

# Package: selectMeta (via r-universe)

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**Type** Package

**Title** Estimation of Weight Functions in Meta Analysis

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**Imports** graphics, stats

**Description** Publication bias, the fact that studies identified for inclusion in a meta analysis do not represent all studies on the topic of interest, is commonly recognized as a threat to the validity of the results of a meta analysis. One way to explicitly model publication bias is via selection models or weighted probability distributions. In this package we provide implementations of several parametric and nonparametric weight functions. The novelty in Rufibach (2011) is the proposal of a non-increasing variant of the nonparametric weight function of Dear & Begg (1992). The new approach potentially offers more insight in the selection process than other methods, but is more flexible than parametric approaches. To maximize the log-likelihood function proposed by Dear & Begg (1992) under a monotonicity constraint we use a differential evolution algorithm proposed by Ardia et al (2010a, b) and implemented in Mullen et al (2009). In addition, we offer a method to compute a confidence interval for the overall effect size  $\theta$ , adjusted for selection bias as well as a function that computes the simulation-based p-value to assess the null hypothesis of no selection as described in Rufibach (2011, Section 6).

**License** GPL (>= 2)

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selectMeta-package	<i>Estimation of Weight Functions in Meta Analysis</i>
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## Description

Publication bias, the fact that studies identified for inclusion in a meta analysis do not represent all studies on the topic of interest, is commonly recognized as a threat to the validity of the results of a meta analysis. One way to explicitly model publication bias is via selection models or weighted probability distributions. For details we refer to Iyengar & Greenhouse (1998), Dear & Begg (1992), and Rufibach (2011). In this package we provide implementations of all the weight functions proposed in these papers. The novelty in Rufibach (2011) is the proposal of a non-increasing variant of the nonparametric weight function of Dear & Begg (1992). Since virtually all parametric weight functions proposed so far in the literature are in fact decreasing and only few studies are included in a typical meta analysis regularization by imposing monotonicity seems a sensible approach. The new approach potentially offers more insight in the selection process than other methods, but is more flexible than parametric approaches. To maximize the log-likelihood function proposed by Dear & Begg (1992) under a monotonicity constraint on  $w$  we use a differential evolution algorithm proposed by Ardia et al (2010a, b) and implemented in Mullen et al (2009).

The main functions in this package are [IyenGreen](#) and [DearBegg](#). Using [DearBeggMonotoneCItheta](#) one can compute a profile likelihood confidence interval for the overall effect size  $\theta$  and using [DearBeggMonotonePvalSelection](#) the simulation-based  $p$ -value to assess the null hypothesis of no selection, as described in Rufibach (2011, Section 6), can be computed. In addition, we provide two datasets: [education](#), a dataset frequently used in illustration of meta analysis and [passive\\_smoking](#), a second dataset that has caused some controversy about whether publication bias is present in this dataset or not.

## Details

Package: selectMeta  
Type: Package  
Version: 1.0.8  
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License: GPL (>=2)

## Author(s)

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## References

- Ardia, D., Boudt, K., Carl, P., Mullen, K.M., Peterson, B.G. (2010). Differential Evolution ('DEoptim') for Non-Convex Portfolio Optimization.
- Ardia, D., Mullen, K.M., et.al. (2010). The 'DEoptim' Package: Differential Evolution Optimization in 'R'. Version 2.0-7.
- Dear, K.B.G. and Begg, C.B. (1992). An Approach for Assessing Publication Bias Prior to Performing a Meta-Analysis. *Statist. Sci.*, **7**(2), 237–245.
- Hedges, L. and Olkin, I. (1985). *Statistical Methods for Meta-Analysis*. Academic, Orlando, Florida.
- Iyengar, S. and Greenhouse, J.B. (1988). Selection models and the file drawer problem. *Statist. Sci.*, **3**, 109–135.
- Mullen, K.M., Ardia, D., Gil, D.L., Windover, D., Cline, J. (2009). 'DEoptim': An 'R' Package for Global Optimization by Differential Evolution.
- Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, **53**(4), 689–704.

## Examples

```
# All functions in this package are illustrated  
# in the help file for the function DearBegg().
```

---

DearBegg                      *Compute the nonparametric weight function from Dear and Begg (1992)*

---

### Description

In Dear and Begg (1992) it was proposed to nonparametrically estimate via maximum likelihood the weight function  $w$  in a selection model via pooling  $p$ -values in groups of 2 and assuming a piecewise constant  $w$ . The function [DearBegg](#) implements estimation of  $w$  via a coordinate-wise Newton-Raphson algorithm as described in Dear and Begg (1992). In addition, the function [DearBeggMonotone](#) enables computation of the weight function in the same model under the constraint that it is non-increasing, see Rufibach (2011). To this end we use the differential evolution algorithm described in Ardia et al (2010a, b) and implemented in Mullen et al (2009). The functions [Hij](#), [DearBeggLoglik](#), and [DearBeggToMinimize](#) are not intended to be called by the user.

### Usage

```
DearBegg(y, u, lam = 2, tolerance = 10^-10, maxiter = 1000,
         trace = TRUE)
DearBeggMonotone(y, u, lam = 2, maxiter = 1000, CR = 0.9,
                 NP = NA, trace = TRUE)
Hij(theta, sigma, y, u, teststat)
DearBeggLoglik(w, theta, sigma, y, u, hij, lam)
DearBeggToMinimize(vec, y, u, lam)
```

### Arguments

<code>y</code>	Normally distributed effect sizes.
<code>u</code>	Associated standard errors.
<code>lam</code>	Weight of the first entry of $w$ in the likelihood function. Dear and Begg (1992) recommend to use $\text{lam} = 2$ .
<code>tolerance</code>	Stopping criterion for Newton-Raphson.
<code>maxiter</code>	Maximal number of iterations for Newton-Raphson.
<code>trace</code>	If TRUE, progress of the algorithm is shown.
<code>CR</code>	Parameter that is given to <code>DEoptim</code> . See the help file of the function <code>DEoptim.control</code> for details.
<code>NP</code>	Parameter that is given to <code>DEoptim</code> . See the help file of the function <code>DEoptim.control</code> for details.
<code>w</code>	Weight function, parametrized as vector of length $1 + \lfloor (n/2) \rfloor$ where $n$ is the number of studies, i.e. the length of $y$ .
<code>theta</code>	Effect size estimate.
<code>sigma</code>	Random effects variance component.
<code>hij</code>	Integral of density over a constant piece of $w$ . See Rufibach (2011, Appendix) for details.

vec                    Vector of parameters over which we maximize.  
 teststat            Vector of test statistics, equals  $|y|/u$ .

### Value

A list consisting of the following elements:

w                    Vector of estimated weights.  
 theta                Estimate of the combined effect in the Dear and Begg model.  
 sigma                Estimate of the random effects component variance.  
 p                     $p$ -values computed from the inputted test statistics, ordered in decreasing order.  
 y                    Effect sizes, ordered in decreasing order of  $p$ -values.  
 u                    Standard errors, ordered in decreasing order of  $p$ -values.  
 loglik              Value of the log-likelihood at the maximum.  
 DEoptim.res        Only available in [DearBeggMonotone](#). Provides the object that is outputted by [DEoptim](#).

### Author(s)

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### References

Ardia, D., Boudt, K., Carl, P., Mullen, K.M., Peterson, B.G. (2010). Differential Evolution ('DEoptim') for Non-Convex Portfolio Optimization.

Ardia, D., Mullen, K.M., et.al. (2010). The 'DEoptim' Package: Differential Evolution Optimization in 'R'. Version 2.0-7.

Dear, K.B.G. and Begg, C.B. (1992). An Approach for Assessing Publication Bias Prior to Performing a Meta-Analysis. *Statist. Sci.*, **7**(2), 237–245.

Mullen, K.M., Ardia, D., Gil, D.L., Windover, D., Cline, J. (2009). 'DEoptim': An 'R' Package for Global Optimization by Differential Evolution.

Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, **53**(4), 689–704.

### See Also

[Iyengreen](#) for a parametric selection model.

### Examples

```
## Not run:
##-----
## Analysis of Hedges & Olkin dataset
## re-analyzed in Iyengar & Greenhouse, Dear & Begg
##-----
data(education)
```

```

t <- education$t
q <- education$q
N <- education$N
y <- education$theta
u <- sqrt(2 / N)
n <- length(y)
k <- 1 + floor(n / 2)
lam1 <- 2

## compute p-values
p <- 2 * pnorm(-abs(t))

##-----
## compute all weight functions available
## in this package
##-----

## weight functions from Iyengar & Greenhouse (1988)
res1 <- IyenGreenMLE(t, q, N, type = 1)
res2 <- IyenGreenMLE(t, q, N, type = 2)

## weight function from Dear & Begg (1992)
res3 <- DearBegg(y, u, lam = lam1)

## monotone version of Dear & Begg, as introduced in Rufibach (2011)
set.seed(1977)
res4 <- DearBeggMonotone(y, u, lam = lam1, maxiter = 1000, CR = 1)

## plot
plot(0, 0, type = "n", xlim = c(0, 1), ylim = c(0, 1), xlab = "p-values",
     ylab = "estimated weight function")
ps <- seq(0, 1, by = 0.01)
rug(p, lwd = 3)
lines(ps, IyenGreenWeight(-qnorm(ps / 2), b = res1$beta, q = 50,
                          type = 1, alpha = 0.05), lwd = 3, col = 2)
lines(ps, IyenGreenWeight(-qnorm(ps / 2), b = res2$beta, q = 50,
                          type = 2, alpha = 0.05), lwd = 3, col = 4)
weightLine(p, w = res3$w, col0 = 3, lwd0 = 3, lty0 = 2)
weightLine(p, w = res4$w, col0 = 6, lwd0 = 2, lty0 = 1)

legend("topright", c(expression("Iyengar & Greenhouse (1988) w"[1]),
                     expression("Iyengar & Greenhouse (1988) w"[2]), "Dear and Begg (1992)",
                     "Rufibach (2011)"), col = c(2, 4, 3, 6), lty = c(1, 1, 2, 1),
      lwd = c(3, 3, 3, 2), bty = "n")

## compute selection bias
eta <- sqrt(res4$sigma ^ 2 + res4$u ^ 2)
bias <- effectBias(res4$y, res4$u, res4$w, res4$theta, eta)
bias

##-----

```

```

## Compute p-value to assess null hypothesis of no selection,
## as described in Rufibach (2011, Section 6)
## We use the package 'meta' to compute initial estimates for
## theta and sigma
##-----
library(meta)

## compute null parameters
meta.edu <- metagen(TE = y, seTE = u, sm = "MD", level = 0.95,
  comb.fixed = TRUE, comb.random = TRUE)
theta0 <- meta.edu$TE.random
sigma0 <- meta.edu$tau

M <- 1000
res <- DearBeggMonotonePvalSelection(y, u, theta0, sigma0, lam = lam1,
  M = M, maxiter = 1000)

## plot all the computed monotone functions
plot(0, 0, xlim = c(0, 1), ylim = c(0, 1), type = "n", xlab = "p-values",
  ylab = expression(w(p)))
abline(v = 0.05, lty = 3)
for (i in 1:M){weightLine(p, w = res$res.mono[1:k, i], col0 = grey(0.8),
  lwd0 = 1, lty0 = 1)}
rug(p, lwd = 2)
weightLine(p, w = res$mono0, col0 = 2, lwd0 = 1, lty0 = 1)

## =====

##-----
## Analysis second-hand tobacco smoke dataset
## Rothstein et al (2005), Publication Bias in Meta-Analysis, Appendix A
##-----
data(passive_smoking)
u <- passive_smoking$selnRR
y <- passive_smoking$lnRR
n <- length(y)
k <- 1 + floor(n / 2)
lam1 <- 2

res2 <- DearBegg(y, u, lam = lam1)
set.seed(1)
res3 <- DearBeggMonotone(y = y, u = u, lam = lam1, maxiter = 2000, CR = 1)

plot(0, 0, type = "n", xlim = c(0, 1), ylim = c(0, 1), pch = 19, col = 1,
  xlab = "p-values", ylab = "estimated weight function")
weightLine(sort(res2$p), w = res2$w, col0 = 2, lwd0 = 3, lty0 = 2)
weightLine(rev(sort(res3$p)), w = res3$w, col0 = 4, lwd0 = 2, lty0 = 1)

legend("bottomright", c("Dear and Begg (1992)", "Rufibach (2011)"), col =
  c(2, 4), lty = c(2, 1), lwd = c(3, 2), bty = "n")

```

```

## compute selection bias
eta <- sqrt(res3$sigma ^ 2 + res3$u ^ 2)
bias <- effectBias(res3$y, res3$u, res3$w, res3$theta, eta)
bias

##-----
## Compute p-value to assess null hypothesis of no selection
##-----
## compute null parameters
meta.toba <- metagen(TE = y, seTE = u, sm = "MD", level = 0.95,
  comb.fixed = TRUE, comb.random = TRUE)
theta0 <- meta.toba$TE.random
sigma0 <- meta.toba$tau

M <- 1000
res <- DearBeggMonotonePvalSelection(y, u, theta0, sigma0, lam = lam1,
  M = M, maxiter = 2000)

## plot all the computed monotone functions
plot(0, 0, xlim = c(0, 1), ylim = c(0, 1), type = "n", xlab = "p-values",
  ylab = expression(w(p)))
abline(v = 0.05, lty = 3)
for (i in 1:M){weightLine(p, w = res$res.mono[1:k, i], col0 = grey(0.8),
  lwd0 = 1, lty0 = 1)}
rug(p, lwd = 2)
weightLine(p, w = res$mono0, col0 = 2, lwd0 = 1, lty0 = 1)

## End(Not run)

```

---

DearBeggMonotoneCItheta

*Compute an approximate profile likelihood ratio confidence interval  
for effect estimate*

---

## Description

Under some assumptions on the true underlying  $p$ -value density the usual likelihood ratio theory for the finite-dimensional parameter of interest,  $\theta$ , holds although we estimate the infinite-dimensional nuisance parameter  $w$ , see Murphy and van der Vaart (2000). These functions implement such a confidence interval. To this end we compute the set

$$\{\theta : \tilde{l}(\theta, \hat{\sigma}(\theta), \hat{w}(\theta)) \geq c\}$$

where  $c = -0.5 \cdot \chi_{1-\alpha}^2(1)$  and  $\tilde{l}$  is the relative profile log-likelihood function.

The functions [DearBeggProfileLL](#) and [DearBeggToMinimizeProfile](#) are not intended to be called by the user directly.



**Usage**

```
DearBeggMonotoneCItheta(res, lam = 2, conf.level = 0.95, maxiter = 500)
DearBeggProfileLL(z, res0, lam, conf.level = 0.95, maxiter = 500)
DearBeggToMinimizeProfile(vec, theta, y, u, lam)
```

**Arguments**

res	Output from function <a href="#">DearBeggMonotone</a> .
lam	Weight of the first entry of $w$ in the likelihood function. Should be the same as used to generate res.
conf.level	Confidence level of confidence interval.
maxiter	Maximum number of iterations of differential evolution algorithm used in computation of confidence limits. Increase this number to get higher accuracy.
z	Variable to maximize over, corresponds to $\theta$ .
res0	Output from <a href="#">DearBeggMonotone</a> , contains initial estimates.
vec	Vector of parameters over which we maximize.
theta	Current $\theta$ .
y	Normally distributed effect sizes.
u	Associated standard errors.

**Value**

A list with the element

`ci.theta` that contains the profile likelihood confidence interval for  $\theta$ .

**Note**

Since we have to numerically find zeros of a suitable function, via [uniroot](#), to get the limits and each iteration involves computation of  $w(\theta)$  via a variant of [DearBeggMonotone](#), computation of a confidence interval may take some time (typically seconds to minutes).

**Author(s)**

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**References**

Murphy, S. and van der Vaart, A. (2000). On profile likelihood. *J. Amer. Statist. Assoc.*, **95**, 449–485.

Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, **53**(4), 689–704.

**See Also**

The estimate under a monotone selection function can be computed using [DearBeggMonotone](#).

**Examples**

```

## Not run:
## compute confidence interval for theta in the education dataset
data(education)
N <- education$N
y <- education$theta
u <- sqrt(2 / N)
lam1 <- 2
res.edu <- DearBeggMonotone(y, u, lam = lam1, maxiter = 1000,
  CR = 1, trace = FALSE)
r1 <- DearBeggMonotoneCItheta(res.edu, lam = 2, conf.level = 0.95)
res.edu$theta
r1$ci.theta

## compute confidence interval for theta in the passive smoking dataset
data(passive_smoking)
u <- passive_smoking$selnRR
y <- passive_smoking$lnRR
lam1 <- 2
res.toba <- DearBeggMonotone(y, u, lam = lam1, maxiter = 1000,
  CR = 1, trace = FALSE)
r2 <- DearBeggMonotoneCItheta(res.toba, lam = 2, conf.level = 0.95)
res.toba$theta
r2$ci.theta

## End(Not run)

```

---

DearBeggMonotonePvalSelection

*Compute simulation-based p-value to assess null hypothesis of no selection*

---

**Description**

This function computes a simulation-based  $p$ -value to assess the null hypothesis of no selection. For details we refer to Rufibach (2011, Section 6).

**Usage**

```

DearBeggMonotonePvalSelection(y, u, theta0, sigma0, lam = 2, M = 1000,
  maxiter = 1000, test.stat = function(x){return(min(x))})

```

**Arguments**

<code>y</code>	Normally distributed effect sizes.
<code>u</code>	Associated standard errors.
<code>theta0</code>	Initial estimate for $\theta$ .
<code>sigma0</code>	Initial estimate for $\sigma$ .

<code>lam</code>	Weight of the first entry of $w$ in the likelihood function. Should be the same as used to generate <code>res</code> .
<code>M</code>	Number of runs to compute $p$ -value.
<code>maxiter</code>	Maximum number of iterations of differential evolution algorithm. Increase this number to get higher accuracy.
<code>test.stat</code>	A function that takes as argument a vector and returns a number. Defines the test statistic to be used on the estimated selection function $w$ .

**Value**

<code>pval</code>	The computed $p$ -value.
<code>res.mono</code>	The monotone estimates for each simulation run.
<code>mono0</code>	The monotone estimates for the original data.
<code>Ti</code>	The test statistics for each simulation run.
<code>T0</code>	The test statistic for the original data.
<code>ran.num</code>	Matrix that contains the generated $p$ -values.

**Author(s)**

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**References**

Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, 53(4), 689–704.

**See Also**

This function is illustrated in the help file for [DearBegg](#).

---

education

*Dataset open vs. traditional education on creativity*

---

**Description**

Dataset of studies of effect of open vs. traditional education on creativity. Standard dataset to illustrate selection models in meta-analysis.

**Usage**

`data(education)`

**Format**

A data frame with 10 observations on the following 5 variables.

i Study number.

N Sample size of study.

theta Estimated effect size.

t  $t$  test statistic,  $t = \theta / \sqrt{2/N}$ .

q Defrees of freedom,  $q = 2N - 2$ .

**References**

Dear, Keith B.G. and Begg, Colin B. (1992). An Approach for Assessing Publication Bias Prior to Performing a Meta-Analysis. *Statist. Sci.*, **7(2)**, 237–245.

Hedges, L. and Olkin, I. (1985). *Statistical Methods for Meta-Analysis*. Academic, Orlando, Florida.

Iyengar, S. and Greenhouse, J.B. (1988). Selection models and the file drawer problem (including rejoinder). *Statist. Sci.*, **3**, 109–135.

**See Also**

This dataset is analyzed in the help file for [DearBegg](#).

---

effectBias

*Compute bias for each effect size based on estimated weight function*

---

**Description**

Based on the estimated weight function an explicit formula for the bias of each initial effect estimate can be derived, see Rufibach (2011). This function implements computation of this bias and is called by [DearBegg](#) and [DearBeggMonotone](#).

**Usage**

```
effectBias(y, u, w, theta, eta)
```

**Arguments**

y	Normally distributed effect sizes.
u	Associated standard errors.
w	Vector of estimated weights as computed by either <a href="#">DearBegg</a> or <a href="#">DearBeggMonotone</a> .
theta	Effect size estimate.
eta	Standard error of effect size estimate.

**Value**

A list consisting of the following elements:

`dat` Matrix with columns  $y$ ,  $u$ ,  $y$ ,  $p$ ,  $\text{bias}$ ,  $y - \text{bias}$ ,  $\text{bias} / y$ , where the rows are provided in decreasing order of  $p$ -values.

**Author(s)**

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**References**

Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, **53**(4), 689–704.

**Examples**

```
# For an illustration see the help file for the function DearBegg().
```

---

IyenGreen	<i>Compute MLE and weight functions of Iyengar and Greenhouse (1988)</i>
-----------	--

---

**Description**

Two parametric weight functions for selection models were introduced in Iyengar and Greenhouse (1988):

$$w_1(x; \beta, q) = |x|^\beta / t(q, \alpha)$$

$$w_2(x; \gamma, q) = e^{-\gamma}$$

if  $|x| \leq t(q, \alpha)$  and  $w_1(x; \beta, q) = w_2(x; \gamma, q) = 1$  otherwise. Here,  $t(q, \alpha)$  is the  $\alpha$ -quantile of a  $t$  distribution with  $q$  degrees of freedom. The functions  $w_1$  and  $w_2$  are used to model the selection process that may be present in a meta analysis, in a model where effect sizes are assumed to follow a  $t$  distribution. We have implemented estimation of the parameters in this model in `IyenGreenMLE` and plotting in `IyenGreenWeight`. The functions `normalizeT` and `IyenGreenLoglikT` are used in computation of ML estimators and not intended to be called by the user. For an example how to use `IyenGreenMLE` and `IyenGreenWeight` we refer to the help file for `DearBegg`.

**Usage**

```
normalizeT(s, theta, b, q, N, type = 1, alpha = 0.05)
IyenGreenLoglikT(para, t, q, N, type = 1)
IyenGreenMLE(t, q, N, type = 1, alpha = 0.05)
IyenGreenWeight(x, b, q, type = 1, alpha = 0.05)
```

**Arguments**

s	Quantile where normalizing integrand should be computed.
theta	Vector containing effect size estimates of the meta analysis.
b	Parameter that governs shape of the weight function. Equals $\beta$ for $w_1$ and $\gamma$ for $w_2$ .
q	Degrees of freedom in the denominator of $w_1, w_2$ . Must be a real number.
N	Number of observations in each trial.
type	Type of weight function in Iyengar & Greenhouse (1988). Either 1 (for $w_1$ ) or 2 (for $w_2$ ).
alpha	Quantile to be used in the denominator of $w_1, w_2$ .
para	Vector in $R^2$ over which log-likelihood function is maximized.
t	Vector of real numbers, $t$ test statistics.
x	Vector of real numbers where weight function should be computed at.

**Details**

Note that these weight functions operate on the scale of  $t$  statistics, not  $p$ -values.

**Value**

See example in [DearBegg](#) for details.

**Author(s)**

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**References**

Iyengar, S. and Greenhouse, J.B. (1988). Selection models and the file drawer problem (including rejoinder). *Statist. Sci.*, **3**, 109–135.

**See Also**

For nonparametric estimation of weight functions see [DearBegg](#).

**Examples**

```
# For an illustration see the help file for the function DearBegg().
```

---

passive_smoking	<i>Dataset on the effect of environmental tobacco smoke</i>
-----------------	---

---

**Description**

Effect of environmental tobacco smoke on lung-cancer in lifetime non-smokers.

**Usage**

```
data(passive_smoking)
```

**Format**

A data frame with 37 observations on the following 2 variables.

lnRR Log-relative risk.

selnRR Standard error of log-relative risk.

**Details**

The sample consists of lung cancer patients and controls that were lifelong non-smokers. The effect of interest is measured by the relative risk of lung cancer according to whether the spouse currently smoked or had never smoked.

**References**

Hackshaw, A. K., Law, M. R., and Wald, N.J. The accumulated evidence on lung cancer and environmental tobacco smoke. *BMJ*, **315**, 980–988.

**See Also**

This dataset is analyzed in the help file for [DearBegg](#).

---

pPool	<i>Pool p-values in pairs</i>
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**Description**

To avoid unidentifiability in estimation of a selection function, Dear and Begg (1992) pool  $p$ -values in pairs.

**Usage**

```
pPool(p)
```

**Arguments**

p                      Vector of  $p$ -values.

**Value**

Vector of pooled  $p$ -values.

**Author(s)**

Kaspar Rufibach (maintainer), <kaspar.rufibach@gmail.com>, <http://www.kasparrufibach.ch>

**References**

Dear, K.B.G. and Begg, C.B. (1992). An Approach for Assessing Publication Bias Prior to Performing a Meta-Analysis. *Statist. Sci.*, **7**(2), 237–245.

Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, **53**(4), 689–704.

**See Also**

This function is used in [weightLine](#).

**Examples**

```
# This function is used in the help file for the function DearBegg().
```

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Pval

*Functions for the distribution of  $p$ -values*

---

**Description**

The density of the  $p$ -value generated by a test of the hypothesis

$$H_0 : Y \sim N(0, \sigma^2) \text{ vs. } H_1 : Y \sim N(\theta, \eta^2)$$

has the form

$$f(p; \theta, \sigma, \eta) = \frac{\sigma}{2\eta} \frac{\phi\left(\frac{-\sigma\Phi^{-1}(p/2) - \theta}{\eta}\right) + \phi\left(\frac{\sigma\Phi^{-1}(p/2) - \theta}{\eta}\right)}{\phi(\Phi^{-1}(p/2))}$$

where  $\eta^2 = u^2 + \sigma^2$ . We refer to Rufibach (2011) for details.



**Usage**

```
dPval(p, u, theta, sigma2)
pPval(q, u, theta, sigma2)
qPval(prob, u, theta, sigma2)
rPval(n, u, theta, sigma2, seed = 1)
```

**Arguments**

p, q	Quantile.
prob	Probability.
u	Standard error of the effect size.
theta	Effect size.
sigma2	Random effect variance component.
n	Number of random numbers to be generated.
seed	Seed to set.

**Value**

dPval gives the density, pPval gives the distribution function, qPval gives the quantile function, and rPval generates random deviates for the density  $f(p; \theta, \sigma, \eta)$ .

**Author(s)**

Kaspar Rufibach (maintainer), <kaspar.rufibach@gmail.com>, <http://www.kasparrufibach.ch>

**References**

Dear, K.B.G. and Begg, C.B. (1992). An Approach for Assessing Publication Bias Prior to Performing a Meta-Analysis. *Statist. Sci.*, **7**(2), 237–245.

Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, **53**(4), 689–704.

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weightLine

*Function to plot estimated weight functions*


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**Description**

This function facilitates plotting of estimated weight functions according to the method in Dear and Begg (1992) or its non-increasing version described in Rufibach (2010).

**Usage**

```
weightLine(p, w, col0, lwd0, lty0 = 1, type = c("pval", "empirical")[1])
```

**Arguments**

p	Vector of $p$ -values.
w	Vector of estimated weights, as outputted by <a href="#">DearBegg</a> or <a href="#">DearBeggMonotone</a> .
col0	Color of line that is drawn.
lwd0	Line width.
lty0	Line type.
type	Should weights be drawn versus original $p$ -values ( <code>type == "pval"</code> ) or versus the empirical distribution of the $p$ -values ( <code>type == "empirical"</code> ).

**Author(s)**

Kaspar Rufibach (maintainer), <[kaspar.rufibach@gmail.com](mailto:kaspar.rufibach@gmail.com)>, <http://www.kasparrufibach.ch>

**References**

- Dear, K.B.G. and Begg, C.B. (1992). An Approach for Assessing Publication Bias Prior to Performing a Meta-Analysis. *Statist. Sci.*, **7(2)**, 237–245.
- Rufibach, K. (2011). Selection Models with Monotone Weight Functions in Meta-Analysis. *Biom. J.*, **53(4)**, 689–704.

**See Also**

This function is used in [weightLine](#).

**Examples**

```
# This function is used in the help file for the function DearBegg().
```

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