Title

> **meta data** — Declare meta-analysis data

Description   Remarks and examples   References   Also see

Description

This entry describes how to prepare your data for meta-analysis using the meta commands.

In a nutshell, do the following:

1. If you have access to summary data, use meta esize to compute and declare effect sizes such as an odds ratio or a Hedges's g.

2. Alternatively, if you have only precomputed (generic) effect sizes, use meta set.

3. To update some of your meta-analysis settings after the declaration, use meta update.

4. To check whether your data are already meta set or to see the current meta settings, use meta query.

5. If you want to perform multivariate meta-regression using meta mvregress, you do not need to meta set your data.

Remarks and examples

Remarks are presented under the following headings:

Overview

The declaration of your data to be meta data is the first step of your meta-analysis in Stata. meta data are your original data that also store key variables and characteristics about your specifications, which will be used by all meta commands during your meta-analysis session. The declaration step helps minimize mistakes and saves you time—you only need to specify the necessary information once.

You can use meta set or meta esize to declare your data to be meta data. If you have access only to precomputed effect sizes and their standard errors, use meta set. If you have access to summary data such as means and standard deviations from individual studies, use meta esize to compute the effect sizes and their standard errors and declare them. The latter is preferable because it provides access to more features such as the Mantel–Haenszel estimation method for a two-group comparison of binary outcomes, which needs access to the actual 2×2 tables and not only the effect sizes for the computations.

For example, suppose that you have variables es and se, which contain the effect sizes and the corresponding standard errors. You can use

```
. meta set es se
```

to declare your data, and all subsequent meta commands will automatically use these variables in the meta-analysis.

To review the current meta settings or to check whether the data are meta set, you can use meta query; see [META] **meta update**. After your data are declared, you can update some of the meta-analysis specifications by using meta update. If you wish to clear the meta settings after your meta-analysis, you can use meta clear; see [META] **meta update**.

Declaring meta-analysis information

Two main components of meta-analysis are study-specific effect sizes and their precision. You must specify them during declaration. Other important components include the underlying meta-analysis model and an estimation method. You can specify them during declaration or later during analysis or use Stata's defaults. You can also specify options that affect the output of the meta commands. Below, we describe how you can declare various meta-analysis information.

Declaring effect sizes and their precision

As we mentioned above, you must declare study-specific effect sizes and their precision. This is done differently for meta set and meta esize.

meta esize computes effect sizes and their standard errors from summary data and then declares them. meta set declares already precomputed effect sizes and their standard errors. Thus, to use meta set, you do not need summary data from each study, but you need them for meta esize. Some analysis may not be available after meta set such as the Mantel–Haenszel estimation method and Harbord's test for the funnel-plot asymmetry because they require access to summary data.

Effect sizes and their precision using meta set. To use meta set, you must specify variables containing study-specific effect sizes and their precision. There are two ways to specify the precision of the effect sizes. You can either specify a variable containing the standard errors,

```
. meta set es se
```

Or, instead of the standard errors, specify the confidence intervals, and meta set will compute the corresponding standard errors based on them:

```
. meta set es cil ciu
```

In the above, the specified CI variables will be assumed to correspond to the 95% CIs. You can change this by specifying the civarlevel() option:

```
. meta set es cil ciu, civarlevel(90)
```

But do not confuse civarlevel() with level(). The former affects the confidence level only for the specified CI variables. The latter specifies the confidence level for the meta-analysis.

Effect sizes and their precision using meta esize. To use meta esize, you must specify summary data for each study. The type of summary data you specify depends on the effect size you wish to compute and consequently on the outcome of interest and type of analysis in the original studies.

meta esize computes and declares various effect sizes for two-group comparisons of continuous and binary outcomes, for estimating a single proportion or prevalence, and for estimating a correlation between two variables of interest. For a two-group comparison of continuous outcomes, you must specify the number of observations, means, and standard deviations for each treatment group (group 1) and control group (group 2).

```
. meta esize n1 m1 sd1 n2 m2 sd2
```

To compute effect sizes and their standard errors, meta esize also needs to know the type of the effect size. The above assumes Hedges's g standardized mean difference, but you can specify others in the esize() option; see effect sizes for a two-group comparison of continuous outcomes in the *estypecnt* table in *Syntax* of [META] **meta esize**.

For a two-group comparison of binary outcomes, you must specify 2×2 contingency tables for each study. You specify them as follows. Each of the four cells is represented by a variable such that each row represents a 2×2 table from a specific study. For instance,

```
. meta esize n11 n12 n21 n22
```

The order in which you specify the four variables is important: the top-left cell first, the top-right cell next, followed by the bottom-left cell, and finally the bottom-right cell. The above computes the log odds-ratio as an effect size, but you can select a different effect size; see effect sizes for a two-group comparison of binary outcomes in the *estypebin* table in *Syntax* of [META] **meta esize**.

meta esize can compute effect sizes for estimating a single proportion. You must specify the number of successes (events) and the study sample size.

```
. meta esize ns n
```

The above computes the Freeman–Tukey-transformed proportions, but you can specify other effect sizes in the esize() option; see effect sizes for a single proportion in the *estypeprop* table in *Syntax* of [META] **meta esize**.

In StataNow, meta esize can compute effect sizes for estimating a correlation between two variables of interest. You must specify the sample correlation coefficients and the study sample size. You must also specify either the fisherz option or the correlation option,

```
. meta esize rho n, fisherz
```

The above computes the Fisher's z-transformed correlations, but you can request untransformed (raw) correlations by specifying the correlation option; see effect sizes for estimating a correlation in the *estypecorr* table in *Syntax* of [META] **meta esize**.

Options affecting effect-size and precision computations with meta esize. Depending on the chosen effect size, meta esize provides alternative ways of computing effect sizes and their standard errors.

For the Hedges's g effect size, there are two ways to compute the bias-correction factor used in its formula. For consistency with meta-analysis literature, meta esize uses an approximation, but you can specify the exact option within esize() to use the exact computation:

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

Note that the esize command uses the exact computation.

Both Hedges's g and Cohen's d effect sizes support standard error adjustment of Hedges and Olkin (1985) with esize()'s option holkinse:

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

For the (unstandardized) mean difference, you can choose to compute standard errors assuming unequal variance between the two groups:

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

For two-sample binary data with log odds-ratios or log risk-ratios as effect sizes, meta esize automatically adjusts for zero cells when computing effect sizes. By default, it adds 0.5 to all cells of the 2×2 tables that contain at least one zero cell. You can specify other adjustments in the zerocells(*zcspec*) option. For example, with log odds-ratios, you can specify the treatment-arm continuity correction of Sweeting, Sutton, and Lambert (2004) as zerocells(tacc), or you can request no zero-cell adjustment:

```
. meta esize n11 n12 n21 n22, zerocells(none)
```

Similarly, for one-sample binary data with the logit-transformed proportions or raw proportions as effect sizes, meta esize also adjusts for zero cells when computing effect sizes. By default, it adds 0.5 to the number of successes and to the number of failures for studies containing zero successes or zero failures. Other adjustments are also possible via the zerocells(*zcspec*) option.

See *Options* in [META] **meta esize**.

Declaring a meta-analysis model

Before you proceed with performing meta-analysis, we want you to think about the model underlying your meta-analysis. This decision is important because the selected meta-analysis model will determine the availability of some of the meta-analysis methods and, more importantly, how you interpret the obtained results; see *Comparison between the models and interpretation of the results* in [META] **Intro**. Also, most likely, you will want to use the chosen model during your entire meta-analysis session. Thus, we made the choices for the meta-analysis model and, consequently, the meta-analysis estimation method be part of the initial declaration step. But fear not! If desired, you can easily switch to a different meta-analysis model or method for the rest of your meta-analysis session or reset it temporarily for a particular analysis; see *Modifying default meta settings*.

We discuss the available models and the differences between them in detail in *Meta-analysis models* in [META] **Intro**.

Briefly, there are three models to choose from: a common-effect, fixed-effects, or random-effects model. They can be requested by specifying options common, fixed, or random. If you omit all of these options, the random-effects model will be assumed.

A common-effect model makes a strong assumption about the underlying true effect size being the same across (common to) all studies. When this assumption is true, this model is a reasonable choice. Most likely, you will want to verify the plausibility of this assumption for your data. So a model that allows the study effect sizes to be different may be a better choice during the initial analysis.

A fixed-effects model allows the effect sizes to be different across studies and assumes that they are fixed. You may ask: What does "fixed" mean? Different disciplines may have different definitions of a fixed effect. In the context of meta-analysis, you can think of fixed effects as effects of particular interest. In other words, your research questions and final inference are focused only on the specific studies that were selected in the meta-analysis.

Conversely, a random-effects model assumes that the study effect sizes are random, meaning that they represent a random sample from a larger population of similar studies. The results obtained from a random-effects model can be extended to the entire population of similar studies and not just the ones that were selected in the meta-analysis. The meta-analysis literature recommends to start with a random-effects model, which is also Stata's default for most `meta` commands.

So, which model should you choose? Our recommendation is to start with a random-effects model and explore the heterogeneity, publication bias, and other aspects of your meta-analysis data. If you are interested only in the inference about the particular studies in your data, a fixed-effects model may be a reasonable alternative. We suggest that you avoid using, or at least starting with, a common-effect model unless you verified that the underlying assumption of the common study effects is plausible for your data.

As we described in *Comparison between the models and interpretation of their results* in [META] **Intro**, a fixed-effects model and a common-effect model produce the same results in a meta-analysis. Although the final estimates are the same, their interpretation is different! In a common-effect model, the estimate of the overall effect size is an estimate of the true common effect size, whereas in a fixed-effects model, it is an estimate of the average of true, different study-specific effect sizes. Thus, the `meta` suite provides the two options `common` and `fixed` to emphasize the conceptual differences between the two models. Additionally, when you assume a common-effect model, you essentially imply that certain issues such as study heterogeneity are of no concern in your data. Therefore, when you specify the `common` option, certain commands such as `meta regression` will not be available. This is again our way of reminding you of the underlying assumption of a common-effect model. For other `meta` commands, specifying `common` versus `fixed` will merely change the reported title from, say, "Common-effect meta-analysis" to "Fixed-effects meta-analysis". Nevertheless, the title change is important because it encourages proper interpretation of the results.

Declaring a meta-analysis estimation method

Depending on a chosen meta-analysis model and effect size, there are a number of methods available to estimate the overall effect size. For a common-effect model and a fixed-effects model, the inverse-variance method, `common(invvariance)` and `fixed(invvariance)`, is used with generic effect sizes, which are declared by `meta set`, and with effect sizes for two-sample continuous data and for one-sample binary data, which are declared by `meta esize`. With effect sizes for two-sample binary data (except Peto's log odds-ratio), which are also declared by `meta esize`, the Mantel–Haenszel method, `common(mhaenszel)` or `fixed(mhaenszel)`, is also available.

For a random-effects model, there are several different methods to estimate the between-study variance, which contributes to the weights used to estimate the overall effect size. The default method is REML, `random(reml)`, but other methods such as ML, `random(ml)`, and DerSimonian–Laird, `random(dlaird)`, are also available. See *Syntax* in [META] **meta set** for a full list.

When you specify `random`, the REML method is assumed. When you specify `common` or `fixed`, the inverse-variance method is assumed for all effect sizes except log odds-ratios, log risk-ratios, and risk differences, as specified with `meta esize`. For these effect sizes, the Mantel–Haenszel method is the default method.

See *Meta-analysis estimation methods* in [META] **Intro** for detailed descriptions of the methods.

Default meta-analysis model and method

During declaration, meta set and meta esize assume a random-effects model unless you specify one of options fixed or common. It also assumes the REML estimation method unless you specify some other method in option random(); see *Declaring a meta-analysis estimation method*.

The declared model will be used by all meta commands except meta funnelplot, meta galbraithplot, and meta labbeplot, which, for historical reasons, assume a common-effect model with the inverse-variance estimation method. But you can change the assumed model and method by specifying the corresponding options such as random(dlaird) with a meta command.

Also see *Modifying default meta settings* for details.

Declaring a confidence level for meta-analysis

By default, meta set and meta esize assume the 95% confidence level (or as set by set level) for the entire meta-analysis. You can change this by specifying the level() option with these commands. You can also modify the confidence level after the declaration as we describe in *Modifying default meta settings*.

Declaring display settings for meta-analysis

meta set and meta esize also provide options to control the output of meta commands.

The studylabel(*varname*) option specifies a string variable that will be used by meta commands such as meta summarize and meta forestplot to label the studies in the output. By default, the generic labels—Study 1, Study 2, and so on—will be used.

The eslabel(*string*) option specifies a string that will be used by meta commands such as meta summarize and meta forestplot to label effect sizes in the output. The default label with meta set is Effect size. The default label with meta esize is specific to the chosen effect size. For instance, it is Log Odds-Ratio for log odds-ratios.

By default, all meta commands display a short summary about the declared meta settings such as the variables containing effect sizes and their standard errors. After the declaration, the meta commands do not require you to specify the effect-size variables and standard error variables again. They simply use the corresponding system variables (see *System variables*) created during declaration. The reported summary reminds you that those variables are part of your meta-analysis. You can suppress this summary from all meta commands by specifying the nometashow option with meta set or meta esize. You can also suppress this summary for a particular meta command by specifying the option with that command; see *Modifying default meta settings*.

Modifying default meta settings

You can modify the default meta settings both during and after the declaration. Some of the settings may even be modified (temporarily) for a particular meta command.

You can modify the default settings during the declaration by simply specifying the corresponding options with meta set or meta esize. For example, when we type

```
. meta set ...
```

a random-effects model with the REML estimation method is assumed. We can specify another estimation method, for example, ML, by using random(ml):

```
. meta set ... , random(ml)
```

Or we can specify a different meta-analysis model, for example, a fixed-effects model:

```
. meta set ... , fixed
```

After the declaration, you can use `meta update` to modify the current settings. For example, we can switch to a common-effect model for the rest of our meta-analysis by typing

```
. meta update, common
```

Now all subsequent `meta` commands will automatically assume a common-effect model.

In the above examples, we used `meta set`, but you can use the same specifications with `meta esize`. We also demonstrated only a few options, but the same principles apply to the other options supported by `meta set` and `meta esize`.

For options `random()`, `common()` (and `common`), `fixed()` (and `fixed`), `level()`, and `nometashow`, we can also modify the current setting temporarily while running a particular `meta` command. For example, suppose that we want to obtain the results assuming a 90% confidence level with meta summarize. We can type

```
. meta summarize, level(90)
```

If we wanted all relevant `meta` commands to use the 90% confidence level, we would have typed

```
. meta update, level(90)
```

Meta-analysis information

When you use `meta set` or `meta esize`, they record information about your study, effect sizes and their precision, and meta-analysis model and meta-analysis estimation method, among other things. This information will be used by subsequent `meta` commands. The summary information is mostly the same between the two commands, but `meta esize` records several additional settings.

Let's get familiar with the meta setting information by looking at examples.

Meta settings with meta set

Consider a fictional dataset, `metaset.dta`, containing generic effect sizes and their standard errors stored in the corresponding variables `es` and `se`.

```
. use https://www.stata-press.com/data/r18/metaset
(Generic effect sizes; fictional data)
. describe es se
```

Variable name	Storage type	Display format	Value label	Variable label
es	double	%10.0g		Effect sizes
se	double	%10.0g		Std. err. for effect sizes

At the minimum, with `meta set`, we must specify the variables containing effect sizes and their standard errors. (For other uses of `meta set`, see *Remarks and examples* in [META] **meta set**.)

```
. meta set es se
Meta-analysis setting information
 Study information
    No. of studies: 10
        Study label: Generic
         Study size: N/A
        Effect size
               Type: <generic>
              Label: Effect size
           Variable: es
          Precision
          Std. err.: se
                 CI: [_meta_cil, _meta_ciu]
           CI level: 95%
   Model and method
              Model: Random effects
             Method: REML
```

The summary is divided into four categories: information about the study, the specified effect sizes, their precision, and meta-analysis model and method. Below, we describe in detail each output category.

```
Study information
   No. of studies:  10
      Study label:  Generic
       Study size:  N/A
```

The study information consists of the number of studies (10 in our example), a study label (`Generic`), and a study size (`N/A`). If the `studylabel(`*varname*`)` option is specified, the `Study label:` will contain the name of the specified variable. Otherwise, a generic study label—`Study 1`, `Study 2`, and so on—will be used in the output of `meta` commands. If the `studysize(`*varname*`)` option is specified with `meta set`, the `Study size:` will contain the name of the specified variable.

```
Effect size
       Type:  Generic
      Label:  Effect size
   Variable:  es
```

The effect-size information consists of the type of the effect size, its label, and the variable containing study-specific effect sizes. The effect-size `Type:` is always `Generic` with `meta set`. The effect-size `Label:` is either a generic `Effect size` or as specified in the `eslabel(`*string*`)` option. This label will be used to label the effect sizes in the output of all `meta` commands. The effect-size `Variable:` displays the name of the declared variable containing effect sizes. After the declaration, both commands store study-specific effect sizes in the system variable `_meta_es` (see *System variables*). `meta set` simply copies them from the declared effect-size variable. Thus, `Variable:` will contain the name of the *esvar* variable, `es` in our example, with `meta set`.

```
Precision
Std. err.:  se
       CI:  [_meta_cil, _meta_ciu]
 CI level:  95%
```

The precision information consists of variables containing effect-size standard errors, confidence intervals, and the declared confidence level. As with the effect sizes, `meta set` uses the standard errors specified in the *sevar* variable (variable `se` here). The corresponding confidence intervals are

computed using the effect sizes and their standard errors and stored in the system variables _meta_cil and _meta_ciu. With meta set, you can specify confidence intervals instead of the standard errors, in which case the standard errors will be computed from the effect sizes and confidence intervals and stored in _meta_se, in which case Std. err.: will contain _meta_se; see *Syntax* in [META] **meta set**. CI: always contains _meta_cil and _meta_ciu. The specified CI variables will be reported in User CI: with their corresponding confidence level reported in User CI level:, which is controlled by the civarlevel() option. The declared CI variables and the system CI variables will be the same only when civarlevel() is the same as level(), and the system variables are the ones that are used in the meta-analysis.

CI level: reports the confidence level, controlled by the level() option, that will be used by all meta commands when computing confidence intervals for various meta-analyses such as the CIs of the overall effect size, regression coefficients, and so on. The default confidence level is 95% or as set by set level.

```
Model and method
          Model:  Random-effects
          Method: REML
```

As we pointed out in *Declaring a meta-analysis model*, the meta-analysis model and, consequently, the meta-analysis estimation method are important aspects of your meta-analysis. As such, we made them be part of your declaration step too. By default, a random-effects model with the REML estimation method is assumed for most meta commands; see *Default meta-analysis model and method*. You can change the defaults as we describe in *Modifying default meta settings*.

Meta settings with meta esize

Consider metaescnt.dta, containing fictional study-specific summary data for continuous outcomes for group 1 and group 2.

```
. use https://www.stata-press.com/data/r18/metaescnt, clear
(Fictional summary data for continuous outcomes)

. describe n1 m1 sd1 n2 m2 sd2

Variable      Storage   Display    Value
    name         type    format    label      Variable label
────────────────────────────────────────────────────────────────────
n1           byte      %9.0g                 Study sizes of group 1
m1           float     %9.0g                 Means of group 1
sd1          float     %9.0g                 Std. dev. of group 1
n2           byte      %9.0g                 Study sizes of group 2
m2           float     %9.0g                 Means of group 2
sd2          float     %9.0g                 Std. dev. of group 2
```

With `meta esize`, we must specify the summary data to compute an effect size. Let's focus on the studies comparing the mean differences between the two groups. Our summary data include the numbers of observations and the estimates of means and standard deviations for each group. We specify the variables containing these summaries following the command name.

```
. meta esize n1 m1 sd1 n2 m2 sd2
Meta-analysis setting information
 Study information
    No. of studies: 10
       Study label: Generic
        Study size: _meta_studysize
      Summary data: n1 m1 sd1 n2 m2 sd2

      Effect size
              Type: hedgesg
             Label: Hedges's g
          Variable: _meta_es
   Bias correction: Approximate

         Precision
         Std. err.: _meta_se
    Std. err. adj.: None
                CI: [_meta_cil, _meta_ciu]
          CI level: 95%

  Model and method
             Model: Random effects
            Method: REML
```

The meta setting information from `meta esize` is almost the same as the one produced by `meta set`, which we described in *Meta settings with meta set*, but has several additional settings. The summary-data variables are listed under `Summary data:`. As we mentioned earlier, `meta esize` computes the effect sizes and their standard errors from the specified summary data, so effect-size `Variable:` and `Std. err.:` contain the names of the corresponding system variables, `_meta_es` and `_meta_se`. The summary data also include the information about the study size, so `Study size:` displays the name of the system variable, `_meta_studysize`, that contains study size, which is equal to the sum of `n1` and `n2` in our example.

By default, `meta esize` computes the Hedges's g effect size for the two-group mean comparison. You can specify the `esize(esspec)` option to select a different effect size. For the Hedges's g effect size, there are two methods to compute the underlying bias-correction term: approximate or exact. For consistency with the meta-analysis literature, `meta esize`, by default, uses an approximation, as indicated in `Bias correction:` under `Effect size`. But you can change this by specifying the `exact` option within `esize()`.

Another additional setting describes the type of adjustment applied when computing the standard errors of the effect sizes; see `Std. err. adj.:` under `Precision`. This adjustment is applicable only with the Hedges's g or Cohen's d effect size. No adjustment is made by default, but you can use the `holkinse` option within `esize()` to specify the adjustment of Hedges and Olkin (1985). For the mean-difference effect size, you can request the adjustment for unequal group variances by specifying `esize()`'s option `unequal`.

Finally, for log odds-ratios or log risk-ratios, `meta esize` additionally reports the type of adjustment made to the zero cells of contingency tables, which represent the summary data for a two-group comparison of binary outcomes. For these effect sizes, the type of adjustment will be listed in `Zero-cells adj.:` under `Effect size` (not applicable in our example). By default, 0.5 is added to each zero cell, but you can specify the `zerocells()` option with `meta esize` to apply a different adjustment or none. The zero-cells adjustment is also reported for meta-analysis of a single proportion when effect sizes are logit-transformed proportions or raw proportions.

System variables

`meta set` and `meta esize` store information about the meta-analysis settings in data characteristics ([P] **char**) and system variables.

`meta` system variables are the variables that begin with `_meta_`. There are four main variables that are stored by the two commands.

`_meta_es` stores study-specific effect sizes.

`_meta_se` stores the standard errors of study-specific effect sizes.

`_meta_cil` and `_meta_ciu` store the lower and upper limits of the CIs for study-specific effect sizes. These variables correspond to the confidence level declared for the meta-analysis, the value of which is stored in the data characteristic `_meta_level`.

Other system variables include integer study identifiers stored in `_meta_id`, study labels stored in a string variable `_meta_studylabel`, and study sizes stored in `_meta_studysize`. `_meta_studysize` is always stored with `meta esize`. With `meta set`, it is stored only when the variable containing study sizes is specified in the `studysize()` option.

Also see *Stored results* in [META] **meta set** and *Stored results* in [META] **meta esize**.

Examples of data declaration for meta-analysis

In this section, we demonstrate how to prepare data for meta-analysis in Stata for several case studies.

Declaring precomputed effect sizes using meta set

We will demonstrate how to use `meta set` to declare generic effect sizes.

▷ Example 1: Precomputed log hazard-ratios using meta set

We demonstrate how to declare the meta-analysis data from Steurer et al. (2006), who studied the effect of purine analogues for the treatment of chronic lymphocytic leukemia. Variables `loghr` and `seloghr` contain the log hazard-ratios and their standard errors.

```
. use https://www.stata-press.com/data/r18/leukemia2, clear
(Single-agent purine analogue treatment for leukemia)
. describe
Contains data from https://www.stata-press.com/data/r18/leukemia2.dta
 Observations:            4                  Single-agent purine analogue
                                               treatment for leukemia
     Variables:            6                  25 Apr 2022 12:09
                                             (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
author	str14	%14s		* Author
year	int	%8.0g		Publication year
ntreat	int	%8.0g		Treatment-group sample size
ncontrol	int	%8.0g		Control-group sample size
loghr	float	%9.0g		Log hazard-ratio
seloghr	float	%9.0g		Standard error for loghr
				* indicated variables have notes

```
Sorted by:
```

We use the `meta set` command to declare the effect sizes (log hazard-ratios) and their standard errors.

```
. meta set loghr seloghr

Meta-analysis setting information

 Study information
    No. of studies: 4
        Study label: Generic
         Study size: N/A

        Effect size
               Type: <generic>
              Label: Effect size
           Variable: loghr

           Precision
           Std. err.: seloghr
                  CI: [_meta_cil, _meta_ciu]
            CI level: 95%

   Model and method
              Model: Random effects
             Method: REML
```

`meta set` reports that there are 4 studies in this dataset. The type of effect size is `Generic` because we used the precalculated effect size. The default label `Effect size` will be used in the output. The command also reports the variables that were used to declare the effect sizes, `loghr`, and their standard errors, `seloghr`. The other settings are as we described in *Meta settings with meta set*.

As we described in *System variables*, `meta set` created several system variables that will be used by other `meta` commands in the computations:

```
. describe _meta*

Variable         Storage   Display   Value
    name            type    format    label        Variable label
─────────────────────────────────────────────────────────────────────────
_meta_id          byte     %9.0g                   Study ID
_meta_studyla~l   str7     %9s                      Study label
_meta_es          float    %9.0g                    Generic ES
_meta_se          float    %9.0g                    Std. err. for ES
_meta_cil         double   %10.0g                   95% lower CI limit for ES
_meta_ciu         double   %10.0g                   95% upper CI limit for ES

. list _meta*
```

	_meta_id	_meta~el	_meta_es	_meta_se	_meta_cil	_meta_ciu
1.	1	Study 1	-.592	.345	-1.2681876	.08418756
2.	2	Study 2	-.0791	.0787	-.23334916	.07514916
3.	3	Study 3	-.237	.144	-.51923481	.0452348
4.	4	Study 4	.163	.312	-.44850877	.77450878

`_meta_id` contains integers identifying the studies, and `_meta_studylabel` contains the study labels. `_meta_es` and `_meta_se` contain log hazard-ratios and their standard errors, and `_meta_cil` and `_meta_ciu` contain the corresponding lower and upper bounds of the 95% CIs for log hazard-ratios.

We did not specify the `studylabel()` option in this example, so generic labels will be used in the output of other `meta` commands such as `meta summarize`:

```
. meta summarize
  Effect-size label: Effect size
        Effect size: loghr
          Std. err.: seloghr
Meta-analysis summary                         Number of studies =        4
Random-effects model                          Heterogeneity:
Method: REML                                             tau2 =   0.0000
                                                       I2 (%) =     0.00
                                                          H2 =     1.00

─────────────────────────────────────────────────────────────────────────
          Study │  Effect size   [95% conf. interval]   % weight
────────────────┼──────────────────────────────────────────────
        Study 1 │       -0.592      -1.268      0.084       3.68
        Study 2 │       -0.079      -0.233      0.075      70.70
        Study 3 │       -0.237      -0.519      0.045      21.12
        Study 4 │        0.163      -0.449      0.775       4.50
────────────────┼──────────────────────────────────────────────
          theta │       -0.120      -0.250      0.009
─────────────────────────────────────────────────────────────────────────

Test of theta = 0: z = -1.82                       Prob > |z| = 0.0688
Test of homogeneity: Q = chi2(3) = 3.62                  Prob > Q = 0.3049
```

Generic labels Study 1, Study 2, Study 3, and Study 4 are used to label the studies. Also, the generic label Effect size is used to label the log hazard-ratios. See [META] **meta summarize** for details about `meta summarize`.

We can provide more descriptive labels for the studies and the effect sizes by specifying options `studylabel()` and `eslabel()`.

```
. generate studylbl = author + " (" + string(year) + ")"
. meta set loghr seloghr, studylabel(studylbl) eslabel("Ln(HR)")
Meta-analysis setting information

 Study information
     No. of studies: 4
        Study label: studylbl
         Study size: N/A

        Effect size
               Type: <generic>
              Label: Ln(HR)
           Variable: loghr

          Precision
          Std. err.: seloghr
                 CI: [_meta_cil, _meta_ciu]
           CI level: 95%

   Model and method
              Model: Random effects
             Method: REML
```

We created a new variable, `studylbl`, that combines the author and year information of the published studies to use as our study labels. `meta set` reported that `studylbl` will be used to label the studies and `Ln(HR)` to label the effect sizes.

If we now rerun `meta summarize` (suppressing the table header), we see the new labels in the output.

```
. meta summarize, noheader
  Effect-size label: Ln(HR)
        Effect size: loghr
          Std. err.: seloghr
        Study label: studylbl
```

Study	Ln(HR)	[95% conf. interval]		% weight
Johnson et al. (1996)	-0.592	-1.268	0.084	3.68
Leporrier (2001)	-0.079	-0.233	0.075	70.70
Rai (2000)	-0.237	-0.519	0.045	21.12
Robak (2000)	0.163	-0.449	0.775	4.50
theta	-0.120	-0.250	0.009	

```
Test of theta = 0: z = -1.82                    Prob > |z| = 0.0688
Test of homogeneity: Q = chi2(3) = 3.62              Prob > Q = 0.3049
```

After the original declaration, we can use `meta update` to update the meta settings instead of repeating `meta set`; see example 6.

◁

Also see *Remarks and examples* in [META] **meta set** for more examples of using `meta set`.

Computing and declaring effect sizes using meta esize

We demonstrate how to use `meta esize` to compute and declare effect sizes for continuous and binary outcomes.

▷ Example 2: Mean differences for two-sample continuous data using meta esize

Consider the study of Gibson et al. (2002), who compared the performance of asthma-management programs for adults with asthma.

The `asthma` dataset contains the following summary-data variables:

```
use https://www.stata-press.com/data/r18/asthma, clear
(Education and medical review for asthma patients)
. describe ni meani sdi nc meanc sdc
```

Variable name	Storage type	Display format	Value label	Variable label
ni	int	%9.0g		Intervention-group sample size
meani	double	%9.0g		Average days off work/school for intervention group
sdi	double	%9.0g		Std. dev. of days off work/school for intervention group
nc	int	%9.0g		Control-group sample size
meanc	double	%9.0g		Average days off work/school for control group
sdc	double	%9.0g		Std. dev. of days off work/school for control group

Variables `ni`, `meani`, and `sdi` record the study-specific sample sizes, mean numbers of days off work/school, and standard deviations in the intervention group, and variables `nc`, `meanc`, and `sdc` record those items in the control group.

To illustrate, we will compute and declare a couple of effect sizes using `meta esize`. We will start with the default effect size—Hedges's g standardized mean. We use `meta esize` to compute this effect size for each study from the summary variables and declare them for further meta-analysis.

```
. meta esize ni meani sdi nc meanc sdc
(2 missing values generated)
Meta-analysis setting information
 Study information
     No. of studies: 13
        Study label: Generic
         Study size: _meta_studysize
       Summary data: ni meani sdi nc meanc sdc

        Effect size
                Type: hedgesg
               Label: Hedges's g
            Variable: _meta_es
    Bias correction: Approximate

            Precision
            Std. err.: _meta_se
      Std. err. adj.: None
                  CI: [_meta_cil, _meta_ciu]
            CI level: 95%

   Model and method
               Model: Random effects
              Method: REML
```

There are missing values in the summary variables, so some of the generated system variables will also contain missing values as reported by the note.

`meta esize` reports that the computed effect size is Hedges's g. See *Meta settings with meta esize* for the explanation of other settings.

The above command is equivalent to

```
. meta esize ni meani sdi nc meanc sdc, esize(hedgesg)
```

With this effect size, we can specify that the adjustment of Hedges and Olkin (1985) be applied to the standard errors.

```
. meta esize ni meani sdi nc meanc sdc, esize(hedgesg, holkinse)
(2 missing values generated)
Meta-analysis setting information
 Study information
     No. of studies: 13
        Study label: Generic
         Study size: _meta_studysize
       Summary data: ni meani sdi nc meanc sdc

        Effect size
               Type: hedgesg
              Label: Hedges's g
           Variable: _meta_es
    Bias correction: Approximate

          Precision
          Std. err.: _meta_se
    Std. err. adj.: Hedges-Olkin
                 CI: [_meta_cil, _meta_ciu]
           CI level: 95%

  Model and method
              Model: Random effects
             Method: REML
```

`meta esize` updates the adjustment in `Std. err. adj.:` under `Precision` to `Hedges-Olkin`.

Because all studies measured our outcome of interest on the same scale (number of days off work or school), we may consider the raw (unstandardized) mean difference as our effect size. We can compute it by specifying the `esize(mdiff)` option.

```
. meta esize ni meani sdi nc meanc sdc, esize(mdiff)
(2 missing values generated)
Meta-analysis setting information
 Study information
     No. of studies: 13
        Study label: Generic
         Study size: _meta_studysize
       Summary data: ni meani sdi nc meanc sdc

        Effect size
               Type: mdiff
              Label: Mean diff.
           Variable: _meta_es

          Precision
          Std. err.: _meta_se
    Std. err. adj.: None
                 CI: [_meta_cil, _meta_ciu]
           CI level: 95%

  Model and method
              Model: Random effects
             Method: REML
```

The information about the type of the effect size and its label is updated to correspond to the mean differences.

As with `meta set`, we could have used `meta update` to update the meta settings after the initial declaration instead of using `meta esize`; see example 6.

◁

▷ Example 3: Log odds-ratios and log risk-ratios for two-sample binary data

Let's revisit the declaration we used in example 1 in [META] **meta** for the bcg dataset from the BCG vaccine study (Colditz et al. 1994). The summary data (contingency tables) are recorded in the following variables:

```
use https://www.stata-press.com/data/r18/bcg, clear
(Efficacy of BCG vaccine against tuberculosis)

. describe npost nnegt nposc nnegc

Variable       Storage   Display    Value
    name          type    format    label       Variable label
─────────────────────────────────────────────────────────────────────────
npost            int     %9.0g                  Number of TB positive cases in
                                                   treated group
nnegt           long     %9.0g                  Number of TB negative cases in
                                                   treated group
nposc            int     %9.0g                  Number of TB positive cases in
                                                   control group
nnegc           long     %9.0g                  Number of TB negative cases in
                                                   control group
```

The summary variables represent the cells of the 2×2 tables for each study.

As with continuous data, we specify the summary variables for binary data following meta esize:

```
. meta esize npost nnegt nposc nnegc
Meta-analysis setting information
 Study information
     No. of studies: 13
        Study label: Generic
         Study size: _meta_studysize
       Summary data: npost nnegt nposc nnegc
        Effect size
               Type: lnoratio
              Label: Log odds-ratio
           Variable: _meta_es
    Zero-cells adj.: None; no zero cells
          Precision
          Std. err.: _meta_se
                 CI: [_meta_cil, _meta_ciu]
           CI level: 95%
  Model and method
              Model: Random effects
             Method: REML
```

The computed default effect sizes are log odds-ratios, whereas the effect of interest in this study is the risk ratio or, equivalently, the log risk-ratio.

To compute log risk-ratios, we specify `esize(lnrratio)`. We also specify the variable `studylbl` containing study labels in the `studylabel()` option.

```
. meta esize npost nnegt nposc nnegc, esize(lnrratio) studylabel(studylbl)
Meta-analysis setting information
 Study information
    No. of studies: 13
        Study label: studylbl
         Study size: _meta_studysize
       Summary data: npost nnegt nposc nnegc

        Effect size
               Type: lnrratio
              Label: Log risk-ratio
           Variable: _meta_es
   Zero-cells adj.: None; no zero cells

          Precision
          Std. err.: _meta_se
                 CI: [_meta_cil, _meta_ciu]
           CI level: 95%

   Model and method
              Model: Random effects
             Method: REML
```

Notice that there are no zero cells in our data, so there is no zero-cells adjustment (see `Zero-cells adj.:` under `Effect size`).

◁

Also see example 6 for how to update the above `meta` settings without having to respecify the summary variables.

▷ Example 4: Freeman–Tukey-transformed proportions for one-sample binary data

We will consider a dataset from Miller (1978) to illustrate `meta esize` to set up data for meta-analysis of a single proportion. The summary data consist of the number of animal deaths (`ndeaths`) and the animal pen size (`pensize`):

```
use https://www.stata-press.com/data/r18/miller1978, clear
(Number of animal deaths)
. describe
Contains data from https://www.stata-press.com/data/r18/miller1978.dta
 Observations:           4                  Number of animal deaths
    Variables:           2                  15 Mar 2022 17:04
                                            (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
ndeaths	byte	%9.0g		Number of animal deaths
pensize	byte	%9.0g		Size of animal pen

```
Sorted by:
```

As with two-group comparisons of continuous and binary data, we specify the summary variables following `meta esize`:

```
. meta esize ndeaths pensize
Meta-analysis setting information
 Study information
     No. of studies: 4
        Study label: Generic
         Study size: _meta_studysize
      Summary data: ndeaths pensize

      Effect size
               Type: ftukeyprop
              Label: Freeman-Tukey's p
           Variable: _meta_es

           Precision
           Std. err.: _meta_se
                 CI: [_meta_cil, _meta_ciu]
            CI level: 95%

   Model and method
              Model: Random effects
             Method: REML
```

By default, `meta esize` computes the Freeman–Tukey-transformed proportions. For meta-analysis using the untransformed (raw) proportions, you can specify the `esize(proportion)` option:

```
. meta esize ndeaths pensize, esize(proportion)
Meta-analysis setting information
 Study information
     No. of studies: 4
        Study label: Generic
         Study size: _meta_studysize
      Summary data: ndeaths pensize

       Effect size
               Type: proportion
              Label: Proportion
           Variable: _meta_es
    Zero-cells adj.: None; no zero cells

           Precision
           Std. err.: _meta_se
                 CI: [_meta_cil, _meta_ciu]
            CI level: 95%

   Model and method
              Model: Random effects
             Method: REML
```

Unlike the Freeman–Tukey-transformed proportions, in the presence of zero successes or failures, the raw proportions require zero-cell adjustments; otherwise, their variances will be undefined. In our example, there are no zero cells, so no zero-cells adjustment was applied (see `Zero-cells adj.:` under `Effect size`).

We could have also used `meta update` to modify the above `meta` settings without having to respecify the summary variables; see example 6.

◁

▷ Example 5: Effect sizes for correlation data (StataNow)

Molloy, O'Carroll, and Ferguson (2013) conducted a meta-analysis to examine to what degree conscientiousness is related to medication adherence. Medication adherence is the extent to which typically chronically ill patients follow medical recommendations as prescribed. Conscientiousness is defined as "*socially prescribed impulse control* that facilitates task- and goal-directed behavior, such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing and prioritizing tasks" (John and Srivastava 1999, 121).

The dataset contains the variables studylbl, rho, and n to indicate the authors and year of publication of the studies, the correlation coefficient between conscientiousness and medication adherence, and the study sample size, respectively.

```
. use https://www.stata-press.com/data/r18/adherence
(Conscientiousness and medication adherence)

. describe rho n studylbl

Variable        Storage   Display    Value
    name           type    format    label      Variable label
─────────────────────────────────────────────────────────────────────
rho             double   %9.0g                * Correlation coefficient
n                  int   %9.0g                  Sample size of the study
studylbl         str26   %26s                   Study label
```

As with one-sample binary data, we specify two summary variables, rho and n, following meta esize. To compute Fisher's z-transformed correlations, we specify the fisherz option:

```
. meta esize rho n, fisherz

Meta-analysis setting information

 Study information
    No. of studies: 16
        Study label: Generic
         Study size: _meta_studysize
       Summary data: rho n

       Effect size
               Type: fisherz
              Label: Fisher's z
           Variable: _meta_es

           Precision
           Std. err.: _meta_se
                  CI: [_meta_cil, _meta_ciu]
            CI level: 95%

   Model and method
              Model: Random effects
             Method: REML
```

For meta-analysis using the untransformed (raw) correlations, you can specify the `correlation` option:

```
. meta esize rho n, correlation
Meta-analysis setting information
 Study information
     No. of studies: 16
        Study label: Generic
         Study size: _meta_studysize
       Summary data: rho n

       Effect size
                Type: correlation
               Label: Correlation
            Variable: _meta_es

           Precision
           Std. err.: _meta_se
                  CI: [_meta_cil, _meta_ciu]
            CI level: 95%

    Model and method
               Model: Random effects
              Method: REML
```

We could have also used `meta update` to modify the above `meta` settings without having to respecify the summary variables; see example 6.

◁

Displaying and updating meta settings

We show examples of how to display the current `meta` settings by using `meta query` and update them by using `meta update`.

▷ Example 6: Commands meta query and meta update

Recall example 3. Let's reload the dataset and use `meta query` to check whether the dataset is `meta` set.

```
. use https://www.stata-press.com/data/r18/bcg, clear
(Efficacy of BCG vaccine against tuberculosis)
. meta query
(data not meta set; use meta set or meta esize to declare as meta data)
```

The data are not `meta` set.

Let's again use `meta esize` to declare the data (quietly) and use `meta query` to display the current settings.

```
. quietly meta esize npost nnegt nposc nnegc
. meta query
-> meta esize npost nnegt nposc nnegc
Meta-analysis setting information from meta esize
 Study information
     No. of studies: 13
         Study label: Generic
          Study size: _meta_studysize
       Summary data: npost nnegt nposc nnegc

       Effect size
                Type: lnoratio
               Label: Log odds-ratio
            Variable: _meta_es
    Zero-cells adj.: None; no zero cells

           Precision
           Std. err.: _meta_se
                  CI: [_meta_cil, _meta_ciu]
            CI level: 95%

   Model and method
               Model: Random effects
              Method: REML
```

In example 3, we redeclared the data to use the log risk-ratios as effect sizes. After the initial declaration, it is more convenient to use `meta update` to update the meta settings because we do not need to respecify the summary variables with `meta update`.

```
. meta update, esize(lnrratio) studylabel(studylbl)
-> meta esize npost nnegt nposc nnegc , esize(lnrratio) studylabel(studylbl)
Meta-analysis setting information from meta esize
 Study information
     No. of studies: 13
         Study label: studylbl
          Study size: _meta_studysize
       Summary data: npost nnegt nposc nnegc

       Effect size
                Type: lnrratio
               Label: Log risk-ratio
            Variable: _meta_es
    Zero-cells adj.: None; no zero cells

           Precision
           Std. err.: _meta_se
                  CI: [_meta_cil, _meta_ciu]
            CI level: 95%

   Model and method
               Model: Random effects
              Method: REML
```

If your summary variables change, however, you must specify them with `meta esize`.

You can use `meta update` after either `meta esize` or `meta set`. `meta update` will respect the options of `meta esize` and `meta set`.

For example, recall the `meta set` declaration from example 1:

```
. use https://www.stata-press.com/data/r18/leukemia2, clear
(Single-agent purine analogue treatment for leukemia)

. quietly meta set loghr seloghr
```

Let's update the meta settings to include the variable containing study sizes.

```
. generate ssize = ntreat + ncontrol

. meta update, studysize(ssize)
-> meta set loghr seloghr , random(reml) studysize(ssize)

Meta-analysis setting information from meta set

 Study information
    No. of studies: 4
        Study label: Generic
         Study size: ssize

        Effect size
               Type: <generic>
              Label: Effect size
           Variable: loghr

           Precision
           Std. err.: seloghr
                  CI: [_meta_cil, _meta_ciu]
           CI level: 95%

   Model and method
              Model: Random effects
             Method: REML
```

The `studysize()` option is supported only with `meta set`. If we tried to specify this option with `meta update` after `meta esize`, we would have received an error message.

◁

References

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Also see

[META] **meta esize** — Compute effect sizes and declare meta-analysis data[+]

[META] **meta set** — Declare meta-analysis data using generic effect sizes

[META] **meta update** — Update, describe, and clear meta-analysis settings

[META] **meta** — Introduction to meta

[META] **Glossary**

[META] **Intro** — Introduction to meta-analysis