Meta-analysis in R - using the metafor package

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Alternatives to the `metafor` package

The `metafor` package seems to be one of the more comprehensive packages for meta-analysis in *R*. Some commonly used alternatives:

- meta: Supposed to be user-friendly
- metaSEM: For meta-analysis using structural equation modeling
- MAVIS: GUI-based comprehensive option for meta-analysis

```
# How to use the MAVIS package:
if (!require(MAVIS)) {
  install.packages("MAVIS", repos = "https://cloud.r-project.org")
  library(MAVIS)
}
startmavis()
```

Recent journal article on options for meta-analysis in *R*:

Polanin, J. R., Hennessy, E. A., & Tanner-Smith, E. E. (2017). A Review of Meta-Analysis Packages in R. *Journal of Educational and Behavioral Statistics, 42*(2), 206–242. https://doi.org/10.3102/1076998616674315

Using `metafor`

Guide to using `metafor`: https://cran.r-project.org/web/packages/metafor/vignettes/metafor_diagram.pdf

1. Read data
2. Calculate effect size (optional)
3. Conduct meta-analysis (including *moderation*)
4. Print results, fitted values, residuals diagnostics, publication bias, inference, plots, …

Demo

Load required packages

```
repo <- "https://cloud.r-project.org"
sapply(c("metafor", "lattice"), function(package_name) { # lattice is not required
  if (!require(package_name, character.only = TRUE)) {
    install.packages(package_name, repos = repo)
    library(package_name, character.only = TRUE)
  }
})
```

```
## $metafor
## NULL
##
## $lattice
## NULL
```

Load dataset

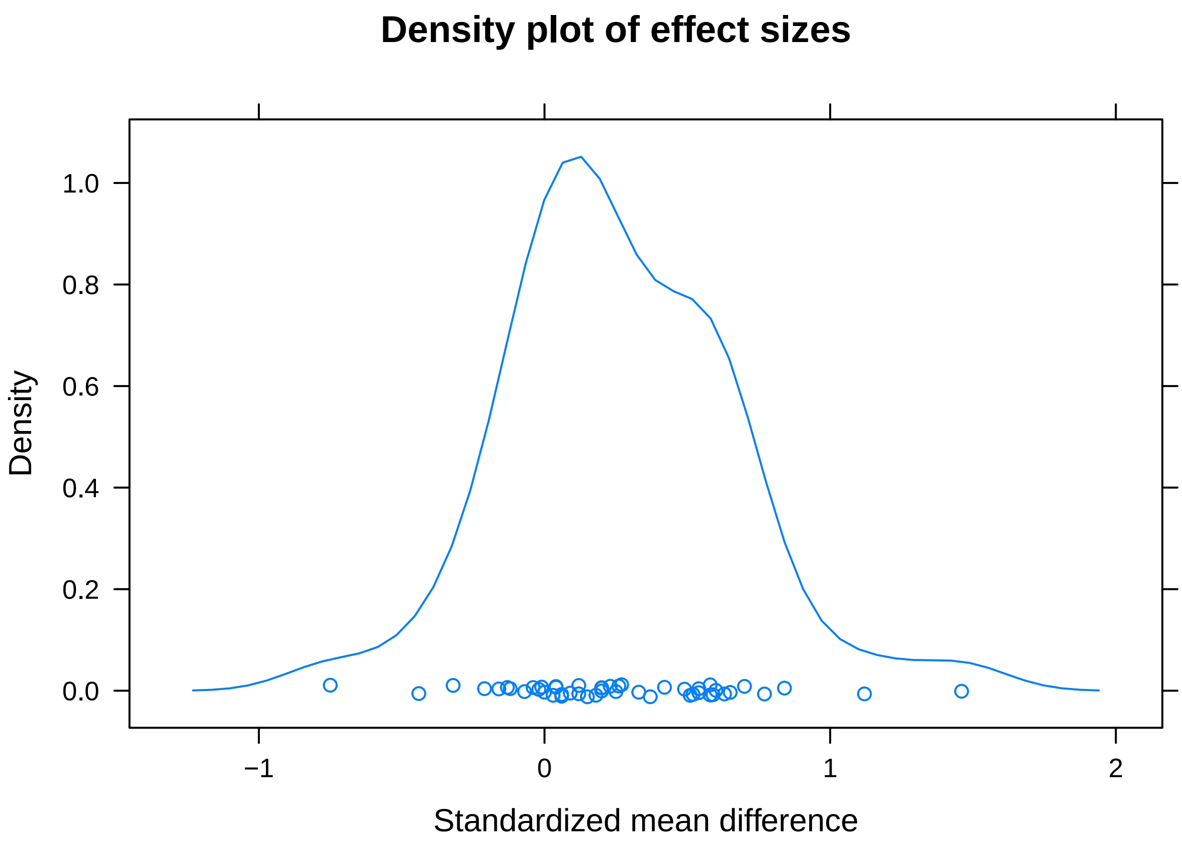
```r
data <- dat.bangertdrowns2004
head(data)
```

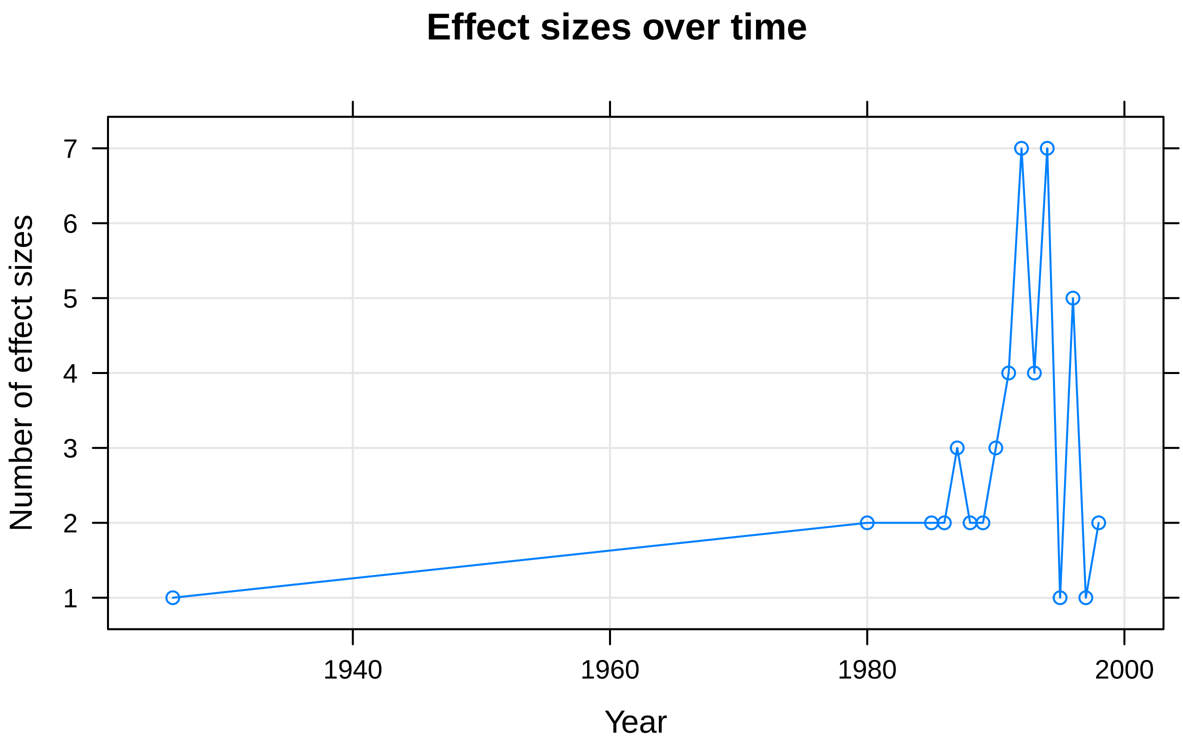
```
##   id   author year grade length minutes wic feedback info pers imag meta
## 1  1 Ashworth 1992     4     15      NA   1        1    1    1    0    1
## 2  2    Ayers 1993     2     10      NA   1       NA    1    1    1    0
## 3  3   Baisch 1990     2      2      NA   1        0    1    1    0    1
## 4  4    Baker 1994     4      9      10   1        1    1    0    0    0
## 5  5   Bauman 1992     1     14      10   1        1    1    1    0    1
## 6  6   Becker 1996     4      1      20   1        0    0    1    0    0
##         subject  ni     yi    vi
## 1       Nursing  60  0.650 0.070
## 2 Earth Science  34 -0.750 0.126
## 3          Math  95 -0.210 0.042
## 4       Algebra 209 -0.040 0.019
## 5          Math 182  0.230 0.022
## 6    Literature 462  0.030 0.009
```

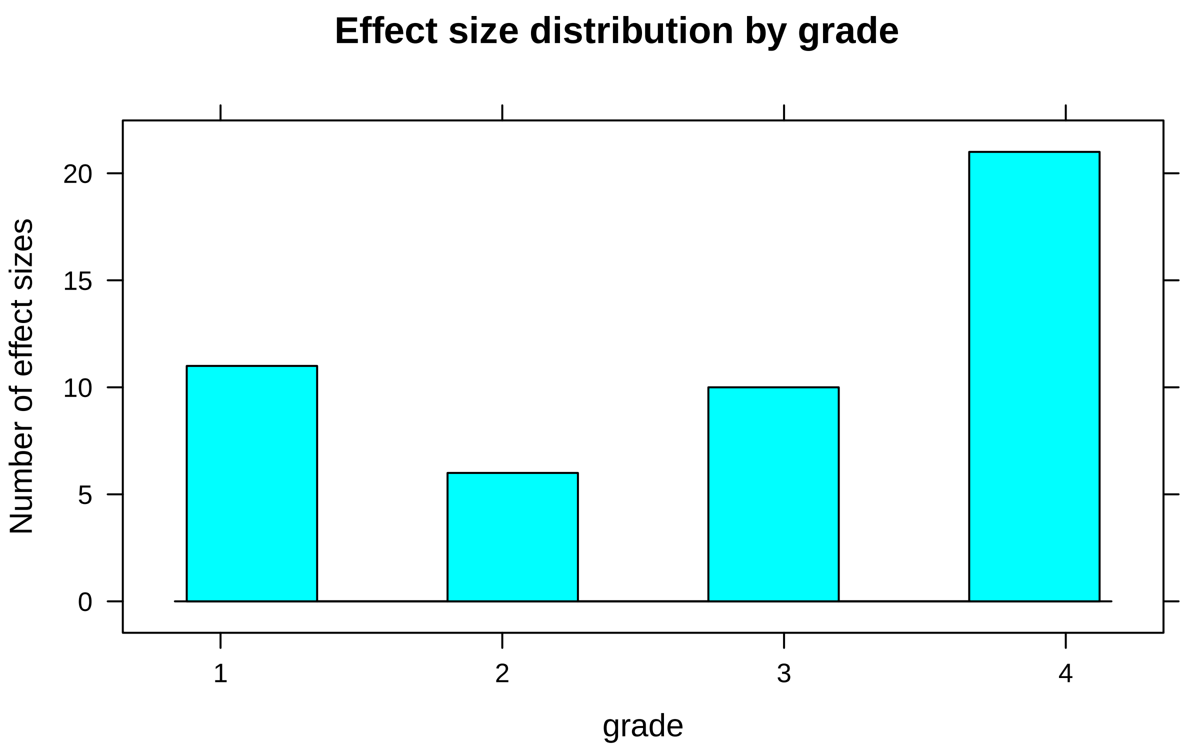
```r
# Run ?dat.bangertdrowns2004 to see what the dataset represents
```

Visualize data

Produced using the `lattice` package




Effect sizes over time
Number of effect sizes
7
6
5
4
3
2
1
1940
1960
1980
2000
Year


Effect size distribution by grade
Number of effect sizes
20
15
10
5
0
1
2
3
4
grade

Conduct meta-analysis

I will conduct a random-effects meta-analysis. Assuming I wanted to conduct a fixed-effects meta-analysis, I would add `method = FE` as one of the arguments to the `rma` function below. The default method of estimation is `REML`.

The effect size `measure` used below, `yi`, is a standardized mean difference (`SMD`), and the Knapp and Hartung (2003) adjustment is used to improve the estimation of standard errors (`test = "knha"`).

```
(res.0 <- rma(
  yi = yi, vi = vi, ni = ni, data = data,
  measure = "SMD", test = "knha"
))
```

```
##
## Random-Effects Model (k = 48; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0499 (SE = 0.0197)
## tau (square root of estimated tau^2 value):      0.2235
## I^2 (total heterogeneity / total variability):   58.37%
## H^2 (total variability / sampling variability):  2.40
##
## Test for Heterogeneity:
## Q(df = 47) = 107.1061, p-val < .0001
##
## Model Results:
##
## estimate      se     tval     pval    ci.lb    ci.ub
##   0.2219  0.0495   4.4810   <.0001   0.1223   0.3216      ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The effect of school-based writing-to-learn interventions on academic achievement was 0.22 standard deviations (95% CI $[0.12, 0.32]$); this effect was statistically different from zero, $t(47) = 4.48, p < .001$.

The result from the Q test for heterogeneity suggests that there was unexplained heterogeneity in the estimate calculated above, $Q(47) = 107, p < .001$. Since we performed a random-effects meta-analysis, we modeled this heterogeneity in the τ^2 statistic.

We can use the following syntax to obtain the 95% confidence interval around the estimates of heterogeneity.

```
confint(res.0, level = .95)
```

```
##
##        estimate   ci.lb   ci.ub
## tau^2    0.0499  0.0274  0.1525
## tau      0.2235  0.1656  0.3905
## I^2(%)  58.3740 43.4940 81.0705
## H^2      2.4023  1.7697  5.2828
```

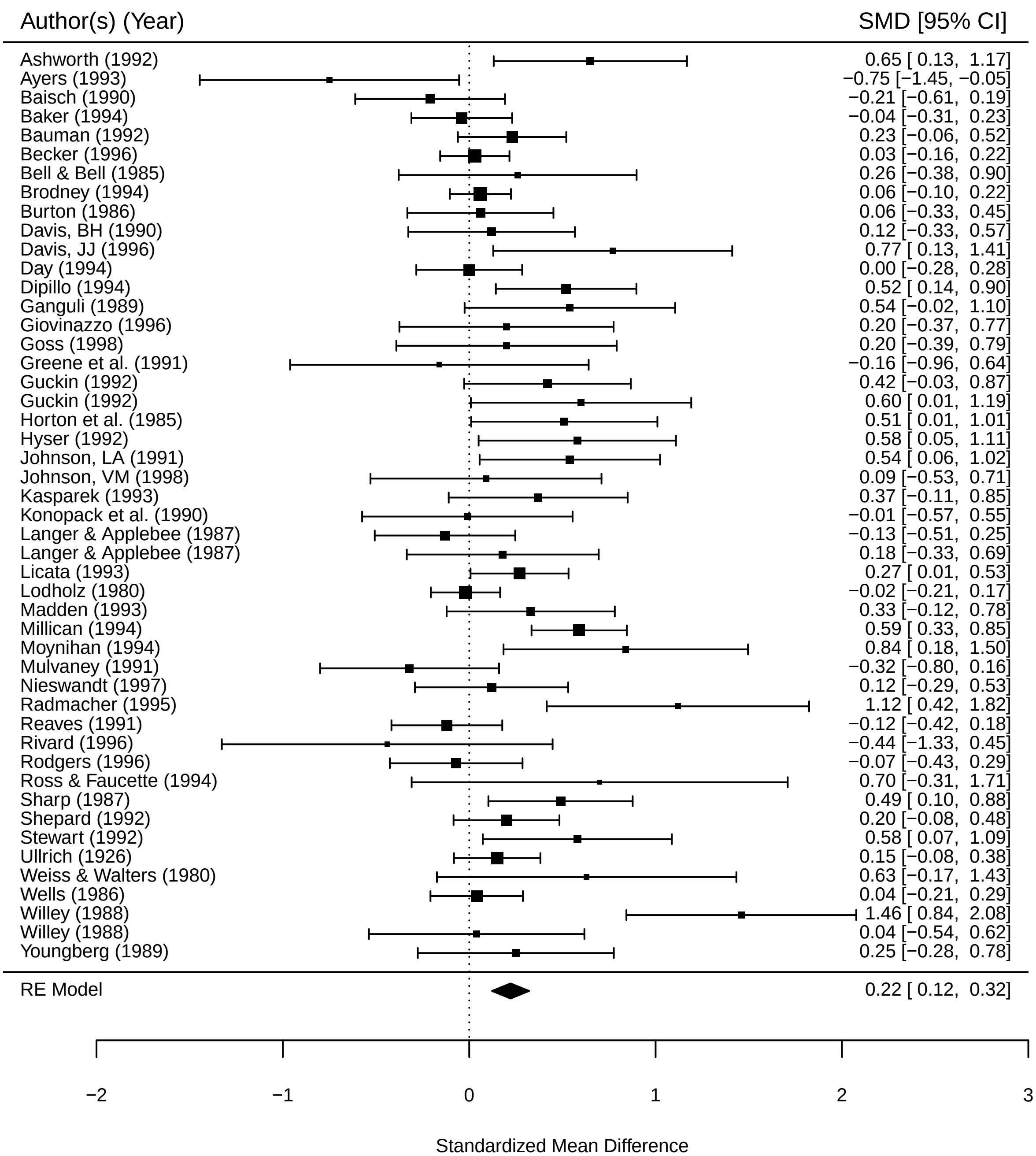
The heterogeneity in our estimate was statistically different from zero, $\tau^2 = .050, 95\%$ CI $[.027, .15]$.

The I^2 statistic estimates how much of the total heterogeneity can be attributed to true heterogeneity in the effects, and this was 58.4%, 95% CI [43.5%, 81.1%]. The confidence intervals for heterogeneity estimates are often large.

Forest plot

We can create a forest plot of the effect sizes in included meta-analysis.

```
forest(
  res.0, slab = paste0(data$author, " (", data$year, ")"),
  xlim = c(-2.5, 2.5), cex = .7
)
op <- par(cex = .8, font = 1)
text(-2.5, 50, "Author(s) (Year)", pos = 4)
text(2.9775, 50, "SMD [95% CI]", pos = 2)
```



We can do a lot more with these forest plots, say separation into subgroups based on moderator variables.

Moderation analysis

We can check how study characteristics influence the average effect calculated earlier. Let's use the `grade` variable as a moderator. By using `factor(grade)`, we specify that `grade` should be dummy coded.

```
(res.1 <- rma(
  yi = yi, vi = vi, ni = ni, data = data,
  mods = ~ factor(grade),
  measure = "SMD", test = "knha"
))
```

```
##
## Mixed-Effects Model (k = 48; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0539 (SE = 0.0216)
## tau (square root of estimated tau^2 value):             0.2322
## I^2 (residual heterogeneity / unaccounted variability): 59.15%
## H^2 (unaccounted variability / sampling variability):   2.45
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 44) = 102.0036, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## F(df1 = 3, df2 = 44) = 1.8783, p-val = 0.1472
##
## Model Results:
##
##                 estimate      se     tval    pval    ci.lb    ci.ub
## intrcpt           0.2639  0.0925   2.8545  0.0066   0.0776   0.4502  **
## factor(grade)2   -0.3727  0.1756  -2.1226  0.0395  -0.7266  -0.0188   *
## factor(grade)3    0.0248  0.1405   0.1769  0.8604  -0.2583   0.3080
## factor(grade)4   -0.0155  0.1195  -0.1300  0.8972  -0.2563   0.2252
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We would interpret the coefficients the same as we would from a regular regression with coefficients as comparisons to the reference group. However, these are interpreted at the effect size level. The `intrcpt` represents the effect at grade 1, with an effect of 0.26 standard deviations, 95% CI $[0.078, 0.45], t(44) = 2.85, p = .007$.

The grade 2 coefficient differed significantly from zero, $b = -0.37, t(44) = -2.12, p = .039$. Hence the effect at second grade was -0.11 standard deviations (0.26 - 0.37). Other grade level effects were not statistically different from the grade 1 effect.

We could modify the syntax as below (adding `-1` when defining the moderators), and this would give us coefficients for the specific grade levels.

```
rma(
  yi = yi, vi = vi, ni = ni, data = data,
  mods = ~ factor(grade) - 1,
  measure = "SMD", test = "knha"
)
```

This would allow us to tell which coefficients were statistically different from zero.[1]

[1] We would not compare to a reference group, however, the math is still all the same.

There are additional elements from moderation analysis.

```
res.1
```

```
##
## Mixed-Effects Model (k = 48; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0539 (SE = 0.0216)
## tau (square root of estimated tau^2 value):             0.2322
## I^2 (residual heterogeneity / unaccounted variability): 59.15%
## H^2 (unaccounted variability / sampling variability):   2.45
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 44) = 102.0036, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## F(df1 = 3, df2 = 44) = 1.8783, p-val = 0.1472
##
## Model Results:
##
##                 estimate      se     tval    pval    ci.lb    ci.ub
## intrcpt           0.2639  0.0925   2.8545  0.0066   0.0776   0.4502  **
## factor(grade)2   -0.3727  0.1756  -2.1226  0.0395  -0.7266  -0.0188   *
## factor(grade)3    0.0248  0.1405   0.1769  0.8604  -0.2583   0.3080
## factor(grade)4   -0.0155  0.1195  -0.1300  0.8972  -0.2563   0.2252
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It is important to note that there remained some residual heterogeneity, $Q(44) = 102, p < .001$. Additionally, an omnibus test of the moderator coefficients suggested that the moderator coefficients were not statistically different from zero, $F(3, 44) = 1.88, p = .15$.

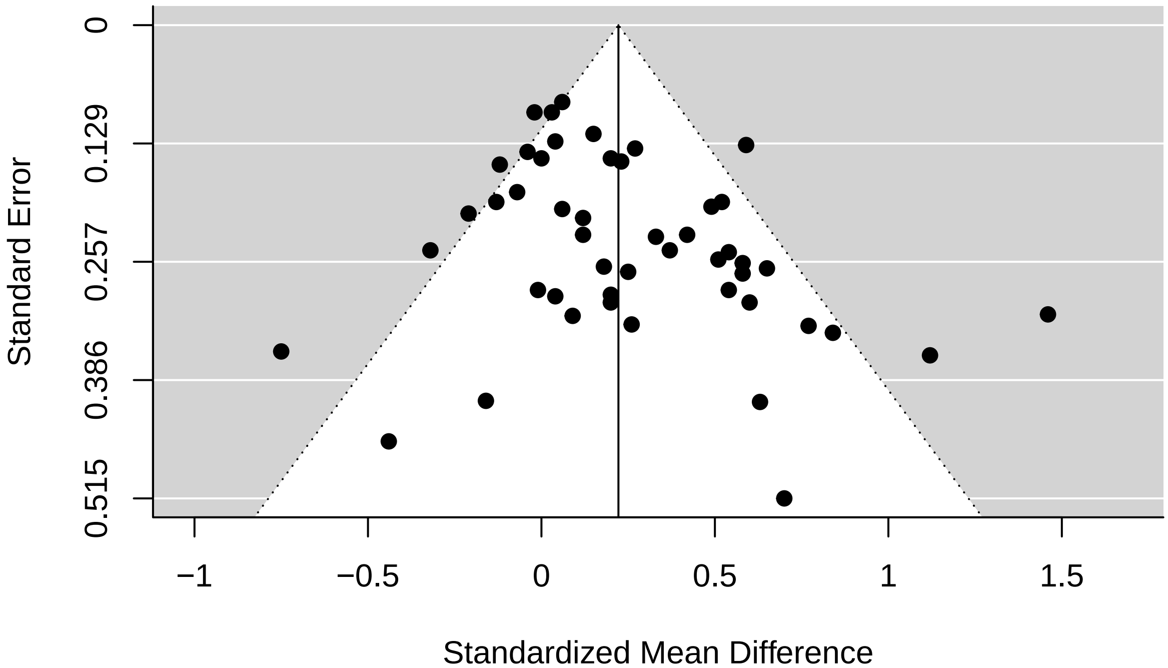
We can also observe the change in τ^2, `metafor` uses this to calculate a pseudo-`R^2` and when this value is negative, it reports 0% as above.

All these pieces of evidence suggest that we were unsuccessful at reducing the heterogeneity in our estimates despite adding `grade` as a moderator.

Publication bias

We can use something called a funnel plot to check for some types of publication bias. If some types of results have been systematically excluded from the meta-analysis, we might see asymmetry about the center in the plot below.

```r
funnel(res.0)
```



It seems like the plot is light on the left at the lower ends, suggesting some negative results with relatively large uncertainty might be missing from our analysis.

We can conduct a test of asymmetry.

```r
regtest(res.0)
```

```
##
## Regression Test for Funnel Plot Asymmetry
##
## model:     mixed-effects meta-regression model
## predictor: standard error
##
## test for funnel plot asymmetry: t = 2.2533, df = 46, p = 0.0291
```

The asymmetry is statistically different from zero ($t(46) = 2.25, p = .029$); this statistical test suggests we have some asymmetry, hence publication bias (towards positive results based on a visual inspection of the funnel plot).

References

- Knapp, G., & Hartung, J. (2003). Improved tests for a random effects meta-regression with a single covariate. *Statistics in Medicine, 22*(17), 2693–2710. https://doi.org/10.1002/sim.1482