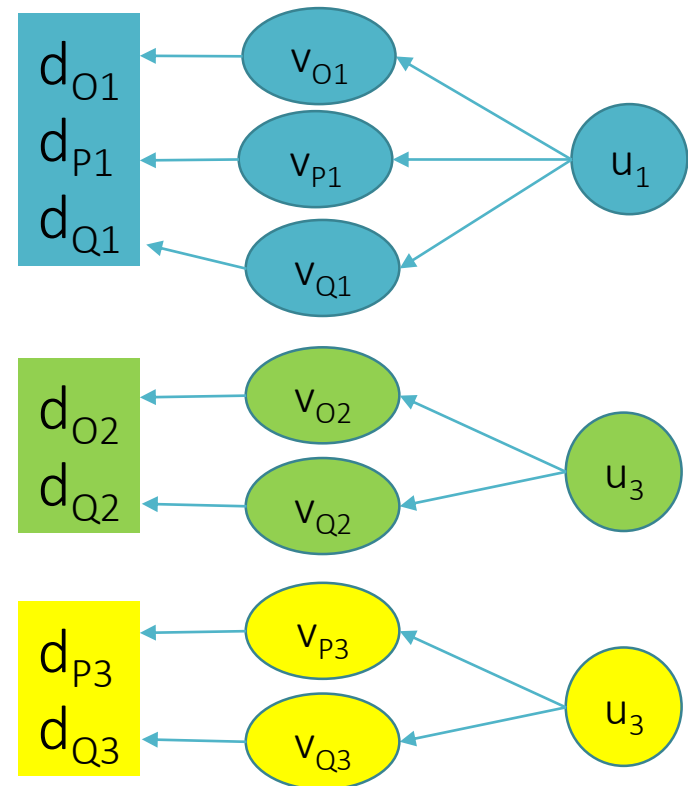
- `rma.mv()` from the `metafor` package (Viechtbauer, 2010) provides a versatile set of multi-level and multi-variate models.
- These can be treated as working models, combined with RVE.

Correlated + Hierarchical Effects Model

- Allows for correlated effect size estimates (using rough guess about degree of correlation).
- Allows for within-study heterogeneity in true effects.
- Estimating equation:

$$d_{ij} = \mu + u_j + v_{ij} + e_{ij}$$

$$\begin{aligned} \text{Var}(u_j) &= \tau^2, \text{Var}(v_{ij}) = \omega^2, \\ \text{Var}(e_{ij}) &= V_{ij}, \text{ and } \text{Cov}(e_{hj}, e_{ij}) = \rho\sqrt{V_{hj}V_{ij}} \end{aligned}$$





RVE with clubSandwich

- `clubSandwich` package (Pustejovsky, 2020) provides robust standard errors, hypothesis tests, confidence intervals for many types of models.
- Supports `rma.mv()` models from `metafor`.
- Includes small-sample corrections for more accurate inference.

Workflow

```
library(metafor)
library(clubSandwich)
TSL15 <- readRDS("Tanner-Smith-Lipsey-2015-subset.rds")

# Create a sampling variance-covariance matrix
V_mat <- impute_covariance_matrix(TSL15$V,
                                   cluster = TSL15$studyid,
                                   r = 0.6)

# fit working model in metafor
mod <- rma.mv(es ~ 0 + dv_cat, V = V_mat,
              random = ~ 1 | studyid / esid,
              data = TSL15)

# clustered SEs and CIs
conf_int(mod, vcov = "CR2")
```


Why metafor + clubSandwich

- Using a better approximation to the real dependence structure will give you *more precise estimates* of average effects/meta-regression coefficients.
- More flexible working models provide *better descriptions of heterogeneity* (e.g., within- and between-study variance).
- Using RVE provides protection against model misspecification.
- Using clubSandwich RVE also provides protection against small-sample issues.

Aside

- `clubSandwich` provides robust variance estimation methods for a wide variety of fitted models:
 - Ordinary/weighted least squares with `lm()`
 - Multivariate least squares with `mlm()`
 - Generalized linear models with `glm()`
 - Two-stage least squares with `aer::ivreg()`
 - Hierarchical linear models with `lme4::lmer()`
 - Hierarchical linear models with `nlme::lme()`

Workflow

```
library(lme4)
library(clusterSandwich)
data(sleepstudy)

# fit working model in lmer
sleep_fit <-
  lmer(Reaction ~ Days + (Days | Subject),
       data = sleepstudy)

# cluster-robust vcov matrix
vcovCR(sleep_fit, type = "CR2")

# clustered SEs and CIs
conf_int(sleep_fit, vcov = "CR2")
```

Thanks

More details, examples, code,
simulation evidence:

Pustejovsky, J. E., & Tipton, E. (2021). Meta-
Analysis with Robust Variance Estimation:
Expanding the Range of Working Models.
Prevention Science, forthcoming.

<https://doi.org/10.1007/s11121-021-01246-3>

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