Correcting for publication bias in a meta-analysis with *p*-uniform*

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Publication bias is omnipresent in science

- ▶ Publication bias → overestimation of effect size in meta-analysis
- The publication bias method *p*-uniform overestimates effect size in case of between-study variance in true effect size
- ► The improved and extended method *p*-uniform*:
 - 1. eliminates overestimation due to between-study variance
 - 2. is a more efficient estimator than *p*-uniform's estimator
 - 3. enables estimating and testing of the between-study variance

- 1. Publication bias
- 2. From *p*-uniform to *p*-uniform*
- 3. Simulation study
- 4. Conclusion and discussion

- Publication bias is "the selective publication of studies with a significant outcome"
- Overwhelming evidence for publication bias:
 - 95% of published articles contain significant results in psychology (1/40!)

From *p*-uniform to *p*-uniform*: *p*-uniform

- Only considers significant effect sizes and discards others
- Distribution of p-values at the true effect size is uniform
- Only significant effect sizes, so conditional probabilities:

$$q_i = \frac{1 - \Phi\left(\frac{y_i - \mu}{\sigma_i}\right)}{1 - \Phi\left(\frac{y_{cv} - \mu}{\sigma_i}\right)}$$

 Tests for uniformity are used to evaluate whether q_i are uniformly distributed

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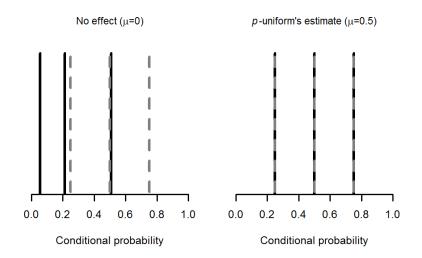
Assumptions:

- Homogeneous true effect size
- All significant effect sizes have an equal probability of getting included in a meta-analysis

From *p*-uniform to *p*-uniform*: *p*-uniform

• Example with three observed effect sizes ($\mu = 0.5$):

t(48)=3.133, p=.0029; t(48)=2.646, p=.011; t(48)=2.302, p=.025



From *p*-uniform to *p*-uniform*: *p*-uniform*

- P-uniform* considers the significant and nonsignificant effect sizes
- Now effect sizes not only conditional on significance but also on nonsignificance
- Maximum likelihood estimation is used \rightarrow truncated densities

Significant	Nonsignificant
$q_i^* = rac{\phi\left(rac{y_i-\mu}{\sqrt{\sigma_i^2+ au^2}} ight)}{1-\Phi\left(rac{y_{cv}-\mu}{\sqrt{\sigma_i^2+ au^2}} ight)}$	$q_i^* = \frac{\phi\left(\frac{y_i - \mu}{\sqrt{\sigma_i^2 + \tau^2}}\right)}{\Phi\left(\frac{y_{cv} - \mu}{\sqrt{\sigma_i^2 + \tau^2}}\right)}$

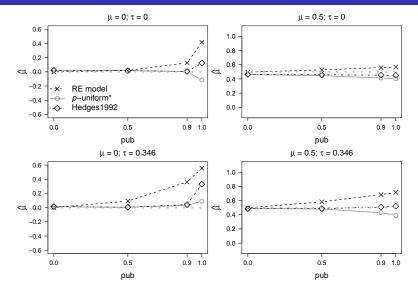
• Likelihood function: $L(\mu, \tau^2) = \prod q_i^*$

- Confidence intervals and testing hypotheses
- We also implemented several methods of moments estimators
- Important assumption:
 - Probability of including a significant and nonsignificant effect size in a meta-analysis is assumed to be constant (but may differ from each other)

Simulation study: Method

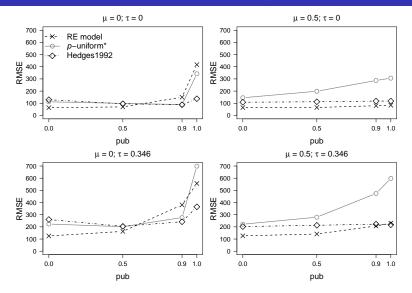
- Goal: Evaluate performance of *p*-uniform* and compare to other methods
- Effect size measure is standardized mean difference with 50 as sample size per group
- Conditions:
 - ▶ µ = 0; 0.2; 0.5
 - $\tau = 0$; 0.163; 0.346 $\rightarrow I^2 = 0\%$; 40%; 75%
 - Number of studies (k) = 10; 30; 60; 120
 - Extent of publication bias (pub) = 0; 0.5; 0.9; 1
- Included methods:
 - p-uniform*
 - random-effects model ightarrow Paule-Mandel estimator for au^2
 - ▶ selection model approach by Hedges (1992) \rightarrow cut-off at α =.05

Simulation study: Estimating μ



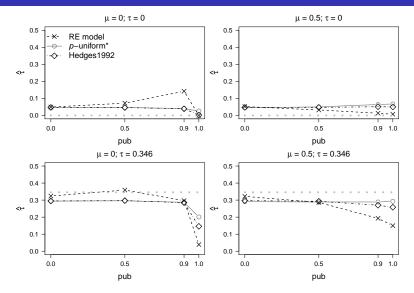
- Random-effects model overestimates μ if pub > 0
- ▶ Bias of *p*-uniform^{*} and Hedges1992 is largest if *pub* = 1

Simulation study: RMSE Estimating μ



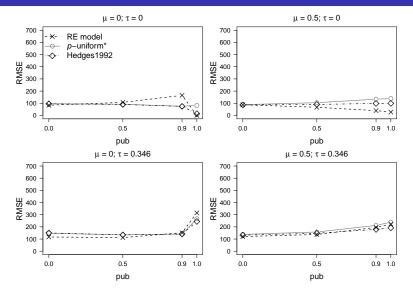
► RMSE of all methods increased as a function of *τ* and *pub* ► RMSE of *p*-uniform* generally larger than Hedges1992

Simulation study: Estimating au



▶ RE model overestimates τ if τ = 0 and underestimates if τ > 0
 ▶ *P*-uniform* less negatively biased than Hedges1992 if τ > 0

Simulation study: RMSE Estimating au



RMSE of all methods increased as a function of *pub* if τ > 0
 RMSE of *p*-uniform* generally slightly larger than Hedges1992 14/18

Conclusion and discussion

- ► *P*-uniform* is an improvement over *p*-uniform, because
 - 1. eliminates overestimation due to between-study variance
 - 2. is a more efficient estimator than *p*-uniform's estimator
 - 3. enables estimating and testing of the between-study variance
- Random-effects model had the best statistical properties in the absence of publication bias
- Statistical properties of *p*-uniform* and the selection model approach by Hedges (1992) were comparable

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- Statistical properties of *p*-uniform* and the selection model approach by Hedges (1992) were comparable
- Recommendations:
 - report results of *p*-uniform* and selection model approach by Hedges (1992) in any meta-analysis
 - be reluctant when extreme publication bias is expected with only significant effect sizes

Conclusion and discussion

Software:

- p-uniform*: R package puniform and web application https://rvanaert.shinyapps.io/p-uniformstar
- Hedges' (1992) selection model approach: R package weightr and web application https://vevealab.shinyapps.io/WeightFunctionModel

Future research:

- Violations of the assumption of equal probabilities of significant and nonsignificant effect sizes for getting published
- P-uniform*'s publication bias test
- Consequences of *p*-hacking

Thank you for your attention