meta multilevel — Multilevel random-intercepts meta-regression

Description Options References

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Description

meta multilevel fits random-intercepts meta-analysis models, which are commonly used in practice. For fitting more complicated multilevel meta-analysis models, including random slopes, see [META] meta meregress. meta multilevel is a convenience wrapper for meta meregress.

meta multilevel is a standalone command in that it does not require you to declare your data as meta data using meta set or meta esize.

Quick start

Perform standard RE meta-analysis by expressing it as a two-level meta-analysis model of the effect size y with random intercepts by trial and effect-size standard errors (se)

meta multilevel y, relevels(trial) essevariable(se)

Same as above, but perform a RE meta-regression on continuous moderator x

meta multilevel y x, relevels(trial) essevariable(se)

- Same as above, but specify effect-size variances (var) instead of the effect-size standard errors meta multilevel y x, relevels(trial) esvarvariable(var)
- Perform a three-level meta-analysis of y with random intercepts by region and by trial nested within region, and request the ML instead of the default REML estimation method

meta multilevel y, relevels(region trial) essevariable(se) mle

Perform a three-level meta-regression of y on x1 and x2 and specify a fixed standard deviation for the trial-within-region random intercepts

```
meta multilevel y x1 x2, relevels(region trial, sd(. .2)) ///
essevariable(se)
```

Menu

Statistics > Meta-analysis

Syntax

meta multilevel depvar [indepvars] [if] [in], relevels(relevspec)
{ essevariable(varname) | esvarvariable(varname) } [options]

options	Description
Model	
noconstant	suppress constant term from the fixed-effects equation
* relevels(<i>relevspec</i>)	specify the grouping structure of the model
[†] essevariable(<i>varname</i>)	specify effect-size (sampling) standard errors
[†] esvarvariable(<i>varname</i>)	specify effect-size (sampling) variances
reml	fit model via restricted maximum likelihood; the default
mle	fit model via maximum likelihood
<u>const</u> raints(<i>constraints</i>)	apply specified linear constraints
Reporting	
level(#)	set confidence level; default is level(95)
stddeviations	show random-effects parameter estimates as standard deviations and correlations; the default
<u>var</u> iance	show random-effects parameter estimates as variances and covariances
<u>estm</u> etric	show parameter estimates as stored in e(b)
<u>nohom</u> test	suppress output for homogeneity test
<u>noret</u> able	suppress random-effects table
<u>nofet</u> able	suppress fixed-effects table
<u>nohead</u> er	suppress output header
nogroup	suppress table summarizing groups
<u>nocnsr</u> eport	do not display constraints
display_options	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
EM options	
emiterate(#)	number of EM iterations; default is emiterate(20)
<pre>emtolerance(#)</pre>	EM convergence tolerance; default is emtolerance(1e-10)
emonly	fit model exclusively using EM
emlog	show EM iteration log
emdots	show EM iterations as dots
Maximization	
maximize_options	control the maximization process; seldom used
<u>col</u> linear	keep collinear variables
<u>coefl</u> egend	display legend instead of statistics

*relevels() is required. The full specification is relevels(*varlist*[, sd(# [# [...]])]).

[†]Either essevariable() or esvarvariable() is required.

indepvars may contain factor variables; see [U] 11.4.3 Factor variables.

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

collinear and coeflegend do not appear in the dialog box.

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

Options

Model

noconstant suppresses the constant (intercept) term from the fixed-effects model.

- relevels(*varlist*[, sd(#[#[...]])]) specifies the grouping structure of the multilevel model. A random intercept corresponding to each level variable in *varlist* is included in the model. The order of *varlist* is important. The first variable is assumed to be the highest grouping level, and each subsequent variable is assumed to be nested within the previous one. For example, relevels(region study) assumes that variable region is the highest grouping level and that study is nested within region. relevels() is required.
 - sd(#[#[...]]) specifies fixed values for the standard deviations of the random intercepts during estimation. The order of the values #[#[...]] should correspond to the order of variables in relevels(). A missing value(.) means that the standard deviation of the corresponding random intercept is to be estimated. This suboption is useful for exploring the sensitivity of the results to different magnitudes of random-intercepts standard deviations.
- essevariable (*varname*) specifies a variable that stores the standard errors of the effect sizes in variable *varname*, also known as sampling standard errors. You must specify one of essevariable() or esvarvariable().
- esvarvariable(varname) specifies a variable that stores the variances of the effect sizes in variable varname, also known as sampling variances. You must specify one of esvarvariable() or essevariable().
- reml and mle specify the statistical method for fitting the model.
 - reml, the default, specifies that the model be fit using restricted maximum likelihood (REML), also known as residual maximum likelihood.

mle specifies that the model be fit using maximum likelihood (ML).

constraints (constraints); see [R] Estimation options.

Reporting

level(#); see [R] Estimation options.

stddeviations, the default, displays the random-effects parameter estimates as standard deviations and correlations.

variance displays the random-effects parameter estimates as variances and covariances.

estmetric; see [ME] mixed.

nohomtest suppresses the homogeneity test based on the Q_M statistic from the output.

noretable, nofetable, noheader, and nogroup; see [ME] mixed.

nocnsreport; see [R] Estimation options.

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.

EM options

emiterate(#), emtolerance(#), emonly, emlog, and emdots; see [ME] mixed.

Maximization

maximize_options: difficult, technique(algorithm_spec), iterate(#), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(#), ltolerance(#), nrtolerance(#), and nonrtolerance; see [R] Maximize. Those that require special mention for meta multilevel are listed below.

For the technique() option, the default is technique(nr). The bhhh algorithm is not available.

matsqrt, the default, and matlog; see [ME] mixed.

The following options are available with meta multilevel but are not shown in the dialog box:

collinear, coeflegend; see [R] Estimation options.

Remarks and examples

Remarks are presented under the following headings:

Introduction Examples of using meta multilevel

Introduction

For an introduction to the general multilevel meta-regression model, see *Introduction* in [META] **meta meregress**.

Let $\mathbf{x}_{jkr} = (1, x_{1,jkr}, \dots, x_{p-1,jkr})$ be a $1 \times p$ vector of moderators and $\boldsymbol{\beta} = (\beta_0, \beta_1, \dots, \beta_{p-1})'$ be the corresponding $p \times 1$ vector of unknown fixed-effects regression coefficients. The three-level random-intercepts meta-regression model (Goldstein et al. [2000]; Thompson, Turner, and Warn [2001]; and Konstantopoulos [2011]) can be expressed as

$$\hat{\theta}_{jkr} = \beta_0 + \beta_1 x_{1,jkr} + \dots + \beta_{p-1} x_{p-1,jkr} + u_j^{(3)} + u_{jk}^{(2)} + \epsilon_{jk} = \mathbf{x}_{jkr} \beta + u_j^{(3)} + u_{jk}^{(2)} + \epsilon_{jkr}$$
(1)

where j = 1, 2, ..., M, $k = 1, 2, ..., m_j$, and $r = 1, 2, ..., m_{jk}$. $u_j^{(3)} \sim N(0, \tau_3^2)$, $u_{jk}^{(2)} \sim N(0, \tau_2^2)$, and $\epsilon_{jkr} \sim N(0, \hat{\sigma}_{jkr}^2)$, with the $\hat{\sigma}_{jkr}^2$'s being the known sampling variances (variances of the effect sizes). The random intercepts (the $u_j^{(3)}$'s, $u_{jk}^{(2)}$'s) and the sampling errors (the ϵ_{jk} 's) are independent. τ_3^2 and τ_2^2 are the random-intercepts variances at the third and second levels, respectively. Model (1) and its higher-level extensions are precisely the models that meta multilevel was designed to fit. If you wish to fit models that incorporate random slopes, see the more general command [META] meta meregress. meta multilevel fits multilevel random-intercepts meta-regression. By default, the REML method is used to estimate the random-intercepts variances τ_3^2 and τ_2^2 . Use the mle option to request ML estimation. REML is typically preferred over ML because it produces unbiased estimates of the random-effects variance parameters by accounting for the loss of degrees of freedom from estimating the fixed-effects vector β .

The relevels() option specifies the variables that identify the different levels of hierarchy that are present in the model. For each level of hierarchy, a random intercept is added to the model. The order of the specified variables is important. The first variable is assumed to be the highest grouping level, and each subsequent variable is assumed to be nested within the previous one.

The sd() suboption within relevels() provides a flexible way to restrict specific random-intercepts standard deviations during estimation while allowing the remaining parameters to be freely estimated. This option can be seen as a generalization of option tau2() in [META] meta regress and thus can be used to perform sensitivity analysis; see suboption sd() in *Options*.

The sampling variances (the $\hat{\sigma}_{jkr}^2$'s) are treated as known and do not require estimation. The variable that stores these values is specified in the esvarvariable() option. Alternatively, if the sampling standard errors (the $\hat{\sigma}_{ikr}$'s) are available, then option essevariable() can be used instead.

For example, suppose we specify the following in Stata:

```
. meta multilevel y x1 x2, relevels(lev3var lev2var) esvarvariable(var)
```

Consider how the above specification relates to the components of (1). Variable y stores the values of the $\hat{\theta}_{jkr}$'s, and the variables x1 and x2 represent the fixed-effects component of the model, $\mathbf{x}_{jkr}\beta$. Three fixed-effects parameters will need to be estimated: an intercept and two coefficients corresponding to variables x1 and x2, respectively. The relevels(lev3var lev2var) option specifies that two random intercepts are to be included in the model: one at level 3 (identified by variable lev3var) and another one at level 2 (identified by variable lev2var). These are the $u_j^{(3)}$ and $u_{jk}^{(2)}$ terms in (1). Level 1 corresponds to the participant or subject-level data, which are not available in meta-analysis. In general, if you specify L variables within relevels(), then L + 1 levels of hierarchy will be present in the model, with the leftmost variable corresponding to the highest level. The esvarvariable(var) option specifies the variable name (var in our example) that stores the sampling variances (the $\hat{\sigma}_{ikr}^2$'s) of the ϵ_{ikr} 's.

You may also use suboption sd() within relevels() to fix certain random-intercepts standard deviations at specified values during estimation, while allowing the remaining standard deviations to be freely estimated as follows:

```
. meta multilevel y x1 x2, relevels(lev3var lev2var, sd(.4 .)) esvarvariable(var)
```

Option sd(.4.) specifies that the standard deviation of $u_j^{(3)}$ is to be fixed at .4 during estimation and that the standard deviation of $u_{ik}^{(2)}$ is to be estimated.

Examples of using meta multilevel

Examples are presented under the following headings:

Example 1: Three-level meta-analysis Example 2: Sensitivity multilevel meta-analysis

Example 1: Three-level meta-analysis

Continuing with example 2 of [META] meta meregress, which explored the effect of a modified school calendar on student achievement (Cooper, Valentine, and Melson 2003), we will fit the same model using the syntax of meta multilevel. Recall that this command fits models that contain random intercepts only (no random slopes). Our three-level random-intercepts model is given by

$$\texttt{stdmdiff}_{jk} = \theta + u_j^{(3)} + u_{jk}^{(2)} + \epsilon_{jk} \tag{2}$$

with $u_j^{(3)} \sim N(0, \tau_3^2), u_{jk}^{(2)} \sim N(0, \tau_2^2)$, and $\epsilon_{jk} \sim N(0, se_{jk}^2)$. Here there is one observation (effect size) reported per school (level-2 group); therefore, $m_{ik} = 1$ in formula (1) in Introduction. This model can be fit using meta multilevel as follows:

```
. use https://www.stata-press.com/data/r19/schoolcal
(Effect of modified school calendar on student achievement)
. meta multilevel stdmdiff, relevels(district school) essevariable(se)
Performing EM optimization ...
Performing gradient-based optimization:
Iteration 0: Log restricted-likelihood = -104.8525
                                                      (not concave)
Iteration 1: Log restricted-likelihood = -49.423286
                                                      (not concave)
Iteration 2: Log restricted-likelihood = -25.793723
                                                     (not concave)
Iteration 3: Log restricted-likelihood = -21.309955
Iteration 4: Log restricted-likelihood = -9.1248907
Iteration 5: Log restricted-likelihood = -8.2630422
Iteration 6:
             Log restricted-likelihood = -7.9588574
Iteration 7:
             Log restricted-likelihood = -7.9587239
Iteration 8: Log restricted-likelihood = -7.9587239
```

Computing standard errors ...

Multilevel REML meta-analysis

Number of obs = 56

Grouping information

Group variable	No. of	Obser	vations per	group
	groups	Minimum	Average	Maximum
district	11	3	5.1	11
school	56	1	1.0	1

z

Log restricted-likelihood = -7.9587239

stdmdiff

_cons

Wald chi2(0) = Prob > chi2 =

Prob > Q M = 0.0000

[95% conf. interval]

	559	2.18	0.029	.0189866	.3504397
--	-----	------	-------	----------	----------

P>|z|

.1847132 Test of homogeneity: Q M = chi2(55) = 578.86

Coefficient Std. err.

.0845

Random-effects]	Estimate	
district: Identity	у	
	sd(_cons)	. 2550724
school: Identity		
	sd(_cons)	.1809324

By typing stdmdiff after meta multilevel, we specified the response variable (stdmdiff) and the fixed-effects portion of our model, which consists of a constant term (fixed-effect intercept), denoted by θ in (2). We could have specified stdmdiff *indepvars* to include additional moderators (independent variables) in the same way that we would if we were using any other estimation command. The relevels(district school) option defines two levels of hierarchy (the model will then have three levels, given that level 1 always corresponds to effect sizes) and includes random intercepts at both levels [the $u_j^{(3)}$ and $u_{jk}^{(2)}$ terms in (2)]. The order in which the variables are specified within relevels() (from left to right) is important—meta multilevel assumes that school is nested within district. This model was specified as follows in example 2 of [META] meta meregress (see that example for output interpretation):

```
. meta meregress stdmdiff || district: || school:, essevariable(se)
```

In other words, the relevels(district school) specification in meta multilevel is equivalent to the || district: || school: specification in meta meregress.

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Example 2: Sensitivity multilevel meta-analysis

We may often wish to fix certain random-intercepts standard deviations at specified values during estimation, while allowing the remaining standard deviations to be freely estimated. This could be done as a form of sensitivity analysis to assess the impact of certain random-effects parameters on estimation overall. The sd() suboption within relevels() can be a useful tool for this. For example, we may fix the value of τ_3^2 at the value reported in example 1 (0.2550724) and check that the estimates of the other parameters match with what was reported in that example. We use options nolog and noheader to suppress the log and header output for a more compact display of the results.

```
. meta multilevel stdmdiff, relevels(district school, sd(.2550724 .))
```

>	<pre>essevariable(se)</pre>	nolog	noheade
---	-----------------------------	-------	---------

stdmdiff	Coefficient S	td. err.	Z	P> z	[95% conf. interval]
_cons	.1847132 .	0845559	2.18	0.029	.0189866 .3504397
Test of homoge	eneity: Q_M = ch	i2(55) = 5	78.86		$Prob > Q_M = 0.0000$
Random-effec	cts parameters	Estima	te		
district: Cust	tom sd(_cons)	. 25507	24*		
school: Identi	ity sd(_cons)	. 18093	24		

(*) fixed during estimation

The order in which you specify values in sd() corresponds to the order in which the variables were specified within relevels(). In other words, the first value corresponds to the standard deviation of the random effects at the district level and the second value to that at the school level. The second . in sd(.2550724.) means that the standard deviation of the random intercepts at the school level, τ_2 , is free and needs to be estimated. The two outputs are essentially identical, as expected. Notice the starred note to indicate which parameter was fixed during estimation.

Next we will assess the impact of five different magnitudes in increasing order of the value of the random-effects standard deviations at the school level on the estimation of the other model parameters (θ and τ_3). We fit five models corresponding to fixing τ_2 at each element of matrix val in a loop and store their results under the names fixsd1, fixsd2, and so on.

```
. matrix val = (.01, .08, .18, .3, .6)
. forvalues i=1/5 {
    2.    quietly meta multilevel stdmdiff,
>         relevels(district school, sd(. '=val[1,'i']')) essevariable(se)
    3.    estimates store fixsd'i'
    4. }
```

We then use estimates table to report $\hat{\theta}$ (option keep(stdmdiff:_cons)) and its standard error from the five models for ease of comparison.

Variable	fixsd1	fixsd2	fixsd3	fixsd4	fixsd5
_cons	0.196 0.090	0.193 0.088	0.185 0.085	0.172 0.081	0.123 0.083
sd2	0.010	0.080	0.180	0.300	0.600
				L	egend: b/se

. estimates table _all, stats(sd2) keep(stdmdiff:_cons) b(%8.3f) se(%8.3f)

As τ_2 (sd2 in the output) increases from 0.01 to 0.6, $\hat{\theta}$ (_cons in the output) decreases from 0.196 to 0.123 and seems to be estimated with more precision (its standard error decreases). This suggests that increased variability among schools leads to a smaller overall standardized mean difference, resulting in less benefit from the modified-calendar program. Recall that a positive mean difference corresponds to higher student achievement in the group on the modified calendar.

The next table shows the estimates of $\tau_3 = \sqrt{\operatorname{Var}(u_j^{(3)})}$ for the different fixed values of τ_2 . The term $\operatorname{lnsl_lic}(\tau_3)$, so we use the eform option to report the exponentiated value.

estimates table _all, stats(sd2) ke	ep(lns1_1_1:_cons)	b(%8.3f)	eform
-------------------------------------	--------------------	----------	-------

Variable	fixsd1	fixsd2	fixsd3	fixsd4	fixsd5
_cons	0.288	0.278	0.255	0.215	0.000
sd2	0.010	0.080	0.180	0.300	0.600

As τ_2 (sd2) increases from 0.01 to 0.6, $\hat{\tau}_3$ (_cons) decreases from 0.288 to nearly 0, indicating that as τ_2 increases, it will eventually capture all the variability (excluding sampling error) among the effect sizes. In this case, the district level (level 3) may be dropped from the model.

Stored results

meta multilevel stores the following in e():

Scalars	
e(N)	total number of observations
e(k)	number of parameters
e(k_f)	number of fixed-effects parameters
e(k_r)	number of random-effects parameters
e(k_rs)	number of variances
e(11)	log (restricted) likelihood
e(rank)	rank of e(V)
e(ic)	number of iterations
e(sd#)	user-specified random-intercepts standard deviation (when suboption sd() of
	relevels() is specified)
e(di_m)	model degrees of freedom
e(ch12)	model χ^2 wald less statistic
e(p)	<i>p</i> -value for model test
e(U_M)	multilevel Cochran Q_M residual homogeneity test statistic
	a value for residual homogeneity test
e(p_Q_M)	<i>p</i> -value for residual homogeneity test
e(converged)	1 il convergea, 0 otnerwise
Macros	
e(cmd)	meta multilevel
e(cmdline)	command as typed
e(method)	REML or ML
e(title)	title in estimation output
e(chi2type)	Wald; type of model χ^2 test
e(depvar)	name of dependent variable
e(ivars)	grouping variables
e(indepvars)	names of independent variables (moderators)
e(esvarvariable)	variable containing sampling variances (when esvarvariable() is specified)
e(essevariable)	variable containing sampling standard errors (when essevariable() is specified)
e(technique)	maximization technique
e(datasignature)	
e(datasignaturevars)	variables used in calculation of checksum
e(emonly)	emonly, il specified
e(mi_method)	type of m1 method
e(opt)	type of optimization
e(optmetric)	matsqrt or matlog; random-enects matrix parameterization
e(properties)	DV
e(predict)	program used to implement predict
e(estat_cmd)	factor variables fugat as ashal anced
e(asobserved)	factor variables fuset as appearved
Matrices	
e(b)	coefficient vector
e(V)	variance–covariance matrix of the estimators
e(Cns)	constraints matrix
e(N_g)	group counts
e(g_min)	group-size minimums
e(g_avg)	group-size averages
e(g_max)	group-size maximums
Functions	
e(sample)	marks estimation 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.

When the esvarvariable() option is specified, metamultilevel creates a system variable, _meta_mereg_se, that contains the sampling standard errors.

Methods and formulas

Let \mathbf{X}_j , $\hat{\boldsymbol{\theta}}_j$, and $\boldsymbol{\epsilon}_j$ be defined as in *Methods and formulas* of [META] **meta meregress**. If we eliminate the explicit reference to specific levels of hierarchy, then (1) can be expressed compactly as

$$\boldsymbol{\theta}_{j} = \mathbf{X}_{j}\boldsymbol{\beta} + \dot{\mathbf{Z}}_{j}\dot{\mathbf{u}}_{j} + \boldsymbol{\epsilon}_{j}$$

where $m_{j.} \times (m_j + 1)$ matrix $\dot{\mathbf{Z}}_j = (\mathbf{1}_{m_j.}, \bigoplus_{k=1}^{m_j} \mathbf{1}_{m_{jk}})$ and $(m_j + 1) \times 1$ vector $\dot{\mathbf{u}}_j = (u_j^{(3)}, u_{j1}^{(2)}, u_{j2}^{(2)}, \dots, u_{jm_j}^{(2)})'$, with a $(m_j + 1) \times (m_j + 1)$ covariance matrix $\dot{\mathbf{\Sigma}}_j$, defined as

$$\dot{\boldsymbol{\Sigma}}_{j} = \operatorname{Var}\left(\dot{\mathbf{u}}_{j}\right) = \begin{bmatrix} \tau_{3}^{2} & \mathbf{0} \\ \mathbf{0} & \tau_{2}^{2} \mathbf{I}_{m_{j}} \end{bmatrix}$$

The formulas used by meta multilevel to estimate β , τ_3^2 , and τ_2^2 are described in Methods and formulas of [META] meta meregress with $\Sigma_j = \dot{\Sigma}_j$, $\mathbf{Z}_j = \dot{\mathbf{Z}}_j$, and $\mathbf{u}_j = \dot{\mathbf{u}}_j$.

References

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Also see

- [META] meta me postestimation Postestimation tools for multilevel mixed-effects meta-analysis
- [META] meta meregress Multilevel mixed-effects meta-regression
- [META] meta regress Meta-analysis regression
- [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

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