Selection models for publication bias in meta-analysis

Methods in Meta-Analysis Meeting

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Publication Bias in Meta-Analysis

- want to synthesize all of the studies conducted on a phenomenon of interest (that fit the inclusion criteria)
- finding all studies is difficult (esp. the 'gray literature')
- at least want to obtain a representative sample thereof
- the studies we find (mostly in the published literature) may have undergone some implicit selection process
- if selection is a function of the outcomes and/or their statistical significance, will get biased estimates of μ and τ^2

Sterling (1959) and Smith (1980)

PUBLICATION DECISIONS AND THEIR POSSIBLE EFFECTS ON INFERENCES DRAWN FROM TESTS OF SIGNIFICANCE —OR VICE VERSA*

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There is some evidence that in fields where statistical tests of significance are commonly used, research which yields nonsignificant results is not published. Such research being unknown to other investigators may be repeated independently until eventually by chance a significant result occurs—an "error of the first kind"—and is published. Significant results published in these fields are seldom verified by independent replication. The possibility thus arises that the literature of such a field consists in substantial part of false conclusions resulting from errors of the first kind in statistical tests of significance.

PUBLICATION BIAS AND META-ANALYSIS

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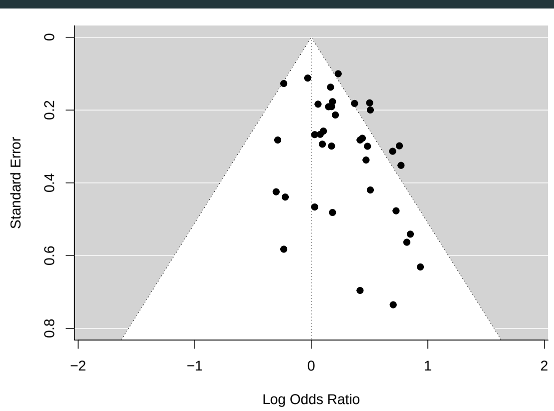
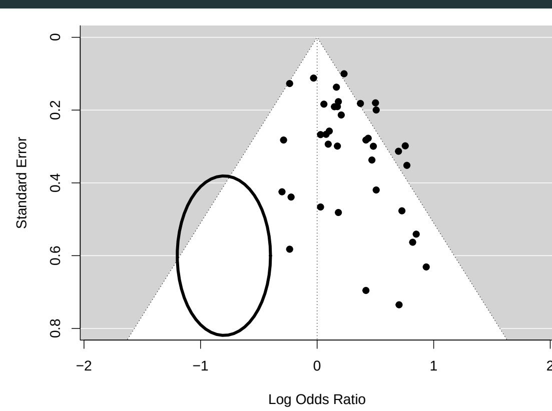
How to Address Publication Bias

- **ultimately:** need to get rid of it (use an evidence basis that is known to be free of publication bias)
- if not available:
  - examine data for evidence of it
  - consider its potential impact
  - try to correct for it

Example: Hackshaw (1998)



Example: Hackshaw (1998)



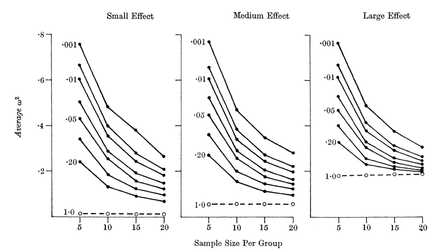
Example: Hackshaw (1998)

```
## Random-Effects Model (k = 37; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0224 (SE = 0.0178)
## tau (square root of estimated tau^2 value):      0.1497
## I^2 (total heterogeneity / total variability):   29.57%
## H^2 (total variability / sampling variability):  1.42
##
## Test for Heterogeneity:
## Q(df = 36) = 47.4979, p-val = 0.0952
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.2189  0.0494  4.4313  <.0001  0.1221  0.3157

##  pred ci.lb ci.ub pi.lb pi.ub
##  1.24  1.13  1.37  0.91  1.70
```


Modeling Selection Effects

- Lane & Dunlap (1978) conducted a simulation study to examine the bias when only significant studies are published[1]
- Hedges (1984) showed how to obtain these results analytically



[1]Also first use of the term ‘publication bias’ according to my searches.

Modeling Selection Effects

- the idea was further extended by Iyengar & Greenhouse (1988)
- proposed two (slightly more realistic) models:

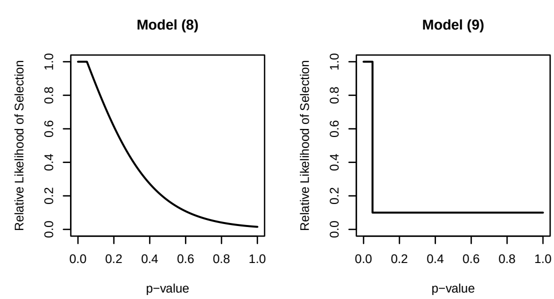
$$(8) \quad w_1(x;\beta,q) = \begin{cases} \dfrac{|x|^\beta}{t(q,.05)^\beta}, & \text{if } |x| \le t(q,.05), \\ 1, & \text{otherwise,} \end{cases}$$

and

$$(9) \quad w_2(x;\gamma,q) = \begin{cases} e^{-\gamma}, & \text{if } |x| \le t(q,.05), \\ 1, & \text{otherwise.} \end{cases}$$

- two special cases:
  - $\beta = 0$ and $\gamma = 0$: no selection
  - $\beta \to \infty$ and $\gamma \to \infty$: as in Hedges (1984)

Modeling Selection Effects

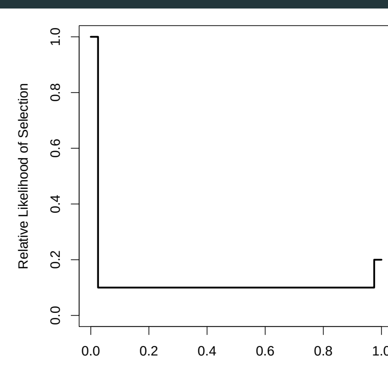


Modeling Selection Effects: Example

- Hedges suggested an extension to random-effects models
- based on other comments, Iyengar and Greenhouse also examined a third (asymmetric) weight function:

$$(2) \quad w_3(x;\alpha,\beta) = \begin{cases} 1 & \text{for } x > t(q,.05), \\ e^{-\alpha} & \text{for } |x| \le t(q,.05), \\ e^{-\beta} & \text{for } x \le -t(q,.05), \end{cases}$$

Modeling Selection Effects: Example



Selection Models

- general class of models that attempt to model and correct for the process by which the studies may have been selected
- various selection models have been proposed:
  - step function model (Hedges, 1992)
  - with estimated thresholds (Dear & Begg, 1992)
  - with moderators (Vevea & Hedges, 1995)
  - with a priori chosen weight functions (Vevea & Woods, 2005)
  - with monotonicity constraints (Rufibach, 2011)
  - Copas selection model (Copas, 1999; Copas & Shi, 2001)
  - exponential decay models (Preston, Ashby, & Smyth, 2004)
  - p-curve (Simonsohn, Nelson, & Simmons, 2014) and p-uniform (Assen, Aert, & Wicherts, 2015) methods
  - beta selection model (Citkowicz & Vevea, 2017)

General Setup

- let y_i denote the outcome observed in the ith study $(i = 1, \ldots, k)$ and v_i the corresponding sampling variance
- let $z_i = y_i / \sqrt{v_i}$ denote the test statistic for H_0: $\theta_i = 0$
- let $p_i = 1 - \Phi(z_i)$, $p_i = \Phi(z_i)$, or $p_i = 2(1 - \Phi(|z_i|)$ denote the corresponding (one- or two-sided) p-value
- let $w(p_i, \vec{\delta})$ denote some function that specifies the relative likelihood of selection given the p-value of a study
- log likelihood:

$$ll = \sum_{i=1}^{k} \left\{ \ln\left(w(p_i, \vec{\delta})\right) - \frac{1}{2}\ln(\tau^2 + v_i) - \frac{1}{2}\frac{(y_i - \mu)^2}{\tau^2 + v_i} - \ln(A_i) \right\}$$

where

$$A_i = \int_{-\infty}^{\infty} w(p_i, \vec{\delta}) f(y_i, \mu, \tau^2 + v_i)\, dy_i$$

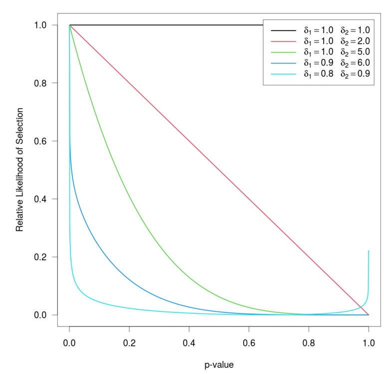
Beta Selection Model

- proposed by Citkowicz & Vevea (2017)

$$w(p_i) = p_i^{\delta_1 - 1} \times (1 - p_i)^{\delta_2 - 1}$$

where $\delta_1 > 0$ and $\delta_2 > 0$
- H_0: $\delta_1 = \delta_2 = 1$ represents the case of no selection

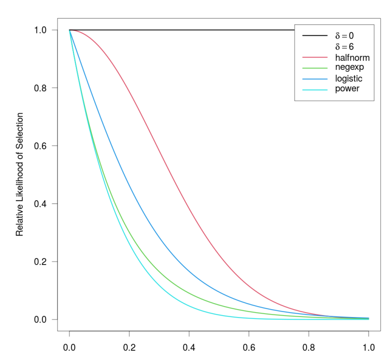
Beta Selection Model



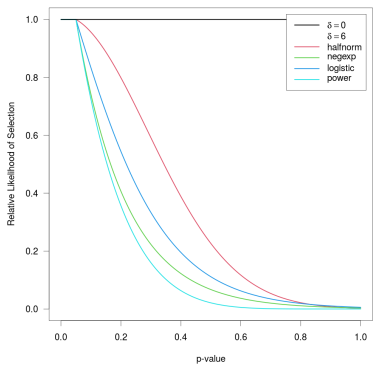
Exponential Decay Models

- proposed by Preston et al. (2004) (except 'power')
- half-normal: $w(p_i) = \exp(-\delta \times p_i^2)$
- negative-exponential: $w(p_i) = \exp(-\delta \times p_i)$
- logistic: $w(p_i) = \dfrac{2 \times \exp(-\delta \times p_i)}{1 + \exp(-\delta \times p_i)}$
- power: $w(p_i) = (1 - p_i)^{\delta}$
- $\delta \geq 0$ and H_0: $\delta = 0$ represents no selection
- can extend these, in the spirit of Iyengar & Greenhouse (1988), to set $w(p_i) = 1$ for p-values below some α threshold

Exponential Decay Models



Exponential Decay Models



Negative Exponential Power Selection Model

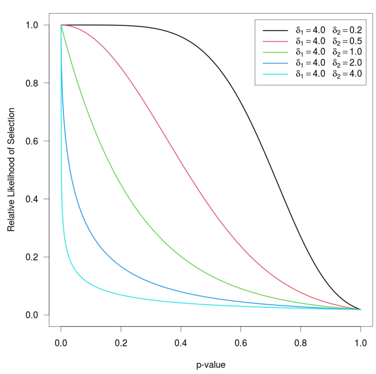
- described by Begg & Mazumdar (1994) for simulating data

$$w(p_i) = \exp(-\delta_1 \times p_i^{1/\delta_2})$$

where $\delta_1 \geq 0$ and $\delta_2 \geq 0$

- H_0: $\delta_1 = 0$ (and H_0: $\delta_2 = 0$) represents the case of no selection

Negative Exponential Power Selection Model



Step Function Models

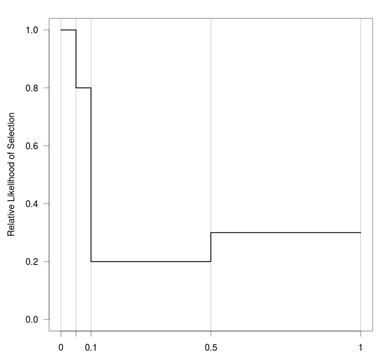
- based on Iyengar & Greenhouse (1988) and then Hedges (1992) and Vevea & Hedges (1995)
- let $\alpha_1 < \alpha_2 < \ldots < \alpha_c$ denote 'cutpoints'
- define $\alpha_0 = 0$ and constrain $\alpha_c = 1$

$$w(p_i) = \delta_j \;\; \text{if} \;\; \alpha_{j-1} < p_i \leq \alpha_j$$

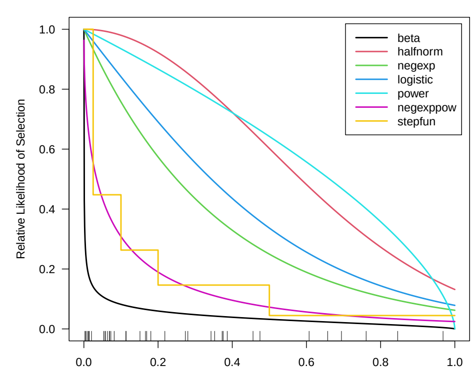
and set $\delta_1 = 1$ for identifiability

- H_0: $\delta_j = 1$ for $j = 1, \ldots, c$ implies no selection
- 'three-parameter selection model' (3PSM) is a special case with a single cutpoint (and parameters μ, τ^2, and δ_2)

Step Function Models



Example: Hackshaw (1998)



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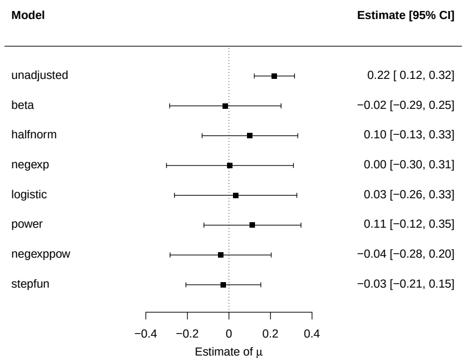

Software (R Packages)

- metasens: Copas selection model
- weightr: step function model
- puniform: p-uniform method
- dmetar: p-curve method
- metafor: various selection models

Example: Hackshaw (1998)

```r
# load metafor package
library(metafor)

# fit random-effects model to data from Hackshaw (1998)
res <- rma(yi, vi, data=dat.hackshaw1998)
res

# fit negative exponential power selection model
sel1 <- selmodel(res, type="negexppow")
sel1

# fit step function model
sel2 <- selmodel(res, type="stepfun", steps=c(.025, .1, .2, .5, 1))
sel2

# plot selection functions
plot(sel1)
plot(sel2, add=TRUE, col="orange")
```


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```

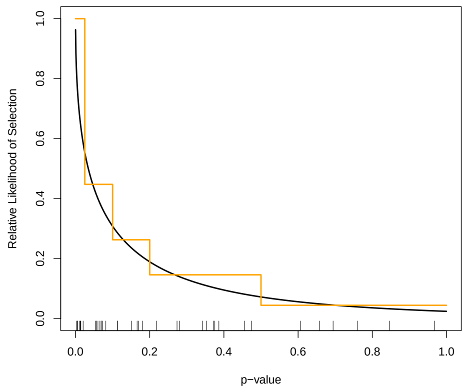

Example: Hackshaw (1998)

```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0120 (SE = 0.0119)
##
## Test for Heterogeneity:
## LRT(df = 1) = 1.3598, p-val = 0.2436
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.0398  0.1242  -0.3204  0.7486  -0.2832  0.2036
##
## Test for Selection Model Parameters:
## LRT(df = 2) = 4.9412, p-val = 0.0845
##
## Selection Model Results:
##
##          estimate      se    zval    pval   ci.lb   ci.ub
## delta.1    3.7063  1.7217  2.1527  0.0313  0.3318  7.0809
## delta.2    2.0080  1.0439  1.9235  0.0544  0.0000  4.0540
```


Example: Hackshaw (1998)

```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0090 (SE = 0.0119)
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.0268  0.0920  -0.2910  0.7711  -0.2070  0.1535
##
## Test for Selection Model Parameters:
## LRT(df = 4) = 7.4988, p-val = 0.1118
##
## Selection Model Results:
##
##                     k  estimate      se      zval    pval   ci.lb   ci.ub
## 0     < p <= 0.025   7    1.0000     ---       ---     ---     ---     ---
## 0.025 < p <= 0.1     8    0.4476  0.2770   -1.9945  0.0461  0.0000  0.9904
## 0.1   < p <= 0.2     6    0.2630  0.1956   -3.7670  0.0002  0.0000  0.6465
## 0.2   < p <= 0.5    10    0.1463  0.1202   -7.1036  <.0001  0.0000  0.3818
## 0.5   < p <= 1       6    0.0446  0.0501  -19.0563  <.0001  0.0000  0.1429
```

Example: Hackshaw (1998)



Features

- implements a wide variety of selection models
- works with fixed/equal/common- and random-effects models
- models can include moderators (i.e., meta-regression)
- Wald-type tests of model coefficients and selection parameters
- LRTs for τ^2 and selection parameters
- profile likelihood CIs for τ^2 and selection parameters
- written so additional selection models can be easily added

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Thank You for Your Attention!

Questions, Comments, Suggestions?

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