Meta-analysis using Stata

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2019 Nordic and Baltic Stata Users Group meeting

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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.

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Meta-analysis using Stata
└─ Brief introduction to meta-analysis
  └─ Does it make sense to combine different studies?

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*."

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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

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Meta-analysis using Stata
└─Brief introduction to meta-analysis
  └─Components of meta-analysis

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.

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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

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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

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Meta-Analysis Control Panel

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

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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: Stratify on variable:
                      Ascending

Submit

No. of studies: 13   Model: Random-effects   Effect size: _meta_es, Log Risk-Ratio
CI level: 95%   Method: REML   Std. Error: _meta_se

? ⟳   Close

Meta-analysis using Stata
└─Motivating example: Effects of teacher expectancy on pupil IQ
　└─Data description

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.

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Meta-analysis using Stata
└─ Motivating example: Effects of teacher expectancy on pupil IQ
   └─ Data description

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
```

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```
. 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

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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.

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- 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.

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Meta-analysis using Stata
└─Prepare data for meta-analysis
  └─Declaring pupil IQ dataset

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
```

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Meta-analysis using Stata
└─ Prepare data for meta-analysis
  └─ Declaring a meta-analysis model

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.

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```
. 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
```

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Meta-analysis using Stata
└─ Meta-analysis summary: Forest plot
  └─ Update meta settings

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
```

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Meta-analysis using Stata
└─Meta-analysis summary: Forest plot
  └─Forest plot
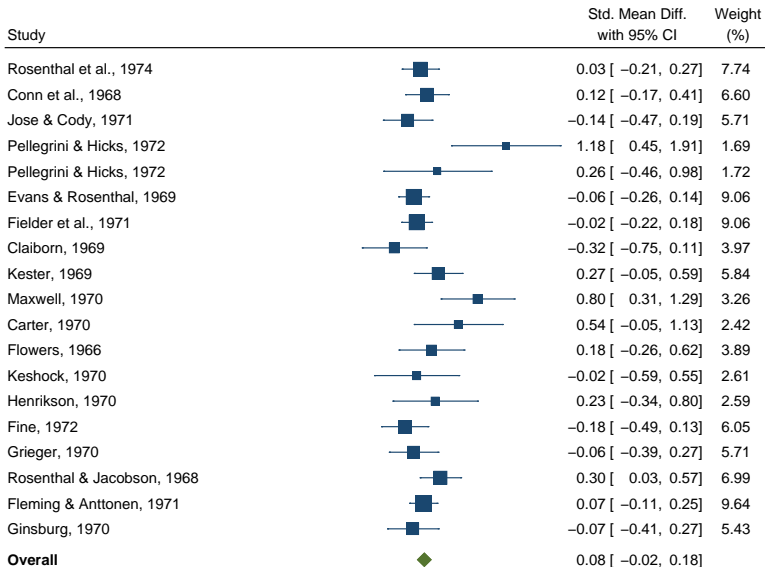
Forest plot

- 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*)

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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

Meta-analysis using Stata
└─Heterogeneity: Subgroup analysis, meta-regression
  └─Between-study heterogeneity

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.
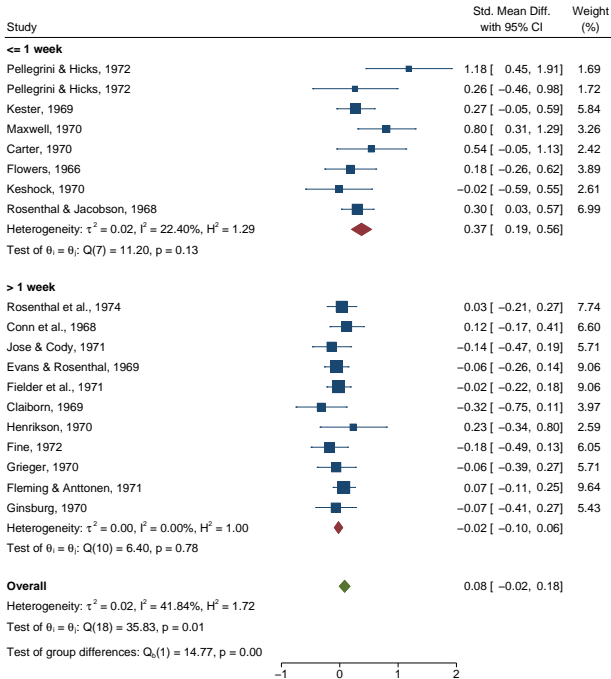
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Heterogeneity: Subgroup analysis

- 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
```

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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: $\tau^2 = 0.02$, $I^2 = 22.40\%$, $H^2 = 1.29$		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: $\tau^2 = 0.00$, $I^2 = 0.00\%$, $H^2 = 1.00$		−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: $\tau^2 = 0.02$, $I^2 = 41.84\%$, $H^2 = 1.72$			
Test of $\theta_i = \theta_j$: Q(18) = 35.83, p = 0.01			
Test of group differences: $Q_b(1)$ = 14.77, p = 0.00			

−1   0   1   2

Random−effects REML model

Meta-analysis using Stata
└─ Heterogeneity: Subgroup analysis, meta-regression
  └─ Heterogeneity: Meta-regression

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
```

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Meta-analysis using Stata
└─Heterogeneity: Subgroup analysis, meta-regression
  └─Meta-regression: Bubble plot

Meta-regression: Bubble plot

- Explore the relationship between effect sizes and weeks.

  `. estat bubbleplot`
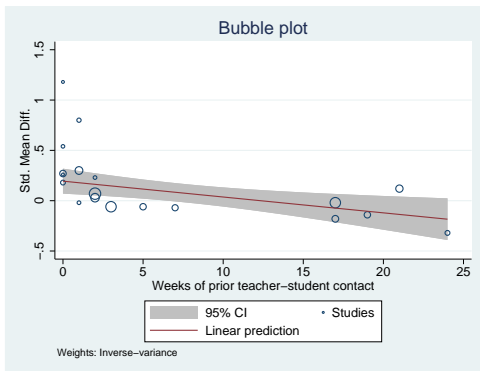
- Negative relationship; some of the more precise studies are outlying studies

Meta-analysis using Stata
└─Small-study effects and publication bias
  └─Funnel plot

Funnel plot

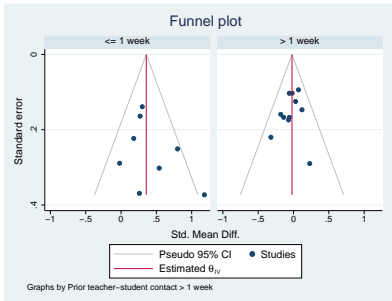- Explore funnel-plot asymmetry visually.

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

Meta-analysis using Stata
└─Small-study effects and publication bias
  └─Test for funnel-plot asymmetry
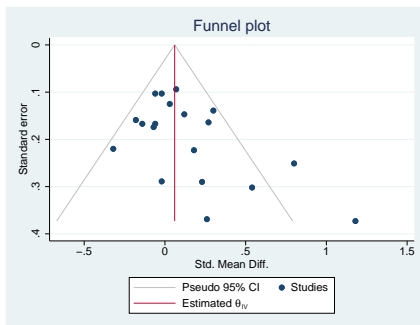
Test for funnel-plot asymmetry

- 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.

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Meta-analysis using Stata
└─ Small-study effects and publication bias
  └─ Contour-enhanced funnel plot

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
```

Meta-analysis using Stata
└─Small-study effects and publication bias
  └─Small-study effects
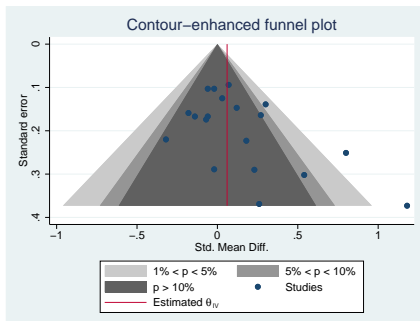
Small-study effects

- 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
```

Meta-analysis using Stata
└─Small-study effects and publication bias
  └─ Assess publication bias

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.

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```
. 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
```

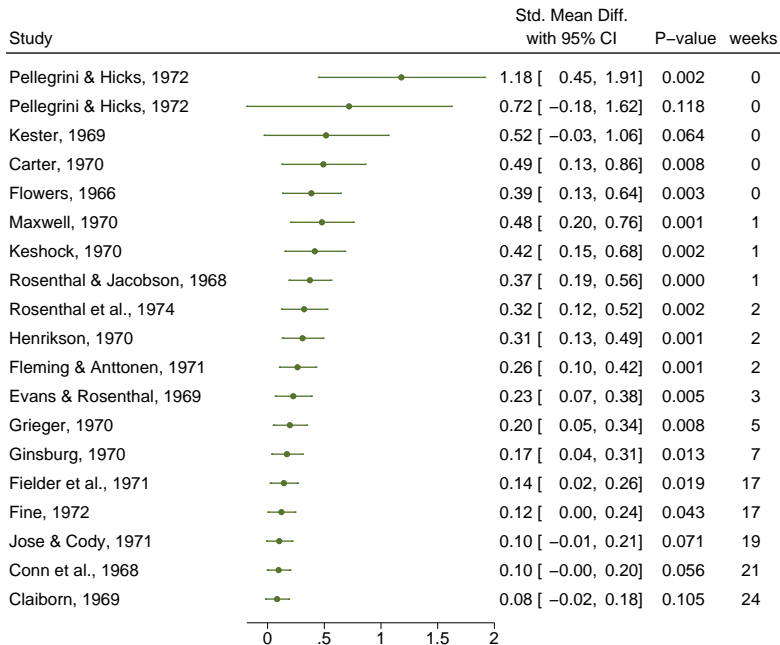| Studies	Std. Mean Diff.	[95% Conf. Interval]	
Observed	0.084	-0.018	0.185
Observed + Imputed	0.028	-0.117	0.173

(*Continued on next page*)

Funnel plot
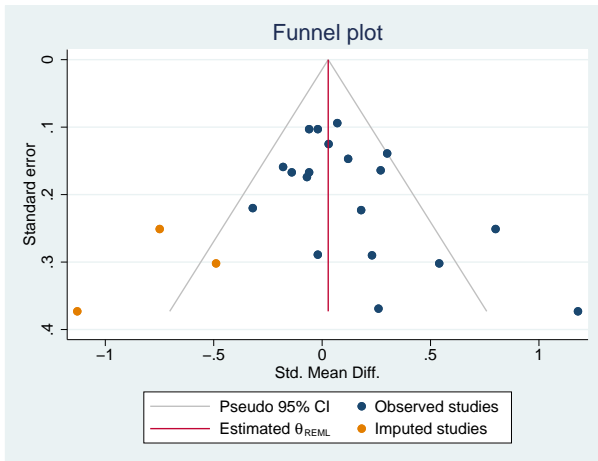
Cumulative meta-analysis

- 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
```

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	Std. Mean Diff. with 95% CI	P-value	weeks

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

STata 16

Meta-analysis using Stata
└─ Details: Meta-analysis models
  └─ Estimator of the overall effect

Estimator of the overall effect

- The three models differ in the population parameter, θ_{pop}, they estimate:
  - CE model: $\theta_{\mathrm{pop}} = \theta$ 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: $\theta_{\mathrm{pop}} = \theta$ is the mean of the distribution of the study effects.
- But they all use the weighted average as the estimator of θ_{pop}:

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

where w_j depends on the model.

STATA 16

Meta-analysis using Stata
└─ Details: Meta-analysis models
   └─ Random-effects model: Stata's default

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.

STaTa 16

```
. 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
```

Meta-analysis using Stata
└─Details: Meta-analysis models
  └─Common-effect model

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, ...

STaTa 16

Meta-analysis using Stata
└─ Details: Meta-analysis models
   └─ Common-effect model

```
. 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
```

STata 16

Meta-analysis using Stata
└─ Details: Meta-analysis models
   └─ Fixed-effects model

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.

STATA 16

```
. 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
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Kester, 1969	0.270	-0.051	0.591	4.95
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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
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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
```

STaTa 16

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.

STATA 16

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()`.

STATA 16

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

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