meta regress — Meta-analysis regression

Description	Quick start
Options	Remarks and examples
References	Also see

Menu Stored results N

Syntax Methods and formulas

Description

meta regress performs meta-analysis regression, or meta-regression, which is a linear regression of the study effect sizes on study-level covariates (moderators). Meta-regression investigates whether between-study heterogeneity can be explained by one or more moderators. You can think of metaregression as a standard meta-analysis that incorporates moderators into the model. meta regress performs both random-effects and fixed-effects meta-regression.

Quick start

Perform meta-regression of the effect size, _meta_es, on covariate (moderator) x1

meta regress x1

Same as above, but assume a DerSimonian-Laird random-effects method instead of the method declared by either meta set or meta esize

meta regress x1, random(dlaird)

- Add a factor variable a, and request a Knapp-Hartung adjustment to the standard errors of coefficients meta regress x1 i.a, random(dlaird) se(khartung)
- Perform a sensitivity analysis by assuming a fixed value of 0.2 for the between-study variance τ^2 meta regress x1 i.a, tau2(0.2)

Menu

Statistics > Meta-analysis

Syntax

Meta-regression using meta-analysis model as declared with meta set or meta esize

```
meta regress moderators [if] [in] [, reopts options]
```

Random-effects meta-regression

```
meta regress moderators [if] [in], random[(remethod)] [reopts options]
```

Fixed-effects meta-regression

```
meta regress moderators [if] [in], fixed [multiplicative options]
```

Constant-only meta-regression

```
meta regress _cons [if] [in] [, modelopts]
```

reopts	Description
tau2(#) i2(#) se(<i>seadj</i>)	sensitivity meta-analysis using a fixed value of between-study variance τ^2 sensitivity meta-analysis using a fixed value of heterogeneity statistic $I_{\rm res}^2$ adjust standard errors of the coefficients
options	Description
Model	
<u>nocons</u> tant	suppress constant term
<u>tdist</u> ribution	report t tests instead of z tests for the coefficients
Reporting	
<u>l</u> evel(#)	set confidence level; default is as declared for meta-analysis
<u>nohead</u> er	suppress output header
[no]metashow	display or suppress meta settings in the output
display_options	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
Maximization	
maximize_options	control the maximization process; seldom used

collect is allowed; see [U] 11.1.10 Prefix commands.

coeflegend does not appear in the dialog box.

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.

remethod	Description
reml	restricted maximum likelihood; the default
mle	maximum likelihood
<u>eb</u> ayes	empirical Bayes
<u>dl</u> aird	DerSimonian-Laird
sjonkman	Sidik–Jonkman
hedges	Hedges
<u>hs</u> chmidt	Hunter-Schmidt

modelopts is any option except noconstant.

Options

Model

noconstant; see [R] Estimation options. This option is not allowed with constant-only metaregression.

Options random() and fixed, when specified with meta regress, temporarily override the global model declared by meta set or meta esize during the computation. Options random(), common, and fixed may not be combined. If these options are omitted, the declared meta-analysis model is assumed; see *Declaring a meta-analysis model* in [META] **meta data**. Also see *Meta-analysis models* in [META] **Intro**.

- random and random(*remethod*) specify that a random-effects model be assumed for meta-regression; see *Random-effects model* in [META] Intro.
 - remethod specifies the type of estimator for the between-study variance τ^2 . remethod is one of reml, mle, ebayes, dlaird, sjonkman, hedges, or hschmidt. random is a synonym for random(reml). See Options in [META] meta esize for more information.
- fixed specifies that a fixed-effects model be assumed for meta-regression; see *Fixed-effects model* in [META] **Intro**. It uses the inverse-variance estimation method; see *Meta-analysis estimation methods* in [META] **Intro**.
- reopts are tau2(#), i2(#), and se(khartung[, truncated]). These options are used with randomeffects meta-regression.
 - tau2(#) specifies the value of the between-study variance parameter, τ^2 , to use for the random-effects meta-regression. This option is useful for exploring the sensitivity of the results to different levels of between-study heterogeneity. Only one of tau2() or i2() may be specified.
 - i2(#) specifies the value of the residual heterogeneity statistic I_{res}^2 (as a percentage) to use for the random-effects meta-regression. This option is useful for exploring the sensitivity of the results to different levels of between-study heterogeneity. Only one of i2() or tau2() may be specified.

- se(seadj) specifies that the adjustment *seadj* be applied to the standard errors of the coefficients. Additionally, the tests of significance of the coefficients are based on a Student's t distribution instead of the normal distribution.
 - seadj is <u>khartung</u> , <u>truncated</u>]. Adjustment khartung specifies that the Knapp-Hartung adjustment (Hartung and Knapp 2001a, 2001b; Knapp and Hartung 2003), also known as the Sidik-Jonkman adjustment (Sidik and Jonkman 2002), be applied to the standard errors of the coefficients. <u>hknapp and sjonkman are synonyms for khartung</u>. truncated specifies that the truncated Knapp-Hartung adjustment (Knapp and Hartung 2003), also known as the modified Knapp-Hartung adjustment, be used.
- multiplicative performs a fixed-effects meta-regression that accounts for residual heterogeneity by including a multiplicative variance parameter ϕ . ϕ is referred to as an "(over)dispersion parameter". See *Introduction* for details.
- tdistribution reports t tests instead of z tests for the coefficients. This option is useful, for instance, when meta regress is used to conduct a regression-based test for funnel-plot asymmetry. Traditionally, the test statistic from this test is compared with critical values from a Student's t distribution instead of the default normal distribution. This option may not be combined with option se().

Reporting

level(#) specifies the confidence level, as a percentage, for confidence intervals. The default is
 as declared for the meta-analysis session; see Declaring a confidence level for meta-analysis in
 [META] meta data. Also see option level() in [META] meta set.

noheader suppresses the output header, either at estimation or upon replay.

- metashow and nometashow display or suppress the meta setting information. By default, this information is displayed at the top of the output. You can also specify nometashow with meta update to suppress the meta setting output for the entire meta-analysis session.
- display_options: noci, nopvalues, noomitted, vsquish, noemptycells, baselevels, allbaselevels, nofvlabel, fvwrap(#), fvwrapon(style), cformat(%fmt), pformat(%fmt), sformat(%fmt), and nolstretch; see [R] Estimation options.

Maximization

- maximize_options: <u>iter</u>ate(#), <u>tol</u>erance(#), <u>nrtol</u>erance(#), <u>nonrtol</u>erance (see [R] <u>Maximize</u>), from(#), and showtrace. These options control the iterative estimation of the between-study variance parameter, τ^2 , with random-effects methods reml, mle, and ebayes. These options are seldom used.
 - from (#) specifies the initial value for τ^2 during estimation. By default, the initial value for τ^2 is the noniterative Hedges estimator.
 - showtrace displays the iteration log that contains the estimated parameter τ^2 , its relative difference with the value from the previous iteration, and the scaled gradient.

The following option is available with meta regress but is not shown in the dialog box:

coeflegend; see [R] Estimation options.

Remarks and examples

Remarks are presented under the following headings:

Introduction Examples of using meta regress

Introduction

Meta-regression is a regression performed in the context of meta-analysis. It is used to study the relationship between study effect sizes and covariates. Meta-regression is analogous to standard regression used when individual data are available, but in meta-regression, the observations are the studies, the outcome of interest is the effect size, and the covariates are recorded at the study level. The study-level covariates in meta-regression are known as moderators. Several examples of moderators include study location, study test environment, drug administration method. For a general overview and discussions about meta-regression, see Berlin and Antman (1992), Berkey et al. (1995), and Thompson and Higgins (2002).

The goal of meta-regression is to explore and explain the between-study heterogeneity as a function of moderators. Two types of regression models, fixed-effects (FE) and random-effects (RE), are available. An FE meta-regression assumes that all heterogeneity between study effect sizes can be accounted for by the included moderators. An RE meta-regression accounts for potential additional variability unexplained by the included moderators, also known as residual heterogeneity. Because a common-effect meta-analysis model implies no study heterogeneity, it is not applicable to meta-regression, except in a less interesting case of a constant-only model, which is equivalent to the standard common-effect meta-analysis; see [META] meta summarize.

meta regress fits meta-regression. Use the random() option to fit an RE meta-regression and the fixed option to fit an FE meta-regression. Also see *Default meta-analysis model and method* in [META] meta data to learn about the default regression model used by meta regress.

For the *j*th study, let $\hat{\theta}_j$ denote the effect size, $\hat{\sigma}_j^2$ its variance, and \mathbf{x}_j be a $1 \times p$ vector of moderators with the corresponding unknown $p \times 1$ coefficient vector $\boldsymbol{\beta}$.

An FE meta-regression (Greenland 1987) is given by

$$\hat{\theta}_j = \mathbf{x}_j \boldsymbol{\beta} + \epsilon_j$$
, weighted by $w_j = \frac{1}{\hat{\sigma}_j^2}$, where $\epsilon_j \sim N\left(0, \hat{\sigma}_j^2\right)$

Residual heterogeneity may be incorporated into an FE meta-regression via a multiplicative factor, ϕ , applied to each of the variances $\hat{\sigma}_j^2$. This leads to a multiplicative meta-regression or FE meta-regression with multiplicative dispersion parameter (Thompson and Sharp 1999)

$$\hat{\theta}_j = \mathbf{x}_j \boldsymbol{\beta} + \epsilon_j^{\phi}$$
, weighted by $w_j = \frac{1}{\hat{\sigma}_j^2}$, where $\epsilon_j^{\phi} \sim N(0, \hat{\sigma}_j^2 \phi)$

This regression model may be specified by the combination of fixed and multiplicative options.

Another method of incorporating residual heterogeneity is to include an additive between-study variance component, τ^2 , that leads to an RE meta-regression (Berkey et al. 1995), also known as a mixed model in the meta-analysis literature:

$$\hat{\theta}_j = \mathbf{x}_j \boldsymbol{\beta} + \epsilon_j^* = \mathbf{x}_j \boldsymbol{\beta} + u_j + \epsilon_j, \text{ weighted by } w_j^* = \frac{1}{\hat{\sigma}_j^2 + \hat{\tau}^2}, \text{ where } \epsilon_j^* \sim N\big(0, \hat{\sigma}_j^2 + \tau^2\big)$$

As we mentioned earlier, an RE meta-regression assumes that the moderators explain only part of the heterogeneity, and a random-effects term $u_i \sim N(0, \tau^2)$ is used to account for the remainder.

Harbord and Higgins (2016) point out that some authors (Thompson and Sharp 1999; Higgins and Thompson 2004) argue that an FE meta-regression should not be used because, in practice, the included moderators rarely capture all the between-study heterogeneity and that the failure of the FE regression to capture the extra between-study heterogeneity can lead to excessive type I errors. Also, the results from an FE meta-regression, including its multiplicative version, may not be generalized to populations from which the observed studies are a sample (Konstantopoulos and Hedges 2009). If you do not specify a meta-analysis model with meta set or meta esize during declaration, an RE meta-regression will be assumed by meta regress.

Meta-regression can also be considered an extension of subgroup analysis (see meta summarize, subgroup() in [META] meta summarize) to include continuous moderators in addition to the categorical ones. In particular, an FE meta-regression with the subgroup variable specified as a factor variable (see [U] 11.4.3 Factor variables) is equivalent to the FE subgroup analysis on that variable.

It is recommended that you have at least 10 studies per moderator to perform meta-regression (Borenstein et al. 2009, chap. 20). Otherwise, you may not be able to estimate the effects of moderators reliably. For more recommendations regarding meta-regression, see Schmidt and Hunter (2015, chap. 9), Deeks, Macaskill, and Irwig (2005), Harbord and Higgins (2016), Sharp (2016), and Thompson and Higgins (2002).

Examples of using meta regress

Consider a dataset from Colditz et al. (1994) of clinical trials that explore the efficacy of a Bacillus Calmette-Guérin (BCG) vaccine in the prevention of tuberculosis (TB). This dataset was introduced in *Efficacy of BCG vaccine against tuberculosis (bcg.dta)* of [META] **meta**. In this section, we use its declared version and focus on the demonstration of various options of meta regress and explanation of its output.

```
. use https://www.stata-press.com/data/r19/bcgset
(Efficacy of BCG vaccine against tuberculosis; set with -meta esize-)
. meta query, short
-> meta esize npost - nnegc, esize(lnrratio) studylabel(studylbl)
Effect-size label: Log risk-ratio
Effect-size type: lnrratio
Effect size: _meta_es
Std. err.: _meta_se
Model: Random effects
Method: REML
```

meta query, short reminds us about the main settings of the declaration step. Our data were declared by using meta esize with variables npost, nnegt, nposc, and nnegc representing the summary data from 2×2 tables, which record the numbers of positive and negative TB cases in the treatment and control groups. The computed effect sizes are log risk-ratios; their values and standard errors are stored in the respective system variables _meta_es and _meta_se. The studylbl variable supplies the study labels to be used in the output. The declared meta-analysis model is the default random-effects model with the REML estimation method. Examples are presented under the following headings:

Example 1: Random-effects meta-regression Example 2: Sidik–Jonkman random-effects method Example 3: Truncated Knapp–Hartung standard-error adjustment Example 4: Sensitivity meta-analysis Example 5: Fixed-effects meta-regression Example 6: Multiplicative meta-regression Example 7: Constant-only model

Example 1: Random-effects meta-regression

In example 9 of [META] meta, following Berkey et al. (1995), we fit a meta-regression with a centered absolute latitude_c, as the moderator to address heterogeneity. Let's refit this model here and focus on the specification and output from meta regress.

. meta regress	s latitude_c						
Effect-size Effect Std	label: Log ri t size: _meta_ . err.: _meta_	sk-ratio es se					
Random-effect:	s meta-regress	ion		Num	ber of obs	=	13
Method: REML				Res	idual hete	rogene	ity:
					ta	au2 =	.07635
					12	(%) =	68.39
						H2 =	3.16
					R-squared	(%) =	75.63
				Wal	d chi2(1)	=	16.36
				Pro	b > chi2	=	0.0001
_meta_es	Coefficient	Std. err.	Z	P> z	[95% coi	nf. in	terval]
latitude_c	0291017	.0071953	-4.04	0.000	0432043	3	0149991
_cons	7223204	.1076535	-6.71	0.000	9333174	4	5113234
	•						

Test of residual homogeneity: Q_res = chi2(11) = 30.73 Prob > Q_res = 0.0012

Unlike with many Stata regression commands, we do not specify the dependent variable with meta regress. The command includes it automatically from the declared meta settings. meta regress provides a short summary of the settings, which you can suppress with the nometashow option. System variable _meta_es contains the effect sizes and is thus used as the dependent variable. System variable _meta_se contains effect-size standard errors; it is used to construct the weights for the regression.

The header includes the information about the meta-analysis model and reports various summaries such as heterogeneity statistics and the model test. For example, the results are based on 13 studies. The reported $I_{\rm res}^2$ statistic is 68%, which still suggests moderate heterogeneity, using the categorization of Higgins et al. (2003), even after including latitude_c as the moderator. In other words, 68% of the variability in the residuals is still attributed to the between-study variation, whereas only 32% is attributed to the within-study variation. The adjusted R^2 statistic can be used to assess the proportion of between-study variance explained by the covariates; see (6) in *Methods and formulas* for its definition used in the meta-analysis literature. Here roughly 76% of the between-study variance is explained by the covariate latitude_c.

The output header also displays a model test that all coefficients other than the intercept are equal to zero based on the χ^2 distribution with p-1 degrees of freedom. In our example, the χ^2 test statistic is 16.36 with a *p*-value of 0.0001. We have only one moderator, so the results of the model test in our example are equivalent to the *z* test (χ^2 value equals squared *z* value) of the coefficient of latitude_c reported in the output table.

The regression coefficient for latitude_c is -0.029, which means that every one degree of latitude corresponds to a decrease of 0.0291 units in log risk-ratio. The intercept, $\hat{\beta}_0$, is -0.722, which means that the overall risk ratio at the mean latitude (latitude_c = 0 corresponds to latitude ≈ 33.46) is $\exp(-0.722) = 0.46$. Both of these coefficients are statistically significantly different from zero based on the reported z tests.

Finally, a test of residual homogeneity is reported at the bottom of the output. The test statistic Q_{res} is 30.73 with a *p*-value of 0.0012, which suggests the presence of heterogeneity among the residuals.

Technical note

Heterogeneity statistics I_{res}^2 and H_{res}^2 , reported under Residual heterogeneity: in the header, are extensions of the corresponding statistics I^2 and H^2 from standard meta-analysis to meta-regression (Higgins and Thompson 2002). They measure the remaining between-study heterogeneity among the residuals after adjusting for the variability due to moderators. Similarly, the test of residual homogeneity based on the Q_{res} statistic is the extension of the standard meta-analysis homogeneity test based on the Cochran's Q statistic to meta-regression. See Residual heterogeneity measures and Residual homogeneity test in Methods and formulas.

Example 2: Sidik–Jonkman random-effects method

Continuing with example 1, let's demonstrate the use of a different RE method, for instance, the Sidik–Jonkman method, instead of the default REML method.

```
. meta regress latitude_c, random(sjonkman)
  Effect-size label: Log risk-ratio
        Effect size: _meta_es
          Std. err.: _meta_se
Random-effects meta-regression
                                                      Number of obs =
                                                                               13
Method: Sidik-Jonkman
                                                      Residual heterogeneity:
                                                                  tau2 =
                                                                            .2318
                                                                I2 (\%) =
                                                                            86.79
                                                                    H2 =
                                                                             7.57
                                                         R-squared (%) =
                                                                            32.90
                                                      Wald chi2(1)
                                                                             6.50
                                                                     =
                                                      Prob > chi2
                                                                     =
                                                                           0.0108
                                                            [95% conf. interval]
               Coefficient Std. err.
                                                  P>|z|
    meta es
                                            7.
                -.0280714
                             .0110142
                                         -2.55
                                                  0.011
                                                           -.0496589
                                                                        -.0064838
  latitude c
                -.7410395
                             .1602117
                                         -4.63
                                                  0.000
                                                           -1.055049
                                                                        -.4270304
       cons
```

Test of residual homogeneity: Q_res = chi2(11) = 30.73 Prob > Q_res = 0.0012

The estimate of the regression coefficient for latitude_c is -0.028 and is similar to the REML estimate of -0.029, but the standard errors are quite different: 0.011 versus 0.007. Recall that REML assumes that the error distribution is normal, whereas the Sidik–Jonkman estimator does not. Thus, its standard error estimates are likely to be larger than those from REML. The estimates of the between-study variance, τ^2 , are also very different: 0.23 compared with the REML estimate of 0.08.

4

4

Example 3: Truncated Knapp–Hartung standard-error adjustment

Continuing with example 1, let's use an alternative standard-error computation sometimes used in practice—the truncated Knapp-Hartung method.

. meta regress	latitude_c,	se(khartung,	truncat	ed)			
Effect-size Effect Std.	label: Log ri size: _meta_ err.: _meta_	sk-ratio es se					
Random-effects	meta-regress	ion		Num	ber of obs =		13
Method: REML				Res	idual heterog	ene	ity:
SE adjustment:	Truncated Kn	app-Hartung			tau2	=	.07635
					I2 (%)	=	68.39
					H2	=	3.16
					R-squared (%)	=	75.63
				Mod	el F(1,11) =		12.59
				Pro	b > F =		0.0046
_meta_es	Coefficient	Std. err.	t	P> t	[95% conf.	int	terval]
latitude_c	0291017	.0082014	-3.55	0.005	0471529	(0110505
_cons	7223204	.1227061	-5.89	0.000	9923946	4	4522462
Test of residu	al homogeneit	y: Q res = c	hi2(11)	= 30.73	Prob > Q re	s =	0.0012

The reported standard errors are larger than those from example 1. This is expected because the Knapp–Hartung adjustment incorporates the uncertainty in estimating τ^2 in the standard error computation. Also, the inferences for the tests of coefficients and the model test are now based on the Student's t and F distributions, respectively, instead of the default normal and χ^2 distributions.

Example 4: Sensitivity meta-analysis

We can perform sensitivity analysis to explore the impact of the various levels of heterogeneity on the regression results. Continuing with example 1, let's fit a meta-regression assuming that the residual heterogeneity statistic I_{res}^2 equals 90%.

. meta regress	s latitude_c,	i2(90)					
Effect-size Effect Std	label: Log ri t size: _meta_ . err.: _meta_	sk-ratio es se					
Random-effects		Num	per of obs	=	13		
Method: User-s	specified I2			Res	idual hete	rogene	eity:
	-				t	au2 =	.3176
					12	(%) =	90.00
						H2 =	10.00
				Wald	d chi2(1)	=	4.89
				Prob	o > chi2	=	0.0269
_meta_es	Coefficient	Std. err.	Z	P> z	[95% co:	nf. ir	iterval]
latitude_c	0277589	.0125474	-2.21	0.027	052351	4	.0031664
_cons	7443082	.1812664	-4.11	0.000	-1.09958	4	3890326

Test of residual homogeneity: $Q_{res} = chi2(11) = 30.73$ Prob > $Q_{res} = 0.0012$

The estimate of the coefficient for latitude_c is now -0.028 with a standard error estimate of 0.01.

Let's now fit a meta-regression assuming the between-study variance of 0.01.

. meta regress	s latitude_c,	tau2(0.01)					
Effect-size Effect Std	label: Log ri t size: _meta_ . err.: _meta_	sk-ratio es se					
Random-effect:	s meta-regress	ion		Numb	er of ob	s =	13
Method: User-	specified tau2			Resi	dual het	erogene	eity:
						tau2 =	.01
					12	(%) =	22.08
						H2 =	1.28
				Wald	chi2(1)	=	57.62
				Prob	> chi2	=	0.0000
_meta_es	Coefficient	Std. err.	Z	P> z	[95% c	onf. ir	iterval]
latitude_c _cons	0295601 6767043	.0038942 .0617892	-7.59 -10.95	0.000	03719 79780	26 39	0219277 5555998
Test of residu	lal homogeneit	y: Q res =	chi2(11)	= 30.73	Prob >] res =	• 0.0012

The specified value of τ^2 corresponds to the I_{res}^2 value of 22.08%. The coefficient estimate is now -0.03 with a standard error of 0.004.

In both sensitivity analyses, latitude_c remained a statistically significant moderator for the log risk-ratios.

Example 5: Fixed-effects meta-regression

Instead of an RE meta-regression as in example 1, we can use the fixed option to fit an FE meta-regression. The use of an FE meta-regression is usually discouraged in the meta-analysis literature because it assumes that all between-study heterogeneity is accounted for by the specified moderators (Harbord and Higgins 2016; Thompson and Sharp 1999; Higgins and Thompson 2004). This is often an unrealistic assumption in meta-analysis. We fit this model in our example for the purpose of demonstration.

. meta regress	s latitude_c,	fixed					
Effect-size Effect Std.	label: Log ri z size: _meta_ . err.: _meta_	sk-ratio es se					
Fixed-effects Method: Invers	meta-regressi se-variance	on		Num Wal Pro	ber of obs d chi2(1) b > chi2	= = =	13 121.50 0.0000
_meta_es	Coefficient	Std. err.	Z	P> z	[95% con	f.	interval]
latitude_c _cons	0292369 6347482	.0026524 .0445446	-11.02 -14.25	0.000	0344356 7220541		0240383 5474423

Because the FE regression assumes no additional residual heterogeneity, the residual heterogeneity statistics and the residual homogeneity test are not reported with meta regress, fixed.

The coefficient estimates are similar to those from example 1, but standard errors from the FE regression are smaller. This is because the FE regression does not account for the residual heterogeneity that is not explained by the included moderators.

4

Considering the presence of residual heterogeneity in these data, we should go back to our RE analysis or explore the multiplicative meta-regression, which we demonstrate in example 6.

4

Example 6: Multiplicative meta-regression

An FE meta-regression in example 5 does not account for residual heterogeneity. An extension of this regression model that does, known as a multiplicative meta-regression (see Introduction and Methods and formulas), has been considered in the meta-analysis literature. An RE meta-regression is the preferred analysis these days, but we provide the multiplicative meta-regression for completeness.

Continuing with example 5, we add the multiplicative option to fit an FE meta-regression with a multiplicative dispersion parameter ϕ .

. meta regress	s latitude_c,	fixed multi	plicative	9		
Effect-size Effect Std	label: Log ri t size: _meta_ . err.: _meta_	sk-ratio es se				
Fixed-effects	meta-regressi	on		Num	ber of obs =	= 13
Error: Multip	licative			Dis	persion phi =	= 2.79
Method: Invers	se-variance			Wal	d chi2(1) =	= 43.49
				Pro	ob > chi2 =	= 0.0000
_meta_es	Coefficient	Std. err.	z	P> z	[95% conf	. interval]
latitude_c	0292369	.0044335	-6.59	0.000	0379265	0205474
_cons	6347482	.0744564	-8.53	0.000	7806801	4888163
Test of residu	al homogeneit	y: Q_res =	chi2(11)	= 30.73	Prob > Q_re	es = 0.0012

The estimate of the dispersion parameter, reported in the header as Dispersion phi, is 2.79. It is greater than 1, which suggests the presence of residual heterogeneity in these data. The coefficient estimates are the same as those in example 5, but the standard errors are about two times larger.

4

Example 7: Constant-only model

The primary use of meta regress is to fit meta-regression models containing moderators. You can also fit a constant-only model (without moderators), although this is less common in the context of metaregression.

To fit a constant-only model with many regression estimation commands, you simply omit the covariates in the command specification. This would not work with meta regress because, without the dependent-variable specification, we would have to type

. meta regress

which means replaying previous estimation results consistently across Stata. The above will either issue an error that previous estimation results are not found or redisplay the results from the previous meta regress specification.

Instead, to fit a constant-only model with meta regress, you specify the designator _cons following the command name.

. meta regress	s _cons						
Effect-size Effect Std	label: Log ri z size: _meta_ . err.: _meta_	sk-ratio es se					
Random-effects	s meta-regress	ion		Numb	er of obs	; =	13
Method: REML				Resi	dual hete	rogene	ity:
					t	au2 =	.3132
					I2	(%) =	92.22
						H2 =	12.86
				Wald	chi2(0)	=	
				Prob	> chi2	=	
_meta_es	Coefficient	Std. err.	z	P> z	[95% cc	onf. in	terval]
_cons	7145323	.1797815	-3.97	0.000	-1.06689	- 8	.362167
Test of residu	al homogeneit	v: Q res = d	chi2(12)	= 152.23	Prob > G	res =	0.0000

Note that the estimated value of $\hat{\tau}^2$ is now 0.313, whereas in example 1 it was 0.076. That is, the inclusion of covariate latitude_c in example 1 reduced $\hat{\tau}^2$ from 0.313 to 0.076 for a relative reduction of $(0.313 - 0.076)/0.313 \approx 76\%$.

The reason a constant-only meta-regression is not as common is because it produces the same results as a standard meta-analysis.

. meta summari	ize, nostudies				
Effect-size Effect Std. Study	label: Log ris size: _meta_e err.: _meta_s label: studylb	k-ratio s e l			
Meta-analysis			Numl	per of studies = 13	
Random-effects model				Hete	erogeneity:
Method: REML					tau2 = 0.3132
					I2 (%) = 92.22
					H2 = 12.86
theta	Overall Log r	isk-ratio			
	Estimate	Std. err.	z	P> z	[95% conf. interval]
theta	7145323	.1797815	-3.97	0.000	-1.066898362167
Test of homogeneity: Q = chi2(12) = 152.23 Prob > Q = 0.0000					

See [META] meta summarize for details.

Stored results

meta regress stores the following in e():

Scalars	
e(N)	number of observations (studies)
e(df_m)	model degrees of freedom
e(df_r)	residual degrees of freedom
e(chi2)	model χ^2 Wald test statistic
e(F)	model F statistic
e(p)	<i>p</i> -value for model test
e(phi)	dispersion parameter
e(tau2)	between-study variance
e(I2_res)	$I_{\rm res}^2$ heterogeneity statistic
e(H2_res)	$H_{\rm res}^2$ heterogeneity statistic
e(R2)	R^2 heterogeneity measure
e(Q_res)	Cochran's Q residual homogeneity test statistic
e(df_Q_res)	degrees of freedom for residual homogeneity test
e(p_Q_res)	p-value for residual homogeneity test
e(seadj)	standard error adjustment
e(converged)	1 if converged, 0 otherwise (with iterative random-effects methods)
Macros	
e(cmd)	meta regress
e(cmdline)	command as typed
e(depvar)	name of dependent variable, _meta_es
e(indepvars)	names of independent variables (moderators)
e(title)	title in estimation output
e(model)	meta-analysis model
e(method)	meta-analysis estimation method
e(seadjtype)	type of standard error adjustment
e(properties)	b V
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsok)	predictions allowed by margins
e(marginsnotok)	predictions disallowed by margins
e(marginsdefault)	default predict() specification for margins
e(asbalanced)	factor variables fyset as asbalanced
e(asobserved)	factor variables fvset as asobserved
Matrices	
e(b)	coefficient vector
e(V)	variance–covariance matrix of the estimators
Functions	
	marks estimation sample
e(sampre)	marks commarion sample

In addition to the above, the following is stored in r():

Matrices

r(table)

matrix containing the coefficients with their standard errors, test statistics, *p*-values, and confidence intervals

Note that results stored in r () are updated when the command is replayed and will be replaced when any r-class command is run after the estimation command.

meta regress also creates a system variable, _meta_regweight, that contains meta-regression weights.

Methods and formulas

Methods and formulas are presented under the following headings:

```
\label{eq:response} \begin{array}{l} \mbox{Fixed-effects meta-regression} \\ \mbox{Random-effects meta-regression} \\ \mbox{Iterative methods for computing } \hat{\tau}^2 \\ \mbox{Noniterative methods for computing } \hat{\tau}^2 \\ \mbox{Knapp-Hartung standard-error adjustment} \\ \mbox{Residual homogeneity test} \\ \mbox{Residual heterogeneity measures} \end{array}
```

Fixed-effects meta-regression

For an overview of estimation methods used by meta-regression, see Berkey et al. (1995), Sidik and Jonkman (2005), and Viechtbauer et al. (2015).

Consider an FE meta-analysis, where $\hat{\theta}_j \sim N(\theta_j, \hat{\sigma}_j^2)$, θ_j is the true effect size for study j, $\hat{\theta}_j$ is the estimated effect size, and $\hat{\sigma}_j^2$ is the variance of $\hat{\theta}_j$. In an FE meta-regression (Greenland 1987), the study-specific mean, θ_j , is expressed as

$$\theta_j = \beta_0 + \beta_1 x_{1j} + \dots + \beta_{p-1} x_{p-1,j} = \mathbf{x}_j \boldsymbol{\beta}$$

where $\mathbf{x}_j = (1, x_{1j}, \dots, x_{p-1,j})$ is a $1 \times p$ vector of categorical and continuous moderators (covariates) and β is a $p \times 1$ vector of regression coefficients to be estimated.

Defining $K \times p$ matrix $\mathbf{X} = (\mathbf{x}'_1, \mathbf{x}'_2, \dots, \mathbf{x}'_K)'$ and $\hat{\boldsymbol{\theta}} = (\hat{\theta}_1, \hat{\theta}_2, \dots, \hat{\theta}_K)'$. Let $w_j = 1/\hat{\sigma}_j^2$ be the weight associated with study j in an FE meta-analysis. The vector of estimated regression coefficients is

$$\widehat{\boldsymbol{\beta}} = \left(\mathbf{X}' \mathbf{W} \mathbf{X} \right)^{-1} \mathbf{X}' \mathbf{W} \widehat{\boldsymbol{\theta}}$$

where $\mathbf{W} = \text{diag}(w_1, w_2, \dots, w_K)$.

The above FE regression does not account for residual heterogeneity. This can lead to coefficient standard errors that are too small. Thompson and Sharp (1999) incorporated residual heterogeneity into the model by including a multiplicative variance parameter:

$$\hat{\theta}_{j} \sim N\left(\mathbf{x}_{j}\boldsymbol{\beta}, \phi\sigma_{j}^{2}\right)$$

For a multiplicative FE meta-regression, **W** in the above is replaced with $\mathbf{W}^{\phi} = \text{diag}(w_1^{\phi}, w_2^{\phi}, \dots, w_K^{\phi})$, where the weights are defined as $w_j^{\phi} = 1/(\hat{\phi}\hat{\sigma}_j^2)$. $\hat{\phi}$ is estimated as the mean squared error from the weighted linear regression with weights proportional to $1/\hat{\sigma}_i^2$.

Next, we present another method of incorporating residual heterogeneity by including an additive between-study variance parameter.

Random-effects meta-regression

An RE meta-regression (Berkey et al. 1995) model may be expressed as

$$\hat{\theta}_j = \mathbf{x}_j \boldsymbol{\beta} + u_j + \epsilon_j \qquad u_j \sim N(0, \tau^2) \qquad \epsilon_j \sim N(0, \hat{\sigma}_j^2)$$

All algorithms for RE meta-regression first estimate the between-study variance, τ^2 . The regression coefficients are then estimated via weighted least squares,

$$\widehat{\boldsymbol{\beta}}^* = \left(\mathbf{X}' \mathbf{W}^* \mathbf{X} \right)^{-1} \mathbf{X}' \mathbf{W}^* \widehat{\boldsymbol{\theta}}$$

where $\mathbf{W}^* = \text{diag}(w_1^*, w_2^*, \dots, w_K^*)$ and $w_j^* = 1/(\hat{\sigma}_j^2 + \hat{\tau}^2)$.

All the estimators of τ^2 can be expressed in terms of the matrix

$$\mathbf{P} = \mathbf{A} - \mathbf{A}\mathbf{X} \left(\mathbf{X}' \mathbf{A} \mathbf{X}\right)^{-1} \mathbf{X}' \mathbf{A}$$
(1)

where A is a $p \times p$ diagonal weight matrix whose elements depend on the type of estimator (Viechtbauer et al. 2015).

The formulas in the following sections are based on Viechtbauer et al. (2015).

Iterative methods for computing $\hat{\tau}^2$

The three estimators described below do not have a closed-form solution, and an iterative algorithm is needed to obtain an estimate of τ^2 . The Fisher scoring algorithm, described below, is used to estimate τ^2 .

All three estimators start with an initial estimate of τ^2 based on the Hedges estimator, $\hat{\tau}_0^2 = \hat{\tau}_{\text{HE}}^2$, but you can specify your own initial estimate in the from() option. The estimate is then updated at each iteration via the formula,

$$\hat{\tau}_{\text{new}}^2 = \hat{\tau}_{\text{current}}^2 + \delta$$

where δ is a function of $\hat{\tau}^2_{\text{current}}$ and its functional form depends on the estimation method.

The iteration terminates when $\text{reldif}(\hat{\tau}_{\text{new}}^2, \hat{\tau}_{\text{current}}^2)$ is less than tolerance() and the scaled gradient, computed based on the log-likelihood functions provided below, is less than nrtolerance(); see [R] Maximize.

The MLE of τ^2 is the value that maximizes the log-likelihood function (Hardy and Thompson 1996)

$$\ln L_{\mathrm{ML}}\left(\tau^{2}\right) = -\frac{1}{2}\left\{K\ln(2\pi) + \left.\ln\left|\tau^{2}\mathbf{I} + \mathbf{W}^{-1}\right| + \hat{\boldsymbol{\theta}}'\mathbf{P}\hat{\boldsymbol{\theta}}\right\}\right.$$

The MLE formula for δ is

$$\delta_{\mathrm{MLE}} = \frac{\hat{\boldsymbol{\theta}}^{'} \mathbf{P} \mathbf{P} \hat{\boldsymbol{\theta}} - \mathrm{tr}(\mathbf{W}^{*})}{\mathrm{tr}(\mathbf{W}^{*} \mathbf{W}^{*})}$$

The MLE estimator of τ^2 does not incorporate the uncertainty about the unknown regression coefficients β and thus can be negatively biased.

The REML estimate of τ^2 is the value that maximizes the restricted log-likelihood function,

$$\ln L_{\mathrm{REML}}\left(\tau^2\right) = \left.\ln L_{\mathrm{ML}}\left(\tau^2\right) - \frac{1}{2}\ln\left|\sum_{j=1}^{K}\frac{1}{\tau^2 + \hat{\sigma}_j^2}\mathbf{x}_j'\mathbf{x}_j\right| + \frac{p}{2}\ln(2\pi)$$

and the REML formula for δ is

$$\delta_{\text{REML}} = \frac{\hat{\theta}' \mathbf{P} \mathbf{P} \hat{\theta} - \text{tr}(\mathbf{P})}{\text{tr}(\mathbf{P}\mathbf{P})}$$

The empirical Bayes estimator for τ^2 was introduced by Morris (1983) and was first used in the metaanalytic context by Berkey et al. (1995). This estimator is also known as the Paule–Mandel estimator (Paule and Mandel 1982). The empirical Bayes formula for δ is

$$\delta_{\rm EB} = \frac{K/(K-p)\hat{\boldsymbol{\theta}}'\,\mathbf{P}\hat{\boldsymbol{\theta}} - K}{\mathrm{tr}(\mathbf{W}^*)}$$

For the three above estimators, $\mathbf{A} = \mathbf{W}^*$ in the definition of the **P** matrix from (1).

Noniterative methods for computing $\hat{\tau}^2$

This section describes noniterative methods, which have closed-form expressions.

The method of moments estimator of τ^2 (DuMouchel and Harris [1983, eq. 3.12]; also see Raudenbush [2009, eq. 16.43]), which can be viewed as an extension of the DerSimonian–Laird estimator from the RE meta-analysis to meta-regression, is

$$\hat{\tau}_{\text{DL}}^{2} = \frac{\hat{\boldsymbol{\theta}}' \, \mathbf{P} \hat{\boldsymbol{\theta}} - (K - p)}{\text{tr}(\mathbf{P})} = \frac{Q_{\text{res}} - (K - p)}{\text{tr}(\mathbf{W}) - \text{tr}\left\{ \mathbf{W} \mathbf{X} \, (\mathbf{X}' \mathbf{W} \mathbf{X})^{-1} \, \mathbf{X}' \mathbf{W} \right\}} = \frac{Q_{\text{res}} - (K - p)}{\sum_{j=1}^{K} w_{j} \left(1 - h_{j}\right)}$$
(2)

where **P** is defined in (1) with $\mathbf{A} = \mathbf{W}$, h_j is the *j*th diagonal element of the "hat" matrix $\mathbf{X}(\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}$, and Q_{res} is defined in (3).

For a constant-only model, when p = 1, (2) reduces to the DerSimonian–Laird estimator from *Non-iterative methods* in [META] **meta summarize**.

Hedges (1983) used OLS to provide a method of moments estimator of $\hat{\tau}^2$ for the RE meta-analysis. In the context of meta-regression, the extension of the Hedges's (HE) estimator introduced by Raudenbush (2009, eq. 16.41) is

$$\begin{split} \hat{\tau}_{\text{HE}}^2 &= \frac{\hat{\boldsymbol{\theta}}' \mathbf{P} \hat{\boldsymbol{\theta}} - \text{tr}(\mathbf{P} \mathbf{W}^{-1})}{K - p} \\ &= \frac{\sum_{j=1}^{K} \left(\hat{\boldsymbol{\theta}}_j - \mathbf{x}_j \hat{\boldsymbol{\beta}}_{\text{ols}} \right)^2 - \sum_{j=1}^{K} \hat{\sigma}_j^2 \left(1 - h_j^{\text{ols}} \right)}{K - p} \end{split}$$

where **P** is defined in (1) with $\mathbf{A} = \mathbf{I}$, $\hat{\boldsymbol{\beta}}_{ols} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}\hat{\boldsymbol{\theta}}$, and h_j^{ols} is the *j*th diagonal element of the OLS hat matrix $\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$.

Sidik and Jonkman (2005) proposed the following estimator. Consider an initial estimate of τ^2 ,

$$\hat{\tau}_0^2 = \frac{\sum_{j=1}^K \left(\hat{\theta}_j - \overline{\theta}\right)^2}{K} \qquad \overline{\theta} = \frac{\sum_{j=1}^K \hat{\theta}_j}{K}$$

Then, the estimator is defined as

$$\hat{\tau}_{\rm SJ}^2 = \frac{\hat{\boldsymbol{\theta}}' \mathbf{P} \hat{\boldsymbol{\theta}}}{K-p} = \frac{\sum_{j=1}^{K} w_j^{\rm SJ} \left(\hat{\boldsymbol{\theta}}_j - \mathbf{x}_j \hat{\boldsymbol{\beta}}_{\rm SJ} \right)^2}{K-p}$$

where $w_j^{\text{SJ}} = \hat{\tau}_0^2 / (\hat{\sigma}_j^2 + \hat{\tau}_0^2)$ is a diagonal element of **A** from (1), $\hat{\boldsymbol{\beta}}_{\text{SJ}} = (\mathbf{X}' \mathbf{W}^{\text{SJ}} \mathbf{X})^{-1} \mathbf{X}' \mathbf{W}^{\text{SJ}} \hat{\boldsymbol{\theta}}$, and \mathbf{W}^{SJ} is a $K \times K$ diagonal matrix with elements w_j^{SJ} .

The Sidik–Jonkman estimator is not truncated because, theoretically, it should always produce a non-negative estimate. However, Viechtbauer et al. (2015) point out that, technically, a negative value can be produced in practice in an unlikely case of all $\hat{\theta}_i$'s being identical.

Viechtbauer et al. (2015) provide the following extension for the estimator of τ^2 , which was originally introduced by Schmidt and Hunter (2015) in the context of RE meta-analysis, to meta-regression

$$\hat{\tau}_{\rm HS}^2 = \frac{\hat{\boldsymbol{\theta}}' \, \mathbf{P} \hat{\boldsymbol{\theta}} - K}{{\rm tr}(\mathbf{W})} = \frac{Q_{\rm res} - K}{{\rm tr}(\mathbf{W})}$$

where **P** is defined in (1) with $\mathbf{A} = \mathbf{W}$.

Knapp–Hartung standard-error adjustment

By default, the inference about the regression coefficients and their confidence intervals from metaregression is based on a normal distribution. The test of the significance of all regression coefficients is based on a χ^2 distribution with p-1 degrees of freedom.

Knapp and Hartung (2003) proposed an adjustment to the standard errors of the estimated regression coefficients to account for the uncertainty in the estimation of τ^2 . They showed that the corresponding tests of individual regression coefficients and their confidence intervals are based on the Student's t distribution with K - p degrees of freedom and that the overall test of significance is based on an F distribution with p - 1 numerator and K - p denominator.

The Knapp-Hartung adjustment first calculates the quadratic form,

$$q_{\rm KH} = \frac{\hat{\boldsymbol{\theta}}' \mathbf{P} \hat{\boldsymbol{\theta}}}{K - p}$$

where **P** is defined in (1) with $\mathbf{A} = \mathbf{W}^*$. It then multiplies the regular expressions of the variances of regression coefficients by q_{KH} or, in the case of the truncated Knapp–Hartung adjustment, by max $(1, q_{\text{KH}})$.

Residual homogeneity test

Consider a test of residual homogeneity, which mathematically translates to H_0 : $\tau^2 = 0$ for the random-effects meta-regression and to H_0 : $\phi = 1$ for the fixed-effects meta-regression with multiplicative dispersion parameter ϕ . This test is based on the residual weighted sum of squares, Q_{res} ,

$$Q_{\rm res} = \sum_{j=1}^{K} w_j \left(\hat{\theta}_j - \mathbf{x}_j \widehat{\boldsymbol{\beta}}\right)^2 = \sum_{j=1}^{K} \left(\frac{\hat{\theta}_j - \mathbf{x}_j \widehat{\boldsymbol{\beta}}}{\hat{\sigma}_j}\right)^2 \tag{3}$$

which is a generalization of the heterogeneity test statistic, Q (see Homogeneity test in [META] meta summarize), to the context of meta-regression.

Under the null hypothesis of residual homogeneity, Q_{res} follows a χ^2 distribution with K - p degrees of freedom (Seber and Lee 2003, sec. 2.4).

Residual heterogeneity measures

The I_{res}^2 statistic represents the percentage of residual between-study variation relative to the total variability. For an RE meta-regression, it is defined by Higgins and Thompson (2002) as

$$I_{\rm res}^2 = \frac{\hat{\tau}^2}{\hat{\tau}^2 + s^2} \times 100\%$$
 (4)

where $s^2 = (K - p)/\text{tr}(\mathbf{P})$ and $\mathbf{A} = \mathbf{W}$ is used to define **P**. In the meta-regression context, the H^2 statistic is defined as

$$H_{\rm res}^2 = \frac{\hat{\tau}^2 + s^2}{s^2} \tag{5}$$

Adjusted R^2 (Harbord and Higgins 2016; Borenstein et al. 2009) measures the proportion of the between-study variance that is explained by the moderators. It is defined as

$$R^{2} = \frac{\hat{\tau}_{c}^{2} - \hat{\tau}^{2}}{\hat{\tau}_{c}^{2}} \times 100\%$$
(6)

where $\hat{\tau}_c^2$ is the between-study variance estimated from a constant-only model.

References

- Berkey, C. S., D. C. Hoaglin, F. Mosteller, and G. A. Colditz. 1995. A random-effects regression model for meta-analysis. Statistics in Medicine 14: 395–411. https://doi.org/10.1002/sim.4780140406.
- Berlin, J. A., and E. M. Antman. 1992. Advantages and limitations of meta-analytic regressions of clinical trials data. Controlled Clinical Trials 13: 422. https://doi.org/10.1016/0197-2456(92)90151-O.
- Borenstein, M., L. V. Hedges, J. P. T. Higgins, and H. R. Rothstein. 2009. Introduction to Meta-Analysis. Chichester, UK: Wiley.
- Colditz, G. A., T. F. Brewer, C. S. Berkey, M. E. Wilson, E. Burdick, H. V. Fineberg, and F. Mosteller. 1994. Efficacy of BCG vaccine in the prevention of tuberculosis: Meta-analysis of the published literature. *Journal of the American Medical Association* 271: 698–702. https://doi.org/10.1001/jama.1994.03510330076038.

- Deeks, J. J., P. Macaskill, and L. Irwig. 2005. The performance of tests of publication bias and other sample size effects in systematic reviews of diagnostic test accuracy was assessed. *Journal of Clinical Epidemiology* 58: 882–893. https: //doi.org/10.1016/j.jclinepi.2005.01.016.
- DuMouchel, W. H., and J. E. Harris. 1983. Bayes methods for combining the results of cancer studies in humans and other species. Journal of the American Statistical Association 78: 293–308. https://doi.org/10.2307/2288631.
- Greenland, S. 1987. Quantitative methods in the review of epidemiologic literature. *Epidemiologic Reviews* 9: 1–30. https://doi.org/10.1093/oxfordjournals.epirev.a036298.
- Harbord, R. M., and J. P. T. Higgins. 2016. "Meta-regression in Stata". In Meta-Analysis in Stata: An Updated Collection from the Stata Journal, edited by T. M. Palmer and J. A. C. Sterne, 85–111. 2nd ed. College Station, TX: Stata Press.
- Hardy, R. J., and S. G. Thompson. 1996. A likelihood approach to meta-analysis with random effects. Statistics in Medicine 15: 619–629. https://doi.org/10.1002/(SICI)1097-0258(19960330)15:6<619::AID-SIM188>3.0.CO;2-A.
- Hartung, J., and G. Knapp. 2001a. On tests of the overall treatment effect in meta-analysis with normally distributed responses. *Statistics in Medicine* 20: 1771–1782. https://doi.org/10.1002/sim.791.
 - 2001b. A refined method for the meta-analysis of controlled clinical trials with binary outcome. *Statistics in Medicine* 20: 3875–3889. https://doi.org/10.1002/sim.1009.
- Hedges, L. V. 1983. A random effects model for effect sizes. Psychological Bulletin 93: 388–395. https://doi.org/10.1037/ 0033-2909.93.2.388.
- Higgins, J. P. T., and S. G. Thompson. 2002. Quantifying heterogeneity in a meta-analysis. Statistics in Medicine 21: 1539–1558. https://doi.org/10.1002/sim.1186.
- ——. 2004. Controlling the risk of spurious findings from meta-regression. *Statistics in Medicine* 23: 1663–1682. https://doi.org/10.1002/sim.1752.
- Higgins, J. P. T., S. G. Thompson, J. J. Deeks, and D. G. Altman. 2003. Measuring inconsistency in meta-analyses. BMJ 327: 557–560. https://doi.org/10.1136/bmj.327.7414.557.
- Knapp, G., and J. Hartung. 2003. Improved tests for a random effects meta-regression with a single covariate. Statistics in Medicine 22: 2693–2710. https://doi.org/10.1002/sim.1482.
- Konstantopoulos, S., and L. V. Hedges. 2009. "Analyzing effect sizes: Fixed-effects models". In *The Handbook of Research Synthesis and Meta-Analysis*, edited by H. Cooper, L. V. Hedges, and J. C. Valentine, 279–293. 2nd ed. New York: Russell Sage Foundation.
- Morris, C. N. 1983. Parametric empirical Bayes inference: Theory and applications. Journal of the American Statistical Association 78: 47–55. https://doi.org/10.2307/2287098.
- Paule, R. C., and J. Mandel. 1982. Consensus values and weighting factors. Journal of Research of the National Bureau of Standards 87: 377–385. https://doi.org/10.6028/jres.087.022.
- Raudenbush, S. W. 2009. "Analyzing effect sizes: Random-effects models". In *The Handbook of Research Synthesis and Meta-Analysis*, edited by H. Cooper, L. V. Hedges, and J. C. Valentine, 295–316. 2nd ed. New York: Russell Sage Foundation.
- Schmidt, F. L., and J. E. Hunter. 2015. Methods of Meta-Analysis: Correcting Error and Bias in Research Findings. 3rd ed. Thousand Oaks, CA: Sage. https://doi.org/10.4135/9781483398105.
- Seber, G. A. F., and A. J. Lee. 2003. Linear Regression Analysis. 2nd ed. Hoboken, NJ: Wiley. https://doi.org/10.1002/ 9780471722199.
- Sharp, S. J. 2016. "Meta-analysis regression". In Meta-Analysis in Stata: An Updated Collection from the Stata Journal, edited by T. M. Palmer and J. A. C. Sterne, 112–120. 2nd ed. College Station, TX: Stata Press.
- Sidik, K., and J. N. Jonkman. 2002. A simple confidence interval for meta-analysis. *Statistics in Medicine* 21: 3153–3159. https://doi.org/10.1002/sim.1262.
 - ——. 2005. A note on variance estimation in random effects meta-regression. *Journal of Biopharmaceutical Statistics* 15: 823–838. https://doi.org/10.1081/BIP-200067915.
- Thompson, S. G., and J. P. T. Higgins. 2002. How should meta-regression analyses be undertaken and interpreted? Statistics in Medicine 21: 1559–1573. https://doi.org/10.1002/sim.1187.
- Thompson, S. G., and S. J. Sharp. 1999. Explaining heterogeneity in meta-analysis: A comparison of methods. Statistics in Medicine 18: 2693–2708. https://doi.org/10.1002/(sici)1097-0258(19991030)18:20<2693::aid-sim235>3.0.co;2-v.

Viechtbauer, W., J. A. López-López, J. Sánchez-Meca, and F. Marín-Martínez. 2015. A comparison of procedures to test for moderators in mixed-effects meta-regression models. *Psychological Methods* 20: 360–374. https://doi.org/10.1037/ met0000023.

Also see

- [META] meta regress postestimation Postestimation tools for meta regress
- [META] meta data Declare meta-analysis data
- [META] meta forestplot Forest plots
- [META] meta galbraithplot Galbraith plots
- [META] meta labbeplot L'Abbé plots
- [META] meta summarize Summarize meta-analysis data
- [META] meta Introduction to meta
- [META] Glossary
- [META] Intro Introduction to meta-analysis
- [U] 20 Estimation and postestimation commands

Stata, Stata Press, Mata, NetCourse, and NetCourseNow are registered trademarks of StataCorp LLC. Stata and Stata Press are registered trademarks with the World Intellectual Property Organization of the United Nations. StataNow is a trademark of StataCorp LLC. Other brand and product names are registered trademarks or trademarks of their respective companies. Copyright © 1985–2025 StataCorp LLC, College Station, TX, USA. All rights reserved.



For suggested citations, see the FAQ on citing Stata documentation.