Glossary

Begg test, Begg and Mazumdar test. A nonparametric rank correlation test for funnel-plot asymmetry of Begg and Mazumdar (1994). It tests whether Kendall's rank correlation between the effect sizes and their variances equals zero. The regression-based tests such as the t end to perform better in terms of type I error than the rank correlation test. This test is no longer recommended in the literature and provided mainly for completeness. See [META] **meta bias**.

between-study covariance matrix. In the context of multivariate meta-regression, the between-study covariance matrix, $\mathbf{\Sigma}$, is the covariance matrix of the random effects. It models heterogeneity between studies. By default, no structure is assumed when estimating $\mathbf{\Sigma}$, but several covariance structures may be considered; see *Random-effects covariance structures* in [META] **meta mvregress**.

between-study sample size. The number of studies in a meta-analysis.

between-study variability. Also known as between-study heterogeneity; see *heterogeneity*.

bubble plot. A scatterplot of effect size against a continuous covariate (moderator) in the meta-regression. The size of points representing the studies is proportional to study weights from a fixed-effects or, optionally, random-effects meta-analysis.

clinical heterogeneity. According to Deeks, Higgins, and Altman (2017), it is "variability in the participants, interventions and outcomes studied". Clinical variation will lead to heterogeneity if the effect size is affected by any of these varying factors.

Cochran's Q statistic. See *Q statistic*.

Cohen's d. An effect-size measure introduced by Cohen (1988) for continuous outcomes. It is a standardized mean difference where the difference between the two group means is usually divided by the standard deviation pooled across both groups. See *Standardized mean difference* of *Methods and formulas* in [META] **meta esize**.

combined effect size. See *overall effect size*.

common-effect meta-analysis model. A meta-analysis model that assumes that a single (common) true effect size underlies all the primary study results. See *Common-effect ("fixed-effect") model* in [META] **Intro**.

cumulative meta-analysis. Cumulative meta-analysis performs multiple meta-analyses by accumulating studies one at a time. The studies are first ordered with respect to the variable of interest, the ordering variable. Meta-analysis summaries are then computed for the first study, for the first two studies, for the first three studies, and so on. The last meta-analysis will correspond to the standard meta-analysis using all studies. See [META] **meta summarize**.

cumulative overall effect sizes. In the context of cumulative meta-analysis, cumulative (overall) effect sizes refer to the overall effect sizes computed by accumulating one study at a time. That is, the first overall effect size is simply the individual effect size of the first study. The second overall effect size is the overall effect size computed based on the first two studies. The third overall effect size is the overall effect size computed based on the first three studies. And so on. The last effect size in a cumulative meta-analysis corresponds to the overall effect size computed using all studies in a standard meta-analysis.

DerSimonian–Laird's method. A noniterative, random-effects estimator of the between-study variance parameter that does not make any assumptions about the distribution of random effects. This method was introduced in DerSimonian and Laird (1986). Historically, random-effects meta-analysis has

been based solely on this method. See *Noniterative methods* of *Methods and formulas* in [META] **meta summarize**.

effect size. A numerical summary of the group differences or of association between factors. For example, effect sizes for two-group comparisons include standardized and unstandardized mean differences, odds ratio, risk ratio, hazard ratio, and correlation coefficient. See [META] **meta esize**.

Egger test. A regression-based test for funnel-plot asymmetry of (Egger et al. 1997). This is the test of a slope coefficient in a weighted regression of the effect sizes on their standard errors. See [META] **meta bias**.

fixed-effects meta-analysis model. A meta-analysis model that assumes effect sizes are different across the studies and estimates a weighted average of their true values. This model is not valid for making inferences about studies beyond those included in the meta-analysis. See *Fixed-effects model* in [META] **Intro**.

fixed-effects meta-regression. Meta-regression that assumes a fixed-effects meta-analysis model. This regression model does not account for residual heterogeneity. See *Introduction* in [META] **meta regress**.

forest plot. A forest plot is a graphical representation of the results of a meta-analysis. In addition to meta-analytic summary such as overall effect size and its confidence interval and heterogeneity statistics and tests, it includes study-specific effect sizes and confidence intervals. See [META] **meta forestplot**.

funnel plot. The funnel plot is a scatterplot of the study-specific effect sizes against measures of study precision. This plot is commonly used to explore small-study effects or publication bias. In the absence of small-study effects, the shape of the scatterplot should resemble a symmetric inverted funnel. See [META] **meta funnelplot**.

Galbraith plot. The Galbraith plot is a scatterplot of the standardized effect sizes (z scores) against precision (inverse standard errors). It is commonly used to assess heterogeneity and for detecting potential outliers. When the number of studies is so large that it becomes inconvenient to present the results on a forest plot, the Galbraith plot provides a good alternative to report the meta-analysis results.

Glass's Δ. An effect-size measure introduced by Smith and Glass (1977) for continuous outcomes. It is a standardized mean difference where the difference between the two group means is divided by the sample standard deviation of the control group. Another variation of this statistic uses the sample standard deviation of the treatment group for the standardization. See *Standardized mean difference* of *Methods and formulas* in [META] **meta esize**.

grey literature. In the context of meta-analysis, grey literature refers to the literature that is difficult to obtain; it is thus rarely included in a meta-analysis.

H^2 statistic. A statistic for assessing heterogeneity. A value of $H^2 = 1$ indicates perfect homogeneity among the studies. See *Heterogeneity measures* of *Methods and formulas* in [META] **meta summarize**.

Hedges's g. An effect-size measure introduced by Hedges (1981) for continuous outcomes. It is a Cohen's d statistic adjusted for bias. See *Standardized mean difference* of *Methods and formulas* in [META] **meta esize**.

heterogeneity. In a meta-analysis, statistical heterogeneity, or simply heterogeneity, refers to the variability between the study-specific effect sizes that cannot be explained by a random variation. See *Heterogeneity* in [META] **Intro**.

heterogeneity parameter. In a random-effects meta-analysis, the variance of the random effects, τ^2, is used to account for the between-study heterogeneity. It is often referred to as the "heterogeneity parameter".

homogeneity. The opposite of heterogeneity.

homogeneity test. A test based on Cochran's Q statistic for assessing whether effect sizes from studies in a meta-analysis are homogeneous. See *Homogeneity test* of *Methods and formulas* in [META] **meta summarize**.

I^2 statistic. A statistic for assessing heterogeneity. It estimates the proportion of variation between the effect sizes due to heterogeneity relative to the pure sampling variation. $I^2 > 50$ indicates substantial heterogeneity. See *Heterogeneity measures* of *Methods and formulas* in [META] **meta summarize**.

intervention effects. See *effect size*.

inverse-variance method. A method of estimating the overall effect size as a weighted average of the study-specific effect sizes by using the weights that are inversely related to the variance (Whitehead and Whitehead 1991). This method is applicable to all meta-analysis models and all types of effect sizes.

Jackson–White–Riley method. In the context of multivariate meta-regression, the Jackson–White–Riley method provides a noniterative random-effects estimator of the between-study covariance matrix $\boldsymbol{\Sigma}$. This method was introduced by Jackson, White, and Riley (2013) and can be thought of as an extension of the univariate DerSimonian–Laird method to the multivariate setting.

L'Abbé plot. A scatterplot of the summary outcome measure such as log odds in the control group on the x axis and of that in the treatment group on the y axis. It is used with binary outcomes to inspect the range of group-level summary outcome measures among the studies to identify excessive heterogeneity. See [META] **meta labbeplot**.

large-strata limiting model. A model assumption for binary data in which the number of studies remains fixed but similar cell sizes in the 2×2 tables increase. See Robins, Breslow, and Greenland (1986).

leave-one-out meta-analysis. The leave-one-out meta-analysis performs multiple meta-analyses, where each analysis is produced by excluding a single study. It is a useful tool to assess the influence of a single study on the meta-analysis results and for identifying potential outliers.

Mantel–Haenszel method. In the context of meta-analysis, the Mantel–Haenszel method combines odds ratios, risk ratios, and risk differences. This method performs well in the presence of sparse data. For nonsparse data, its results are similar to those of the inverse-variance method. It was introduced by Mantel and Haenszel (1959) for odds ratios and extended to risk ratios and risk differences by Greenland and Robins (1985). See *Mantel–Haenszel method for binary outcomes* of *Methods and formulas* in [META] **meta summarize**.

meta data. `meta` data are the data that were `meta` set (or declared) by either `meta set` or `meta esize`. `meta` data store key variables and characteristics about your meta-analysis specifications, which will be used by all `meta` commands during your meta-analysis session. Thus, declaration of your data as `meta` data is the first step of your meta-analysis in Stata. This step helps minimize mistakes and saves you time—you need to specify the necessary information only once. Also see [META] **meta data**.

meta settings. Meta settings refers to the meta-analysis information specified during the declaration of the `meta` data via `meta set` or `meta esize`. This includes the declared effect size, meta-analysis model, estimation method, confidence level, and more. See *Declaring meta-analysis information* in [META] **meta data** for details.

meta-analysis. The statistical analysis that combines quantitative results from multiple individual studies into a single result. It is often performed as part of a systematic review. See *Brief overview of meta-analysis* in [META] **Intro**.

meta-regression. A weighted regression of study effect sizes on study-level covariates or moderators. You can think of it as an extension of standard meta-analysis to incorporate the moderators to account for between-study heterogeneity. See [META] **meta regress**.

methodological heterogeneity. Variability in study design and conduct (Deeks, Higgins, and Altman 2017). See *Heterogeneity* in [META] **Intro**.

mixed-treatment studies. See *multiple-treatment studies*.

moderator. A moderator is a study-level covariate that may help explain between-study heterogeneity. If the moderator is categorical, its effect may be investigated by a subgroup analysis (see [META] **meta summarize**); if the moderator is continuous, its effect may be investigated by a meta-regression. See [META] **meta regress**.

multiple subgroup analyses. Subgroup analysis performed separately for each of multiple categorical variables. See [META] **meta summarize**.

multiple-endpoint studies. Studies that compare a treatment group with a control group just like in standard meta-analysis, but more than one outcome (endpoint) is usually of interest. In the context of multivariate meta-regression, the effect sizes that compare these endpoints across the two groups are usually correlated because they were computed on the same set of subjects for each endpoint.

multiple-treatment studies. Studies that compare multiple (more than two) treatment groups. In the context of multivariate meta-regression, effect sizes that compare these groups are usually correlated because they share a common group. For example, an odds ratio that compares group A with group B is correlated with an odds ratio that compares group B with group C because they were computed based on the common group B.

multiplicative dispersion parameter. In a fixed-effects meta-regression, the multiplicative dispersion parameter is a multiplicative factor applied to the variance of each effect size to account for residual heterogeneity. See *Introduction* of [META] **meta regress**.

multiplicative meta-regression. A fixed-effects meta-regression that accounts for residual heterogeneity through a dispersion parameter ϕ applied (multiplicatively) to each effect-size variance. See *Introduction* of [META] **meta regress**.

multivariate meta-analysis. An extension of (univariate) meta-analysis to the analysis of multiple, usually dependent, effect sizes reported by each study. Like univariate meta-analysis, the goal of multivariate meta-analysis is to obtain an estimate of the multivariate overall effect size when it is sensible. See [META] **meta mvregress**.

multivariate meta-regression. A multivariate regression of study effect sizes on study-level covariates or moderators. You can think of it as an extension of multivariate meta-analysis to incorporate moderators to account for between-study heterogeneity. You may also view it as a generalization of a (univariate) meta-regression to multiple outcomes. See [META] **meta mvregress**.

narrative review. In a narrative review, the conclusion about the findings from multiple studies is given by a person, an expert in a particular field, based on his or her research of the studies. This approach is typically subjective and does not allow to account for certain aspects of the studies such as study heterogeneity and publication bias.

odds ratio. A ratio of the odds of a success in one group (treatment group) to those of another group (control group). It is often used as an effect size for comparing binary outcomes of two groups. See [META] **meta esize**.

overall effect size. The main target of interest in meta-analysis. Its interpretation depends on the assumed meta-analysis model. In a common-effect model, it is the common effect size of the studies. In a fixed-effects model, it is a weighted average of the true study-specific effect sizes. In a random-effects model, it is the mean of the distribution of the effect sizes. The overall effect size is usually denoted by `theta` in the output. Also see *Meta-analysis models* in [META] **Intro**.

Peto's method. A method for combining odds ratios that is often used with sparse 2×2 tables. This method does not require a zero-cell adjustment. See *Peto's method for odds ratios* of *Methods and formulas* in [META] **meta summarize**.

pooled effect size. See *overall effect size*.

prediction interval. In a random-effects meta-analysis, a $100(1-\alpha)\%$ prediction interval indicates that the true effect sizes in $100(1-\alpha)\%$ of new studies will lie within the interval. See *Prediction intervals* of *Methods and formulas* in [META] **meta summarize**.

primary study. The original study in which data are collected. An observation in a meta-analysis represents a primary study.

pseudo confidence interval. Pseudo confidence intervals refer to the confidence intervals as constructed by the standard funnel plot. See [META] **meta funnelplot**.

publication bias. Publication bias is known in the meta-analysis literature as an association between the likelihood of a publication and the statistical significance of a study result. See *Publication bias* in [META] **Intro**.

Q **statistic**. The test statistic of the homogeneity test. See *Homogeneity test* of *Methods and formulas* in [META] **meta summarize**.

random-effects meta-analysis model. A meta-analysis model that assumes that the study effects are random; that is, the studies used in the meta-analysis represent a random sample from a larger population of similar studies. See *Random-effects model* in [META] **Intro**.

random-effects meta-regression. Meta-regression that assumes a random-effects meta-analysis model. This regression model accounts for residual heterogeneity via an additive error term. See *Introduction* in [META] **meta regress**.

randomized controlled trial. A randomized controlled trial is an experiment in which participants are randomly assigned to two or more different treatment groups. Randomized controlled trials are commonly used in clinical research to determine the effectiveness of new treatments. By design, they avoid bias in the treatment estimates.

rate ratio. See *risk ratio*.

relative risk. See *risk ratio*.

reporting bias. Systematic difference between the studies selected in a meta-analysis and all the studies relevant to the research question of interest. Also see *publication bias*.

residual heterogeneity. In the meta-regression context, this is the remaining variability between the studies not accounted for by the moderators. It is usually captured by the heterogeneity parameter in a random-effects meta-regression or by a multiplicative dispersion parameter in a fixed-effects meta-regression.

risk ratio. A ratio of the success probability in one group (treatment) to that of another group (control). It is often used as an effect size for comparing binary outcomes of two groups. See [META] **meta esize**.

sensitivity analysis. In the context of meta-analysis, sensitivity analyses are used to assess how robust the meta-analysis results are to assumptions made about the data and meta-analysis models. See [META] **meta summarize**, [META] **meta regress**, and [META] **meta mvregress**.

significance contours. In the context of a funnel plot ([META] **meta funnelplot**), significance contours (or contour lines of statistical significance) are the contour lines corresponding to the tests of significance of individual effect sizes for a given significance level $\alpha = c/100$. In other words, if a study falls in the shaded area of a c-level contour, it is considered not statistically significant at the α level based on a test of significance of the study effect size.

single subgroup analysis. Subgroup analysis performed for one categorical variable. See [META] **meta summarize**.

small-study effects. Small-study effects arise when the results of smaller studies differ systematically from the results of larger studies. See *Introduction* of [META] **meta funnelplot**.

sparse data. For binary data, a 2×2 table is considered sparse if any of the cell counts are small.

sparse data limiting model. A model assumption for binary data in which the number of 2×2 tables (studies) increases but the cell sizes remain fixed. See Robins, Breslow, and Greenland (1986).

statistical heterogeneity. See *heterogeneity*.

study precision. Study precision is a function of a study sample size or study variability. Typically, study precision is measured by the inverse of the effect-sizes standard errors, $1/\widehat{\sigma}_j$, but other measures are also used. For instance, in a funnel pot, multiple precision metrics such as variances and sample sizes are considered. More precise studies (with larger sample sizes and smaller variances) are assigned larger weights in a meta-analysis.

subgroup analysis. A subgroup analysis divides the studies into groups and then estimates the overall effect size for each of the groups. The goal of subgroup analysis is to compare the overall effect sizes and explore heterogeneity between the subgroups. See [META] **meta summarize** and [META] **meta forestplot**.

subgroup heterogeneity. In the context of meta-analysis, subgroup heterogeneity is between-study heterogeneity induced by the differences between effect sizes of groups defined by one or more categorical variables. See [META] **meta** and [META] **meta summarize**.

summary data. In the context of meta-analysis, we use the term summary data to mean summary statistics that are used to compute the effect sizes and their standard errors for each study in the meta-analysis. For example, for a two-group comparison of continuous outcomes, the summary data contain the number of observations, means, and standard deviations in each group for each study. For a two-group comparison of binary outcomes, the summary data contain the 2×2 tables for each study. See [META] **meta esize**.

summary effect. See *overall effect size*.

systematic review. A procedure that uses systematic and well-defined methods to find, select, and evaluate relevant research studies to answer a specific research question. It typically involves collecting and analyzing summary data of the selected studies. Meta-analysis is the statistical analysis used as part of a systematic review.

trim-and-fill method. A method of testing and adjusting for publication bias in meta-analysis; see [META] **meta trimfill**.

typical within-study variance, **typical sampling variance**. A term coined by Higgins and Thompson (2002) to describe a summary or an "average" of the within-study variances. The value of the typical within-study variance is used in the computation of the heterogeneity statistic I^2.

within-study covariance matrix. In the context of multivariate meta-regression, the within-study covariance matrix, $\mathbf{\Lambda}_j$, is the covariance matrix that models the dependence among the effect sizes within each study. The matrix is assumed to be known and does not require estimation.

zero-cell adjustment. Adjustment made to cells of 2×2 tables containing zero cells. In the meta-analysis of binary data, zero-cell counts pose difficulties when computing odds ratios and risk ratios. Therefore, it is common to make zero-cell adjustments, such as adding a small number to all cells containing zeros. See *Zero-cells adjustments* in *Methods and formulas* of [META] **meta esize**.

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