

# COMBINING ROBUST VARIANCE ESTIMATION WITH MODELS FOR DEPENDENT EFFECT SIZES

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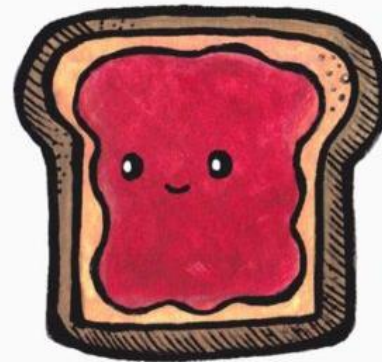
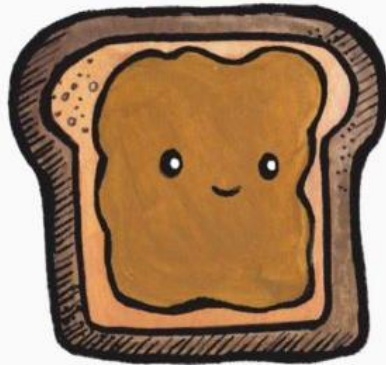
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# THESIS

- Meta-analyses often involve statistically dependent effect sizes.
- Many methods available for meta-analyzing dependent effect size estimates.
  - ad hoc methods (Hammering the screws)
  - model-based methods
  - robust variance estimation (RVE)
- Useful to combine RVE with model-based approaches.
  - Addresses limitations of model-based approaches.
  - Addresses limitations of default RVE implementation.

Model-based  
meta-analysis  
methods

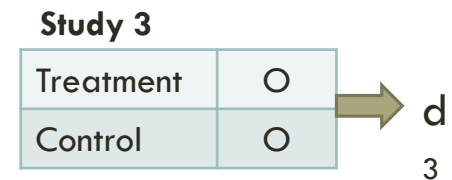
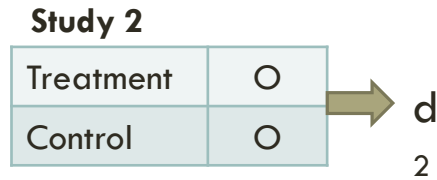
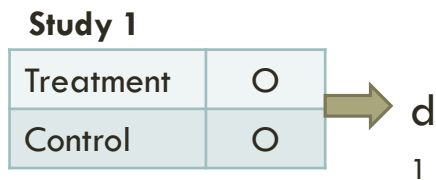


Robust  
variance  
estimation

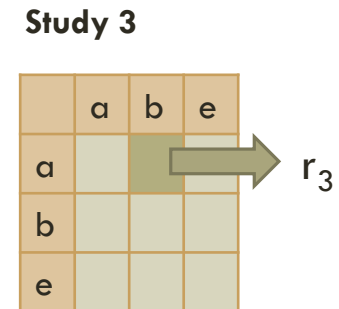
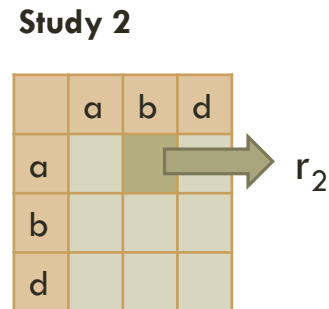
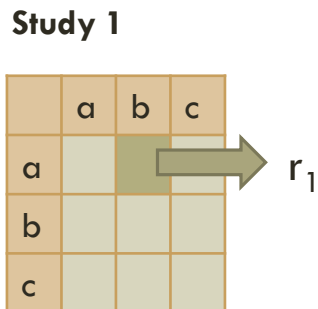
**better together**

# BASIC META-ANALYSIS METHODS ASSUME INDEPENDENT EFFECT SIZES

In a meta-analysis of experiments:

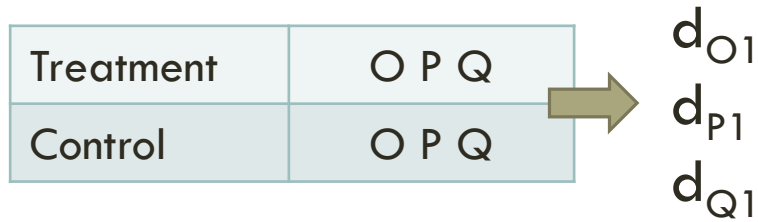


In a meta-analysis of correlations:

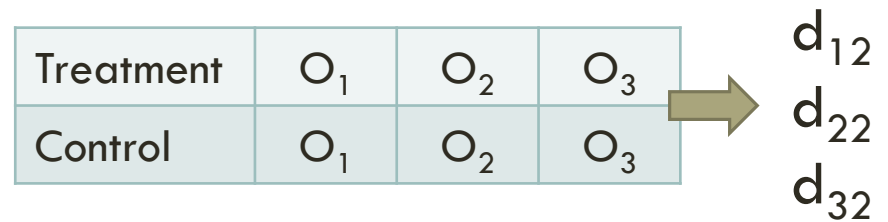


# DEPENDENT EFFECT SIZES ARE VERY COMMON

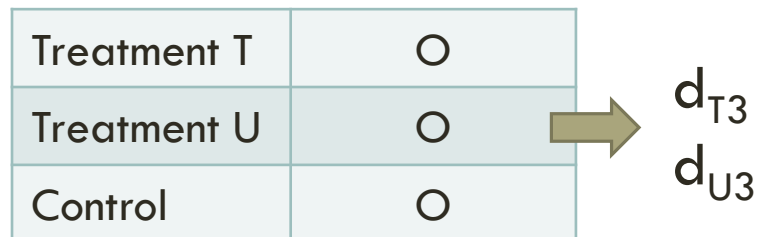
**Multiple outcomes measured on common set of participants**



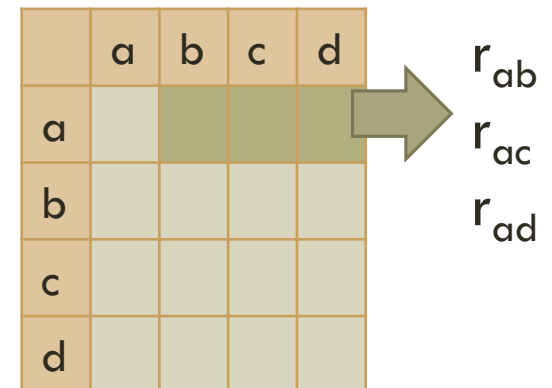
**Outcome measured at multiple follow-up times**



**Multiple treatment conditions compared to a common control**



**Multiple correlations from a common sample**



# FRIESE, FRANKENBACH, JOB, & LOSCHELDER (2017). DOES SELF-CONTROL TRAINING IMPROVE SELF- CONTROL: A META-ANALYSIS.

33 experimental studies, 166 effect size estimates  
(standardized mean differences)

- ✓ 1-52 effect size estimates per study (median = 2)
- ✓ Multiple outcomes (1-13 outcomes per study, median = 2)
- ✓ Multiple follow-up times (immediate post-test and/or later follow-up)
- ✓ Multiple treatment conditions (1-4 treatment conditions per study)
- ✓ Multiple control conditions (active and/or passive control)

# LEHTONEN ET AL. (2018). IS BILINGUALISM ASSOCIATED WITH ENHANCED EXECUTIVE FUNCTIONING IN ADULTS?

152 studies, 891 effect size estimates (standardized mean differences comparing performance of bilingual and monolingual adults)

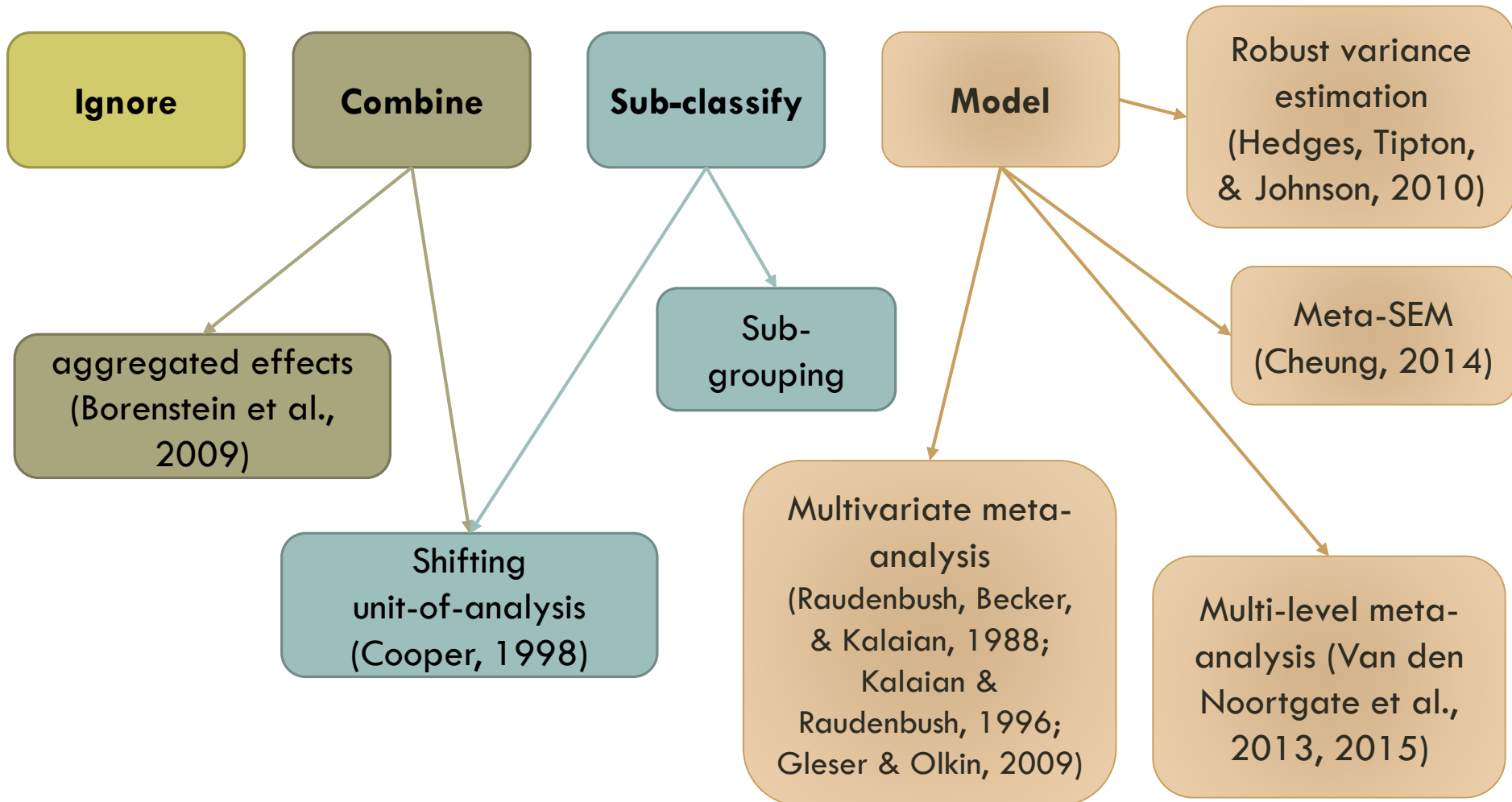
- ✓ 1-40 effect size estimates per study (median = 4)
- ✓ Multiple outcomes (1-7 outcomes per study, median = 2)
- ✓ Multiple bilingual groups
- ✓ Multiple monolingual groups

# CORRELATIONS BETWEEN ES ESTIMATES ARE OFTEN NOT AVAILABLE

- Multiple treatments compared to common control
  - known formulas (Gleser & Olkin, 2009), easy enough to calculate
- Multiple outcomes/multiple follow-ups
  - known formulas (Gleser & Olkin, 2009)
  - require knowing correlations among outcomes/repeated measures, which are not often reported
- Multiple correlations from common sample
  - known, icky formulas (Olkin & Siotani, 1976)
  - need to know correlations between ALL variables involved



# BECKER (2000) DESCRIBED FOUR BROAD STRATEGIES FOR HANDLING DEPENDENCE:



# AGGREGATED EFFECTS

- Average estimates to generate single “synthetic” ES per study.

Study	ES	V	Predictors		Study	ES	V	Predictors
A	$ES_{A1}$	$V_{A1}$	$X_{A1}$					
A	$ES_{A2}$	$V_{A2}$	$X_{A2}$	→	A	$\overline{ES}_A$	$\overline{V}_A$	$\overline{X}_A$
A	$ES_{A3}$	$V_{A3}$	$X_{A3}$					
B	$ES_{B1}$	$V_{B1}$	$X_{B1}$	→	B	$\overline{ES}_B$	$\overline{V}_B$	$\overline{X}_B$
C	$ES_{C1}$	$V_{C1}$	$X_{C1}$	→	C	$\overline{ES}_C$	$\overline{V}_C$	$\overline{X}_C$
C	$ES_{C2}$	$V_{C2}$	$X_{C2}$					

- Estimating variance of synthetic ES requires correlations among component ES (Borenstein et al., 2009).
- Limits moderator/meta-regression analyses to between-study predictors.

# SUB-GROUPS/SHIFTING UNIT-OF-ANALYSIS

- Classify ES into sub-groups where each study contributes  $\leq 1$  ES.
- If there are still multiple ES per sub-group, aggregate (Cooper, 1998).

Study	ES	V	Category
A	$ES_{A1}$	$V_{A1}$	1
A	$ES_{A2}$	$V_{A2}$	2
A	$ES_{A3}$	$V_{A3}$	2
B	$ES_{B1}$	$V_{B1}$	1
C	$ES_{C1}$	$V_{C1}$	1
C	$ES_{C2}$	$V_{C2}$	2

Study	Category 1	Category 2
A	$ES_{A1}$	$V_{A1}$
A		$\overline{ES}_{A2}$ $\overline{V}_{A2}$
B	$ES_{B1}$	$V_{B1}$
C	$ES_{C1}$	$V_{C1}$
C		$ES_{C2}$ $V_{C2}$

- Use univariate meta-analysis within sub-groups.

# PROBLEMS WITH SHIFTING UNIT-OF-ANALYSIS

- Average effects by sub-group are not independent.
  - How to make comparisons between average effects by sub-group?
- Different ES estimates for each moderator analysis.
  - How to do meta-regression with multiple predictors?

Study	ES	V	Category
A	$ES_{A1}$	$V_{A1}$	1
A	$ES_{A2}$	$V_{A2}$	2
A	$ES_{A3}$	$V_{A3}$	2
B	$ES_{B1}$	$V_{B1}$	1
C	$ES_{C1}$	$V_{C1}$	1
C	$ES_{C2}$	$V_{C2}$	2

Study	Category 1		Category 2	
A	$ES_{A1}$	$V_{A1}$		
A			$\overline{ES}_{A2}$	$\overline{V}_{A2}$
B	$ES_{B1}$	$V_{B1}$		
C	$ES_{C1}$	$V_{C1}$		
C			$ES_{C2}$	$V_{C2}$

# MULTIVARIATE META-ANALYSIS

(Raudenbush, Becker, & Kalaian, 1988; Kalaian & Raudenbush, 1996)

- Hierarchical model for component ES estimates nested within studies

$$T_{ij} = \mathbf{x}_{ij}\boldsymbol{\beta} + u_j + v_{ij} + e_{ij}$$

where  $u_j \sim N(0, \tau^2)$ ,  $v_{ij} \sim N(0, \omega^2)$ ,  $e_{ij} \sim N(0, s_{ij}^2)$ , and

$$\text{Cov}(e_{hj}, e_{ij}) = r_{hij}s_{hj}s_{ij}.$$

- Requires estimates/assumptions about ES correlations  $r_{hij}$ .
- Allows for modeling of between- and within-study variation in the ES.
- Makes use of between- and within-study variation in predictors.

# MULTI-LEVEL META-ANALYSIS

(Van den Noortgate, López-López, Marín-Martínez, & Sánchez-Meca, 2013, 2015)

- Use multi-level model to account for dependence between ES estimates within studies, **ignoring the sampling correlations**:

$$T_{ij} = \mathbf{x}_{ij}\boldsymbol{\beta} + u_j + v_{ij} + e_{ij}$$

where  $u_j \sim N(0, \tau^2)$ ,  $v_{ij} \sim N(0, \omega^2)$ ,  $e_{ij} \sim N(0, s_{ij}^2)$ ,  $\text{Cov}(e_{hj}, e_{ij}) = 0$ .

- Simulation evidence indicates that this approach can be “robust” to mis-specified correlation structure.
- But unclear whether robustness holds generally.

# RE-ANALYSIS OF BILINGUALISM STUDIES

	(1) Aggregated effects	(2) Shifting unit-of- analysis	(3) Multivariate meta-analysis	(4) Multi-level meta- analysis
<b>Overall Average ES</b> (152 studies, 869 ES)	0.028 [0.026]		0.047* [0.022]	0.055* [0.023]
Between-study SD	0.168		0.157	0.254
Within-study SD			0.289	0.232

# BILINGUALISM EFFECTS BY DOMAIN

	(1) Aggregated effects	(2) Shifting unit-of- analysis	(3) Multivariate meta-analysis	(4) Multi-level meta- analysis
<b>Inhibition</b> (95 studies, 212 ES)	0.077 [0.003]	0.114** [0.037]	0.106*** [0.031]	0.115*** [0.032]
<b>Monitoring</b> (81 studies, 184 ES)	0.003 [0.100]	0.077 [0.039]	0.058 [0.033]	0.065 [0.034]
<b>Shifting</b> (37 studies, 79 ES)	0.147 [0.127]	0.147** [0.056]	0.141** [0.046]	0.148** [0.047]
<b>Attention</b> (18 studies, 53 ES)	0.230 [0.193]	-0.013 [0.080]	-0.031 [0.058]	-0.021 [0.058]
<b>Working Memory</b> (73 studies, 243 ES)	0.045 [0.059]	0.058 [0.042]	0.057 [0.032]	0.064* [0.033]
<b>Fluency</b> (28 studies, 98 ES)	-0.313** [0.106]	-0.260*** [0.066]	-0.211*** [0.045]	-0.196*** [0.045]
Between-study SD	0.155	0.224	0.150	0.249
Within-study SD			0.276	0.217



# COMPARISON

Method	Requires making assumptions about ES covariances
Aggregated effects	✓
Sub-grouping	✓
Shifting unit-of-analysis	✓
Multivariate meta-analysis	✓
Multi-level meta-analysis	✓

# ROBUST VARIANCE ESTIMATION

(Hedges, Tipton, & Johnson, 2010)

- Meta-analysis/meta-regression method using “sandwich” variance estimators (a.k.a., “clustered” SEs)
  - Robust to mis-specified assumptions about variance-covariance structure within independent studies.
- Sandwich methods work with very general classes of models, including any of the other methods for handling dependent effects.
  - Proof: See Hedges et al. (2010, Appendix A).
- Conventional sandwich estimators require large number of studies.
  - But small-sample corrections are available (Tipton, 2015; Tipton & Pustejovsky, 2015).

# ROBUST VARIANCE ESTIMATION THEORY

- A generic meta-regression model (in matrix form):

$$\mathbf{T}_j = \mathbf{X}_j \boldsymbol{\beta} + \mathbf{e}_j$$

where  $E(\mathbf{e}_j) = \mathbf{0}$  and  $\text{Var}(\mathbf{e}_j) = \boldsymbol{\Omega}_j$ , for  $j = 1, \dots, m$ .

- Estimate  $\boldsymbol{\beta}$  using weighted least squares for some weight matrices  $\mathbf{W}_j$ :

$$\hat{\boldsymbol{\beta}} = \left( \sum_{j=1}^J \mathbf{X}_j' \mathbf{W}_j \mathbf{X}_j \right)^{-1} \sum_{j=1}^J \mathbf{X}_j' \mathbf{W}_j \mathbf{T}_j.$$

# HOW TO ESTIMATE $\text{VAR}(\hat{\beta})$ ?

- The true variance of  $\hat{\beta}$ :

$$\text{Var}(\hat{\beta}) = \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1} \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \Omega_j \mathbf{W}_j \mathbf{X}_j \right) \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1}$$

- **Model-based variance estimation** assumes a correct model for  $\Omega_j$ :

$$\mathbf{V}^{model} = \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1} \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \hat{\Omega}_j \mathbf{W}_j \mathbf{X}_j \right) \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1} .$$

# HOW TO ESTIMATE $\text{VAR}(\hat{\beta})$ ?

- The true variance of  $\hat{\beta}$ :

$$\text{Var}(\hat{\beta}) = \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1} \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \Omega_j \mathbf{W}_j \mathbf{X}_j \right) \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1}$$

- **Robust variance estimation** avoids relying on a model for  $\Omega_j$  by using the regression residuals:

$$\mathbf{V}^{\text{robust}} = \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1} \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{A}_j \hat{\mathbf{e}}_j \hat{\mathbf{e}}'_j \mathbf{A}_j \mathbf{W}_j \mathbf{X}_j \right) \left( \sum_{j=1}^J \mathbf{X}'_j \mathbf{W}_j \mathbf{X}_j \right)^{-1}$$

- Residuals are lousy estimates of specific  $\Omega_j$ , but they **work well on average**.

# COMPARISON

Method	Requires making assumptions about ES covariances	Robustness to assumptions about ES covariances
Aggregated effects	✓	Robust*
Sub-grouping	✓	Robust*
Shifting unit-of-analysis	✓	Robust*
Multivariate meta-analysis	✓	Robust*
Multi-level meta-analysis	✓	Robust*
Robust variance estimation	✓ (Working model)	Robust

\* When combined with robust (sandwich) variance estimation

# BILINGUALISM EFFECTS BY DOMAIN [ROBUST SE]

	(1) Aggregated effects	(2) Shifting unit-of- analysis	(3) Multivariate meta-analysis	(4) Multi-level meta- analysis
<b>Inhibition</b> (95 studies, 212 ES)	0.077 [0.080]	0.114*** [0.033]	0.106** [0.035]	0.115*** [0.036]
<b>Monitoring</b> (81 studies, 184 ES)	0.003 [0.111]	0.077 [0.041]	0.058 [0.036]	0.065 [0.037]
<b>Shifting</b> (37 studies, 79 ES)	0.147 [0.117]	0.147* [0.059]	0.141** [0.057]	0.148** [0.058]
<b>Attention</b> (18 studies, 53 ES)	0.230 [0.173]	-0.013 [0.076]	-0.031 [0.087]	-0.021 [0.085]
<b>Working Memory</b> (73 studies, 243 ES)	0.045 [0.073]	0.058 [0.043]	0.057 [0.036]	0.064* [0.037]
<b>Fluency</b> (28 studies, 98 ES)	-0.313** [0.127]	-0.260*** [0.071]	-0.211** [0.057]	-0.196*** [0.057]
Between-study SD	0.155	0.224	0.150	0.249
Within-study SD			0.276	0.217

# DEFAULT RVE IMPLEMENTATION HAS LIMITATIONS

- Implementation in **robumeta** packages for R and Stata.
- Limited to two “working models”: correlated effects or hierarchical effects.
- Uses semi-efficient diagonal weights:

$$w_{ij} = \frac{1}{n_j(\bar{s}_j^2 + \hat{\tau}^2)}, \quad \text{where } \bar{s}_j^2 = \frac{1}{n_j} \sum_{i=1}^{n_j} s_{ij}^2$$

- Studies contributing more effects get less weight in meta-regressions that have within-study predictors.
  - Similar to meta-regression after aggregating to the study level.



# BILINGUALISM EFFECTS BY DOMAIN [ROBUST SE]

	(1) Aggregated effects	(2) Shifting unit-of-analysis	(3) Multivariate meta-analysis	(4) Multi-level meta-analysis	(5) Default RVE (HIER weights)
<b>Inhibition</b> (95 studies, 212 ES)	0.077 [0.080]	0.114*** [0.033]	0.106** [0.035]	0.115*** [0.036]	0.103*** [0.032]
<b>Monitoring</b> (81 studies, 184 ES)	0.003 [0.111]	0.077 [0.041]	0.058 [0.036]	0.065 [0.037]	0.061* [0.036]
<b>Shifting</b> (37 studies, 79 ES)	0.147 [0.117]	0.147* [0.059]	0.141** [0.057]	0.148** [0.058]	0.135** [0.061]
<b>Attention</b> (18 studies, 53 ES)	0.230 [0.173]	-0.013 [0.076]	-0.031 [0.087]	-0.021 [0.085]	0.015 [0.103]
<b>Working Memory</b> (73 studies, 243 ES)	0.045 [0.073]	0.058 [0.043]	0.057 [0.036]	0.064* [0.037]	0.072 [0.048]
<b>Fluency</b> (28 studies, 98 ES)	-0.313** [0.127]	-0.260*** [0.071]	-0.211** [0.057]	-0.196*** [0.057]	-0.222*** [0.056]
Between-study SD	0.155	0.224	0.150	0.249	0.220
Within-study SD			0.276	0.217	0.211

# RE-ANALYSIS OF SELF-CONTROL TRAINING STUDIES

	(1) Aggregated effects	(2) Shifting unit- of-analysis	(3) Multivariate meta-analysis	(4) Multi-level meta-analysis	(5) Robust variance estimation
<b>Overall Average ES</b> (33 studies, 166 ES)	0.281*** [0.059]		0.261*** [0.052]	0.263*** [0.054]	0.289*** [0.060]
Between-study SD	0.207		0.202	0.254	0.289
Within-study SD			0.143	0.027	
<b>Moderator analysis by type of outcome</b>					
Stamina (16 studies, 31 ES)	0.579*** [0.157]	0.413** [0.093]	0.359*** [0.077]	0.351*** [0.071]	0.579*** [0.123]
Strength (28 studies, 135 ES)	0.199** [0.071]	0.171** [0.064]	0.236*** [0.054]	0.238*** [0.055]	0.203** [0.065]
Difference	-0.380* [0.185]	-0.243* [0.113]	-0.123 [0.072]	-0.112 [0.059]	-0.376* [0.136]

# DISCUSSION

- Robust “sandwich” variance estimation can be used with **any** of the available methods for handling dependence.
  - R packages metafor + clubSandwich.
- Default RVE should not be used for meta-regression with predictors that vary within study.
- Meta-analysts need to pay more attention to within- versus between-study variation in moderators.
- Improve software to make multivariate meta-analysis easier to implement.
- Outstanding problem: methods for examining **publication/outcome reporting bias** while handling dependent effects.

# THANKS

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