



Meta analysis Tutorial



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Meta analysis

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1 Meta analysis Basics

Meta Analysis is quantitative methodology used for combining researches that have a common subject, in order to make an overall conclusion.

As in many statistical methods Metanalysis has advantages and disadvantages.

pros:

- Provides an objective synthesis of many related studies or experiments for a particular problem, in order to drive a single overall conclusion.
- This methodology allows an partiality (BIAS) assessment.

cons:

- one number cannot summarise a research field“: A good meta analysis will model variability in true effect sizes and model the uncertainty of estimates.
- “the file drawer problem invalidates meta-analysis”: Funnel plots and related tools allows you to see whether sample size is related to effect size in order to check for publication bias. Good meta-analyses endeavour to obtain unpublished studies. This issue is shared with narrative studies.
- “Mixing apples and oranges”: Good meta-analyses provide a rigorous coding system for categorising included studies and justifying the inclusion and exclusion of studies in the meta-analysis. After studies have been classified, moderator analysis can be performed to see whether effect sizes vary across study type.
- “Important studies are ignored”: You can code for the evaluated quality of the studies. Large samples can be given greater weighting.
- “meta analysis can disagree with randomised trials”:
- “meta-analyses are performed poorly”: This is merely an argument for improving the standards of meta-analytic methods.
- “Is a narrative review better?”: Many of the critiques of meta-analysis (e.g., publication bias) are shared by narrative reviews. It is just that the methods of inference are less explicit and less rigorous in narrative reviews.



2 Which Metanalysis method to use?

A common question in Metanalysis is **which analysis to use?** It all depends on what type of Data we have and if we want a Fixed, Random or Mixed Effects model.

Type of data	Effect measure	Fixed-effect methods	Random-effects methods
Dichotomous	Odds ratio (OR)	Mantel-Haenszel	Mantel-Haenszel
		Inverse variance	Inverse variance
		Peto	
	Risk ratio (RR)	Mantel-Haenszel	Mantel-Haenszel
		Inverse variance	Inverse variance
	Risk difference (RD)	Mantel-Haenszel	Mantel-Haenszel
		Inverse variance	Inverse variance
Continuous	Mean difference (MD)	Inverse variance	Inverse variance
	Standardized mean difference (SMD)	Inverse variance	Inverse variance
O – E and Variance	<i>User-specified</i>	Peto	None
Generic in-verse variance	<i>User-specified</i>	Inverse variance	Inverse variance
Other data	<i>User-specified</i>	None	None

Some notes:

- An “effect” could be almost any aggregate statistic of interest:
 - Mean, Mean difference, Mean change
 - Risk ratio, Odds ratio, Risk difference
 - Incidence rate, Prevalence, Proportion
 - Correlation
- Conventional meta-analytic models assume normality of ESs.
- To normalize ESs, a log-transform is common.

Some examples and basic calculation of the ESs are.

- Log-Odds Ratio:
 - $\log(\text{OR}) = \log\left(\frac{a*d}{b*c}\right)$
 - $\log(V) = \frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}$



- Log-Relative Risk:

$$\begin{aligned} - \log(\text{RR}) &= \log\left(\frac{a/a+b}{c/c+d}\right) \\ - \log(\text{V}) &= \frac{1}{a} + \frac{1}{c} + \frac{1}{a+b} + \frac{1}{c+d} \end{aligned}$$

- Incidence rate

$$\begin{aligned} - \text{IR} &= \log\left(\frac{a/a+b}{c/c+d}\right) \\ - \end{aligned}$$

- Risk Difference:

$$\begin{aligned} - \frac{a}{a+b} - \frac{c}{c+d} \\ - \text{Variance} &= \frac{axb}{(a+b)^3} - \frac{cxd}{(c+d)^3} \end{aligned}$$



3 Fixed Effects Model

The **beta_full_prac1.dta** file contains results from 20 randomized clinical trials on the use of beta-blockers for the prevention of esophageal bleeding in patients with cirrhosis.

The file is described below:

Table 1: The 20 randomized clinical trials

id	Ttotal	Tcases	Ctotal	Ccases	quality
1	35	3	36	22	6
2	56	5	53	30	38
3	16	5	18	6	31
4	23	3	22	9	0
5	49	11	46	31	38
6	53	19	60	9	52
7	53	17	60	26	75
8	71	10	69	29	71
9	41	12	41	14	81
10	21	1	20	3	63
11	42	9	41	13	75
12	33	13	35	14	71
13	143	31	138	23	68
14	55	20	51	19	58
15	73	13	72	13	83
16	13	3	16	12	NA
17	21	3	28	5	NA
18	18	4	19	1	NA
19	22	6	24	2	NA

- The **Ttotal** variable shows the total amount of patients in the **treatment** group.
- The **Tcases** variable shows the number of cases in the **treatment** group.
- The **Ctotal** variable shows the total amount of patients in the **Cases** group.
- The **Ccases** variable shows the number of cases in the **Cases** group.
- The **quality** variable contains a score of “quality” of each study based on several criteria (quality of randomization, compliance, patient withdrawals, etc.). The range of the variable that ranges from 0 to 100 (higher values indicate better quality studies) whereas for studies published only as abstracts there is no recorded value. Other variables are described by the corresponding variable labels.

3.1 Inverse Variance weights

A good package for Metanalysis is the **metafor** which provides a more step by step procedure. Firstly we shall calculate effect sizes (in our case Odds Ratios) and outcome measures we are



3.1 Inverse Variance weights

interested in, using the `escalc()` function. The `escalc()` function main option is the measure, in which we declare the E.S. or outcome measure that will be calculated. Since we choose the Odds Ratio we need to provide the a, b etc for each 2x2 matrix.

For example for the *ith* study the matrix is:

	Treatment	Control	Total
Disease = Yes	a (Tcases)	b (Ccases)	a+b
Disease = No	c (Tnocases)	d (Cnocases)	c+d
	a+c (Ttotal)	b+d (Ctotal)	N

So we input the a, b, c, d, n1,n2 needed to calculate the log-OR for each study.

Table 3: Log-Scale Odds Ratios, Variance, Standard Error and 95% CI bounds

yi	vi	sei	zi	ci.lb	ci.ub
-2.8191087	0.4814665	0.6938778	-4.0628315	-4.1790843	-1.4591332
-2.5880909	0.2964194	0.5444442	-4.7536389	-3.6551818	-1.5210000
-0.0953102	0.5409091	0.7354652	-0.1295917	-1.5367955	1.3461752
-1.5293952	0.5713675	0.7558886	-2.0233078	-3.0109096	-0.0478808
-1.9656279	0.2161496	0.4649189	-4.2278939	-2.8768522	-1.0544035
1.1526795	0.2127623	0.4612616	2.4989711	0.2486233	2.0567357
-0.4820416	0.1544746	0.3930326	-1.2264673	-1.2523713	0.2882881
-1.4867051	0.1758762	0.4193760	-3.5450414	-2.3086669	-0.6647434
-0.2256096	0.2262817	0.4756908	-0.4742780	-1.1579464	0.7067271
-1.2611312	1.4421569	1.2008984	-1.0501565	-3.6148487	1.0925863
-0.5320278	0.2540515	0.5040352	-1.0555370	-1.5199187	0.4558630
-0.0253178	0.2459707	0.4959543	-0.0510487	-0.9973704	0.9467348
0.3249262	0.0933605	0.3055496	1.0634158	-0.2739399	0.9237924
-0.0383189	0.1624530	0.4030546	-0.0950712	-0.8282914	0.7516536
-0.0168071	0.1874620	0.4329688	-0.0388183	-0.8654104	0.8317961
-2.3025851	0.7666667	0.8755950	-2.6297375	-4.0187198	-0.5864504
-0.2657032	0.6323671	0.7952152	-0.3341274	-1.8242962	1.2928899
1.6376088	1.3769841	1.1734497	1.3955509	-0.6623103	3.9375279
1.4170660	0.7746212	0.8801257	1.6100723	-0.3079486	3.1420807

The output:

- **yi**: log-OR of the studies
- **vi**: The Variance of the OR
- **sei**: The Standard Error (the square root of the above measure)
- **zi**: The Z-statistic for the significance



3.1 Inverse Variance weights

- `ci.lb`: The Lower bound C.I.
- `ci.ub`: The Upper bound C.I.

Since everything is calculated in the log scale, we need to exponentiate the measure we are interested.

Table 4: First 5 studies Odds Ratio with 95% bounds of each study

yi	ci.lb	ci.ub
0.0596591	0.0153125	0.2324377
0.0751634	0.0258568	0.2184933
0.9090909	0.2150692	3.8426997
0.2166667	0.0492469	0.9532474
0.1400679	0.0563117	0.3484002

Fixed-Effects Model (k = 19)

Test for Heterogeneity:

Q(df = 18) = 80.213, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub	
-0.481	0.119	-4.043	<.001	-0.714	-0.248	***

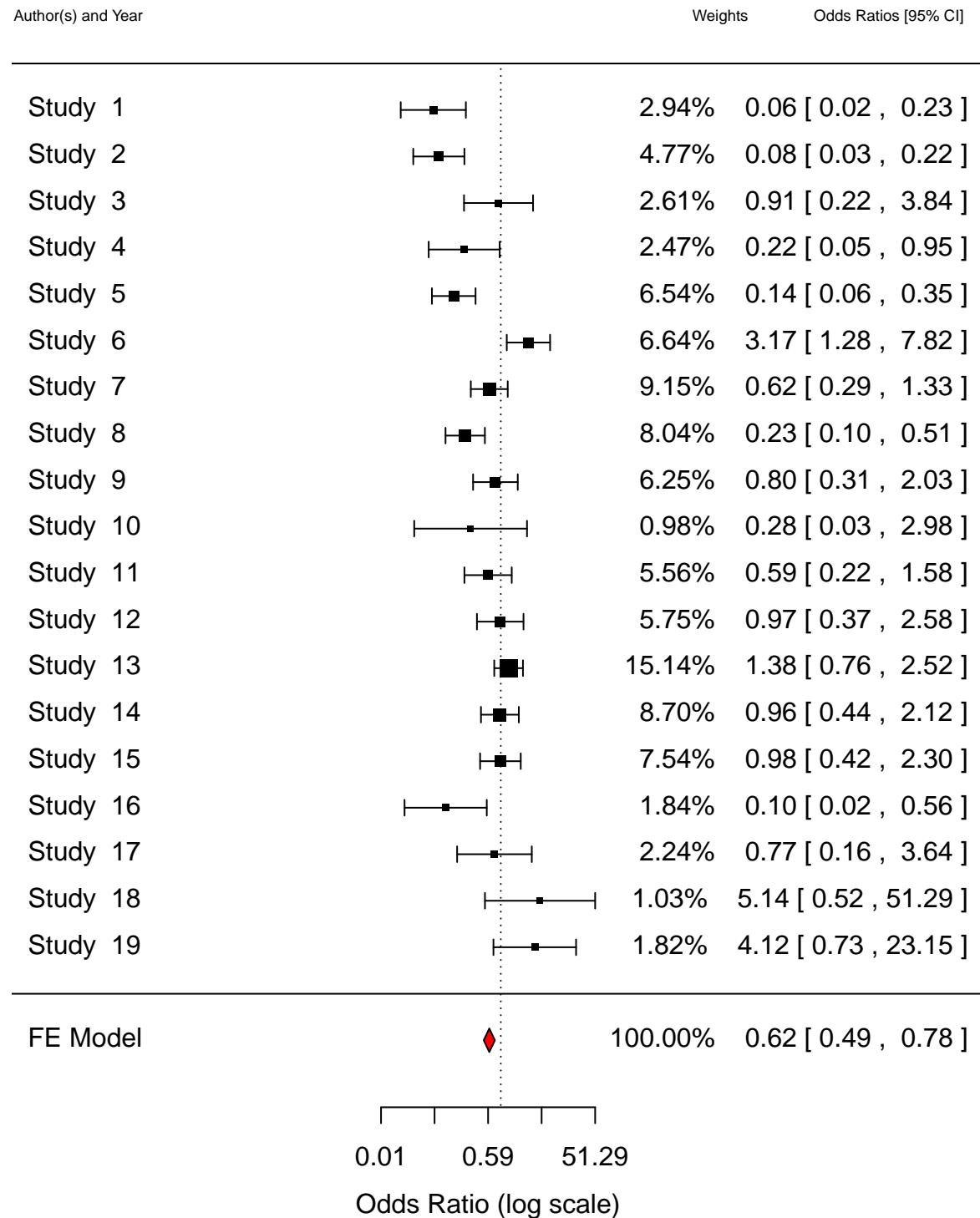
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

In the summary above we may observe that the overall Fixed Effects model Estimate is log_Odds: -0.4807 (0.62 exponentiated) with 95% C.I. (-0.7137, -0.2476) in exponentiated form [0.49, 0.78], the result is statistically significant in the 5% level of significance. The summary also suggests that the studies are highly Heterogeneous with p-value lower than 0.0001 !! The test of heterogeneity is a χ^2 test with k degrees of freedom where k is the number of the studies -1.

```
forest(res, showweights = T, col="red", attransf = exp, refline = 0,
       alim=c(-5, max(as.numeric(res$yi.f + 1.96*sqrt(res$vi.f))))
)
text(-21, 21, "Author(s) and Year", pos=4, cex = 0.55)
text( 11, 21, "Weights", pos=2, cex = 0.55)
text( 20, 21, "Odds Ratios [95% CI]", pos=2, cex=0.55)
```



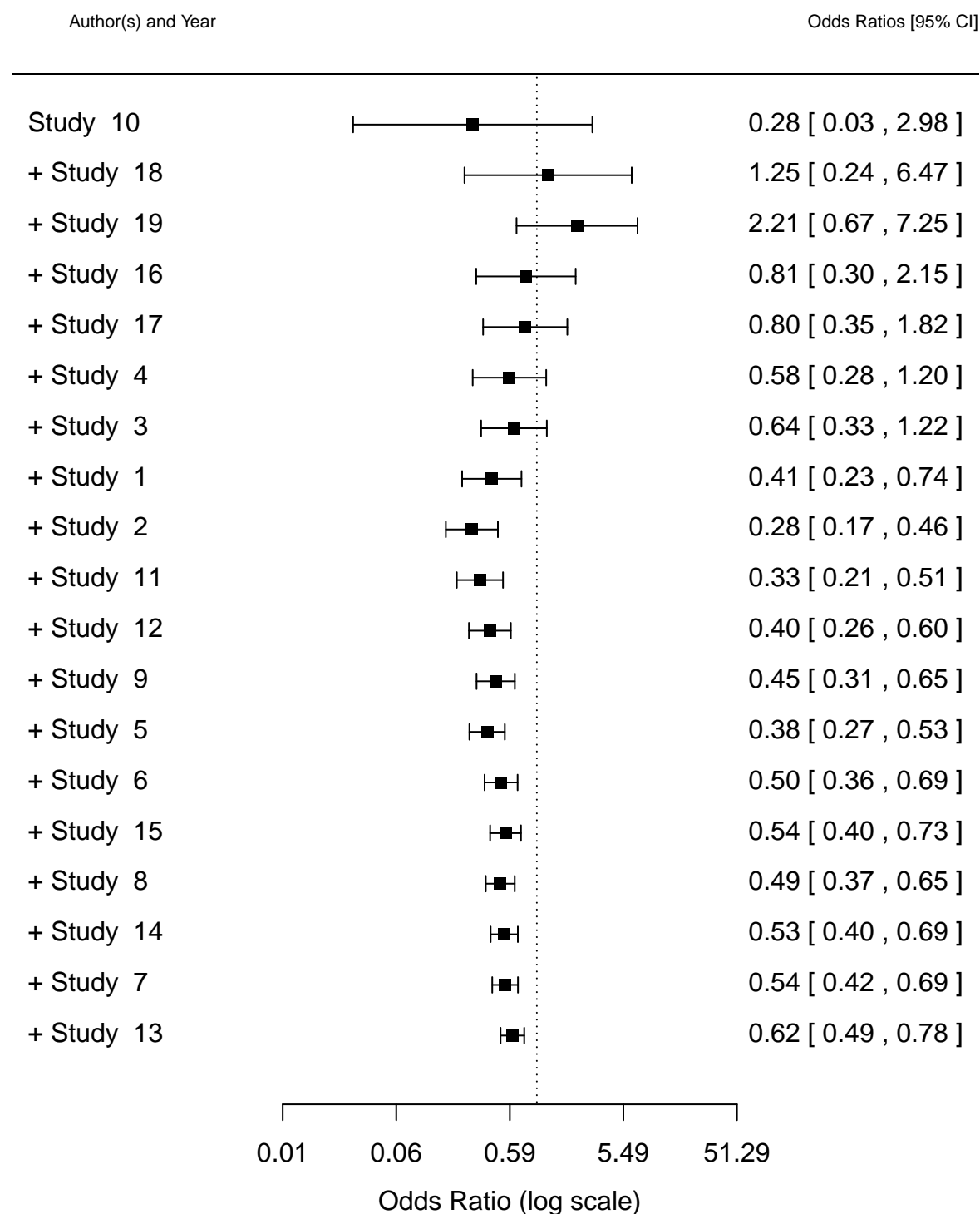

3.1 Inverse Variance weights



Further more we can observe the cumulative Forest plot with ordering in order to better observe the effect of each study.



3.1 Inverse Variance weights



A funnel plot shows the observed effect sizes or outcomes on the x-axis against some measure of precision of the observed effect sizes or outcomes on the y-axis. Based on Sterne and Egger (2001), the recommended choice for the y-axis is the standard error (in decreasing order) and this is also the default for the `funnel()` function in the `metafor` package. In the absence of publication bias and heterogeneity, one would then expect to see the points forming a funnel shape, with the majority of the points falling inside of the pseudo-confidence region with



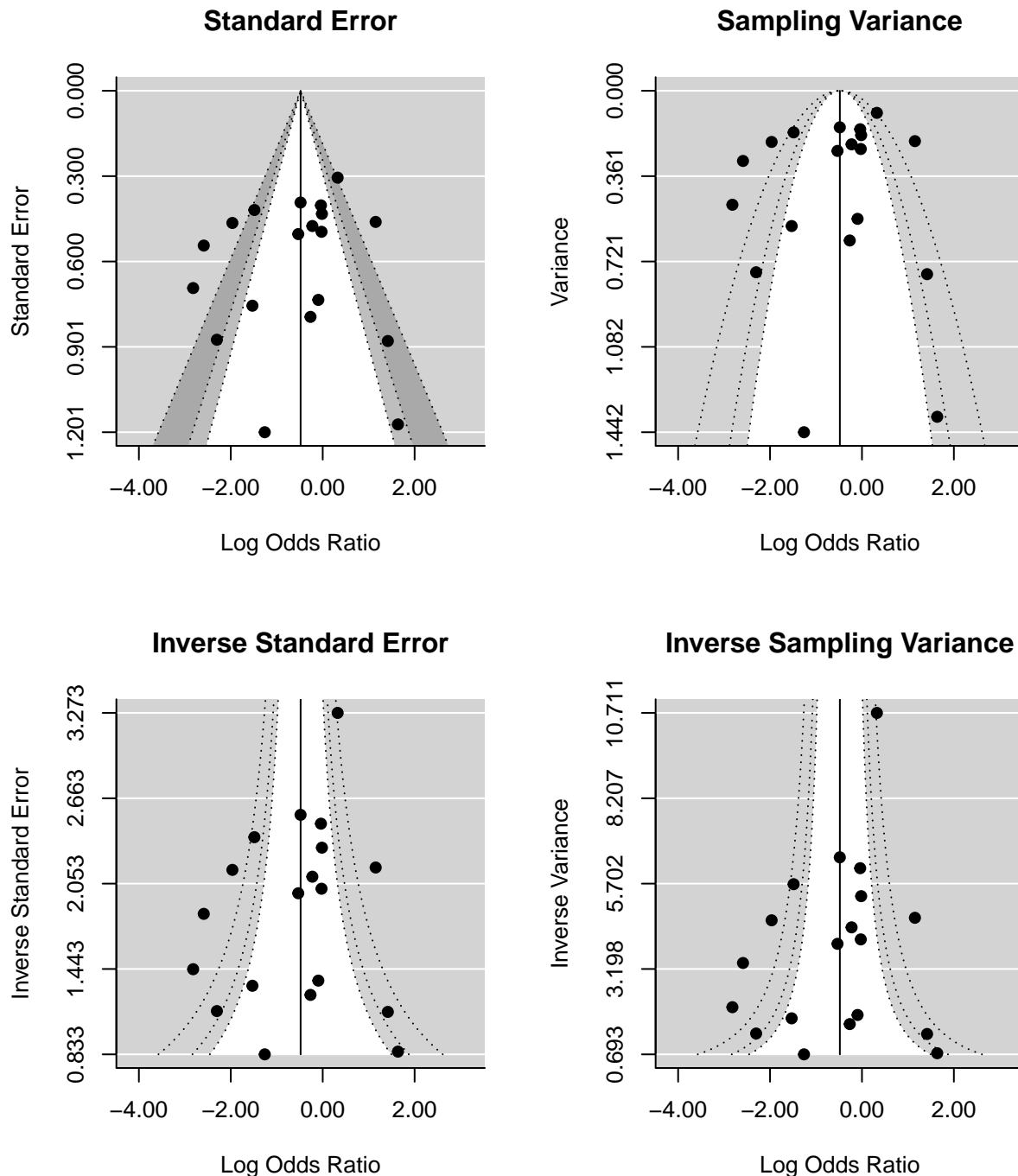
3.1 Inverse Variance weights

bounds $\hat{\theta} \pm SE$, where $\hat{\theta}$ is the estimated effect or outcome based on the fixed-effects model and SE is the standard error value from the y-axis. With other measures of precision for the y-axis, the expected shape of the funnel can be rather different. The plot below shows a variety of choices for the y-axis and how this impacts the shape of the funnel plot (and the form of the pseudo-confidence region). Furthermore we can add various levels of significance in order to create a Contour-like Funnelpoint.

Various levels of statistical significance of the points/studies are indicated by the shaded regions. In particular, the unshaded (i.e., white) region in the middle corresponds to p-values greater than .10, the gray-shaded region corresponds to p-values between .10 and .05, the dark gray-shaded region corresponds to p-values between .05 and .01, and the region outside of the funnel corresponds to p-values below .01. Funnel plots drawn in this way are more useful for detecting publication bias due to the suppression of non-significant findings.



3.1 Inverse Variance weights



3.1.1 Mantel-Haenszel weights

In `metafor` package the *default* weighting method is the Inverse-Variance as shown before. Sometime it is better to use in Metanalysis the M-H weighting method. So if that was the case then we would have the following results:

```
res<-rma.mh("OR", ai = Meta_data$Tcases,  
            bi = Meta_data$Tnocases,
```



3.1 Inverse Variance weights

```
ci = Meta_data$Ccases,  
di = Meta_data$Cnocases,  
n1i = Meta_data$Ttotal ,  
n2i = Meta_data$Ctotal ,digits = 3 )  
res
```

Fixed-Effects Model (k = 19)

Test for Heterogeneity:

Q(df = 18) = 80.366, p-val < .001

Model Results (log scale):

estimate	se	zval	pval	ci.lb	ci.ub
-0.527	0.109	-4.827	<.001	-0.741	-0.313

Model Results (OR scale):

estimate	ci.lb	ci.ub
0.590	0.477	0.731

Cochran-Mantel-Haenszel Test: CMH = 24.078, df = 1, p-val < .001

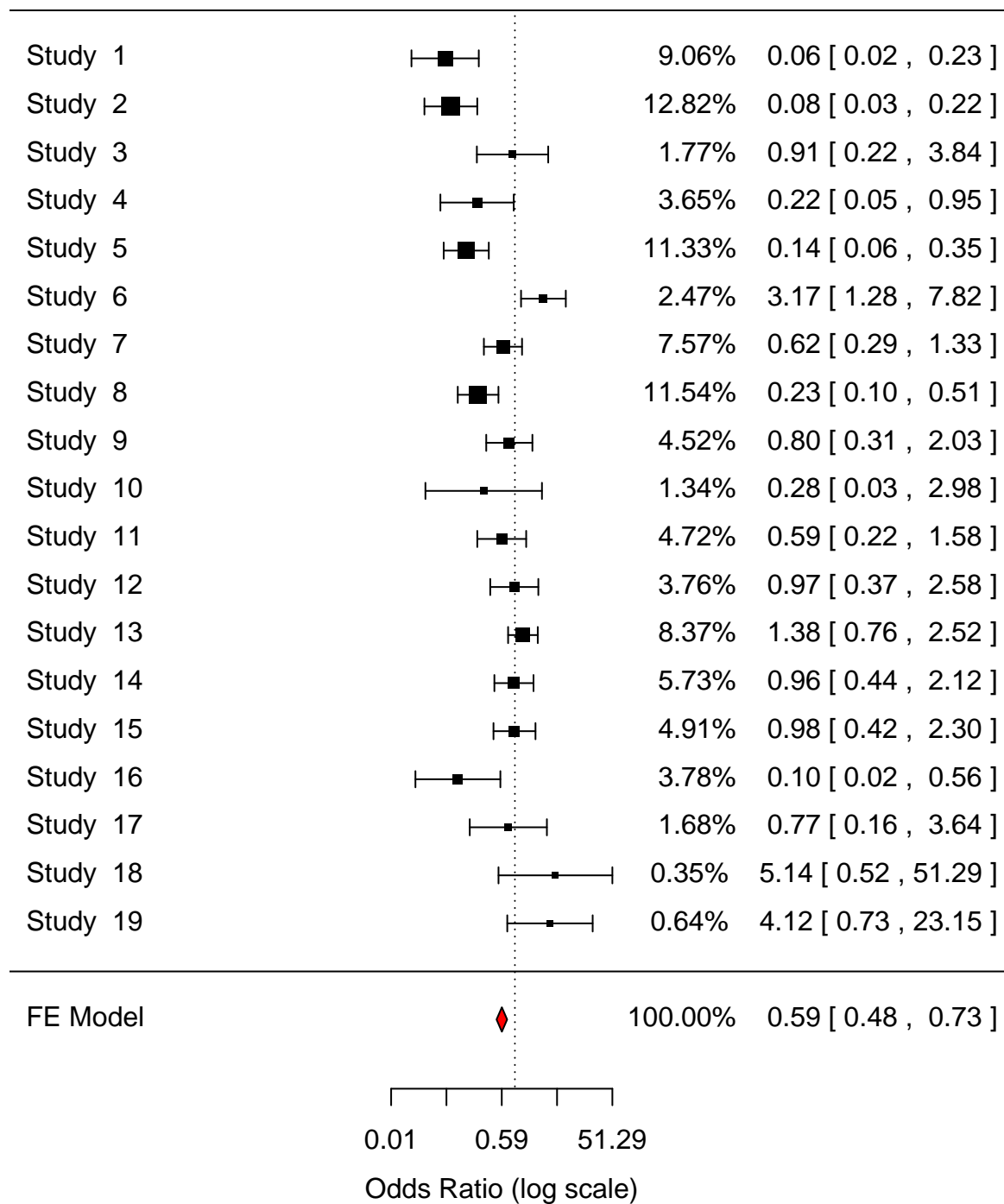
Tarone's Test for Heterogeneity: X^2 = 89.652, df = 18, p-val < .001

In the summary above we may observe that the overall Fixed Effects model Estimate is log_Odds: -0.5271 (0.59 exponentiated) with 95% C.I. (-0.7412,-0.3131) in exponentiated form [0.48,0.73], the result is statistically significant in the 5% level of significance. The summary also suggests that the studies are highly Heterogeneous with p-value lower than 0.0001.

The forest plot is a little bit different also:



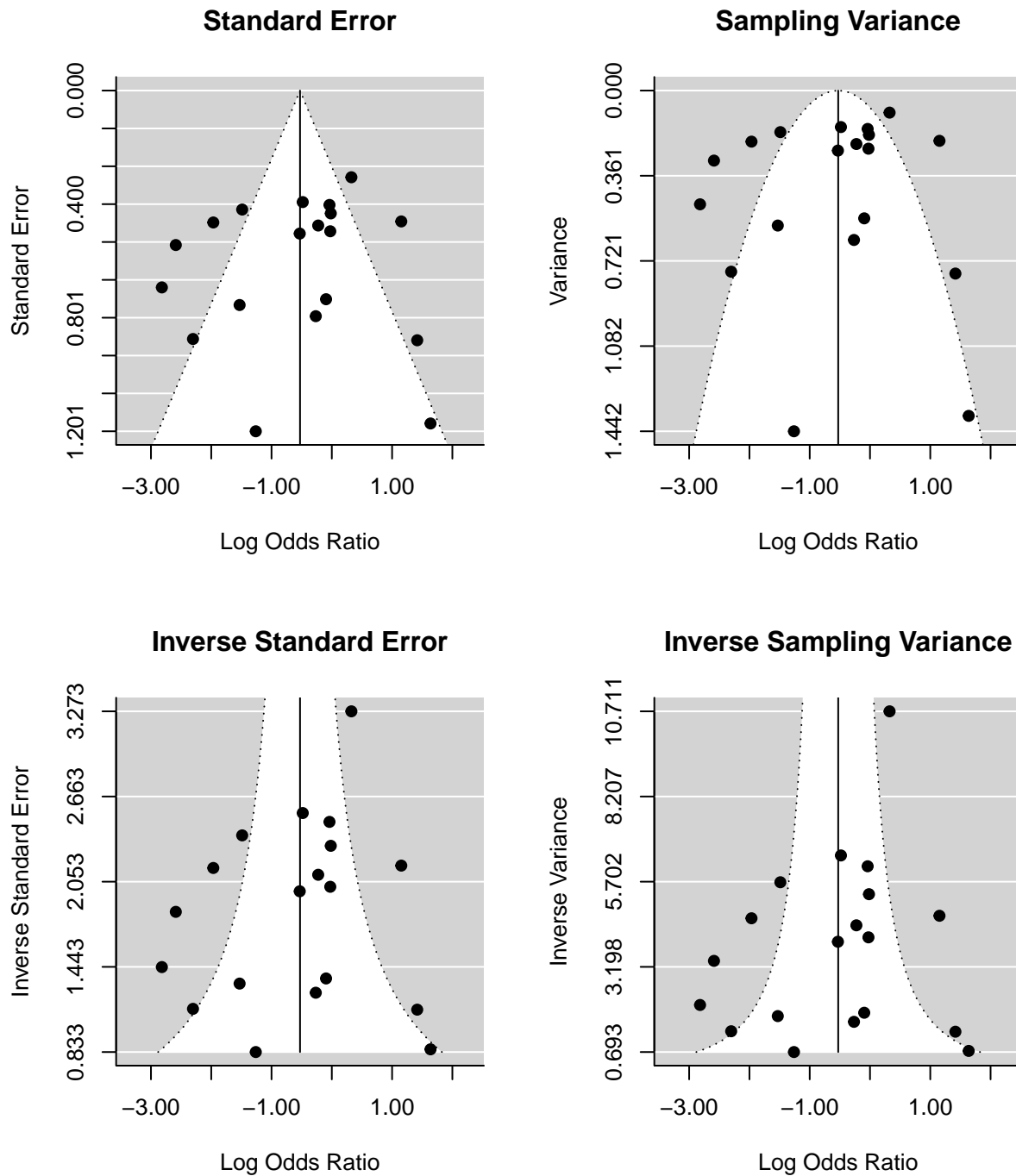
3.1 Inverse Variance weights



And the funnel plots:



3.1 Inverse Variance weights





4 Calculate Fixed-Effects Model by hand

4.1 Effect size calculation and CI bounds

We will calculate “by hand” the fixed-effects summary estimator of Odds Ratio using data on the number of patients with and without occurrence of bleeding in each arm of the respective study. The Odds Ratio is calculated from the **2x2 matrix** of each study.

	Treatment	Control	Total
Disease = Yes	a (Tcases)	b (Ccases)	a+b
Disease = No	c (Tnocases)	d (Cnocases)	c+d
	a+c (Ttotal)	b+d (Ctotal)	N

with the following type : $OR = (a * d) / (b * c)$

As we can see we miss the c_i and d_i but we can easily count them subtracting the cases from the total number of patients.

```
Meta_data$Tnocases = with(Meta_data, Ttotal-Tcases)
Meta_data$Cnocases = with(Meta_data, Ctotal-Ccases)
```

Now we can easily calculate the Odds Ratio of each study.

```
Meta_data$OR=with(Meta_data, (Tcases* Cnocases)/( Ccases* Tnocases))
```

The Variance and Standard Error is easily calculated in the log-scale. We know that the $\log(\text{Variance}) = \frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}$ and that the Standard Error is the square root of the Variance.

```
Var_logOR=1/Meta_data$Tcases+1/Meta_data$Tnocases+
1/Meta_data$Ccases+1/Meta_data$Cnocases

SE_logOR=sqrt(Var_logOR)
logOR=log(Meta_data$OR)
```

So we can calculate the 95% C.I. in exponentiated form.

```
##qnorm(0.975) = 1.96
Meta_data$Lower95 = exp(logOR- qnorm(0.975)*SE_logOR)
Meta_data$Upper95 = exp(logOR+ qnorm(0.975)*SE_logOR)
```




Table 6: Odds Ratios of each study with 95% C.I.

ID	Odds Ratios	Lower 95% Bound	Upper 95% Bound
1	0.06	0.02	0.23
2	0.08	0.03	0.22
3	0.91	0.22	3.84
4	0.22	0.05	0.95
5	0.14	0.06	0.35
6	3.17	1.28	7.82
7	0.62	0.29	1.33
8	0.23	0.10	0.51
9	0.80	0.31	2.03
10	0.28	0.03	2.98
11	0.59	0.22	1.58
12	0.98	0.37	2.58
13	1.38	0.76	2.52
14	0.96	0.44	2.12
15	0.98	0.42	2.30
16	0.10	0.02	0.56
17	0.77	0.16	3.64
18	5.14	0.52	51.29
19	4.12	0.73	23.15



4.2 Weight Calculation

4.2.1 Inverse-Variance weight calculation

To find the overall Estimate of the Odds Ratios we need to calculate the weight of each research. The *default* method used to calculate the summary estimator in the `rma` function is *inverse-variance* the weights have to be calculated by the formula:

$$W_i = \frac{\frac{1}{V_i}}{\sum_{i=1}^k \frac{1}{V_i}} :$$

```
Wi <- 1/res$vi
Wi <- Wi/sum(Wi, na.rm = TRUE)
```

Table 7: Odds Ratios of each study with 95% C.I. and Weights

ID	Odds Ratios	Weights (I-V method)	Lower 95% Bound	Upper 95% Bound
1	0.06	2.94 %	0.02	0.23
2	0.08	4.77 %	0.03	0.22
3	0.91	2.61 %	0.22	3.84
4	0.22	2.47 %	0.05	0.95
5	0.14	6.54 %	0.06	0.35
6	3.17	6.64 %	1.28	7.82
7	0.62	9.15 %	0.29	1.33
8	0.23	8.04 %	0.1	0.51
9	0.8	6.25 %	0.31	2.03
10	0.28	0.98 %	0.03	2.98
11	0.59	5.56 %	0.22	1.58
12	0.98	5.75 %	0.37	2.58
13	1.38	15.14 %	0.76	2.52
14	0.96	8.7 %	0.44	2.12
15	0.98	7.54 %	0.42	2.3
16	0.1	1.84 %	0.02	0.56
17	0.77	2.24 %	0.16	3.64
18	5.14	1.03 %	0.52	51.29
19	4.12	1.82 %	0.73	23.15

Finally we get an weighted average of the Odds Ratios and we have the pooled I-V estimate

$$= \log OR_{pooledIV}^- = \frac{\sum_{i=1}^k w_i \log OR_i}{\sum_{i=1}^k w_i}, \text{ which means: } \log OR_{pooledIV}^- = \frac{w_1 \log OR_1 + w_2 \log OR_2 + \dots + w_n \log OR_n}{w_1 + w_2 + \dots + w_n} =$$

$$-0.4806502 \Rightarrow \exp(\log OR_{pooledIV}^-) = 0.62$$



4.2 Weight Calculation

4.2.2 Mantel-Haenszel weight calculation

In STATA the *default* weight calculation method is the Mantel-Haenszel which is calculated as shown below:

- $W_i = \frac{(b_i * c_i)}{N_i}$

The b_i, c_i (Ccases,Tnocases) are already available. All we need to calculate are the total number of patients both in treatment and Control in each study (N_i).

`Meta_data$Total= Meta_data$Ctotal+ Meta_data$Ttotal`

Now we can calculate the above weights:

`Meta_data$Weight= Meta_data$Ccases* Meta_data$Tnocases/Meta_data$Total`

If we calculate the weights this way they add up to 109.49 so a better

`Meta_data$Relative_Weight = Meta_data$Weight*100/sum(Meta_data$Weight)`

Table 8: Weights and Relative Weights of the Studies

ID	Weights	Relative Weights
1	9.9154930	9.0560686
2	14.0366972	12.8200679
3	1.9411765	1.7729252
4	4.0000000	3.6533004
5	12.4000000	11.3252312
6	2.7079646	2.4732520
7	8.2831858	7.5652415
8	12.6357143	11.5405150
9	4.9512195	4.5220730
10	1.4634146	1.3365733
11	5.1686747	4.7206803
12	4.1176471	3.7607504
13	9.1672598	8.3726884
14	6.2735849	5.7298225
15	5.3793103	4.9130591
16	4.1379310	3.7792763
17	1.8367347	1.6775359
18	0.3783784	0.3455825
19	0.6956522	0.6353566



Now let's calculate the M-H pooled OR of all the researches.

[1] 0.5902876

5 Random effects model

In this example we will demonstrate clearly the difference that may occur if we have a huge study in our Meta-Analysis and the necessity of a random effects model. The `magnes.dta` file contains results from 16 randomized clinical trials that were designed to investigate the effect of magnesium intake on mortality of patients with acute myocardial infarction.

The file is described below:

trial	trialnam	year	tot1	dead1	tot0	dead0
1	Morton	1984	40	1	36	2
2	Rasmussen	1986	135	9	135	23
3	Smith	1986	200	2	200	7
4	Abraham	1987	48	1	46	1
5	Feldstedt	1988	150	10	148	8
6	Schechter	1989	59	1	56	9
7	Ceremuzynski	1989	25	1	23	3
8	Bertschat	1989	22	0	21	1
9	Singh	1990	76	6	75	11
10	Pereira	1990	27	1	27	7
11	Schechter 1	1991	89	2	80	12
12	Golf	1991	23	5	33	13
13	Thogersen	1991	130	4	122	8
14	LIMIT-2	1992	1159	90	1157	118
15	Schechter 2	1995	107	4	108	17
16	ISIS-4	1995	29011	2216	29039	2103

- The first column shows the year the study was conducted.
- The columns named `tot` are showing the total amount of patients in Treatment (1) and Control (0), while
- The `dead` columns shows the diseased in Treatment (1) and Control (0).

We shall calculate the summary estimator for the death Odds Ratio and create the corresponding forest-plot both in fixed (I-V weighting method) and random effects (DL) approach.



First we have the Fixed-effects model.

Fixed-Effects Model (k = 16)

logLik	deviance	AIC	BIC	AICc
-30.111	47.059	62.222	62.994	62.508

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

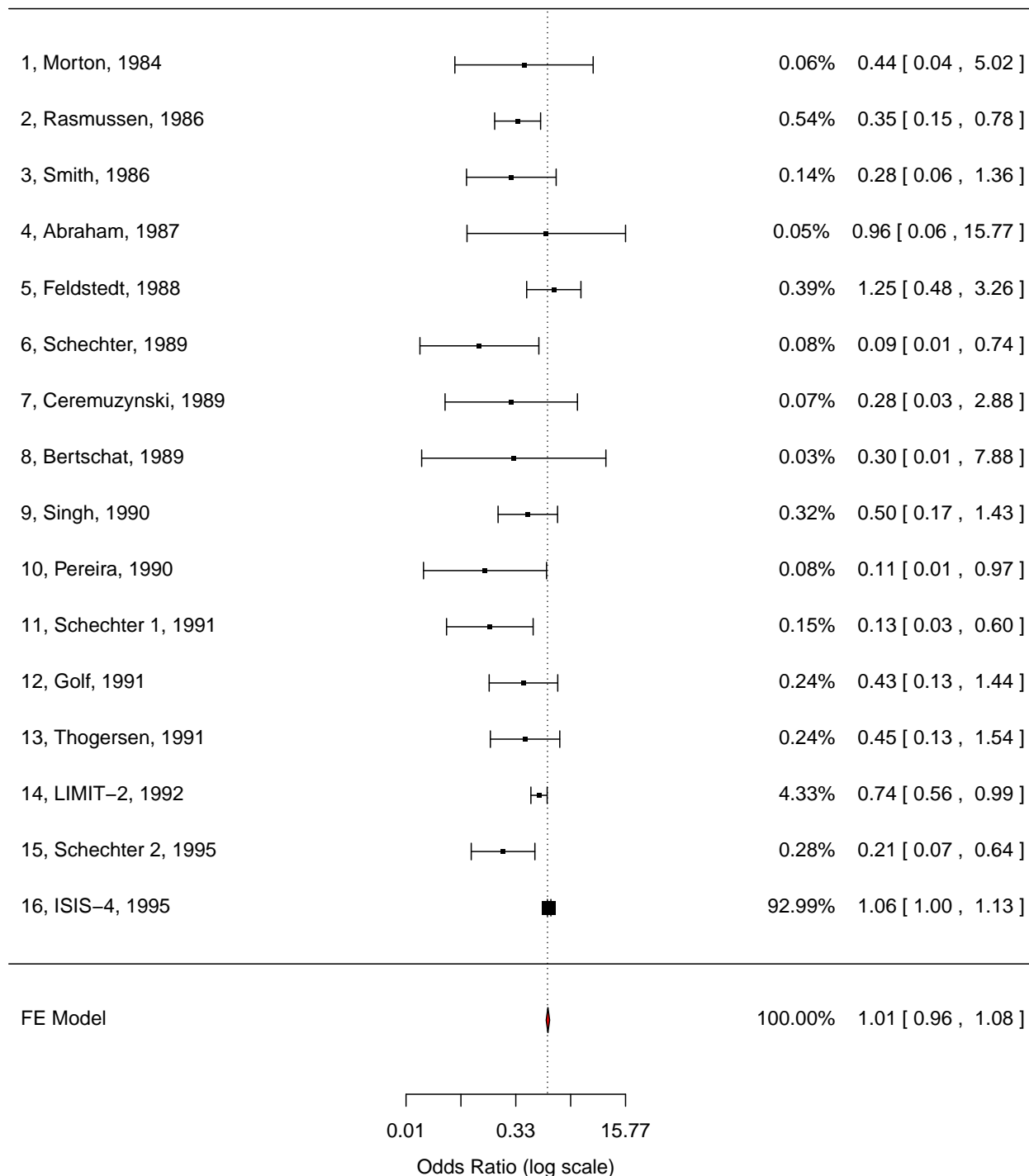
Model Results:

estimate	se	zval	pval	ci.lb	ci.ub
0.015	0.031	0.484	0.629	-0.045	0.075

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

In the summary above we may observe that the overall Random Effects model Estimate is log_Odds: 0.015 (1.015 exponentiated) with 95% C.I. (-0.05,0.07) , [0.96,1.08] exponentiated . The result is not statistically significant in the 5% level of significance since p-value = 0.63. The summary also suggests that the studies are highly Heterogeneous with p-value lower than 0.0001.

Let's have a look in the forest plot.



As we may observe there is a study (ISIS-4) that has nearly the 93% of the total weight and although it seems that all the studies have a lower than 1 odds ratio this study pulls the overall pooled MH Odds Ratio to above 1. A good solution is to use the Random-Effects model, that will reduce the weight of this study. The method we choose is the DerSimonian-Laird, that is making the weights to be more uniformly distributed.



Random-Effects Model (k = 16; tau² estimator: DL)

logLik	deviance	AIC	BIC	AICc
-19.700	26.238	43.400	44.946	44.324

tau² (estimated amount of total heterogeneity): 0.224 (SE = 0.247)

tau (square root of estimated tau² value): 0.473

I² (total heterogeneity / total variability): 68.13%

H² (total variability / sampling variability): 3.14

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub	
-0.728	0.196	-3.706	<.001	-1.112	-0.343	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

In the summary above we may observe that the overall Random Effects model Estimate is log(Odds Ratio)= -0.7276 (0.4831 exponentiated) with 95% C.I. (-1.11,-0.34) , [0.33,0.71] exponentiated.

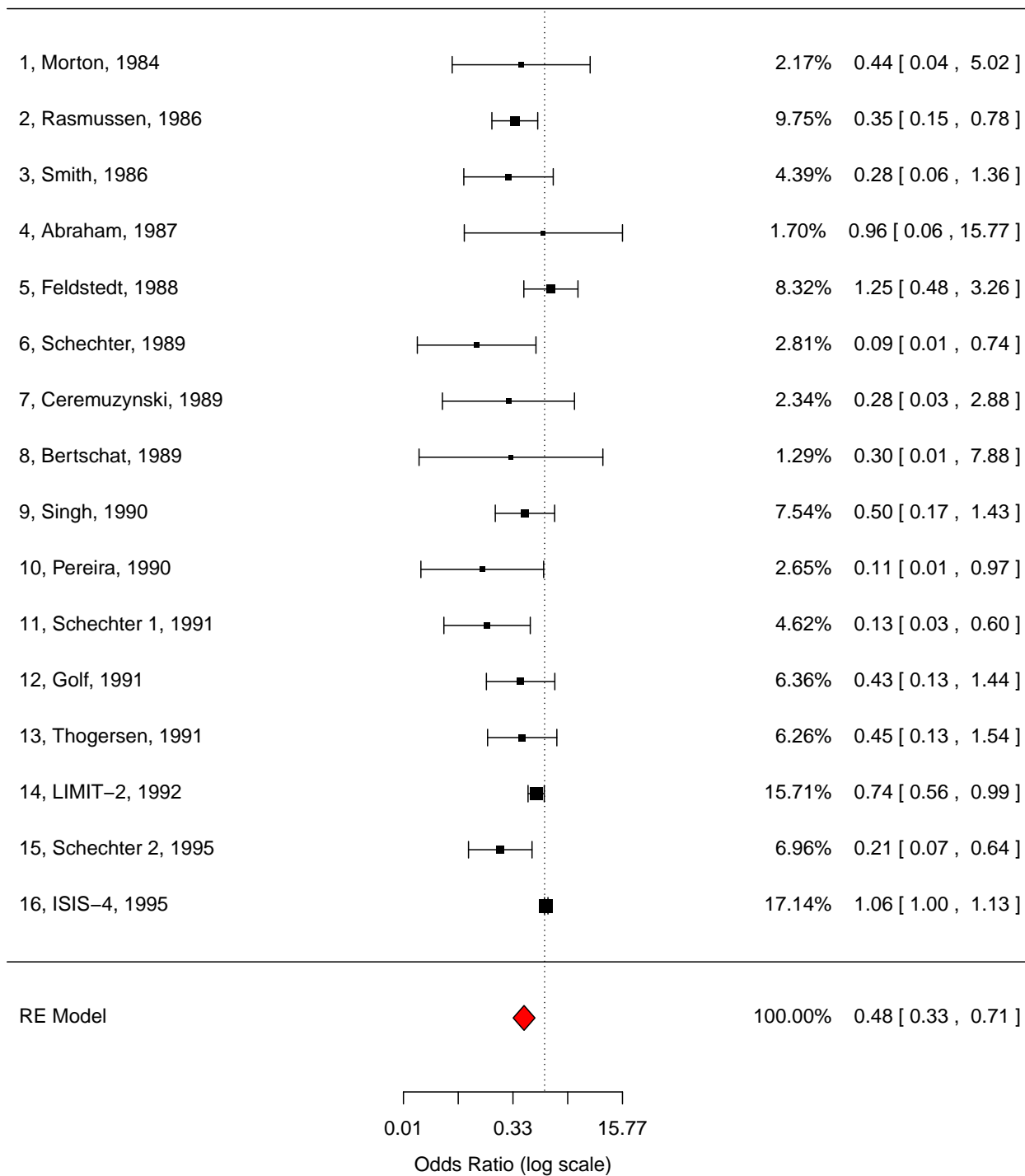
The result is statistically significant in the 5% level of significance since p-value < .0001.

The Cochran's test for Heterogeneity is the same as before.

In the Random effects model there are some outputs that need attention.

The amount of heterogeneity is calculated $\tau^2 = 0.224 \Rightarrow \tau = \sqrt{0.224} = 0.473$, the $I^2 = (Q - df)/Q * 100\%$ where Q is Cochran's heterogeneity statistic and df the degrees of freedom. The I^2 lies between 0% and 100%. A value of 0% indicates no observed heterogeneity, while larger values show increasing heterogeneity. Finally the H^2 is a measure of variability

The forest plot is a little bit different also. The weights have changed and now ISIS-4 has a weight nearly 17%.





What is the difference between the results of Fixed versus Random effects model?

In the fixed effects analysis ISIS-4 study takes a huge burden compared to the others because ISIS has a much larger size. As a result the final pooled MH odds ratio is calculated mainly out of this study. On the other hand in the random effects analysis the weight of this study is much smaller and comparable with the LIMIT-2 study which is approximately 30 times smaller. This affected pooled OR because it is calculated “more” uniformly by all the studies.

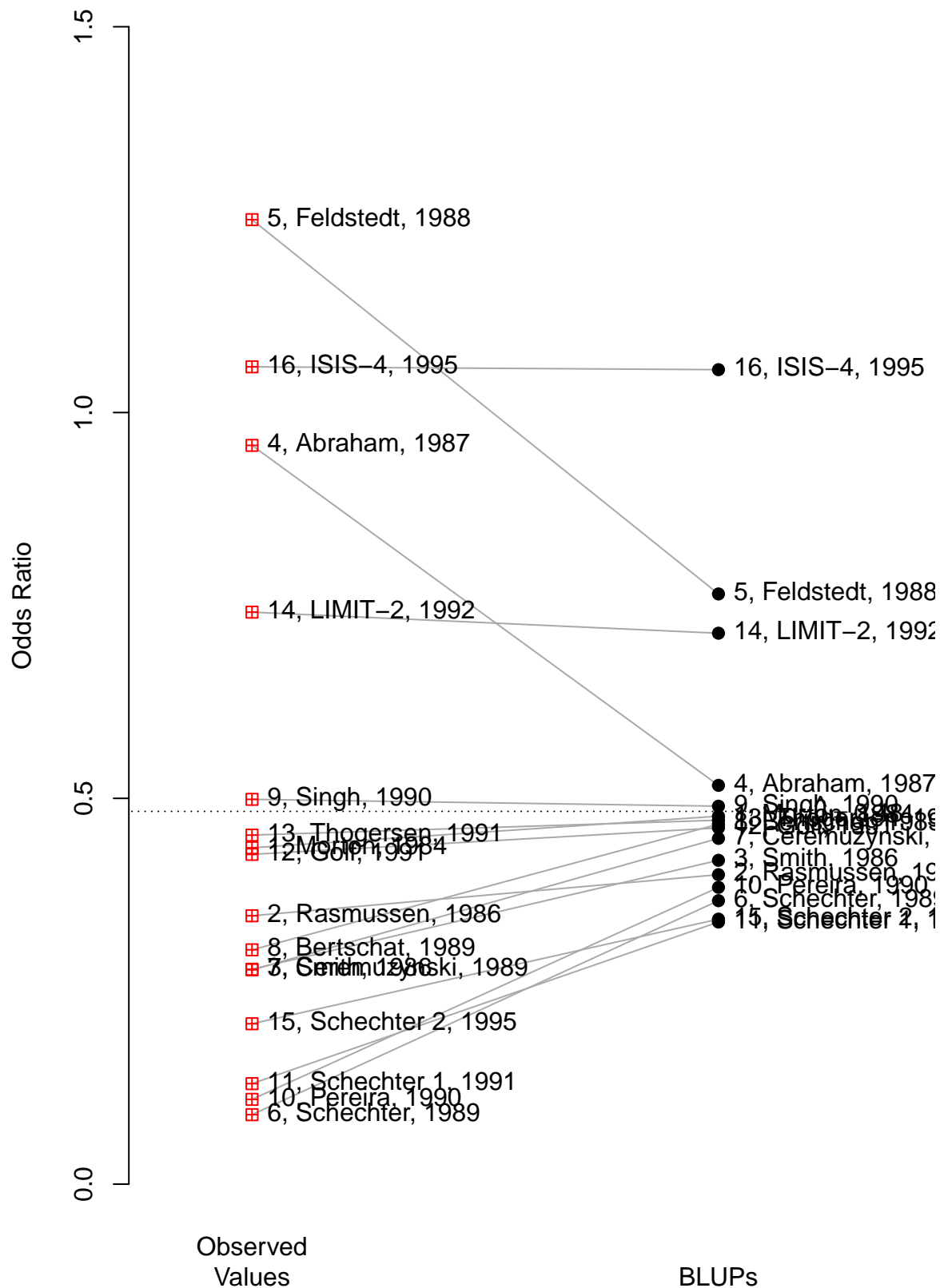
Let's see the difference into the calculation of the Empirical Bayes Estimate a

Note however that the Empirical Bayes estimate the effect of ISIS-4 study is essentially the same as the individual assessment of the study (the very small within-study variance results in shrinkage effect is negligible).

	pred	pi.lb	pi.ub
1, Morton, 1984	0.48	0.19	1.21
2, Rasmussen, 1986	0.40	0.21	0.76
3, Smith, 1986	0.42	0.18	0.98
4, Abraham, 1987	0.52	0.20	1.33
5, Feldstedt, 1988	0.76	0.38	1.53
6, Schechter, 1989	0.37	0.15	0.91
7, Ceremuzynski, 1989	0.45	0.18	1.13
8, Bertschat, 1989	0.47	0.18	1.22
9, Singh, 1990	0.49	0.24	1.01
10, Pereira, 1990	0.38	0.15	0.96
11, Schechter 1, 1991	0.34	0.15	0.79
12, Golf, 1991	0.46	0.21	1.00
13, Thogersen, 1991	0.47	0.22	1.03
14, LIMIT-2, 1992	0.71	0.54	0.94
15, Schechter 2, 1995	0.34	0.16	0.73
16, ISIS-4, 1995	1.06	0.99	1.12



Shrinkage Effect of studies





5.1 Weight Calculation

5.1.1 DerSimonian-Laird (default) method

The weights in the DerSimonian-Laird method are calculated through the following equations.

$$W_i = \frac{1}{v_i + \tau^2} \text{ and then we calculate as usual a weighted average for the } \log(OR) = \log OR = \frac{\sum_1^k W_i * OR_i}{\sum_1^k W_i} \Rightarrow \bar{OR} = \exp(\log OR)$$

```
wi=1/(res$vi + res$tau2)
exp(sum(wi*res$yi)/sum(wi))
```

```
[1] 0.4830752
```

5.1.2 Other Estimators

The DerSimonian-Laird estimation is the most simple of all and is the default method in R, Stata and SAS. But there are seven other estimation methods :

- Hedges ('variance component estimator' or 'Cochran estimator') estimator
- Hunter-Schmidt estimator
- Sidik-Jonkman estimator
- maximum-likelihood estimator
- restricted maximum-likelihood estimator
- empirical Bayes estimator

```
$`DerSimonian-Laird`
```

```
Random-Effects Model (k = 16; tau^2 estimator: DL)
```

```
tau^2 (estimated amount of total heterogeneity): 0.224 (SE = 0.247)
```

```
tau (square root of estimated tau^2 value):      0.473
```

```
I^2 (total heterogeneity / total variability):   68.13%
```

```
H^2 (total variability / sampling variability):  3.14
```

```
Test for Heterogeneity:
```

```
Q(df = 15) = 47.059, p-val < .001
```

```
Model Results:
```

estimate	se	zval	pval	ci.lb	ci.ub	
-0.728	0.196	-3.706	<.001	-1.112	-0.343	***

```
---
```



5.1 Weight Calculation

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

\$Hedges

Random-Effects Model (k = 16; tau² estimator: HE)

tau² (estimated amount of total heterogeneity): 0 (SE = 0.406)

tau (square root of estimated tau² value): 0

I² (total heterogeneity / total variability): 0.00%

H² (total variability / sampling variability): 1.00

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub
0.015	0.031	0.484	0.629	-0.045	0.075

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

\$`Paule-Mandel`

Random-Effects Model (k = 16; tau² estimator: PM)

tau² (estimated amount of total heterogeneity): 0.177 (SE = 0.198)

tau (square root of estimated tau² value): 0.420

I² (total heterogeneity / total variability): 62.76%

H² (total variability / sampling variability): 2.69

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub	
-0.691	0.184	-3.756	<.001	-1.051	-0.330	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1



5.1 Weight Calculation

\$`Hunter-Schmid`

Random-Effects Model (k = 16; tau² estimator: HS)

tau² (estimated amount of total heterogeneity): 0.029 (SE = 0.007)
tau (square root of estimated tau² value): 0.170
I² (total heterogeneity / total variability): 21.63%
H² (total variability / sampling variability): 1.28

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub	
-0.373	0.112	-3.330	<.001	-0.593	-0.154	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

\$`Sidik-Jonkman`

Random-Effects Model (k = 16; tau² estimator: SJ)

tau² (estimated amount of total heterogeneity): 0.313 (SE = 0.162)
tau (square root of estimated tau² value): 0.560
I² (total heterogeneity / total variability): 74.95%
H² (total variability / sampling variability): 3.99

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub	
-0.776	0.216	-3.592	<.001	-1.200	-0.353	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

\$`Maximum Likelihood`

Random-Effects Model (k = 16; tau² estimator: ML)



5.1 Weight Calculation

```
tau^2 (estimated amount of total heterogeneity): 0.254 (SE = 0.193)
tau (square root of estimated tau^2 value):      0.504
I^2 (total heterogeneity / total variability):    70.80%
H^2 (total variability / sampling variability):    3.42
```

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub	
-0.746	0.203	-3.669	<.001	-1.145	-0.348	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

\$`Restricted Maximum Likelihood`

Random-Effects Model (k = 16; tau^2 estimator: REML)

```
tau^2 (estimated amount of total heterogeneity): 0.293 (SE = 0.229)
tau (square root of estimated tau^2 value):      0.541
I^2 (total heterogeneity / total variability):    73.64%
H^2 (total variability / sampling variability):    3.79
```

Test for Heterogeneity:

Q(df = 15) = 47.059, p-val < .001

Model Results:

estimate	se	zval	pval	ci.lb	ci.ub	
-0.767	0.212	-3.619	<.001	-1.182	-0.351	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

\$`Empirical Bayes`

Random-Effects Model (k = 16; tau^2 estimator: EB)

```
tau^2 (estimated amount of total heterogeneity): 0.177 (SE = 0.198)
tau (square root of estimated tau^2 value):      0.420
```



5.1 Weight Calculation

```
I^2 (total heterogeneity / total variability): 62.76%
H^2 (total variability / sampling variability): 2.69
```

```
Test for Heterogeneity:
Q(df = 15) = 47.059, p-val < .001
```

Model Results:

```
estimate      se      zval      pval      ci.lb      ci.ub
   -0.691    0.184   -3.756    <.001    -1.051    -0.330      ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Objects `res.DL` , `res.HE`, and `res.PM` include the results when using the Paule-Mandel, Cochran, and DerSimonian-Laird estimators (the Cochran estimator is referred to as the Hedges estimator in the metafor package). Next, we obtain the results using the empirical Bayes (`res.EB`) , maximum-likelihood (`res.ML`) and restricted maximum-likelihood estimators (`res.REML`) , the Hunter-Schmidt estimator (`res.HS`) , and the Sidik-Jonkman (`res.SJ`) estimator.

The next two models (`res.CA2` and `res.DL2`) use the generalized Q-statistic estimator of τ^2 (referred to as the general method-of-moments estimator in the paper), where the weights are set equal to the usual (random-effects model) inverse-variance weights, once using the Cochran and once using the DerSimonian-Laird estimator values. This will provide us with the two-step Cochran and two-step DerSimonian-Laird estimator values. However, note that the weights specified are used not only to estimate τ^2 but also to estimate μ the average effect. If we now want to use the usual inverse-variance weights but using the two-step estimator values, we have to fit each model one more time, but this time with specified values for τ^2 as obtained from the two-step procedure.

Finally, to obtain the improved Sidik-Jonkman estimator, we must use the control argument to set the initial estimate of τ^2 to that of the Cochran estimator, which then gets updated using the method described by Sidik and Jonkman.

	tau	mu	se
DL	0.4732	0.4831	0.1963
HE	0.0000	1.0149	0.0305
PM	0.4202	0.5012	0.1839
HS	0.1701	0.6885	0.1121
SJ	0.5598	0.4602	0.2161
ML	0.5040	0.4741	0.2034
REML	0.5410	0.4646	0.2118
EB	0.4202	0.5012	0.1839
SJ2	0.0000	1.0149	0.0305
CA2	0.4732	0.4831	0.1963



5.1 *Weight Calculation*

DL2 0.3983 0.5099 0.1786