Meta-analysis using Stata

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Acknowledgments

Stata has a long history of meta-analysis methods contributed by Stata researchers, e.g. Palmer and Sterne (2016). We want to express our deep gratitude to Jonathan Sterne, Roger Harbord, Tom Palmer, David Fisher, Ian White, Ross Harris, Thomas Steichen, Mike Bradburn, Doug Altman (1948–2018), Ben Dwamena, and many more for their invaluable contributions. Their previous and still ongoing work on meta-analysis in Stata influenced the design and development of the official `meta` suite.

What is meta-analysis?

Meta-analysis (MA, Glass 1976) combines the results of multiple studies to provide a unified answer to a research question.

For instance,

- Does taking vitamin C prevent colds?
- Does exercise prolong life?
- Does lack of sleep increase the risk of cancer?
- Does daylight saving save energy?
- And more.

Does it make sense to combine different studies?

From Borenstein et al. (2009, chap. 40):

"In the early days of meta-analysis, Robert Rosenthal was asked whether it makes sense to perform a meta-analysis, given that the studies differ in various ways and that the analysis amounts to combining apples and oranges. Rosenthal answered that *combining apples and oranges makes sense if your goal is to produce a fruit salad*."

Meta-analysis goals

Main goals of MA are:

- Provide an overall estimate of an effect, if sensible
- Explore between-study heterogeneity: studies often report different (and sometimes conflicting) results in terms of the magnitudes and even direction of the effects
- Evaluate the presence of publication bias—underreporting of nonsignificant results in the literature

Components of meta-analysis

- **Effect size**: standardized and raw mean differences, odds and risk ratios, risk difference, etc.
- **MA model**: common-effect, fixed-effects, random-effects
- **MA summary—forest plot**
- **Heterogeneity**—differences between effect-size estimates across studies in an MA
- **Small-study effects**—systematic differences between effect sizes reported by small versus large studies
- **Publication bias** or, more generally, **reporting bias**—systematic differences between studies included in an MA and all available relevant studies.

Stata's meta-analysis suite

Command	*Description*
Declaration	
`meta set`	declare data using precalculated effect sizes
`meta esize`	calculate effect sizes and declare data
`meta update`	modify declaration of meta data
`meta query`	report how meta data are set
Summary	
`meta summarize`	summarize MA results
`meta forestplot`	graph forest plots

Heterogeneity

`meta summarize, subgroup()`	subgroup MA summary
`meta forestplot, subgroup()`	subgroup forest plots
`meta regress`	perform meta-regression
`predict`	predict random effects, etc.
`estat bubbleplot`	graph bubble plots
`meta labbeplot`	graph L'Abbé plots

Small-study effects/ publication bias

`meta funnelplot`	graph funnel plots
`meta bias`	test for small-study effects
`meta trimfill`	trim-and-fill analysis

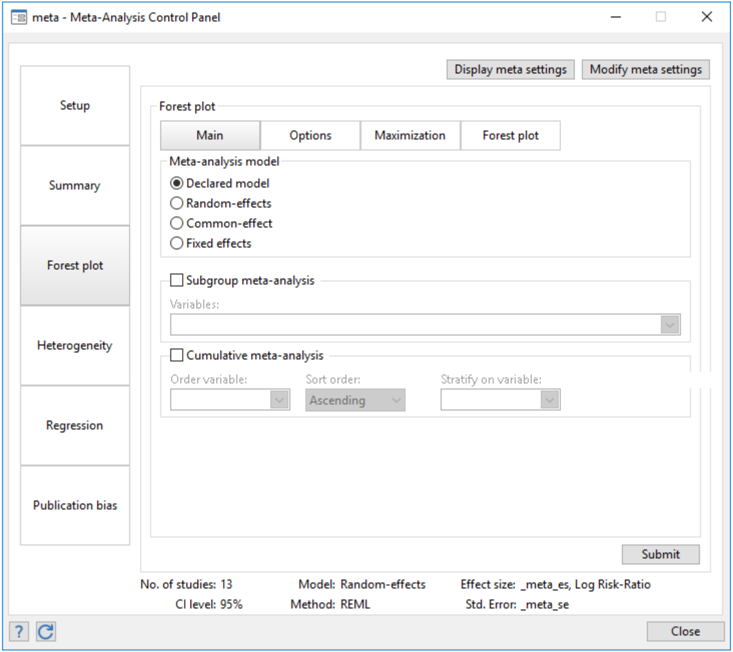
Cumulative analysis

`meta summarize, cumulative()`	cumulative MA summary
`meta forestplot, cumulative()`	cumulative forest plots

Meta-Analysis Control Panel

You can work via commands or by using point-and-click: **Statistics** > **Meta-analysis**.

(*Continued on next page*)


meta - Meta-Analysis Control Panel
Display meta settings
Modify meta settings
Setup
Summary
Forest plot
Heterogeneity
Regression
Publication bias
Forest plot
Main
Options
Maximization
Forest plot
Meta-analysis model
Declared model
Random-effects
Common-effect
Fixed effects
Subgroup meta-analysis
Variables:
Cumulative meta-analysis
Order variable:
Sort order:
Ascending
Stratify on variable:
Submit
No. of studies: 13
CI level: 95%
Model: Random-effects
Method: REML
Effect size: _meta_es, Log Risk-Ratio
Std. Error: _meta_se
Close

Motivating example: Effects of teacher expectancy on pupil IQ

- Consider the famous meta-analysis study of Raudenbush (1984) that evaluated the effects of teacher expectancy on pupil IQ.
- The original study of Rosenthal and Jacobson (1968) discovered the so-called Pygmalion effect, in which expectations of teachers affected outcomes of their students.
- Later studies had trouble replicating the result.
- Raudenbush (1984) performed a meta-analysis of 19 studies to investigate the findings of multiple studies.

Data description

```
. webuse pupiliq
(Effects of teacher expectancy on pupil IQ)

. describe studylbl stdmdiff se weeks week1

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------
studylbl        str26   %26s                  Study label
stdmdiff        double  %9.0g                 Standardized difference in means
se              double  %10.0g                Standard error of stdmdiff
weeks           byte    %9.0g                 Weeks of prior teacher-student
                                                contact
week1           byte    %9.0g      catweek1   Prior teacher-student contact > 1
                                                week
```

```
. list studylbl stdmdiff se
```

	studylbl	stdmdiff	se
1.	Rosenthal et al., 1974	.03	.125
2.	Conn et al., 1968	.12	.147
3.	Jose & Cody, 1971	-.14	.167
4.	Pellegrini & Hicks, 1972	1.18	.373
5.	Pellegrini & Hicks, 1972	.26	.369
6.	Evans & Rosenthal, 1969	-.06	.103
7.	Fielder et al., 1971	-.02	.103
8.	Claiborn, 1969	-.32	.22
9.	Kester, 1969	.27	.164
10.	Maxwell, 1970	.8	.251
11.	Carter, 1970	.54	.302
12.	Flowers, 1966	.18	.223
13.	Keshock, 1970	-.02	.289
14.	Henrikson, 1970	.23	.29
15.	Fine, 1972	-.18	.159
16.	Grieger, 1970	-.06	.167
17.	Rosenthal & Jacobson, 1968	.3	.139
18.	Fleming & Anttonen, 1971	.07	.094
19.	Ginsburg, 1970	-.07	.174

Prepare data for meta-analysis

- Declaration of your MA data is the first step of your MA in Stata.
- Use `meta set` to declare precomputed effect sizes.
- Use `meta esize` to compute (and declare) effect sizes from summary data.

- Declare precomputed effect sizes and their standard errors stored in variables `es` and `se`, respectively:

```
. meta set es se
```

- Or, compute, say, log odds-ratios from binary summary data stored in variables `n11`, `n12`, `n21`, and `n22`:

```
. meta esize n11 n12 n21 n22, esize(lnoratio)
```

- Or, compute, say, Hedges's g standardized mean differences from continuous summary data stored in variables `n1`, `m1`, `sd1`, `n2`, `m2`, `sd2`:

```
. meta esize n1 m1 sd1 n2 m2 sd2, esize(hedgesg)
```

- See [META] **meta data** for details.

Declaring pupil IQ dataset

- Let's use `meta set` to declare our pupil IQ data that contains precomputed effect sizes and their standard errors.

```
. meta set stdmdiff se
Meta-analysis setting information
 Study information
    No. of studies:  19
       Study label:  Generic
        Study size:  N/A
       Effect size
              Type:  Generic
             Label:  Effect Size
          Variable:  stdmdiff
         Precision
         Std. Err.:  se
                CI:  [_meta_cil, _meta_ciu]
          CI level:  95%
  Model and method
             Model:  Random-effects
            Method:  REML
```

Declaring a meta-analysis model

- In addition to effect sizes and their standard errors, one of the main components of your MA declaration is that of an MA model.
- `meta` offers three models: random-effects (`random`), the default, common-effect (aka "fixed-effect", `common`), and fixed-effects (`fixed`).
- The selected MA model determines the availability of the MA methods and, more importantly, how you interpret the obtained results.
- See **Details: Meta-analysis models** below as well as *Meta-analysis models* in [META] **Intro** and *Declaring a meta-analysis model* in [META] **meta data**.

Meta-analysis summary

- Use `meta summarize` to obtain MA summary in a table.
- Use `meta forestplot` to summarize MA data graphically—produce forest plot.
- See [META] **meta summarize** and [META] **meta forestplot** for details.

```
. meta summarize
  Effect-size label:  Effect Size
        Effect size:  stdmdiff
          Std. Err.:  se

Meta-analysis summary                     Number of studies =     19
Random-effects model                      Heterogeneity:
Method: REML                                          tau2 =  0.0188
                                                    I2 (%) =   41.84
                                                        H2 =    1.72

--------------------------------------------------------------------
            Study |     Effect Size    [95% Conf. Interval]  % Weight
------------------+-------------------------------------------------
         Study  1 |           0.030      -0.215       0.275      7.74
         Study  2 |           0.120      -0.168       0.408      6.60
         Study  3 |          -0.140      -0.467       0.187      5.71
         Study  4 |           1.180       0.449       1.911      1.69
         Study  5 |           0.260      -0.463       0.983      1.72
         Study  6 |          -0.060      -0.262       0.142      9.06
         Study  7 |          -0.020      -0.222       0.182      9.06
         Study  8 |          -0.320      -0.751       0.111      3.97
         Study  9 |           0.270      -0.051       0.591      5.84
         Study 10 |           0.800       0.308       1.292      3.26
         Study 11 |           0.540      -0.052       1.132      2.42
         Study 12 |           0.180      -0.257       0.617      3.89
         Study 13 |          -0.020      -0.586       0.546      2.61
         Study 14 |           0.230      -0.338       0.798      2.59
         Study 15 |          -0.180      -0.492       0.132      6.05
         Study 16 |          -0.060      -0.387       0.267      5.71
         Study 17 |           0.300       0.028       0.572      6.99
         Study 18 |           0.070      -0.114       0.254      9.64
         Study 19 |          -0.070      -0.411       0.271      5.43
------------------+-------------------------------------------------
            theta |           0.084      -0.018       0.185
--------------------------------------------------------------------
Test of theta = 0: z = 1.62                     Prob > |z| = 0.1052
Test of homogeneity: Q = chi2(18) = 35.83         Prob > Q = 0.0074
```

Update meta settings

- Use `meta update` to modify your MA settings.

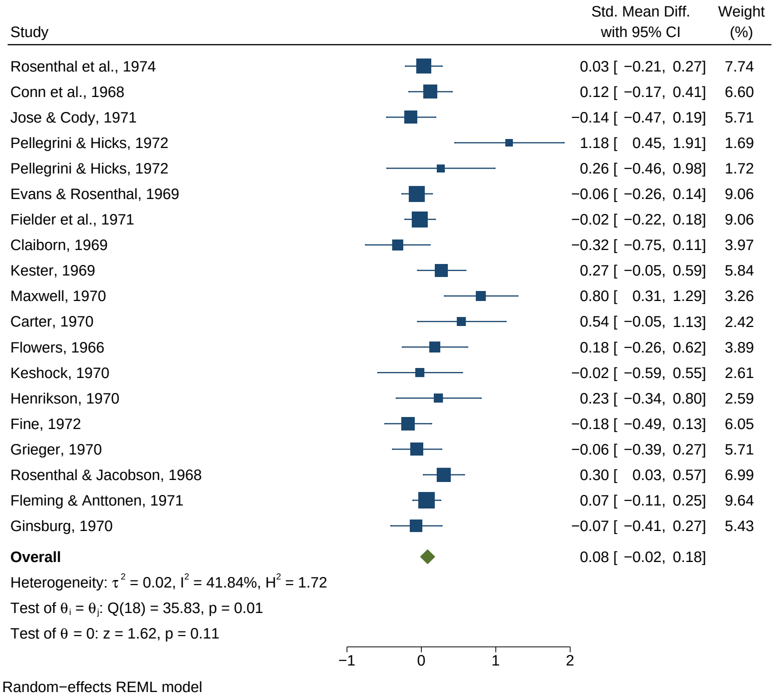
```
. meta update, studylabel(studylbl) eslabel(Std. Mean Diff.)
-> meta set stdmdiff se , random(reml) studylabel(studylbl) eslabel(Std. Mean Diff.)
Meta-analysis setting information from meta set
 Study information
    No. of studies:  19
       Study label:  studylbl
        Study size:  N/A
       Effect size
              Type:  Generic
             Label:  Std. Mean Diff.
          Variable:  stdmdiff
         Precision
         Std. Err.:  se
                CI:  [_meta_cil, _meta_ciu]
          CI level:  95%
  Model and method
             Model:  Random-effects
            Method:  REML
```

Forest plot

- Use `meta forestplot` to produce forest plots.
- Specify options or use the **Graph Editor** to modify the default look.

```
. meta forestplot
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
        Study label:  studylbl
```

(*Continued on next page*)


Study
Std. Mean Diff. with 95% CI
Weight (%)
Rosenthal et al., 1974 0.03 [−0.21, 0.27] 7.74
Conn et al., 1968 0.12 [−0.17, 0.41] 6.60
Jose & Cody, 1971 −0.14 [−0.47, 0.19] 5.71
Pellegrini & Hicks, 1972 1.18 [0.45, 1.91] 1.69
Pellegrini & Hicks, 1972 0.26 [−0.46, 0.98] 1.72
Evans & Rosenthal, 1969 −0.06 [−0.26, 0.14] 9.06
Fielder et al., 1971 −0.02 [−0.22, 0.18] 9.06
Claiborn, 1969 −0.32 [−0.75, 0.11] 3.97
Kester, 1969 0.27 [−0.05, 0.59] 5.84
Maxwell, 1970 0.80 [0.31, 1.29] 3.26
Carter, 1970 0.54 [−0.05, 1.13] 2.42
Flowers, 1966 0.18 [−0.26, 0.62] 3.89
Keshock, 1970 −0.02 [−0.59, 0.55] 2.61
Henrikson, 1970 0.23 [−0.34, 0.80] 2.59
Fine, 1972 −0.18 [−0.49, 0.13] 6.05
Grieger, 1970 −0.06 [−0.39, 0.27] 5.71
Rosenthal & Jacobson, 1968 0.30 [0.03, 0.57] 6.99
Fleming & Anttonen, 1971 0.07 [−0.11, 0.25] 9.64
Ginsburg, 1970 −0.07 [−0.41, 0.27] 5.43
Overall 0.08 [−0.02, 0.18]
Heterogeneity: $\tau^2 = 0.02$, $I^2 = 41.84\%$, $H^2 = 1.72$
Test of $\theta_i = \theta_j$: Q(18) = 35.83, p = 0.01
Test of $\theta = 0$: z = 1.62, p = 0.11
−1
0
1
2
Random−effects REML model

Between-study heterogeneity

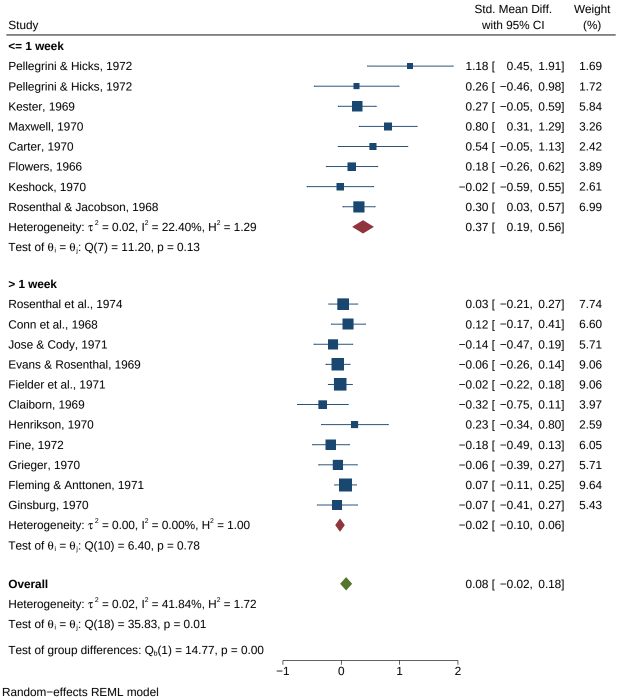
- The previous forest plot reveals noticeable between-study variation.
- Raudenbush (1984) suspected that the amount of time that the teachers spent with students prior to the experiment may influence the teachers' susceptibility to researchers' categorization of students.
- One solution is to incorporate moderators (study-level covariates) into an MA.
- Subgroup analysis for categorical moderators.
- Meta-regression for continuous and a mixture of moderators.

Heterogeneity: Subgroup analysis

- Binary variable `week1` divides the studies into high-contact (`week1=1`) and low-contact (`week1=0`) groups.

```
. meta forestplot, subgroup(week1)
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
        Study label:  studylbl
```

(*Continued on next page*)


Study
Std. Mean Diff. with 95% CI
Weight (%)
<= 1 week
Pellegrini & Hicks, 1972 1.18 [0.45, 1.91] 1.69
Pellegrini & Hicks, 1972 0.26 [−0.46, 0.98] 1.72
Kester, 1969 0.27 [−0.05, 0.59] 5.84
Maxwell, 1970 0.80 [0.31, 1.29] 3.26
Carter, 1970 0.54 [−0.05, 1.13] 2.42
Flowers, 1966 0.18 [−0.26, 0.62] 3.89
Keshock, 1970 −0.02 [−0.59, 0.55] 2.61
Rosenthal & Jacobson, 1968 0.30 [0.03, 0.57] 6.99
Heterogeneity: τ^2 = 0.02, I^2 = 22.40%, H^2 = 1.29 0.37 [0.19, 0.56]
Test of $\theta_i = \theta_j$: Q(7) = 11.20, p = 0.13
> 1 week
Rosenthal et al., 1974 0.03 [−0.21, 0.27] 7.74
Conn et al., 1968 0.12 [−0.17, 0.41] 6.60
Jose & Cody, 1971 −0.14 [−0.47, 0.19] 5.71
Evans & Rosenthal, 1969 −0.06 [−0.26, 0.14] 9.06
Fielder et al., 1971 −0.02 [−0.22, 0.18] 9.06
Claiborn, 1969 −0.32 [−0.75, 0.11] 3.97
Henrikson, 1970 0.23 [−0.34, 0.80] 2.59
Fine, 1972 −0.18 [−0.49, 0.13] 6.05
Grieger, 1970 −0.06 [−0.39, 0.27] 5.71
Fleming & Anttonen, 1971 0.07 [−0.11, 0.25] 9.64
Ginsburg, 1970 −0.07 [−0.41, 0.27] 5.43
Heterogeneity: τ^2 = 0.00, I^2 = 0.00%, H^2 = 1.00 −0.02 [−0.10, 0.06]
Test of $\theta_i = \theta_j$: Q(10) = 6.40, p = 0.78
Overall 0.08 [−0.02, 0.18]
Heterogeneity: τ^2 = 0.02, I^2 = 41.84%, H^2 = 1.72
Test of $\theta_i = \theta_j$: Q(18) = 35.83, p = 0.01
Test of group differences: $Q_b(1)$ = 14.77, p = 0.00
−1
0
1
2
Random−effects REML model

Heterogeneity: Meta-regression

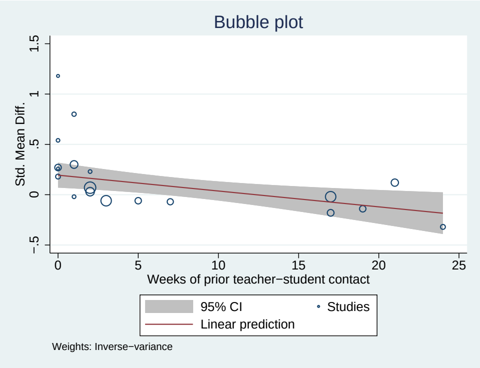
- Perform meta-regression using a continuous variable, weeks.

```
. meta regress weeks

  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se

Random-effects meta-regression                  Number of obs  =         19
Method: REML                                    Residual heterogeneity:
                                                            tau2 =   .01117
                                                          I2 (%) =    29.36
                                                              H2 =     1.42
                                                   R-squared (%) =    40.70
                                                Wald chi2(1)    =     7.51
                                                Prob > chi2     =   0.0061

------------------------------------------------------------------------------
     _meta_es |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        weeks |  -.0157453   .0057447    -2.74   0.006    -.0270046   -.0044859
        _cons |   .1941774   .0633563     3.06   0.002     .0700013    .3183535
------------------------------------------------------------------------------
Test of residual homogeneity: Q_res = chi2(17) = 27.66   Prob > Q_res = 0.0490
```

Meta-regression: Bubble plot

- Explore the relationship between effect sizes and `weeks`.

```
. estat bubbleplot
```

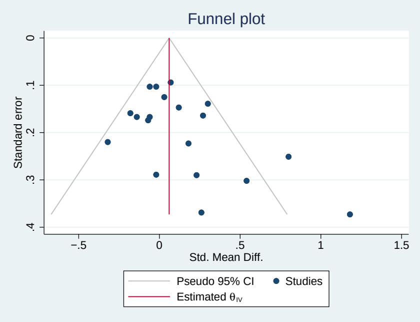


- Negative relationship; some of the more precise studies are outlying studies

Funnel plot

- Explore funnel-plot asymmetry visually.

```
. meta funnelplot

  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
              Model:  Common-effect
             Method:  Inverse-variance
```



Test for funnel-plot asymmetry

- Explore funnel-plot asymmetry more formally.

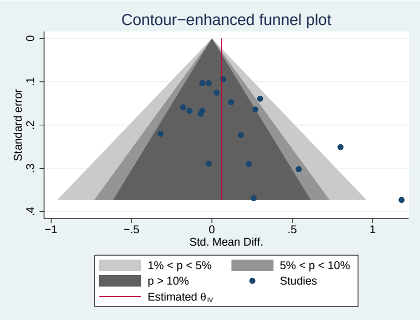
```
. meta bias, egger
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
Regression-based Egger test for small-study effects
Random-effects model
Method: REML
H0: beta1 = 0; no small-study effects
            beta1 =      1.83
      SE of beta1 =     0.724
                z =      2.53
       Prob > |z| =    0.0115
```

- Beware of the presence of heterogeneity! See **Small-study effects** below.

Contour-enhanced funnel plot

- Add 1%, 5%, and 10% significance contours

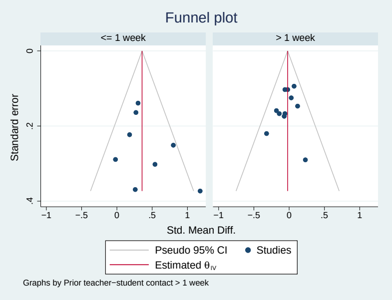
```
. meta funnelplot, contours(1 5 10)
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
              Model:  Common-effect
             Method:  Inverse-variance
```



Small-study effects

- Keeping in mind the presence of heterogeneity in these data, let's produce funnel plots separately for each group of `week1`.

```
. meta funnelplot, by(week1)
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
              Model:  Common-effect
             Method:  Inverse-variance
```



- Or, more formally,

```
. meta bias i.week1, egger
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
Regression-based Egger test for small-study effects
Random-effects model
Method: REML
Moderators: week1
H0: beta1 = 0; no small-study effects
            beta1 =      0.30
      SE of beta1 =     0.729
                z =      0.41
       Prob > |z| =    0.6839
```

Assess publication bias

- When publication bias is suspect, you can use the trim-and-fill method to assess the impact of publication bias on the MA results.
- In our example, the asymmetry of the funnel plot is likely due to heterogeneity, not publication bias.
- But, for the purpose of demonstration, let's go ahead and apply the trim-and-fill method to these data.

```
. meta trimfill, funnel
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se

Nonparametric trim-and-fill analysis of publication bias
Linear estimator, imputing on the left

Iteration                            Number of studies =     22
  Model: Random-effects                       observed =     19
 Method: REML                                 imputed =      3

Pooling
  Model: Random-effects
 Method: REML

--------------------------------------------------------------
             Studies |  Std. Mean Diff.    [95% Conf. Interval]
---------------------+----------------------------------------
            Observed |            0.084      -0.018       0.185
  Observed + Imputed |            0.028      -0.117       0.173
--------------------------------------------------------------
```

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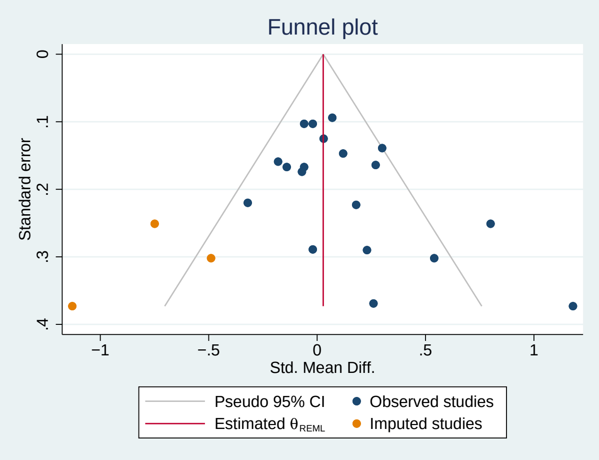
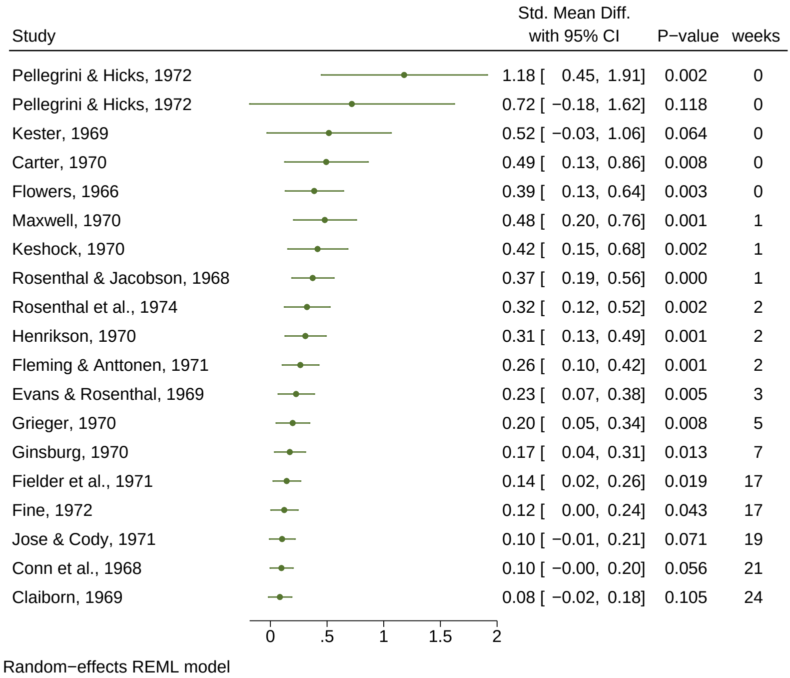

Funnel plot
Standard error
0
.1
.2
.3
.4
−1
−.5
0
.5
1
Std. Mean Diff.
Pseudo 95% CI
Estimated θ$_{REML}$
Observed studies
Imputed studies

Cumulative meta-analysis

- Cumulative MA performs multiple MAs by accumulating studies one at a time after ordering them with respect to the variable of interest.
- Cumulative MA is useful for monitoring the trends in effect-size estimates with respect to the ordering variable.
- Use option `cumulative()` with `meta summarize` or `meta forestplot` to perform cumulative MA.

```
. meta forestplot, cumulative(weeks)
  Effect-size label:  Std. Mean Diff.
        Effect size:  stdmdiff
          Std. Err.:  se
        Study label:  studylbl
```

(*Continued on next page*)


Study
Std. Mean Diff. with 95% CI
P−value
weeks
Pellegrini & Hicks, 1972 1.18 [0.45, 1.91] 0.002 0
Pellegrini & Hicks, 1972 0.72 [−0.18, 1.62] 0.118 0
Kester, 1969 0.52 [−0.03, 1.06] 0.064 0
Carter, 1970 0.49 [0.13, 0.86] 0.008 0
Flowers, 1966 0.39 [0.13, 0.64] 0.003 0
Maxwell, 1970 0.48 [0.20, 0.76] 0.001 1
Keshock, 1970 0.42 [0.15, 0.68] 0.002 1
Rosenthal & Jacobson, 1968 0.37 [0.19, 0.56] 0.000 1
Rosenthal et al., 1974 0.32 [0.12, 0.52] 0.002 2
Henrikson, 1970 0.31 [0.13, 0.49] 0.001 2
Fleming & Anttonen, 1971 0.26 [0.10, 0.42] 0.001 2
Evans & Rosenthal, 1969 0.23 [0.07, 0.38] 0.005 3
Grieger, 1970 0.20 [0.05, 0.34] 0.008 5
Ginsburg, 1970 0.17 [0.04, 0.31] 0.013 7
Fielder et al., 1971 0.14 [0.02, 0.26] 0.019 17
Fine, 1972 0.12 [0.00, 0.24] 0.043 17
Jose & Cody, 1971 0.10 [−0.01, 0.21] 0.071 19
Conn et al., 1968 0.10 [−0.00, 0.20] 0.056 21
Claiborn, 1969 0.08 [−0.02, 0.18] 0.105 24
0
.5
1
1.5
2
Random−effects REML model

Details: Meta-analysis models

- **Common-effect (CE) model** (aka fixed-effect model, notice singular "fixed"):

$$\hat{\theta}_j = \theta + \epsilon_j$$

  θ is the true common effect, $\hat{\theta}_j$'s are K previously estimated study-specific effects with their standard errors $\hat{\sigma}_j^2$'s, and $\epsilon_j \sim N(0, \hat{\sigma}_j^2)$.
- **Fixed-effects (FE) model**:

$$\hat{\theta}_j = \theta_j + \epsilon_j$$

  θ_j's are unknown, "fixed" study-specific effects.
- **Random-effects (RE) model**:

$$\hat{\theta}_j = \theta_j + \epsilon_j = \theta + u_j + \epsilon_j$$

  $\theta_j \sim N(\theta, \tau^2)$ or $u_j \sim N(0, \tau^2)$.

Estimator of the overall effect

- The three models differ in the population parameter, θ_{pop}, they estimate:
  - CE model: $\theta_{\text{pop}} = \theta$ is a common effect;
  - FE model: θ_{pop} is a weighted average of the K true study effects (Rice, Higgins, and Lumley 2018); and
  - RE model: $\theta_{\text{pop}} = \theta$ is the mean of the distribution of the study effects.
- But they all use the weighted average as the estimator of θ_{pop}:

$$\hat{\theta}_{\text{pop}} = \frac{\sum_{j=1}^{K} w_j \hat{\theta}_j}{\sum_{j=1}^{K} w_j}$$

where w_j depends on the model.

Random-effects model: Stata's default

- Study-specific effects may vary between studies.
- They are viewed as a random sample from a larger population of studies.
- RE model adjusts for unexplained between-study variability.
- RE model is Stata's default for MA.

```
. quietly meta update, nometashow

. meta summarize

Meta-analysis summary                     Number of studies =     19
Random-effects model                      Heterogeneity:
Method: REML                                          tau2 =  0.0188
                                                    I2 (%) =   41.84
                                                        H2 =    1.72

                Effect Size: Std. Mean Diff.

--------------------------------------------------------------------------
                 Study |  Effect Size    [95% Conf. Interval]   % Weight
-----------------------+--------------------------------------------------
 Rosenthal et al., 1974 |        0.030    -0.215       0.275       7.74
      Conn et al., 1968 |        0.120    -0.168       0.408       6.60
      Jose & Cody, 1971 |       -0.140    -0.467       0.187       5.71
 Pellegrini & Hicks, 1972 |        1.180     0.449       1.911       1.69
 Pellegrini & Hicks, 1972 |        0.260    -0.463       0.983       1.72
  Evans & Rosenthal, 1969 |       -0.060    -0.262       0.142       9.06
    Fielder et al., 1971 |       -0.020    -0.222       0.182       9.06
          Claiborn, 1969 |       -0.320    -0.751       0.111       3.97
            Kester, 1969 |        0.270    -0.051       0.591       5.84
           Maxwell, 1970 |        0.800     0.308       1.292       3.26
            Carter, 1970 |        0.540    -0.052       1.132       2.42
           Flowers, 1966 |        0.180    -0.257       0.617       3.89
           Keshock, 1970 |       -0.020    -0.586       0.546       2.61
         Henrikson, 1970 |        0.230    -0.338       0.798       2.59
              Fine, 1972 |       -0.180    -0.492       0.132       6.05
           Grieger, 1970 |       -0.060    -0.387       0.267       5.71
Rosenthal & Jacobson, 1968 |        0.300     0.028       0.572       6.99
  Fleming & Anttonen, 1971 |        0.070    -0.114       0.254       9.64
          Ginsburg, 1970 |       -0.070    -0.411       0.271       5.43
-----------------------+--------------------------------------------------
                 theta |        0.084    -0.018       0.185
--------------------------------------------------------------------------
Test of theta = 0: z = 1.62                       Prob > |z| = 0.1052
Test of homogeneity: Q = chi2(18) = 35.83           Prob > Q = 0.0074
```

Common-effect model

- Historically known as a “fixed-effect model” (singular “fixed”)
- New terminology due to Rice, Higgins, and Lumley (2018)
- One common effect: $\theta_1 = \theta_2 = \ldots = \theta_K = \theta$
- Should not be used in the presence of study heterogeneity
- For demonstration purposes only here, ...

```
. meta summarize, common

Meta-analysis summary                     Number of studies =     19
Common-effect model
Method: Inverse-variance
                Effect Size: Std. Mean Diff.
```

Study	Effect Size	[95% Conf.	Interval]	% Weight
Rosenthal et al., 1974	0.030	-0.215	0.275	8.52
Conn et al., 1968	0.120	-0.168	0.408	6.16
Jose & Cody, 1971	-0.140	-0.467	0.187	4.77
Pellegrini & Hicks, 1972	1.180	0.449	1.911	0.96
Pellegrini & Hicks, 1972	0.260	-0.463	0.983	0.98
Evans & Rosenthal, 1969	-0.060	-0.262	0.142	12.55
Fielder et al., 1971	-0.020	-0.222	0.182	12.55
Claiborn, 1969	-0.320	-0.751	0.111	2.75
Kester, 1969	0.270	-0.051	0.591	4.95
Maxwell, 1970	0.800	0.308	1.292	2.11
Carter, 1970	0.540	-0.052	1.132	1.46
Flowers, 1966	0.180	-0.257	0.617	2.68
Keshock, 1970	-0.020	-0.586	0.546	1.59
Henrikson, 1970	0.230	-0.338	0.798	1.58
Fine, 1972	-0.180	-0.492	0.132	5.27
Grieger, 1970	-0.060	-0.387	0.267	4.77
Rosenthal & Jacobson, 1968	0.300	0.028	0.572	6.89
Fleming & Anttonen, 1971	0.070	-0.114	0.254	15.07
Ginsburg, 1970	-0.070	-0.411	0.271	4.40
theta	0.060	-0.011	0.132	

```
Test of theta = 0: z = 1.65                     Prob > |z| = 0.0981
```

Fixed-effects model

- Study-specific effects may vary between studies.
- They are considered "fixed".
- FE model produces the same estimates as the CE model but their interpretation is different!
- Two different options, `common` and `fixed`, are provided to emphasize the conceptual differences between the two models.

```
. meta summarize, fixed

Meta-analysis summary                    Number of studies =     19
Fixed-effects model                      Heterogeneity:
Method: Inverse-variance                           I2 (%) =   49.76
                                                       H2 =    1.99

                Effect Size: Std. Mean Diff.

-----------------------------------------------------------------------------
                     Study |  Effect Size   [95% Conf. Interval]   % Weight
---------------------------+-------------------------------------------------
   Rosenthal et al., 1974 |        0.030     -0.215      0.275       8.52
        Conn et al., 1968 |        0.120     -0.168      0.408       6.16
        Jose & Cody, 1971 |       -0.140     -0.467      0.187       4.77
  Pellegrini & Hicks, 1972 |        1.180      0.449      1.911       0.96
  Pellegrini & Hicks, 1972 |        0.260     -0.463      0.983       0.98
   Evans & Rosenthal, 1969 |       -0.060     -0.262      0.142      12.55
      Fielder et al., 1971 |       -0.020     -0.222      0.182      12.55
            Claiborn, 1969 |       -0.320     -0.751      0.111       2.75
              Kester, 1969 |        0.270     -0.051      0.591       4.95
             Maxwell, 1970 |        0.800      0.308      1.292       2.11
              Carter, 1970 |        0.540     -0.052      1.132       1.46
             Flowers, 1966 |        0.180     -0.257      0.617       2.68
             Keshock, 1970 |       -0.020     -0.586      0.546       1.59
           Henrikson, 1970 |        0.230     -0.338      0.798       1.58
                Fine, 1972 |       -0.180     -0.492      0.132       5.27
             Grieger, 1970 |       -0.060     -0.387      0.267       4.77
Rosenthal & Jacobson, 1968 |        0.300      0.028      0.572       6.89
  Fleming & Anttonen, 1971 |        0.070     -0.114      0.254      15.07
            Ginsburg, 1970 |       -0.070     -0.411      0.271       4.40
---------------------------+-------------------------------------------------
                     theta |        0.060     -0.011      0.132
-----------------------------------------------------------------------------
Test of theta = 0: z = 1.65                         Prob > |z| = 0.0981
Test of homogeneity: Q = chi2(18) = 35.83             Prob > Q = 0.0074
```

Summary

- `meta` is a new suite of commands available in Stata 16 to perform MA.
- Three MA models are supported: random-effects (default, `random`), common-effect (aka "fixed-effect", `common`), and fixed-effects (`fixed`).
- Various estimation methods are supported including DerSimonian–Laird and Mantel–Haenszel.
- Declare and compute your effect sizes and standard errors upfront using `meta set` or `meta esize`. Declare other information for your entire MA session. Use `meta update` to update any meta settings during your MA session.

Summary (cont.)

- Compute basic MA summary using `meta summarize` and produce forest plots using `meta forestplot`.
- Explore heterogeneity via subgroup analysis (e.g., `meta forestplot, subgroup()`) or meta-regression (`meta regress`).
- Explore small-study effects and publication bias by producing funnel plots (`meta funnelplot`, `meta funnelplot, contours()`) and by testing for funnel-plot asymmetry (`meta bias`).
- Assess the impact of publication bias, when it is suspected, by using `meta trimfill`.
- Perform cumulative MA by using `meta forestplot, cumulative()` and `meta summarize, cumulative()`.

Additional resources

- Quick overview of MA in Stata: https://www.stata.com/new-in-stata/meta-analysis/
- Full list of MA features: https://www.stata.com/features/meta-analysis/
- Full documentation: *Stata Meta-Analysis Reference Manual*, and, particularly, *Introduction to meta-analysis* ([META] **Intro**) and *Introduction to meta* ([META] **meta**).
- YouTube: Meta-analysis in Stata—https://youtu.be/8zzZojXnXJg

References

Borenstein, M., L. V. Hedges, J. P. T. Higgins, and H. R. Rothstein. 2009. *Introduction to Meta-Analysis*. Chichester, UK: Wiley.

Glass, G. V. 1976. Primary, secondary, and meta-analysis of research. *Educational Researcher* 5: 3–8.

Palmer, T. M., and J. A. C. Sterne, ed. 2016. *Meta-Analysis in Stata: An Updated Collection from the Stata Journal*. 2nd ed. College Station, TX: Stata Press.

Raudenbush, S. W. 1984. Magnitude of teacher expectancy effects on pupil IQ as a function of the credibility of expectancy induction:

References (cont.)

A synthesis of findings from 18 experiments. *Journal of Educational Psychology* 76: 85–97.

Rice, K., J. P. T. Higgins, and T. S. Lumley. 2018. A re-evaluation of fixed effect(s) meta-analysis. *Journal of the Royal Statistical Society, Series A* 181: 205–227.

Rosenthal, R., and L. Jacobson. 1968. Pygmalion in the classroom. *Urban Review* 3: 16–20.