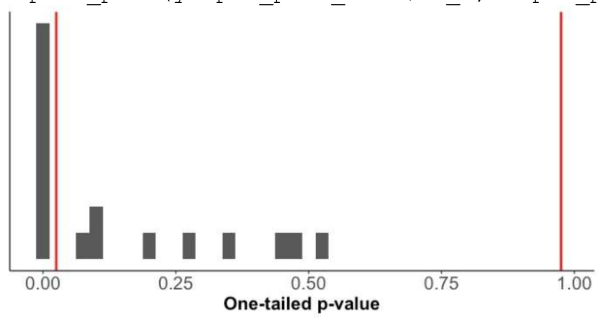
```
> ####################################
> ##### PUBLICATION BIAS TEST ########
> ####################################

> library(PublicationBias) # interpretation tutorial link: https://cran.r-project.org/web/packages/multibiasmeta/vignettes/tutorial.html#significance-funnel-plot

> #set working directory
> setwd("/Users/jspaan/Desktop/puniform_publication_Bias")

> ####################################
> ######### Dataset: 2-arm ###########
> ####################################

> #Pre-post (2-arm)
> pre_post_data = read.csv("Data_for_CMA_import_Pre_Post.csv")

> head(pre_post_data)
   Study_Name   ES_d     LL    UL Sampl_.size   CI Variance Effect_Direction
1      Damiao  0.100 -0.231 0.430          70 0.95    0.027        Postitive
2  Danilewitz  0.336 -0.520 1.191          13 0.95    0.154        Postitive
3      Erogul  0.610  0.088 1.133          29 0.95    0.065        Postitive
4 Finkelstein  0.027 -0.522 0.576          26 0.95    0.071        Postitive
5        Keng  0.448  0.101 0.795          77 0.95    0.030        Postitive
6     Kraemer -0.011 -0.556 0.534          28 0.95    0.071         Negative
  Home_practice M_E Yoga
1      Practice   E   No
2      Practice   E Yoga
3      Practice   M Yoga
4      Practice   E   No
5      Practice   E   No
6      Practice   E   No

> str(pre_post_data)
'data.frame':18 obs. of  11 variables:
 $ Study_Name      : chr  "Damiao" "Danilewitz" "Erogul" "Finkelstein" ...
 $ ES_d            : num  0.1 0.336 0.61 0.027 0.448 -0.011 0.013 0.611 0.442 0.863
...
 $ LL              : num  -0.231 -0.52 0.088 -0.522 0.101 -0.556 -0.39 0.139 0.11
0.324 ...
 $ UL              : num  0.43 1.191 1.133 0.576 0.795 ...
 $ Sampl_.size     : int  70 13 29 26 77 28 35 21 68 30 ...
 $ CI              : num  0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 ...
 $ Variance        : num  0.027 0.154 0.065 0.071 0.03 0.071 0.039 0.051 0.028 0.069
...
 $ Effect_Direction: chr  "Postitive" "Postitive" "Postitive" "Postitive" ...
 $ Home_practice   : chr  "Practice" "Practice" "Practice" "Practice" ...
 $ M_E             : chr  "E" "E" "M" "E" ...
 $ Yoga            : chr  "No" "Yoga" "Yoga" "No" ...

> #publication bias results depends on the selection ratio
> #"selection_ratio = 1" says there is no publication bias;
> #"selection_ratio = 5" says affirmative results are 5x more likely to be published
than nonaffirmative ones
> #Ratios to use based on your results:
> #For the 2-group studies: 9/18 have positive and sig results
> #(7 have positive non-sig results and 2 have negative non-sig results)
> #Thus --> use a selection_ratio = 1 (9 affirmative and 9 non-affirmative)
> #For the 1-group studies: 12/18 have positive sig results
> #(4 have positive non-sig results and 2 have negative sig results)
> #Thus --> use a selection_ratio = 1.5
> #"selection_ratio = 1" says there is no publication bias;
```

```
> #"selection_ratio = 5" says affirmative results are 5x more likely to be published than nonaffirmative ones
> #Ratios to use based on your results:
> #For the 2-group studies: 9/18 have positive and sig results
> #(7 have positive non-sig results and 2 have negative non-sig results)
> #Thus --> use a selection_ratio = 1 (9 affirmative and 9 non-affirmative)
> #For the 1-group studies: 12/18 have positive sig results
> #(4 have positive non-sig results and 2 have negative sig results)
> #Thus --> use a selection_ratio = 1.5

> ########
> pval_plot(yi=pre_post_data$ES_d,vi=pre_post_data$Variance,alpha_select = 0.05)
```



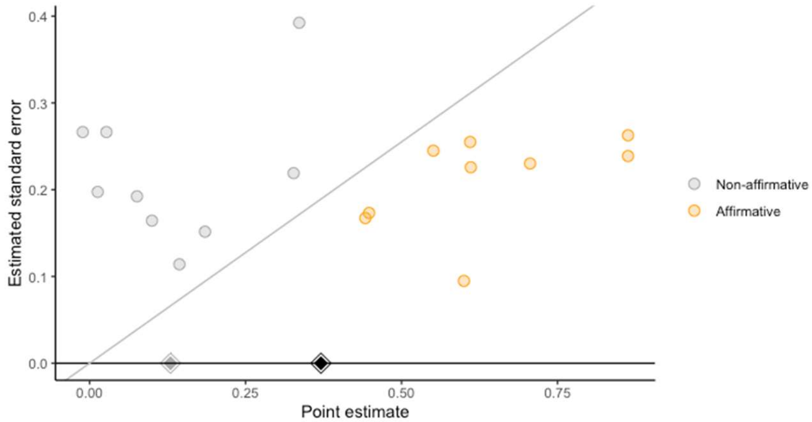

```
> # none of the values falls outside of 1 - thus no need to run a two-tailed p-value
> # selection ratio = 1

> a1<-
pubbias_meta(yi=pre_post_data$ES_d,vi=pre_post_data$Variance,selection_ratio=1,alpha_select=0.05,ci_level=0.95,favor_positive = TRUE,return_worst_meta = TRUE)
> a1
$data
# A tibble: 18 × 5
       yi    yif    vi affirm cluster
    <dbl>  <dbl> <dbl> <lgl>    <int>
 1  0.1    0.1   0.027 FALSE        1
 2  0.336  0.336 0.154 FALSE        2
 3  0.61   0.61  0.065 TRUE         3
 4  0.027  0.027 0.071 FALSE        4
 5  0.448  0.448 0.03  TRUE         5
 6 -0.011 -0.011 0.071 FALSE        6
 7  0.013  0.013 0.039 FALSE        7
 8  0.611  0.611 0.051 TRUE         8
 9  0.442  0.442 0.028 TRUE         9
10  0.863  0.863 0.069 TRUE        10
11  0.706  0.706 0.053 TRUE        11
12  0.144  0.144 0.013 FALSE       12
13  0.6    0.6   0.009 TRUE        13
14  0.863  0.863 0.057 TRUE        14
15  0.185  0.185 0.023 FALSE       15
16  0.076  0.076 0.037 FALSE       16
17  0.551  0.551 0.06  TRUE        17
18  0.327  0.327 0.048 FALSE       18

$values
$values$selection_ratio
[1] 1

$values$selection_tails
[1] 1

$values$model_type
[1] "robust"
```

```
$values$favor_positive
[1] TRUE

$values$alpha_select
[1] 0.05

$values$ci_level
[1] 0.95

$values$small
[1] TRUE

$values$k
[1] 18

$values$k_affirmative
[1] 9

$values$k_nonaffirmative
[1] 9


$stats
       model  estimate         se   ci_lower  ci_upper      p_value
1    pubbias 0.3699240 0.06543339 0.22832426 0.5115237 8.392018e-05
2 worst_case 0.1264667 0.03363022 0.04462594 0.2083074 9.004011e-03
```

→ This independent robust-effects meta-analysis indicates that if there are no publication bias between affirmative (i.e., significant and positive) and non-affirmative (i.e., nonsignificant or negative) studies (selection ratio = 1), the meta-analytic point estimate corrected for publication bias would be 0.37 (95% CI [0.23, 0.51]).
→ If there were worst-case publication bias (i.e., that favors affirmative results infinitely more than non-affirmative results), the corrected meta-analytic point estimate would be 0.13 (95% CI [0.04, 0.21]).

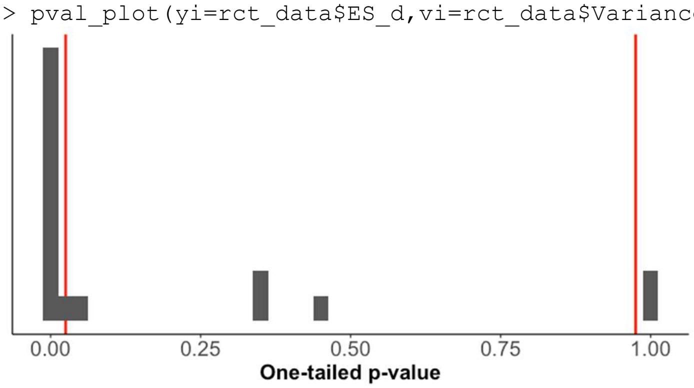
```
$fits
$fits$robust
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 18
Number of outcomes = 18 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value  dfs   P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.     0.37 0.0654    5.65 12.8 0.0000839    0.228    0.512 ***
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results
$fits$meta_worst
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 9
Number of outcomes = 9 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value  dfs P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.    0.126 0.0336    3.76 6.14   0.009   0.0446    0.208 ***
---
```

```
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results

attr(,"class")
[1] "metabias" "list"
> #
> significance_funnel(yi=pre_post_data$ES_d,vi=pre_post_data$Variance,favor_positive =
TRUE)
```



→The significance funnel plot is a visual supplement to the proposed sensitivity analyses above. This plot distinguishes between affirmative and non-affirmative studies, helping to detect the extent to which the non-affirmative studies' point estimates are systematically smaller than the entire set of point estimates. The estimate among only non-affirmative studies (gray diamond) represents a corrected estimate under worst-case publication bias. If the gray diamond represents a negligible effect size or if it is much smaller than the pooled estimate among all studies (black diamond), this suggests that the meta-analysis may not be robust to extreme publication bias.

```
> ####################################
> ######### Dataset: 1-arm ###########
> ####################################

> #RCT (1-arm data)
> rct_data = read.csv("Data_for_CMA_import_RCT.csv")
> head(rct_data)
   Study_Name   ES_d     LL     UL Sampl_.size   CI Variance Effect_Direction
1      Bansal  0.338  0.115  0.560          82 0.95    0.013         Positive
2        Bond  0.081 -0.320  0.481          24 0.95    0.042         Positive
3       Bughi  0.414  0.213  0.614         104 0.95    0.010         Positive
4 Dyrbye 2014 -0.759 -0.206 -0.438          48 0.95    0.027         Negative
5 Dyrbye 2015 -0.510 -0.814 -0.206          47 0.95    0.024         Negative
6     Garneau  0.301  0.038  0.564          58 0.95    0.018         Positive
> str(rct_data)
'data.frame':18 obs. of  8 variables:
 $ Study_Name      : chr  "Bansal" "Bond" "Bughi" "Dyrbye 2014" ...
 $ ES_d            : num  0.338 0.081 0.414 -0.759 -0.51 ...
 $ LL              : num  0.115 -0.32 0.213 -0.206 -0.814 0.038 0.805 0.023 0.133 -
0.698 ...
 $ UL              : num  0.56 0.481 0.614 -0.438 -0.206 ...
 $ Sampl_.size     : int  82 24 104 48 47 58 44 239 205 5 ...
 $ CI              : num  0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 ...
 $ Variance        : num  0.013 0.042 0.01 0.027 0.024 0.018 0.039 0.004 0.005 0.203
...
 $ Effect_Direction: chr  "Positive" "Positive" "Positive" "Negative" ...
> pval_plot(yi=rct_data$ES_d,vi=rct_data$Variance,alpha_select = 0.05)
```

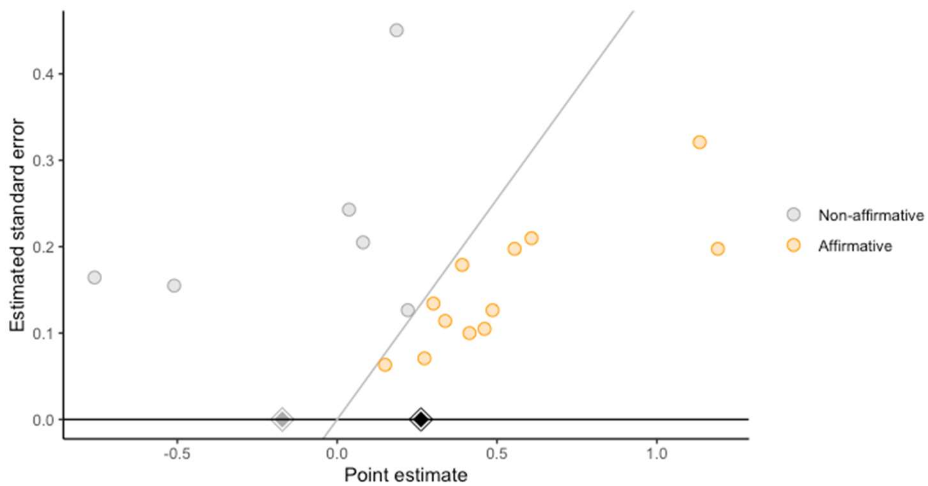



```
# some of the values falls outside of 1 - thus include a two-tailed p-value
# selection_tail=2

> b1<-
pubbias_meta(yi=rct_data$ES_d,vi=rct_data$Variance,selection_ratio=1.5,favor_positive
= TRUE,selection_tails = 2,alpha_select=0.05,ci_level=0.95,return_worst_meta = TRUE)
> b1
$data
# A tibble: 18 × 5
       yi    yif    vi affirm cluster
    <dbl>  <dbl> <dbl> <lgl>    <int>
 1  0.338  0.338 0.013 TRUE         1
 2  0.081  0.081 0.042 FALSE        2
 3  0.414  0.414 0.01  TRUE         3
 4 -0.759 -0.759 0.027 TRUE         4
```

```
 5 -0.51   -0.51   0.024 TRUE          5
 6  0.301   0.301 0.018 TRUE          6
 7  1.19    1.19  0.039 TRUE          7
 8  0.15    0.15  0.004 TRUE          8
 9  0.273   0.273 0.005 TRUE          9
10  0.186   0.186 0.203 FALSE        10
11  0.391   0.391 0.032 TRUE         11
12  0.486   0.486 0.016 TRUE         12
13  0.221   0.221 0.016 FALSE        13
14  0.608   0.608 0.044 TRUE         14
15  1.13    1.13  0.103 TRUE         15
16  0.555   0.555 0.039 TRUE         16
17  0.037   0.037 0.059 FALSE        17
18  0.461   0.461 0.011 TRUE         18

$values
$values$selection_ratio
[1] 1.5

$values$selection_tails
[1] 2

$values$model_type
[1] "robust"

$values$favor_positive
[1] TRUE

$values$alpha_select
[1] 0.05

$values$ci_level
[1] 0.95

$values$small
[1] TRUE

$values$k
[1] 18

$values$k_affirmative
[1] 14

$values$k_nonaffirmative
[1] 4


$stats
       model  estimate         se    ci_lower  ci_upper    p_value
1    pubbias 0.2817657 0.09708062  0.07432416 0.4892072 0.01119945
2 worst_case 0.1301404 0.04229338 -0.01330523 0.2735860 0.06228379
```

→ This independent robust-effects meta-analysis indicates that if there are no publication bias between affirmative (i.e., significant and positive) and non-affirmative (i.e., nonsignificant or negative) studies (selection ratio = 1.5), the meta-analytic point estimate corrected for publication bias would be 0.28 (95% CI [0.07, 0.49]).
→ If there were worst-case publication bias (i.e., that favors affirmative results infinitely more than non-affirmative results), the corrected meta-analytic point estimate would be 0.13 (95% CI [-0.01, 0.27]).

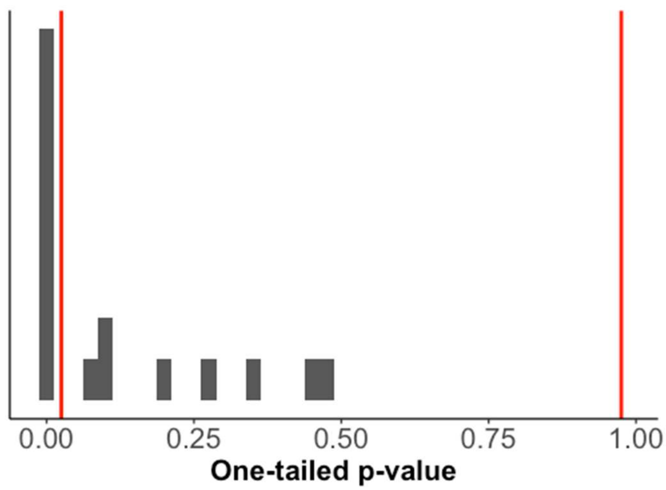
```
$fits
$fits$robust
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 18
Number of outcomes = 18 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value  dfs P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.    0.282 0.0971     2.9 14.6  0.0112   0.0743    0.489  **
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results
$fits$meta_worst
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 4
Number of outcomes = 4 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value dfs P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.     0.13 0.0423    3.08 2.7  0.0623  -0.0133    0.274   *
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results

attr(,"class")
[1] "metabias" "list"

> significance_funnel(yi=rct_data$ES_d,vi=rct_data$Variance,favor_positive = TRUE)
>
```



→The significance funnel plot is a visual supplement to the proposed sensitivity analyses above. This plot distinguishes between affirmative and non-affirmative studies, helping to detect the extent to which the non-affirmative studies' point estimates are systematically smaller than the entire set of point estimates. The estimate among only non-affirmative studies (gray diamond) represents a corrected estimate under worst-case publication bias. If the gray diamond represents a negligible effect size or if it is much smaller than the pooled estimate among all studies (black diamond), this suggests that the meta-analysis may not be robust to extreme publication bias.

Note → when the two diamonds (grey and black) are close to one another = fairly robust to publication bias.

```
> ###########################################################
> ######### REMOVAL OF POTENTIAL BIAS STUDIES ###########
> ###########################################################

> ####################################
> ######### Dataset: 2-arm ###########
> ####################################

> ###################################################
> ######### Remove the two Kraemer study ############
> ###################################################
   Study_Name   ES_d      LL     UL Sampl_.size   CI Variance Effect_Direction
6      Kraemer -0.011 -0.556 0.534          28 0.95    0.071         Negative
> ###################################################
> pval_plot(yi=pre_post_data_WO$ES_d,vi=pre_post_data_WO$Variance,alpha_select =
0.05)# none of the values falls outside of 1 - thus no need to run a two-tailed p-
value
```



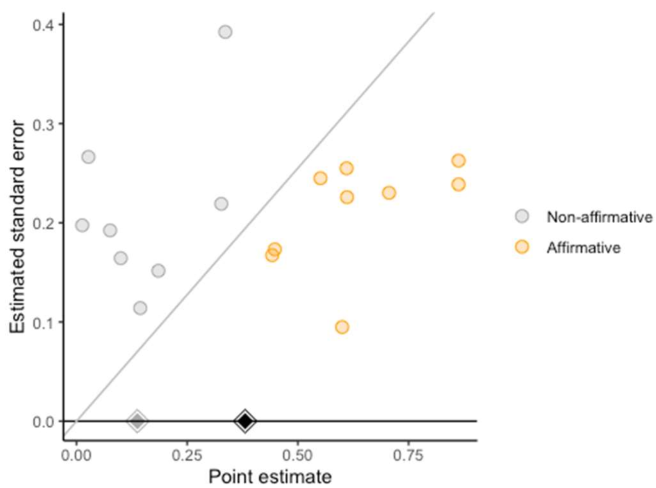

```
#
> a1_WO<-
pubbias_meta(yi=pre_post_data_WO$ES_d,vi=pre_post_data_WO$Variance,selection_ratio=1,a
lpha_select=0.05,ci_level=0.95,favor_positive = TRUE,return_worst_meta = TRUE)
> a1_WO
$data
# A tibble: 17 × 5
      yi   yif    vi affirm cluster
   <dbl> <dbl> <dbl> <lgl>    <int>
 1 0.1   0.1   0.027 FALSE        1
 2 0.336 0.336 0.154 FALSE        2
 3 0.61  0.61  0.065 TRUE         3
 4 0.027 0.027 0.071 FALSE        4
 5 0.448 0.448 0.03  TRUE         5
 6 0.013 0.013 0.039 FALSE        6
```

```
 7 0.611 0.611 0.051 TRUE         7
 8 0.442 0.442 0.028 TRUE         8
 9 0.863 0.863 0.069 TRUE         9
10 0.706 0.706 0.053 TRUE        10
11 0.144 0.144 0.013 FALSE       11
12 0.6   0.6   0.009 TRUE        12
13 0.863 0.863 0.057 TRUE        13
14 0.185 0.185 0.023 FALSE       14
15 0.076 0.076 0.037 FALSE       15
16 0.551 0.551 0.06  TRUE        16
17 0.327 0.327 0.048 FALSE       17

$values
$values$selection_ratio
[1] 1

$values$selection_tails
[1] 1

$values$model_type
[1] "robust"

$values$favor_positive
[1] TRUE

$values$alpha_select
[1] 0.05

$values$ci_level
[1] 0.95

$values$small
[1] TRUE

$values$k
[1] 17

$values$k_affirmative
[1] 9

$values$k_nonaffirmative
[1] 8


$stats
       model  estimate         se   ci_lower  ci_upper      p_value
1    pubbias 0.3857988 0.06644851 0.24116135 0.5304363 8.105928e-05
2 worst_case 0.1385324 0.03437299 0.05242659 0.2246382 8.315722e-03
```

→ This independent robust-effects meta-analysis indicates that if there are no publication bias between affirmative (i.e., significant and positive) and non-affirmative (i.e., nonsignificant or negative) studies (selection ratio = 1), the meta-analytic point estimate corrected for publication bias would be 0.39 (95% CI [0.24, 0.53]).
→ If there were worst-case publication bias (i.e., that favors affirmative results infinitely more than non-affirmative results), the corrected meta-analytic point estimate would be 0.14 (95% CI [0.05, 0.22]).

```
$fits
$fits$robust
RVE: User Specified Weights with Small-Sample Corrections
```

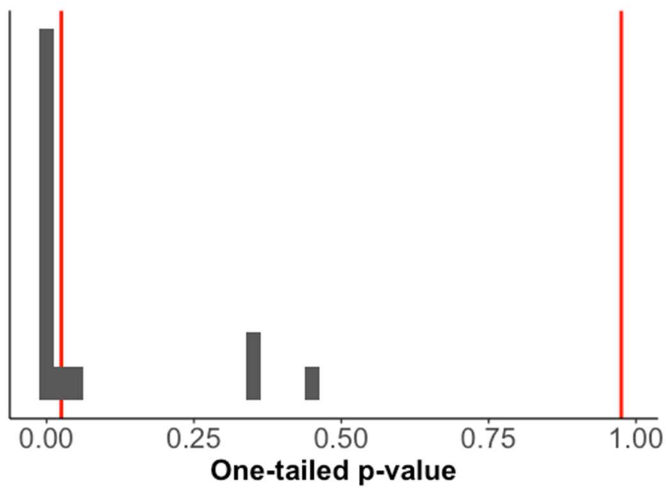
```
Model: yi ~ 1

Number of studies = 17
Number of outcomes = 17 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value  dfs   P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.    0.386 0.0664    5.81 12.1 0.0000811    0.241     0.53 ***
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results
$fits$meta_worst
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 8
Number of outcomes = 8 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value  dfs P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.    0.139 0.0344    4.03 5.47 0.00832   0.0524    0.225 ***
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results

attr(,"class")
[1] "metabias" "list"
>
significance_funnel(yi=pre_post_data_WO$ES_d,vi=pre_post_data_WO$Variance,favor_positi
ve = TRUE)
```



→The significance funnel plot is a visual supplement to the proposed sensitivity analyses above. This plot distinguishes between affirmative and non-affirmative studies, helping to detect the extent to which the non-affirmative studies' point estimates are systematically smaller than the entire set of point estimates. The estimate among only non-affirmative studies (gray diamond) represents a corrected estimate under worst-case publication bias. If the gray diamond represents a negligible effect size or if it is much smaller than the pooled estimate among all studies (black diamond), this suggests that the meta-analysis may not be robust to extreme publication bias.

→not significantly visually changed when removing the Kraemer study.

```
> ####################################
> ######### Dataset: 1-arm ###########
> ####################################

> ###################################################
> ######### Remove the two Dyrbye studies ###########
> ###################################################
   Study_Name   ES_d     LL     UL Sampl_.size   CI Variance Effect_Direction
4 Dyrbye 2014 -0.759 -0.206 -0.438          48 0.95    0.027         Negative
5 Dyrbye 2015 -0.510 -0.814 -0.206          47 0.95    0.024         Negative
> ###################################################
pval_plot(yi=rct_data_WO$ES_d,vi=rct_data_WO$Variance,alpha_select = 0.05)# none of
the values falls outside of 1 - thus no need for a two-tailed p-value anymore
```




```
b1WO<-
pubbias_meta(yi=rct_data_WO$ES_d,vi=rct_data_WO$Variance,selection_ratio=1.5,favor_pos
itive = TRUE,selection_tails = 1,alpha_select=0.05,ci_level=0.95,return_worst_meta =
TRUE)
> b1WO
$data
# A tibble: 16 × 5
      yi   yif    vi affirm cluster
   <dbl> <dbl> <dbl> <lgl>    <int>
 1 0.338 0.338 0.013 TRUE         1
 2 0.081 0.081 0.042 FALSE        2
 3 0.414 0.414 0.01  TRUE         3
 4 0.301 0.301 0.018 TRUE         4
 5 1.19  1.19  0.039 TRUE         5
```

```
 6 0.15  0.15  0.004 TRUE         6
 7 0.273 0.273 0.005 TRUE         7
 8 0.186 0.186 0.203 FALSE        8
 9 0.391 0.391 0.032 TRUE         9
10 0.486 0.486 0.016 TRUE        10
11 0.221 0.221 0.016 FALSE       11
12 0.608 0.608 0.044 TRUE        12
13 1.13  1.13  0.103 TRUE        13
14 0.555 0.555 0.039 TRUE        14
15 0.037 0.037 0.059 FALSE       15
16 0.461 0.461 0.011 TRUE        16

$values
$values$selection_ratio
[1] 1.5

$values$selection_tails
[1] 1

$values$model_type
[1] "robust"

$values$favor_positive
[1] TRUE

$values$alpha_select
[1] 0.05

$values$ci_level
[1] 0.95

$values$small
[1] TRUE

$values$k
[1] 16

$values$k_affirmative
[1] 12

$values$k_nonaffirmative
[1] 4


$stats
       model  estimate         se    ci_lower  ci_upper      p_value
1    pubbias 0.3758178 0.06294373  0.23773547 0.5139002 8.317543e-05
2 worst_case 0.1371933 0.04920662 -0.06497409 0.3393606 1.023779e-01
```

→ This independent robust-effects meta-analysis indicates that if there are no publication bias between affirmative (i.e., significant and positive) and non-affirmative (i.e., nonsignificant or negative) studies (selection ratio = 1), the meta-analytic point estimate corrected for publication bias would be 0.38 (95% CI [0.24, 0.51]).
→ If there were worst-case publication bias (i.e., that favors affirmative results infinitely more than non-affirmative results), the corrected meta-analytic point estimate would be 0.14 (95% CI [-0.06, 0.34]).

```
$fits
$fits$robust
RVE: User Specified Weights with Small-Sample Corrections
```

```
Model: yi ~ 1

Number of studies = 16
Number of outcomes = 16 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value  dfs   P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.    0.376 0.0629    5.97 11.3 0.0000832    0.238    0.514 ***
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results
$fits$meta_worst
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 4
Number of outcomes = 4 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value dfs P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.    0.137 0.0492    2.79 2.1   0.102   -0.065    0.339
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results

attr(,"class")
[1] "metabias" "list"
> significance_funnel(yi=rct_data_WO$ES_d,vi=rct_data_WO$Variance,favor_positive =
TRUE)
> b1WO<-
pubbias_meta(yi=rct_data_WO$ES_d,vi=rct_data_WO$Variance,selection_ratio=1.5,favor_pos
itive = TRUE,selection_tails = 2,alpha_select=0.05,ci_level=0.95,return_worst_meta =
TRUE)
> b1WO
$data
# A tibble: 16 × 5
      yi   yif    vi affirm cluster
   <dbl> <dbl> <dbl> <lgl>    <int>
 1 0.338 0.338 0.013 TRUE         1
 2 0.081 0.081 0.042 FALSE        2
 3 0.414 0.414 0.01  TRUE         3
 4 0.301 0.301 0.018 TRUE         4
 5 1.19  1.19  0.039 TRUE         5
 6 0.15  0.15  0.004 TRUE         6
 7 0.273 0.273 0.005 TRUE         7
 8 0.186 0.186 0.203 FALSE        8
 9 0.391 0.391 0.032 TRUE         9
10 0.486 0.486 0.016 TRUE        10
11 0.221 0.221 0.016 FALSE       11
12 0.608 0.608 0.044 TRUE        12
13 1.13  1.13  0.103 TRUE        13
14 0.555 0.555 0.039 TRUE        14
15 0.037 0.037 0.059 FALSE       15
16 0.461 0.461 0.011 TRUE        16

$values
$values$selection_ratio
[1] 1.5

$values$selection_tails
[1] 2

$values$model_type
```

```
[1] "robust"

$values$favor_positive
[1] TRUE

$values$alpha_select
[1] 0.05

$values$ci_level
[1] 0.95

$values$small
[1] TRUE

$values$k
[1] 16

$values$k_affirmative
[1] 12

$values$k_nonaffirmative
[1] 4


$stats
       model  estimate         se    ci_lower  ci_upper      p_value
1    pubbias 0.3758178 0.06294373  0.23773547 0.5139002 8.317543e-05
2 worst_case 0.1371933 0.04920662 -0.06497409 0.3393606 1.023779e-01

$fits
$fits$robust
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 16
Number of outcomes = 16 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value  dfs   P(|t|>) 95% CI.L 95% CI.U Sig
1 X.Intercept.    0.376 0.0629    5.97 11.3 0.0000832    0.238    0.514 ***
---
Signif. codes: < .01 *** < .05 ** < .10 *
---
Note: If df < 4, do not trust the results
$fits$meta_worst
RVE: User Specified Weights with Small-Sample Corrections

Model: yi ~ 1

Number of studies = 4
Number of outcomes = 4 (min = 1 , mean = 1 , median = 1 , max = 1 )
               Estimate StdErr t-value dfs P(|t|>) 95% CI.L 95% CI.U Sig
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[1] "metabias" "list"
> significance_funnel(yi=rct_data_WO$ES_d,vi=rct_data_WO$Variance,favor_positive =
TRUE)
```

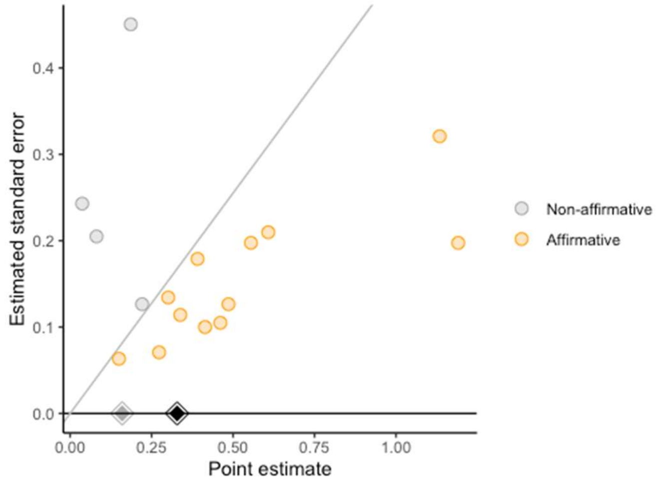

→ Removing the two Dyrbye studies caused the two diamonds to be much closer and thus much more robust to publication bias when excluded compared to when included.

Note → when the two diamonds (grey and black) are close to one another = fairly robust to publication bias.