meglm fits multilevel mixed-effects generalized linear models. meglm allows a variety of distributions for the response conditional on normally distributed random effects.

Quick start

Without weights

Random-effects probit regression of y on x1 with random intercepts by lev2
meglm y x1 || lev2:, family(binomial) link(probit)

Same as above, but fit a logit model and report odds ratios
meglm y x1 || lev2:, family(binomial) or

Two-level gamma model of y with fixed and random coefficients on x1
meglm y x1 || lev2: x1, family(gamma)

Nested three-level random-intercept Poisson model reporting incidence-rate ratios
meglm y x1 || lev3: || lev2:, family(poisson) irr

Two-level linear regression of y on x1 and x2 with random intercepts by lev2, random coefficients on x2, and robust standard errors
meglm y x1 x2 || lev2: x2, vce(robust)

With weights

Two-level linear regression of y on x with random intercepts by psu for two-stage sampling with PSU-level and observation-level sampling weights wvar2 and wvar1, respectively
meglm y x [pweight=wvar1] || psu:, pweight(wvar2)

Add secondary sampling stage with units identified by ssu having weights wvar2 and PSU-level weights wvar3 for a three-level random-intercept model
meglm y x [pw=wvar1] || psu:, pw(wvar3) || ssu:, pw(wvar2)

Same as above, but svyset data first
svyset psu, weight(wvar3) || ssu, weight(wvar2) || _n, weight(wvar1)
svy: meglm y x || psu: || ssu:
Menu

Statistics > Multilevel mixed-effects models > Generalized linear models (GLM)

Syntax

```
meglm depvar fe_equation [ || re_equation] [ || re_equation ...] [ , options ]
```

where the syntax of `fe_equation` is

```
[ indepvars] [ if] [ in] [ weight] [ , fe_options ]
```

and the syntax of `re_equation` is one of the following:

- for random coefficients and intercepts
  
  `levelvar: [ varlist] [ , re_options ]`

- for random effects among the values of a factor variable in a crossed-effects model

  `levelvar: R.varname`

`levelvar` is a variable identifying the group structure for the random effects at that level or is `_all` representing one group comprising all observations.

### fe_options

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### re_options

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<tr>
<td><code>dnumerical</code></td>
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<tr>
<td><code>collinear</code></td>
</tr>
<tr>
<td><code>coeflegend</code></td>
</tr>
</tbody>
</table>
### vartype

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>independent</strong> one unique variance parameter per random effect and all covariances 0; the default unless the R. notation is used</td>
</tr>
<tr>
<td><strong>exchangeable</strong> equal variances for random effects and one common pairwise covariance</td>
</tr>
<tr>
<td><strong>identity</strong> equal variances for random effects and all covariances 0; the default if the R. notation is used</td>
</tr>
<tr>
<td><strong>unstructured</strong> all variances and covariances to be distinctly estimated</td>
</tr>
<tr>
<td><strong>fixed(matname)</strong> user-selected variances and covariances constrained to specified values; the remaining variances and covariances unrestricted</td>
</tr>
<tr>
<td><strong>pattern(matname)</strong> user-selected variances and covariances constrained to be equal; the remaining variances and covariances unrestricted</td>
</tr>
</tbody>
</table>

### family

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>gaussian</strong> Gaussian (normal); the default</td>
</tr>
<tr>
<td><strong>bernoulli</strong> Bernoulli</td>
</tr>
<tr>
<td>**binomial [#</td>
</tr>
<tr>
<td><strong>gamma</strong> gamma</td>
</tr>
<tr>
<td>**nbinomial [mean</td>
</tr>
<tr>
<td><strong>ordinal</strong> ordinal</td>
</tr>
<tr>
<td><strong>poisson</strong> Poisson</td>
</tr>
</tbody>
</table>

### link

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>identity</strong> identity</td>
</tr>
<tr>
<td><strong>log</strong> log</td>
</tr>
<tr>
<td><strong>logit</strong> logit</td>
</tr>
<tr>
<td><strong>probit</strong> probit</td>
</tr>
<tr>
<td><strong>cloglog</strong> complementary log–log</td>
</tr>
</tbody>
</table>

### intmethod

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>mvaghermite</strong> mean–variance adaptive Gauss–Hermite quadrature; the default unless a crossed random-effects model is fit</td>
</tr>
<tr>
<td><strong>mcaghermite</strong> mode-curvature adaptive Gauss–Hermite quadrature</td>
</tr>
<tr>
<td><strong>pcaghermite</strong> Pinheiro–Chao mode-curvature adaptive Gauss–Hermite quadrature</td>
</tr>
<tr>
<td><strong>ghermite</strong> nonadaptive Gauss–Hermite quadrature</td>
</tr>
<tr>
<td><strong>laplace</strong> Laplacian approximation; the default for crossed random-effects models</td>
</tr>
<tr>
<td><strong>pclaplace</strong> Pinheiro–Chao Laplacian approximation</td>
</tr>
</tbody>
</table>
indepsvars and varlist may contain factor variables; see [U] 11.4.3 Factor variables.
depvar, indepsvars, and varlist may contain time-series operators; see [U] 11.4.4 Time-series varlists.

bayes, by, collect, and svy are allowed; see [U] 11.1.10 Prefix commands. For more details, see [BAYES] bayes: meglm.
vce() and weights are not allowed with the svy prefix; see [SVY] svy.

fweights, iweights, and pweights are allowed; see [U] 11.1.6 weight. Only one type of weight may be specified.

Weights are not supported under the Laplacian approximation or for crossed models.

startvalues(), startgrid, noestimate, dnumerical, collinear, and coeflegend do not appear in the dialog box.

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

Options

<table>
<thead>
<tr>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>noconstant suppresses the constant (intercept) term and may be specified for the fixed-effects equation and for any of or all the random-effects equations.</td>
</tr>
<tr>
<td>exposure(varname_e) specifies a variable that reflects the amount of exposure over which the depvar events were observed for each observation; ln(varname_e) is included in the fixed-effects portion of the model with the coefficient constrained to be 1.</td>
</tr>
<tr>
<td>offset(varname_o) specifies that varname_o be included in the fixed-effects portion of the model with the coefficient constrained to be 1.</td>
</tr>
<tr>
<td>asis forces retention of perfect predictor variables and their associated, perfectly predicted observations and may produce instabilities in maximization; see [R] probit.</td>
</tr>
<tr>
<td>covariance(vartype) specifies the structure of the covariance matrix for the random effects and may be specified for each random-effects equation. vartype is one of the following: independent, exchangeable, identity, unstructured, fixed(matname), or pattern(matname).</td>
</tr>
</tbody>
</table>

- covariance(independent) covariance structure allows for a distinct variance for each random effect within a random-effects equation and assumes that all covariances are 0. The default is covariance(independent) unless a crossed random-effects model is fit, in which case the default is covariance(identity). |
- covariance(exchangeable) structure specifies one common variance for all random effects and one common pairwise covariance. |
- covariance(identity) is short for “multiple of the identity”; that is, all variances are equal and all covariances are 0. |
- covariance(unstructured) allows for all variances and covariances to be distinct. If an equation consists of p random-effects terms, the unstructured covariance matrix will have p(p + 1)/2 unique parameters. |
- covariance(fixed(matname)) and covariance(pattern(matname)) covariance structures provide a convenient way to impose constraints on variances and covariances of random effects. Each specification requires a matname that defines the restrictions placed on variances and covariances. Only elements in the lower triangle of matname are used, and row and column names of matname are ignored. A missing value in matname means that a given element is unrestricted. In a fixed(matname) covariance structure, (co)variance (i, j) is constrained to equal the value specified in the i, jth entry of matname. In a pattern(matname) covariance structure, (co)variances (i, j) and (k, l) are constrained to be equal if matname[i, j] = matname[k, l]. |
fweight(varname) specifies frequency weights at higher levels in a multilevel model, whereas frequency weights at the first level (the observation level) are specified in the usual manner, for example, [fw=fwtvar1]. varname can be any valid Stata variable name, and you can specify fweight() at levels two and higher of a multilevel model. For example, in the two-level model

```
.mecmd fixed_portion [fw = wt1] || school: ... , fweight(wt2) ... 
```

the variable wt1 would hold the first-level (the observation-level) frequency weights, and wt2 would hold the second-level (the school-level) frequency weights.

iweight(varname) specifies importance weights at higher levels in a multilevel model, whereas importance weights at the first level (the observation level) are specified in the usual manner, for example, [iw=iwtvar1]. varname can be any valid Stata variable name, and you can specify iweight() at levels two and higher of a multilevel model. For example, in the two-level model

```
.mecmd fixed_portion [iw = wt1] || school: ... , iweight(wt2) ... 
```

the variable wt1 would hold the first-level (the observation-level) importance weights, and wt2 would hold the second-level (the school-level) importance weights.

pweight(varname) specifies sampling weights at higher levels in a multilevel model, whereas sampling weights at the first level (the observation level) are specified in the usual manner, for example, [pw=pwtvar1]. varname can be any valid Stata variable name, and you can specify pweight() at levels two and higher of a multilevel model. For example, in the two-level model

```
.mecmd fixed_portion [pw = wt1] || school: ... , pweight(wt2) ... 
```

the variable wt1 would hold the first-level (the observation-level) sampling weights, and wt2 would hold the second-level (the school-level) sampling weights.

family(family) specifies the distribution of depvar; family(gaussian) is the default.

link(link) specifies the link function; the default is the canonical link for the family() specified except for the gamma and negative binomial families.

If you specify both family() and link(), not all combinations make sense. You may choose from the following combinations:

<table>
<thead>
<tr>
<th></th>
<th>identity</th>
<th>log</th>
<th>logit</th>
<th>probit</th>
<th>cloglog</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian</td>
<td>D</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bernoulli</td>
<td>D</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>binomial</td>
<td>D</td>
<td></td>
<td>x</td>
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<td></td>
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<tr>
<td>gamma</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>negative binomial</td>
<td>D</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ordinal</td>
<td>D</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poisson</td>
<td>D</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

D denotes the default.

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

vce(vcetype) specifies the type of standard error reported, which includes types that are derived from asymptotic theory (oim, opg), that are robust to some kinds of misspecification (robust), and that allow for intragroup correlation (cluster clustvar); see [R] vce_option. If vce(robust) is specified, robust variances are clustered at the highest level in the multilevel model.
Reporting

level(#) ; see [R] Estimation options.
eform reports exponentiated fixed-effects coefficients and corresponding standard errors and confidence intervals. This option may be specified either at estimation or upon replay.

irr reports estimated fixed-effects coefficients transformed to incidence-rate ratios, that is, exp(\(\beta\)) rather than \(\beta\). Standard errors and confidence intervals are similarly transformed. This option affects how results are displayed, not how they are estimated or stored. irr may be specified either at estimation or upon replay. This option is allowed for count models only.

or reports estimated fixed-effects coefficients transformed to odds ratios, that is, exp(\(\beta\)) rather than \(\beta\). Standard errors and confidence intervals are similarly transformed. This option affects how results are displayed, not how they are estimated. or may be specified at estimation or upon replay. This option is allowed for logistic models only.

cncsr report; see [R] Estimation options.

notable suppresses the estimation table, either at estimation or upon replay.

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

nogroup suppresses the display of group summary information (number of groups, average group size, minimum, and maximum) from the output header.

display_options: noci, nopvalues, noomitted, vsquish, noemptycells, baselevels, allbaselevels, noflabel, fvwrap(#), fvwrapon(style), cformat(%,fmt), pformat(%,fmt), sformat(%,fmt), and nolstretch; see [R] Estimation options.

Integration

intmethod(intmethod) specifies the integration method to be used for the random-effects model. mvaghermite performs mean–variance adaptive Gauss–Hermite quadrature; mcaghermite and pcaghermite perform mode-curvature adaptive Gauss–Hermite quadrature; ghermite performs nonadaptive Gauss–Hermite quadrature; and laplace and pclaplace perform the Laplacian approximation, equivalent to mode-curvature adaptive Gaussian quadrature with one integration point. Techniques pcaghermite and pclaplace are available only with family(binomial) and family(bernoulli) combined with link(logit) and with family(poisson); these techniques obtain the random-effects mode and curvature using the efficient hierarchical decomposition algorithm described in Pinheiro and Chao (2006). For hierarchical models, this algorithm takes advantage of the design structure to minimize memory use and utilizes a series of orthogonal triangulations to compute the factored random-effects Hessian indirectly, avoiding the sparse full Hessian. Techniques mcaghermite and laplace use Cholesky factorization on the full Hessian. For four- and higher-level hierarchical designs, there can be dramatic computation-time differences.

The default integration method is mvaghermite unless a crossed random-effects model is fit, in which case the default integration method is laplace. The Laplacian approximation has been known to produce biased parameter estimates; however, the bias tends to be more prominent in the estimates of the variance components rather than in the estimates of the fixed effects.

For crossed random-effects models, estimation with more than one quadrature point may be prohibitively intensive even for a small number of levels. For this reason, the integration method defaults to the Laplacian approximation. You may override this behavior by specifying a different integration method.

intpoints(#) sets the number of integration points for quadrature. The default is intpoints(7), which means that seven quadrature points are used for each level of random effects. This option is not allowed with intmethod(laplace).
The more integration points, the more accurate the approximation to the log likelihood. However, computation time increases as a function of the number of quadrature points raised to a power equaling the dimension of the random-effects specification. In crossed random-effects models and in models with many levels or many random coefficients, this increase can be substantial.

Maximization

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

from() accepts a properly labeled vector of initial values or a list of coefficient names with values. A list of values is not allowed.

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

startvalues(svmethod) specifies how starting values are to be computed. Starting values specified in from() override the computed starting values.

startvalues(zero) specifies that starting values be set to 0.

startvalues(constantonly) builds on startvalues(zero) by fitting a constant-only model to obtain estimates of the intercept and auxiliary parameters, and it substitutes 1 for the variances of random effects.

startvalues(fixedonly[, iterate(#)]) builds on startvalues(constantonly) by fitting a full fixed-effects model to obtain estimates of coefficients along with intercept and auxiliary parameters, and it continues to use 1 for the variances of random effects. This is the default behavior. iterate(#) limits the number of iterations for fitting the fixed-effects model.

startvalues(iv[, iterate(#)]) builds on startvalues(fixedonly) by using instrumental-variable methods with generalized residuals to obtain variances of random effects. iterate(#) limits the number of iterations for fitting the instrumental-variable model.

startvalues(iterate(#)) limits the number of iterations for fitting the default model (fixed effects).

startgrid[ (gridspec) ] performs a grid search on variance components of random effects to improve starting values. No grid search is performed by default unless the starting values are found to be not feasible, in which case meglm runs startgrid() to perform a “minimal” search involving \( q^3 \) likelihood evaluations, where \( q \) is the number of random effects. Sometimes this resolves the problem. Usually, however, there is no problem and startgrid() is not run by default. There can be benefits from running startgrid() to get better starting values even when starting values are feasible.

startgrid() is a brute-force approach that tries various values for variances and covariances and chooses the ones that work best. You may already be using a default form of startgrid() without knowing it. If you see meglm displaying Grid node 1, Grid node 2, ... following Grid node 0 in the iteration log, that is meglm doing a default search because the original starting values were not feasible. The default form tries 0.1, 1, and 10 for all variances of all random effects.

startgrid(numlist) specifies values to try for variances of random effects.

startgrid(covspec) specifies the particular variances and covariances in which grid searches are to be performed. covspec is name[level] for variances and name1[level]*name2[level] for covariances. For example, the variance of the random intercept at level id is specified as _cons[id], and the variance of the random slope on variable week at the same level is specified as week[id].
The residual variance for the linear mixed-effects model is specified as `e.depvar`, where `depvar` is the name of the dependent variable. The covariance between the random slope and the random intercept above is specified as `_cons[id]*week[id]`.

`startgrid(numlist covspec)` combines the two syntaxes. You may also specify `startgrid()` multiple times so that you can search the different ranges for different variances and covariances.

`noestimate` specifies that the model is not to be fit. Instead, starting values are to be shown (as modified by the above options if modifications were made), and they are to be shown using the `coeflegend` style of output.

`dnumerical` specifies that during optimization, the gradient vector and Hessian matrix be computed using numerical techniques instead of analytical formulas. By default, analytical formulas for computing the gradient and Hessian are used for all integration methods except `intmethod(laplace)`. `collinear, coeflegend; see [R] Estimation options.`

Remarks and examples

For a general introduction to `me` commands, see [ME] me. For additional examples of mixed-effects models for binary and binomial outcomes, see [ME] melogit, [ME] meprobit, and [ME] mecloglog. For additional examples of mixed-effects models for ordinal responses, see [ME] meologit and [ME] meoprobit. For additional examples of mixed-effects models for multinomial outcomes, see [SEM] Example 41g. For additional examples of mixed-effects models for count outcomes, see [ME] mepoisson and [ME] membreg. For additional examples of mixed-effects models for censored outcomes, see [ME] metobit and [ME] meintreg.

Remarks are presented under the following headings:

- Introduction
- Two-level models for continuous responses
- Two-level models for nonlinear responses
- Three-level models for nonlinear responses
- Crossed-effects models
- Obtaining better starting values
- Survey data
- Video example

Introduction

`meglm` fits multilevel mixed-effects generalized linear models of the form

\[ g\{E(y|X, u)\} = X\beta + Zu, \quad y \sim F \]  

where \(y\) is the \(n \times 1\) vector of responses from the distributional family \(F\), \(X\) is an \(n \times p\) design/covariate matrix for the fixed effects \(\beta\), and \(Z\) is the \(n \times q\) design/covariate matrix for the random effects \(u\). The \(X\beta + Zu\) part is called the linear predictor, and it is often denoted as \(\eta\). The linear predictor also contains the offset or exposure variable when `offset()` or `exposure()` is specified. \(g(\cdot)\) is called the link function and is assumed to be invertible such that

\[ E(y|X, u) = g^{-1}(X\beta + Zu) = H(\eta) = \mu \]
For notational convenience here and throughout this manual entry, we suppress the dependence of \( y \) on \( X \). Substituting various definitions for \( g(\cdot) \) and \( F \) results in a wide array of models. For instance, if \( y \) is distributed as Gaussian (normal) and \( g(\cdot) \) is the identity function, we have
\[
E(y) = X\beta + Zu, \quad y \sim \text{normal}
\]
or mixed-effects linear regression. If \( g(\cdot) \) is the logit function and \( y \) is distributed as Bernoulli, we have
\[
\logit\{ E(y) \} = X\beta + Zu, \quad y \sim \text{Bernoulli}
\]
or mixed-effects logistic regression. If \( g(\cdot) \) is the natural log function and \( y \) is distributed as Poisson, we have
\[
\ln\{ E(y) \} = X\beta + Zu, \quad y \sim \text{Poisson}
\]
or mixed-effects Poisson regression. In fact, some combinations of families and links are so common that we implemented them as separate commands in terms of \texttt{meglm}.

<table>
<thead>
<tr>
<th>Command</th>
<th>\texttt{meglm} equivalent</th>
</tr>
</thead>
<tbody>
<tr>
<td>melogit</td>
<td>family(bernoulli) link(logit)</td>
</tr>
<tr>
<td>meprobit</td>
<td>family(bernoulli) link(probit)</td>
</tr>
<tr>
<td>mecloglog</td>
<td>family(bernoulli) link(cloglog)</td>
</tr>
<tr>
<td>meologit</td>
<td>family(ordinal) link(logit)</td>
</tr>
<tr>
<td>meoprobit</td>
<td>family(ordinal) link(probit)</td>
</tr>
<tr>
<td>mepoisson</td>
<td>family(poisson) link(log)</td>
</tr>
<tr>
<td>membreg</td>
<td>family(nbinomial) link(log)</td>
</tr>
</tbody>
</table>

When no family–link combination is specified, \texttt{meglm} defaults to a Gaussian family with an identity link. Thus \texttt{meglm} can be used to fit linear mixed-effects models; however, for those models we recommend using the more specialized \texttt{mixed}, which, in addition to \texttt{meglm} capabilities, allows for modeling of the structure of the residual errors; see [ME] \texttt{mixed} for details.

The random effects \( u \) are assumed to be distributed as multivariate normal with mean \( 0 \) and \( q \times q \) variance matrix \( \Sigma \). The random effects are not directly estimated (although they may be predicted), but instead are characterized by the variance components, the elements of \( G = \text{Var}(u) \).

The general forms of the design matrices \( X \) and \( Z \) allow estimation for a broad class of generalized mixed-effects models: blocked designs, split-plot designs, growth curves, multilevel or hierarchical designs, etc. They also allow a flexible method of modeling within-cluster correlation. Subjects within the same cluster can be correlated as a result of a shared random intercept, or through a shared random slope on a covariate, or both. The general specification of variance components also provides additional flexibility—the random intercept and random slope could themselves be modeled as independent, or correlated, or independent with equal variances, and so forth.

Comprehensive treatments of mixed models are provided by, for example, Searle, Casella, and McCulloch (1992); Verbeke and Molenberghs (2000); Raudenbush and Bryk (2002); Hedeker and Gibbons (2006); McCulloch, Searle, and Neuhaus (2008); and Rabe-Hesketh and Skrondal (2022).

The key to fitting mixed models lies in estimating the variance components, and for that there exist many methods; see, for example, Breslow and Clayton (1993); Lin and Breslow (1996); Bates and Pinheiro (1998); and Ng et al. (2006). \texttt{meglm} uses maximum likelihood (ML) to estimate model parameters. The ML estimates are based on the usual application of likelihood theory, given the distributional assumptions of the model.
Returning to (1): in clustered-data situations, it is convenient not to consider all \( n \) observations at once but instead to organize the mixed model as a series of \( M \) independent groups (or clusters)

\[
g\{E(y_j)\} = X_j \beta + Z_j u_j
\]  

for \( j = 1, \ldots, M \), with cluster \( j \) consisting of \( n_j \) observations. The response \( y_j \) comprises the rows of \( y \) corresponding with the \( j \)th cluster, with \( X_j \) defined analogously. The random effects \( u_j \) can now be thought of as \( M \) realizations of a \( q \times 1 \) vector that is normally distributed with mean \( 0 \) and \( q \times q \) variance matrix \( \Sigma \). The matrix \( Z_i \) is the \( n_j \times q \) design matrix for the \( j \)th cluster random effects. Relating this to (1), note that

\[
Z = \begin{bmatrix}
Z_1 & 0 & \cdots & 0 \\
0 & Z_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & Z_M
\end{bmatrix} \quad ; \quad u = \begin{bmatrix}
u_1 \\
\vdots \\
u_M
\end{bmatrix} \quad ; \quad G = I_M \otimes \Sigma
\]

where \( I_M \) is the \( M \times M \) identity matrix and \( \otimes \) is the Kronecker product.

The mixed-model formula (2) is from Laird and Ware (1982) and offers two key advantages. First, it makes specifications of random-effects terms easier. If the clusters are schools, you can simply specify a random effect at the school level, as opposed to thinking of what a school-level random effect would mean when all the data are considered as a whole (if it helps, think Kronecker products). Second, representing a mixed-model with (2) generalizes easily to more than one set of random effects. For example, if classes are nested within schools, then (2) can be generalized to allow random effects at both the school and the class-within-school levels.

### Two-level models for continuous responses

We begin with a simple application of (2).

#### Example 1: Two-level linear mixed model

Consider a longitudinal dataset, used by both Ruppert, Wand, and Carroll (2003) and Diggle et al. (2002), consisting of weight measurements of 48 pigs on 9 successive weeks. Pigs are identified by the variable \( \text{id} \). Each pig experiences a linear trend in growth but overall weight measurements vary from pig to pig. Because we are not really interested in these particular 48 pigs per se, we instead treat them as a random sample from a larger population and model the between-pig variability as a random effect, or in the terminology of (2), as a random-intercept term at the pig level. We thus wish to fit the model

\[
\text{weight}_{ij} = \beta_0 + \beta_1 \text{week}_{ij} + u_j + \epsilon_{ij}
\]

for \( i = 1, \ldots, 9 \) weeks and \( j = 1, \ldots, 48 \) pigs. The fixed portion of the model, \( \beta_0 + \beta_1 \text{week}_{ij} \), simply states that we want one overall regression line representing the population average. The random effect \( u_j \) serves to shift this regression line up or down according to each pig. Because the random effects occur at the pig level (\( \text{id} \)), we fit the model by typing
At this point, a guided tour of the model specification and output is in order:

1. By typing `weight week`, we specified the response, `weight`, and the fixed portion of the model in the same way that we would if we were using `regress` or any other estimation command. Our fixed effects are a coefficient on `week` and a constant term.

2. When we added `|| id:`, we specified random effects at the level identified by the group variable `id`, that is, the pig level (level two). Because we wanted only a random intercept, that is all we had to type.

3. The estimation log displays a set of iterations from optimizing the log likelihood. By default, these are Newton–Raphson iterations, but other methods are available by specifying the appropriate `maximize_options`; see [R] Maximize.

4. The header describes the model, presents a summary of the random-effects group, reports the integration method used to fit the model, and reports a Wald test against the null hypothesis that all the coefficients on the independent variables in the mean equation are 0. Here the null hypothesis is rejected at all conventional levels. You can suppress the group information with the `nogroup` or the `noheader` option, which will suppress the rest of the header as well.
5. The estimation table reports the fixed effects, followed by the random effects, followed by the overall error term.

a. For the fixed-effects part, we estimate $\beta_0 = 19.36$ and $\beta_1 = 6.21$.

b. The random-effects equation is labeled `id`, meaning that these are random effects at the `id` (pig) level. We have only one random effect at this level, the random intercept. The variance of the level-two errors, $\sigma_u^2$, is estimated as 14.82 with standard error 3.12.

c. The row labeled `var(e.weight)` displays the estimated variance of the overall error term: $\hat{\sigma}_\epsilon^2 = 4.38$. This is the variance of the level-one errors, that is, the residuals.

6. Finally, a likelihood-ratio test comparing the model with ordinary linear regression is provided and is highly significant for these data. See Distribution theory for likelihood-ratio test in [ME] me for a discussion of likelihood-ratio testing of variance components.

See Remarks and examples in [ME] mixed for further analysis of these data including a random-slope model and a model with an unstructured covariance structure.

### Two-level models for nonlinear responses

By specifying different family–link combinations, we can fit a variety of mixed-effects models for nonlinear responses. Here we replicate one of the models from example 2 of melogit.

#### Example 2: Two-level logistic regression model

Ng et al. (2006) analyzed a subsample of data from the 1989 Bangladesh fertility survey (Huq and Cleland 1990), which polled 1,934 Bangladeshi women on their use of contraception. The women sampled were from 60 districts, identified by the variable `district`. Each district contained either urban or rural areas (variable `urban`) or both. The variable `c_use` is the binary response, with a value of 1 indicating contraceptive use. Other covariates include mean-centered `age` and a factor variable for the number of `children`.

We fit a standard logistic regression model, amended to have a random intercept for each district and a random slope on the `urban` factor variable. We fit the model by typing

```
. use https://www.stata-press.com/data/r18/bangladesh
(Bangladesh Fertility Survey, 1989)
. meglm c_use i.urban age i.children
> || district: i.urban, family(bernoulli) link(logit) nofvlabel
```

Fitting fixed-effects model:

- Iteration 0: Log likelihood = -1229.5485
- Iteration 1: Log likelihood = -1228.5268
- Iteration 2: Log likelihood = -1228.5263
- Iteration 3: Log likelihood = -1228.5263

Refining starting values:

- Grid node 0: Log likelihood = -1215.8592

Fitting full model:

- Iteration 0: Log likelihood = -1215.8592 (not concave)
- Iteration 1: Log likelihood = -1209.6285
- Iteration 2: Log likelihood = -1205.7903
- Iteration 3: Log likelihood = -1205.1337
- Iteration 4: Log likelihood = -1205.0034
- Iteration 5: Log likelihood = -1205.0025
Iteration 6:  Log likelihood = -1205.0025
Mixed-effects GLM Number of obs = 1,934
Family: Bernoulli
Link: Logit
Group variable: district Number of groups = 60
Obs per group:
  min = 2
  avg = 32.2
  max = 118
Integration method: mvaghermite Integration pts. = 7
Wald chi2(5) = 97.30
Log likelihood = -1205.0025 Prob > chi2 = 0.0000

| c_use | Coefficient | Std. err. | z     | P>|z| | [95% conf. interval] |
|-------|-------------|-----------|-------|------|----------------------|
| 1.urban | .7143927    | .1513595  | 4.72  | 0.000| .4177335 1.011052   |
| age   | -.0262261   | .0079656  | -3.29 | 0.001| -.0418384 -.0106138 |
| children |           |           |       |      |                      |
| 1     | 1.128973    | .1599347  | 7.06  | 0.000| .815507  1.442439   |
| 2     | 1.365165    | .1761804  | 7.74  | 0.000| 1.017857 1.708472   |
| 3     | 1.352238    | .1815608  | 7.45  | 0.000| .9963853 1.708091   |
| _cons | -1.698137   | .1505019  | -11.28| 0.000| -1.993115 -1.403159 |

| district | var(1.urban) | .2741013 | .2131525 | .059701 | 1.258463 |
|          | var(_cons)   | .2390807 | .0857012 | .1184191| .4826891 |

LR test vs. logistic model: chi2(2) = 47.05 Prob > chi2 = 0.0000
Note: LR test is conservative and provided only for reference.

Because we did not specify a covariance structure for the random effects \((u_{1j}, u_{0j})\)', \texttt{meglm} used the default independent structure:

\[
\Sigma = \text{Var}
\begin{bmatrix}
    u_{1j} \\
    u_{0j}
\end{bmatrix} =
\begin{bmatrix}
    \hat{\sigma}_{u1}^2 & 0 \\
    0 & \hat{\sigma}_{u0}^2
\end{bmatrix}
\]

with \(\hat{\sigma}_{u1}^2 = 0.27\) and \(\hat{\sigma}_{u0}^2 = 0.24\). You can request a different covariance structure by specifying the covariance(\() option. See examples 1–3 in \texttt{melogit} for further analysis of these data, and see [ME] \texttt{me} and [ME] \texttt{mixed} for further examples of covariance structures.

Three-level models for nonlinear responses

Two-level models extend naturally to models with three or more levels with nested random effects. Here we replicate the model from example 2 of [ME] \texttt{meologit}.

Example 3: Three-level ordered logistic regression model

We use the data from the Television, School, and Family Smoking Prevention and Cessation Project (Flay et al. 1988; Rabe-Hesketh and Skrondal 2022, chap. 11), where schools were randomly assigned into one of four groups defined by two treatment variables. Students within each school are nested in classes, and classes are nested in schools. The dependent variable is the tobacco and health
knowledge (THK) scale score collapsed into four ordered categories. We regress the outcome on the treatment variables, social resistance classroom curriculum and TV intervention, and their interaction and control for the pretreatment score.

```
. use https://www.stata-press.com/data/r18/tvsfpors
(Television, School, and Family Project)
. meglm thk prethk cc##tv || school: || class:, family(ordinal) link(logit)
```

Fitting fixed-effects model:
Iteration 0: Log likelihood = -2212.775
Iteration 1: Log likelihood = -2125.509
Iteration 2: Log likelihood = -2125.1034
Iteration 3: Log likelihood = -2125.1032

Refining starting values:
Grid node 0: Log likelihood = -2152.1514

Fitting full model:
Iteration 0: Log likelihood = -2152.1514 (not concave)
Iteration 1: Log likelihood = -2125.9213 (not concave)
Iteration 2: Log likelihood = -2120.1861
Iteration 3: Log likelihood = -2115.6177
Iteration 4: Log likelihood = -2114.5896
Iteration 5: Log likelihood = -2114.5881
Iteration 6: Log likelihood = -2114.5881

Mixed-effects GLM Number of obs = 1,600
Family: Ordinal
Link: Logit

Grouping information

<table>
<thead>
<tr>
<th>Group variable</th>
<th>No. of groups</th>
<th>Minimum</th>
<th>Average</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>school</td>
<td>28</td>
<td>18</td>
<td>57.1</td>
<td>137</td>
</tr>
<tr>
<td>class</td>
<td>135</td>
<td>1</td>
<td>11.9</td>
<td>28</td>
</tr>
</tbody>
</table>

Integration method: mvaghermite
Integration pts. = 7
Wald chi2(4) = 124.39
Log likelihood = -2114.5881
Prob > chi2 = 0.0000

| thk     | Coefficient | Std. err. | z     | P>|z|  | [95% conf. interval] |
|---------|-------------|-----------|-------|------|----------------------|
| prethk  | .4085273    | .039616   | 10.31 | 0.000 | .3308814 .4861731   |
| 1.cc    | .8844369    | .2099124  | 4.21  | 0.000 | .4730161 1.2958858 |
| 1.tv    | .236448     | .2049065  | 1.15  | 0.249 | -.1651614 .6380575 |
| cc#tv   | - .3717699  | .2958887  | -1.26 | 0.209 | -.951701  .2081612 |
| /cut1   | -.0959459   | .168898   | - .4269815 .2350896 |
| /cut2   | 1.177478    | .1704946  | .8433151 1.511642 |
| /cut3   | 2.383672    | .1786736  | 2.033478  2.733865 |

<table>
<thead>
<tr>
<th>school</th>
<th>var(_cons)</th>
<th>0.0448735</th>
<th>.0425387</th>
<th>.0069997</th>
<th>.2876749</th>
</tr>
</thead>
<tbody>
<tr>
<td>school&gt;class</td>
<td>var(_cons)</td>
<td>.1482157</td>
<td>.0637521</td>
<td>.063792</td>
<td>.3443674</td>
</tr>
</tbody>
</table>

LR test vs. ologit model: chid2(2) = 21.03
Prob > chid2 = 0.0000

Note: LR test is conservative and provided only for reference.
Notes:

1. Our model now has two random-effects equations, separated by \(|\)\. The first is a random intercept (constant only) at the school level (level three), and the second is a random intercept at the class level (level two). The order in which these are specified (from left to right) is significant—meglm assumes that class is nested within school.

2. The information on groups is now displayed as a table, with one row for each grouping. You can suppress this table with the nogroup or the noheader option, which will suppress the rest of the header, as well.

3. The variance-component estimates are now organized and labeled according to level. The variance component for class is labeled school>class to emphasize that classes are nested within schools.

We refer you to example 2 of [ME] meologit and example 1 of [ME] meologit postestimation for a substantive interpretation of the results.

The above extends to models with more than two levels of nesting by adding more random-effects equations, each separated by \(|\)\. The order of nesting goes from left to right as the groups go from biggest (highest level) to smallest (lowest level).

**Crossed-effects models**

Not all mixed models contain nested levels of random effects. In this section, we consider a crossed-effects model, that is, a mixed-effects model in which the levels of random effects are not nested; see [ME] me for more information on crossed-effects models.

**Example 4: Crossed-effects logistic regression model**

We use the salamander cross-breeding data from Karim and Zeger (1992) as analyzed in Rabe-Hesketh and Skrondal (2022, sec. 16.8). The salamanders come from two populations—whiteside and roughbutt—and are labeled whiteside males (wsm), whiteside females (waf), roughbutt males (rbm), and roughbutt females (rbf). Male identifiers are recorded in the variable male, and female identifiers are recorded in the variable female. The salamanders were divided into groups such that each group contained 60 male–female pairs, with each salamander having three potential partners from the same population and three potential partners from the other population. The outcome (y) is coded 1 if there was a successful mating and is coded 0 otherwise; see the references for a detailed description of the mating experiment.

We fit a crossed-effects logistic regression for successful mating, where each male has the same value of his random intercept across all females, and each female has the same value of her random intercept across all males.

To fit a crossed-effects model in Stata, we use the \(\_all\) : R.varname syntax. We treat the entire dataset as one super cluster, denoted \(\_all\), and we nest each gender within the super cluster by using the R.varname notation. R.male requests a random intercept for each level of male and imposes an identity covariance structure on the random effects; that is, the variances of the random intercepts are restricted to be equal for all male salamanders. R.female accomplishes the same for the female salamanders. In Stata, we type
. use https://www.stata-press.com/data/r18/salamander
. meglm y wsm##wsf || _all: R.male || _all: R.female, family(bernoulli)
   > link(logit) or
note: crossed random-effects model specified; option intmethod(laplace)
implied.
Fitting fixed-effects model:
Iteration 0:  Log likelihood = -223.13998
Iteration 1:  Log likelihood = -222.78752
Iteration 2:  Log likelihood = -222.78735
Iteration 3:  Log likelihood = -222.78735
Refining starting values:
Grid node 0:  Log likelihood = -211.58149
Fitting full model:
Iteration 0:  Log likelihood = -211.58149
Iteration 1:  Log likelihood = -209.33737  (not concave)
Iteration 2:  Log likelihood = -209.30822
Iteration 3:  Log likelihood = -209.27666
Iteration 4:  Log likelihood = -209.27659
Iteration 5:  Log likelihood = -209.27659
Mixed-effects GLM Number of obs = 360
Family:  Bernoulli
Link:  Logit
Group variable: _all Number of groups = 1
Obs per group:
  min = 360
  avg = 360.0
  max = 360
Integration method: laplace
Wald chi2(3) = 42.55
Log likelihood = -209.27659  Prob > chi2 = 0.0000

y      Odds ratio   Std. err.      z    P>|z|   [95% conf. interval]

1.wsm   .4956232   .221259   -1.57   0.116   .2066109   1.188913
1.wsf   .0547959   .0287997   -5.53   0.000   .0195602   .1535053
wsm#wsf  36.17442  21.75035    5.97   0.000  11.13283   117.5432
   _cons  2.74053   1.050653   2.63   0.009   1.29272   5.809847
   _all>male
var(_cons)  1.040939  .4983886   .4072683   2.660541
   _all>female
var(_cons)  1.174381  .5404486   .476527   2.894215

Note: Estimates are transformed only in the first equation to odds ratios.
Note: _cons estimates baseline odds (conditional on zero random effects).
LR test vs. logistic model: chi2(2) = 27.02  Prob > chi2 = 0.0000
Note: LR test is conservative and provided only for reference.

Because we specified a crossed-effects model, meglm defaulted to the method of Laplacian approximation to calculate the likelihood; see Computation time and the Laplacian approximation in [ME] me for a discussion of computational complexity of mixed-effects models, and see Methods and formulas below for the formulas used by the Laplacian approximation method.

The estimates of the random intercepts suggest that the heterogeneity among the female salamanders, 1.17, is larger than the heterogeneity among the male salamanders, 1.04.
Setting both random intercepts to 0, the odds of successful mating for a roughbutt male–female pair are given by the estimate of _cons, 2.74. Rabe-Hesketh and Skrondal (2022, sec. 16.8) show how to calculate the odds ratios for the other three salamander pairings.

The R. varname notation is equivalent to giving a list of overparameterized (none dropped) indicator variables for use in a random-effects specification. When you specify R. varname, meglm handles the calculations internally rather than creating the indicators in the data. Because the set of indicators is overparameterized, R. varname implies noconstant.

Technical note

We fit the salamander model by using

```
.meglm y wsm##wsf || _all: R.male || _all: R.female ...
```

as a direct way to demonstrate the R. notation. However, we can technically treat female salamanders as nested within the _all group, yielding the equivalent way to fit the model:

```
.meglm y wsm##wsf || _all: R.male || female: ...
```

We leave it to you to verify that both produce identical results. As we note in example 8 of [ME] me, the latter specification, organized at the cluster (female) level with random-effects dimension one (a random intercept) is, in general, much more computationally efficient.

Obtaining better starting values

Given the flexibility of mixed-effects models, you will find that some models “fail to converge” when used with your data; see Diagnosing convergence problems in [ME] me for details. What we say below applies regardless of how the convergence problem revealed itself. You might have seen the error message “initial values not feasible” or some other error message, or you might have an infinite iteration log.

meglm provides two options to help you obtain better starting values: startvalues() and startgrid().

startvalues(svmethod) allows you to specify one of four starting-value calculation methods: zero, constantonly, fixedonly, or iv. By default, meglm uses startvalues(fixedonly). Evidently, that did not work for you. Try the other methods, starting with startvalues(iv):

```
.meglm ..., ... startvalues(iv)
```

If that does not solve the problem, proceed through the others.

By the way, if you have starting values for some parameters but not others—perhaps you fit a simplified model to get them—you can combine the options startvalues() and from():

```
.meglm ..., ... // simplified model
.matrix b = e(b)
.meglm ..., ... from(b) startvalues(iv) // full model
```

The other special option meglm provides is startgrid(), which can be used with or without startvalues(). startgrid() is a brute-force approach that tries various values for variances and covariances and chooses the ones that work best.
1. You may already be using a default form of `startgrid()` without knowing it. If you see `meglm` displaying Grid node 1, Grid node 2, ... following Grid node 0 in the iteration log, that is `meglm` doing a default search because the original starting values were not feasible. The default form tries 0.1, 1, and 10 for all variances of all random effects and, if applicable, for the residual variance.

2. `startgrid(numlist)` specifies values to try for variances of random effects.

3. `startgrid(covspec)` specifies the particular variances and covariances in which grid searches are to be performed. Variances and covariances are specified in the usual way. `startgrid(_cons[id] x[id] _cons[id]*x[id])` specifies that 0.1, 1, and 10 be tried for each member of the list.

4. `startgrid(numlist covspec)` combines the two syntaxes. You can specify `startgrid()` multiple times so that you can search the different ranges for different variances and covariances.

Our advice to you is the following:

1. If you receive an iteration log and it does not contain Grid node 1, Grid node 2, ..., then specify `startgrid(.1 1 10)`. Do that whether the iteration log was infinite or ended with some other error. In this case, we know that `meglm` did not run `startgrid()` on its own because it did not report Grid node 1, Grid node 2, etc. Your problem is poor starting values, not infeasible ones.

A synonym for `startgrid(.1 1 10)` is just `startgrid` without parentheses.

Be careful, however, if you have many random effects. Specifying `startgrid()` could run a long time because it runs all possible combinations. If you have 10 random effects, that means $10^3 = 1,000$ likelihood evaluations.

If you have many random effects, rerun your difficult `meglm` command including option `iterate(#)` and look at the results. Identify the problematic variances and search across them only. Do not just look for variances going to 0. Variances getting really big can be a problem, too, and even reasonable values can be a problem. Use your knowledge and intuition about the model.

Perhaps you will try to fit your model by specifying `startgrid(.1 1 10 _cons[id] x[id] _cons[id]*x[id])`.

Values 0.1, 1, and 10 are the default. Equivalent to specifying `startgrid(.1 1 10 _cons[id] x[id] _cons[id]*x[id])` is `startgrid(_cons[id] x[id] _cons[id]*x[id])`.

Look at covariances as well as variances. If you expect a covariance to be negative but it is positive, then try negative starting values for the covariance by specifying `startgrid(-.1 -1 -10 _cons[id]*x[id])`.

Remember that you can specify `startgrid()` multiple times. Thus you might specify both `startgrid(_cons[id] x[id])` and `startgrid(-.1 -1 -10 _cons[id]*x[id])`. 
2. If you receive the message “initial values not feasible”, you know that \texttt{meglm} already tried the default \texttt{startgrid()}. The default \texttt{startgrid()} only tried the values 0.1, 1, and 10, and only tried them on the variances of random effects. You may need to try different values or try the same values on covariances or variances of errors of observed endogenous variables.

We suggest you first rerun the model causing difficulty and include the \texttt{noestimate} option. If, looking at the results, you have an idea of which variance or covariance is a problem, or if you have few variances and covariances, we would recommend running \texttt{startgrid()} first. On the other hand, if you have no idea as to which variance or covariance is the problem and you have many of them, you will be better off if you first simplify the model. After doing that, if your simplified model does not include all the variances and covariances, you can specify a combination of \texttt{from()} and \texttt{startgrid()}.

**Survey data**

Multilevel modeling of survey data is a little different from standard modeling in that weighted sampling can take place at multiple levels in the model, resulting in multiple sampling weights. Most survey datasets, regardless of the design, contain one overall inclusion weight for each observation in the data. This weight reflects the inverse of the probability of ultimate selection, and by “ultimate” we mean that it factors in all levels of clustered sampling, corrections for noninclusion and oversampling, poststratification, etc.

For simplicity, in what follows, assume a simple two-stage sampling design where groups are randomly sampled and then individuals within groups are sampled. Also assume that no additional weight corrections are performed; that is, sampling weights are simply the inverse of the probability of selection. The sampling weight for observation $i$ in cluster $j$ in our two-level sample is then $w_{ij} = 1/\pi_{ij}$, where $\pi_{ij}$ is the probability that observation $i, j$ is selected. If you were performing a standard analysis such as OLS regression with \texttt{regress}, you would simply use a variable holding $w_{ij}$ as your \texttt{pweight} variable, and the fact that it came from two levels of sampling would not concern you. Perhaps you would type \texttt{vce(cluster groupvar)} where \texttt{groupvar} identifies the top-level groups to get standard errors that control for correlation within these groups, but you would still use only one weight variable.

Now take these same data and fit a two-level model with \texttt{meglm}. As seen in (5) in \textit{Methods and formulas} later in this entry, it is not sufficient to use the single sampling weight $w_{ij}$, because weights enter the log likelihood at both the group level and the individual level. Instead, what is required for a two-level model under this sampling design is $w_j$, the inverse of the probability that group $j$ is selected in the first stage, and $w_{ij}$, the inverse of the probability that individual $i$ from group $j$ is selected at the second stage conditional on group $j$ already being selected. You cannot use $w_{ij}$ without making any assumptions about $w_j$.

Given the rules of conditional probability, $w_{ij} = w_jw_{ij}$. If your dataset has only $w_{ij}$, then you will need to either assume equal probability sampling at the first stage ($w_j = 1$ for all $j$) or find some way to recover $w_j$ from other variables in your data; see Rabe-Hesketh and Skrondal (2006) and the references therein for some suggestions on how to do this, but realize that there is little yet known about how well these approximations perform in practice.

What you really need to fit your two-level model are data that contain $w_j$ in addition to either $w_{ij}$ or $w_{ij,j}$. If you have $w_{ij}$—that is, the unconditional inclusion weight for observation $i, j$—then you need to divide $w_{ij}$ by $w_j$ to obtain $w_{ij,j}$.
Example 5: Two-level logistic regression model with weights

Rabe-Hesketh and Skrondal (2006) analyzed data from the 2000 Programme for International Student Assessment (PISA) study on reading proficiency among 15-year-old American students, as performed by the Organisation for Economic Co-operation and Development (OECD). The original study was a three-stage cluster sample, where geographic areas were sampled at the first stage, schools at the second, and students at the third. Our version of the data does not contain the geographic-areas variable, so we treat this as a two-stage sample where schools are sampled at the first stage and students at the second.

   (Programme for International Student Assessment (PISA) 2000 data)
. describe
Observations: 2,069 Programme for International Student Assessment (PISA) 2000 data
Variables: 11 12 Jun 2022 10:08
(_dta has notes)

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Storage type</th>
<th>Display format</th>
<th>Value label</th>
<th>Variable label</th>
</tr>
</thead>
<tbody>
<tr>
<td>female</td>
<td>byte</td>
<td>%8.0g</td>
<td>1 if female</td>
<td>International socioeconomic index</td>
</tr>
<tr>
<td>isei</td>
<td>byte</td>
<td>%8.0g</td>
<td>International socioeconomic index</td>
<td></td>
</tr>
<tr>
<td>w_fstuwt</td>
<td>float</td>
<td>%9.0g</td>
<td>Student-level weight</td>
<td></td>
</tr>
<tr>
<td>wnrschbw</td>
<td>float</td>
<td>%9.0g</td>
<td>School-level weight</td>
<td></td>
</tr>
<tr>
<td>high_school</td>
<td>byte</td>
<td>%8.0g</td>
<td>1 if highest level by either parent is high school</td>
<td></td>
</tr>
<tr>
<td>college</td>
<td>byte</td>
<td>%8.0g</td>
<td>1 if highest level by either parent is college</td>
<td></td>
</tr>
<tr>
<td>one_for</td>
<td>byte</td>
<td>%8.0g</td>
<td>1 if one parent foreign born</td>
<td></td>
</tr>
<tr>
<td>both_for</td>
<td>byte</td>
<td>%8.0g</td>
<td>1 if both parents are foreign born</td>
<td></td>
</tr>
<tr>
<td>test_lang</td>
<td>byte</td>
<td>%8.0g</td>
<td>1 if English (the test language) is spoken at home</td>
<td></td>
</tr>
<tr>
<td>pass_read</td>
<td>byte</td>
<td>%8.0g</td>
<td>1 if passed reading proficiency threshold</td>
<td></td>
</tr>
<tr>
<td>id_school</td>
<td>int</td>
<td>%8.0g</td>
<td>School ID</td>
<td></td>
</tr>
</tbody>
</table>

Sorted by:

For student $i$ in school $j$, where the variable id_school identifies the schools, the variable $w_{fstuwt}$ is a student-level overall inclusion weight ($w_{ij}$, not $w_{ij}|j$) adjusted for noninclusion and nonparticipation of students, and the variable $wnrschbw$ is the school-level weight $w_j$ adjusted for oversampling of schools with more minority students. The weight adjustments do not interfere with the methods prescribed above, and thus we can treat the weight variables simply as $w_{ij}$ and $w_j$, respectively.

Rabe-Hesketh and Skrondal (2006) fit a two-level logistic model for passing a reading proficiency threshold. We will do the same using `meglm`, but first we must reproduce the “method 1” adjusted weight variables that were used. The “method 1” adjustment scales the first-level weights so that they sum to the effective sample size of their corresponding second-level cluster.

. sort id_school
. generate sqw = w_fstuwt * w_fstuwt
. by id_school: egen sumw = sum(w_fstuwt)
. by id_school: egen sumsqw = sum(sqw)
. generate pst1s1 = w_fstuwt*sumw/sumsqw
The new variable pst1s1 holds the adjusted first-level weights. Rabe-Hesketh and Skrondal (2006) also included the school mean socioeconomic index as a covariate in their analysis. We reproduce this variable using egen.

```
. by id_school: egen mn_isei = mean(isei)
```

Here is the fitted model:

```
. meglm pass_read female isei mn_isei high_school college test_lang one_for > both_for [pw=pst1s1], family(bernoulli) link(logit) > || id_school:, pweight(wnrschbw)
```

(output omitted)

Mixed-effects GLM Number of obs = 2,069
Family: Bernoulli
Link: Logit
Group variable: id_school Number of groups = 148
Obs per group:
  min = 1
  avg = 14.0
  max = 28
Integration method: mvaghermite Integration pts. = 7
Wald chi2(8) = 88.30
Log pseudolikelihood = -197395.98 Prob > chi2 = 0.0000
(Std. err. adjusted for 148 clusters in id_school)

| pass_read      | Robust Coefficient | std. err. | z     | P>|z| | [95% conf. interval] |
|----------------|--------------------|-----------|-------|------|----------------------|
| female         | .6221369           | .1540088  | 4.04  | 0.000 | .3202852 .9239887    |
| isei           | .018215            | .0048057  | 3.79  | 0.000 | .0087959 .027634     |
| mn_isei        | .0682472           | .0164337  | 4.15  | 0.000 | .0360378 .1004566    |
| high_school    | .1028108           | .077141   | 4.12  | 0.000 | .1328683 .172753     |
| college        | .4531688           | .5053447  | 4.15  | 0.000 | .360378 .546566      |
| test_lang      | .6251822           | .3821182  | 1.64  | 0.102 | -.8323683 1.080775    |
| one_for        | -.1089314          | .2739724  | 0.40  | 0.691 | -.6459075 .4280447   |
| both_for       | -.2804038          | .3264681  | 0.86  | 0.390 | -.9202696 .359462    |
| _cons          | 5.877565           | .895452   | 6.16  | 0.000 | -.7484 -4.006731     |

id_school

var(_cons) | .2955769 | .1243375 | 1.295996 .6741201 |

Notes:

1. We specified the level-one weights using standard Stata weight syntax, that is, [pw=pst1s1].

2. We specified the level-two weights via the pweight(wnrschbw) option as part of the random-effects specification for the id_school level. As such, it is treated as a school-level weight. Accordingly, wnrschbw needs to be constant within schools, and meglm did check for that before estimating.

3. As is the case with other estimation commands in Stata, standard errors in the presence of sampling weights are robust.

4. Robust standard errors are clustered at the top level of the model, and this will always be true unless you specify vce(cluster clustvar), where clustvar identifies an even higher level of grouping.
Example 6: Two-level logistic regression model with survey weights

meglm also supports the svy prefix (see [SVY] svy) for the linearized variance estimator. Here we refit the model from the previous example using the svy prefix after we svyset (see [SVY] svyset) the survey design variables.

```
.svysset id_school, weight(wnrschbw) || _n, weight(pst1s1)
note: stage 1 is sampled with replacement; further stages will be ignored for variance estimation.
Sampling weights: <none>
VCE: linearized
Single unit: missing
Strata 1: <one>
Sampling unit 1: id_school
FPC 1: <zero>
Weight 1: wnrschbw
Strata 2: <one>
Sampling unit 2: <observations>
FPC 2: <zero>
Weight 2: pst1s1
```

```
.svymeglm pass_read female isei mn_isei high_school college test_lang > one_for both_for, family(bernoulli) link(logit) || id_school:
(running meglm on estimation sample)
```

Survey: Mixed-effects GLM
Number of strata = 1 Number of obs = 2,069
Number of PSUs = 148 Population size = 346,373.74
Design df = 147
F(8, 140) = 10.51 Prob > F = 0.0000

| pass_read | Coefficient | std. err. | t | P>|t| | [95% conf. interval] |
|-----------|-------------|-----------|---|------|----------------------|
| female    | .6221369    | .1540088  | 4.04| 0.000 | .3177796 .9264943 |
| isei      | .018215     | .0048057  | 3.79| 0.000 | .0087177 .0277122 |
| mn_isei   | .0682472    | .0164337  | 4.15| 0.000 | .0357704 .100724  |
| high_school| .1028108    | .0714141  | 0.22| 0.830 | -.8401311 1.045753 |
| college   | .4531688    | .05053447 | 9.09| 0.000 | .3565101 1.545184 |
| test_lang | .6251822    | .3821182  | 1.64| 0.104 | -.1299725 1.380337 |
| one_for   | -.1089314   | .2739724  | -0.40| 0.692 | -.6503648 .432502 |
| both_for  | -.2804038   | .3264681  | -0.86| 0.392 | -.925581 1.3647734 |
| _cons     | -5.877565   | .964525   | -6.16| 0.000 | -7.763929 -3.991201 |

id_school
| var(_cons) | .2955769 | .1243375 | 2.37 | 0.018 | .0499079 .541245 |

Notes:
1. We svyset the design variables: id_school is the PSU variable, wnrschbw contains weights at the PSU level, _n specifies that the students are identified by the individual observations, and pst1s1 contains our adjusted student-level conditional weights.
2. svyset notes the lack of a finite population correction in the first stage and informs us that only the first-stage unit information will be used in the linearized variance estimator. However, the svy prefix will still pass the stage-two weights to meglm.
3. svy produces a different header, giving us an estimate of the population size, the design degrees of freedom, and the number of first-stage sampling units.
Video example

Tour of multilevel GLMs

Stored results

meglm stores the following in e():

Scalars

- \( e(N) \): number of observations
- \( e(k) \): number of parameters
- \( e(k_{dv}) \): number of dependent variables
- \( e(k_{eq}) \): number of equations in e(b)
- \( e(k_{eq\_model}) \): number of equations in overall model test
- \( e(k_{cat}) \): number of categories (with ordinal outcomes)
- \( e(k_f) \): number of fixed-effects parameters
- \( e(k_r) \): number of random-effects parameters
- \( e(k_{rs}) \): number of covariances
- \( e(k_{rc}) \): number of variances
- \( e(df_m) \): model degrees of freedom
- \( e(ll) \): log likelihood
- \( e(chi2) \): \( \chi^2 \)
- \( e(p) \): \( p \)-value for model test
- \( e(ll_c) \): log likelihood, comparison model
- \( e(chi2_c) \): \( \chi^2 \), comparison test
- \( e(df_c) \): degrees of freedom, comparison test
- \( e(p_c) \): \( p \)-value for comparison test
- \( e(N_clust) \): number of clusters
- \( e(rank) \): rank of e(V)
- \( e(ic) \): number of iterations
- \( e(rc) \): return code
- \( e(converged) \): 1 if converged, 0 otherwise

Macros

- \( e(cmd) \): gsem
- \( e(cmd2) \): meglm
- \( e(cmdline) \): command as typed
- \( e(depvar) \): name of dependent variable
- \( e(wtype) \): weight type
- \( e(wexp) \): weight expression (first-level weights)
- \( e(fweight_k) \): fweight variable for \( k \)th highest level, if specified
- \( e(iweight_k) \): iweight variable for \( k \)th highest level, if specified
- \( e(pweight_k) \): pweight variable for \( k \)th highest level, if specified
- \( e(covariates) \): list of covariates
- \( e(ivars) \): grouping variables
- \( e(model) \): name of marginal model
- \( e(title) \): title in estimation output
- \( e(link) \): link
- \( e(family) \): family
- \( e(clustvar) \): name of cluster variable
- \( e(offset) \): offset
- \( e(binomial) \): binomial number of trials (with binomial models)
- \( e(dispersion) \): mean or constant (with negative binomial models)
- \( e(intmethod) \): integration method
- \( e(n_quad) \): number of integration points
- \( e(chi2type) \): \( \chi^2 \) Wald; type of model \( \chi^2 \)
- \( e(vce) \): vctype specified in vce()
- \( e(vcetype) \): title used to label Std. err.
- \( e(opt) \): type of optimization
- \( e(which) \): max or min; whether optimizer is to perform maximization or minimization
- \( e(ml\_method) \): type of ml method
- \( e(user) \): name of likelihood-evaluator program
Without a loss of generality, consider a two-level generalized mixed-effects model

\[ E(y_j | X_j, u_j) = g^{-1}(X_j\beta + Z_ju_j), \quad y \sim F \]

for \( j = 1, \ldots, M \) clusters, with the \( j \)th cluster consisting of \( n_j \) observations, where, for the \( j \)th cluster, \( y_j \) is the \( n_j \times 1 \) response vector, \( X_j \) is the \( n_j \times p \) matrix of fixed predictors, \( Z_j \) is the \( n_j \times q \) matrix of random predictors, \( u_j \) is the \( q \times 1 \) vector of random effects, \( \beta \) is the \( p \times 1 \) vector of regression coefficients on the fixed predictors, and we use \( \Sigma \) to denote the unknown \( q \times q \) variance matrix of the random effects. For simplicity, we consider a model with no auxiliary parameters.
Let $\eta_j$ be the linear predictor, $\eta_j = X_j \beta + Z_j u_j$, that also includes the offset or the exposure variable when `offset()` or `exposure()` is specified. Let $y_{ij}$ and $\eta_{ij}$ be the $i$th individual elements of $y_j$ and $\eta_j$, $i = 1, \ldots, n_j$. Let $f(y_{ij} | \eta_{ij})$ be the conditional density function for the response at observation $i$. Because the observations are assumed to be conditionally independent, we can overload the definition of $f(\cdot)$ with vector inputs to mean

$$
\log f(y_j | \eta_j) = \sum_{j=1}^{n_j} \log f(y_{ij} | \eta_{ij})
$$

The random effects $u_j$ are assumed to be multivariate normal with mean 0 and variance $\Sigma$. The likelihood function for cluster $j$ is given by

$$
L_j(\beta, \Sigma) = (2\pi)^{-q/2} |\Sigma|^{-1/2} \int_{\mathbb{R}^q} f(y_j | \eta_j) \exp \left( -\frac{1}{2} u_j' \Sigma^{-1} u_j \right) \, du_j
$$

$$
= (2\pi)^{-q/2} |\Sigma|^{-1/2} \int_{\mathbb{R}^q} \exp \left\{ \log f(y_j | \eta_j) - \frac{1}{2} u_j' \Sigma^{-1} u_j \right\} \, du_j
$$

where $\mathbb{R}$ denotes the set of values on the real line and $\mathbb{R}^q$ is the analog in $q$-dimensional space.

The multivariate integral in (3) is generally not tractable, so we must use numerical methods to approximate the integral. We can use a change-of-variables technique to transform this multivariate integral into a set of nested univariate integrals. Each univariate integral can then be evaluated using a form of Gaussian quadrature. `meglm` supports three types of Gauss–Hermite quadratures: mean–variance adaptive Gauss–Hermite quadrature (MVAGH), mode-curvature adaptive Gauss–Hermite quadrature (MCAGH), and nonadaptive Gauss–Hermite quadrature (GHQ). `meglm` also offers the Laplacian-approximation method, which is used as a default method for crossed mixed-effects models. Below we describe the four methods. The methods described below are based on Skrondal and Rabe-Hesketh (2004, chap. 6.3).

**Gauss–Hermite quadrature**

Let $u_j = L v_j$, where $v_j$ is a $q \times 1$ random vector whose elements are independently standard normal variables and $L$ is the Cholesky decomposition of $\Sigma$, $\Sigma = LL'$. Then $\eta_j = X_j \beta + Z_j L v_j$, and the likelihood in (3) becomes

$$
L_j(\beta, \Sigma) = (2\pi)^{-q/2} \int_{\mathbb{R}^q} \exp \left\{ \log f(y_j | \eta_j) - \frac{1}{2} v_j' v_j \right\} \, dv_j
$$

$$
= (2\pi)^{-q/2} \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \exp \left\{ \log f(y_j | \eta_j) - \frac{1}{2} \sum_{k=1}^{q} v_{jk}^2 \right\} \, dv_{j1}, \ldots, dv_{jq}
$$

Consider a $q$-dimensional quadrature grid containing $r$ quadrature points in each dimension. Let $a_k = (a_{k1}, \ldots, a_{kq})'$ be a point on this grid, and let $w_k = (w_{k1}, \ldots, w_{kq})'$ be the vector of corresponding weights. The GHQ approximation to the likelihood is
\[ \mathcal{L}_j^{GHQ}(\beta, \Sigma) = \sum_{k_1=1}^{r} \cdots \sum_{k_q=1}^{r} \left[ \exp \left\{ \log f(y_j | \eta_{jk}) \right\} \prod_{p=1}^{q} w_{kp} \right] \]

\[ = \sum_{k_1=1}^{r} \cdots \sum_{k_q=1}^{r} \left[ \exp \left\{ \sum_{i=1}^{n_j} \log f(y_{ij} | \eta_{ijk}) \right\} \prod_{p=1}^{q} w_{kp} \right] \]

where

\[ \eta_{jk} = X_j \beta + Z_j L a_{jk} \]

and \( \eta_{ijk} \) is the \( i \)th element of \( \eta_{jk} \).

**Adaptive Gauss–Hermite quadrature**

This section sets the stage for MVAGH quadrature and MCAGH quadrature.

Let’s reconsider the likelihood in (4). We use \( \phi(v_j) \) to denote a multivariate standard normal with mean 0 and variance \( I_q \), and we use \( \phi(v_j | \mu_j, \Lambda_j) \) to denote a multivariate normal with mean \( \mu_j \) and variance \( \Lambda_j \).

For fixed model parameters, the posterior density for \( v_j \) is proportional to

\[ \phi(v_j) f(y_j | \eta_j) \]

where

\[ \eta_j = X_j \beta + Z_j L v_j \]

It is reasonable to assume that this posterior density can be approximated by a multivariate normal density with mean vector \( \mu_j \) and variance matrix \( \Lambda_j \). Instead of using the prior density of \( v_j \) as the weighting distribution in the integral, we can use our approximation for the posterior density,

\[ \mathcal{L}_j^{MVAGH}(\beta, \Sigma) = \sum_{k_1=1}^{r} \cdots \sum_{k_q=1}^{r} \left[ \exp \left\{ \log f(y_j | \eta_{jk}) \right\} \prod_{p=1}^{q} w_{jkp}^* \right] \]

where

\[ \eta_{jk} = X_j \beta + Z_j L a_{jk}^* \]

and \( a_{jk}^* \) and \( w_{jkp}^* \) are the abscissas and weights after an orthogonalizing transformation of \( a_{jk} \) and \( w_{jkp} \), respectively, which eliminates posterior covariances between the random effects.
Estimates of $\mu_j$ and $\Lambda_j$ are computed using one of two different methods. The mean $\mu_j$ and variance $\Lambda_j$ are computed iteratively by updating the posterior moments with the MVAGH approximation, starting with a 0 mean vector and identity variance matrix. For the MCAGH approximation, $\mu_j$ and $\Lambda_j$ are computed by optimizing the integrand with respect to $\nu_j$, where $\mu_j$ is the optimal value and $\Lambda_j$ is the curvature at $\mu_j$.

### Laplacian approximation

Consider the likelihood in (3) and denote the argument in the exponential function by

$$h(\beta, \Sigma, u_j) = \log f(y_j | X_j \beta + Z_j u_j) - \frac{1}{2} u_j' \Sigma^{-1} u_j$$

The Laplacian approximation is based on a second-order Taylor expansion of $h(\beta, \Sigma, u_j)$ about the value of $u_j$ that maximizes it. The first and second partial derivatives with respect to $u_j$ are

$$h'(\beta, \Sigma, u_j) = \frac{\partial h(\beta, \Sigma, u_j)}{\partial u_j} = Z_j' \frac{\partial \log f(y_j | \eta_j)}{\partial \eta_j} - \Sigma^{-1} u_j$$

$$h''(\beta, \Sigma, u_j) = \frac{\partial^2 h(\beta, \Sigma, u_j)}{\partial u_j \partial u_j'} = Z_j' \frac{\partial^2 \log f(y_j | \eta_j)}{\partial \eta_j \partial \eta_j'} Z_j - \Sigma^{-1}$$

The maximizer of $h(\beta, \Sigma, u_j)$ is $\hat{u}_j$ such that $h'(\beta, \Sigma, \hat{u}_j) = 0$. The integral in (3) is proportional to the posterior density of $u_j$ given the data, so $\hat{u}_j$ is also the posterior mode.

Pinheiro and Chao (2006) show that the posterior mode, $\hat{u}_j$, and curvature, $h''(\beta, \Sigma, \hat{u}_j)^{-1}$, can be efficiently computed as the iterative solution to a least-squares problem by using matrix decomposition methods similar to those used in fitting linear mixed-effects models (Bates and Pinheiro 1998; Pinheiro and Bates 2000).

Let

$$\hat{p}_j = X_j \beta + Z_j \hat{u}_j$$

$$S_1 = \frac{\partial \log f(y_j | \hat{p}_j)}{\partial \hat{p}_j}$$

$$S_2 = \frac{\partial S_1}{\partial \hat{p}_j} = \frac{\partial^2 \log f(y_j | \hat{p}_j)}{\partial \hat{p}_j \partial \hat{p}_j'}$$

$$H_j = h''(\beta, \Sigma, \hat{u}_j) = Z_j' S_2 Z_j - \Sigma^{-1}$$

then

$$0 = h'(\beta, \Sigma, \hat{u}_j) = Z_j' S_1 - \Sigma^{-1} \hat{u}_j$$
Given the above, the second-order Taylor approximation takes the form

\[ h(\beta, \Sigma, u_j) \approx h(\beta, \Sigma, \hat{u}_j) + \frac{1}{2}(u_j - \hat{u}_j)'H_j(u_j - \hat{u}_j) \]

because the first-order derivative term is 0. The integral is approximated by

\[ \int_{\mathbb{R}^q} \exp\{h(\beta, \Sigma, u_j)\} \, du_j \approx (2\pi)^{q/2} |\Sigma|^{-1/2} \exp\{h(\beta, \Sigma, \hat{u}_j)\} \]

Thus the Laplacian approximated log likelihood is

\[ \log L_{Lap}^j(\beta, \Sigma) = -\frac{1}{2} \log|\Sigma| - \frac{1}{2} \log|H_j| + h(\beta, \Sigma, \hat{u}_j) \]

The log likelihood for the entire dataset is simply the sum of the contributions of the \( M \) individual clusters, namely, \( L(\beta, \Sigma) = \sum_{j=1}^M L_j(\beta, \Sigma) \).

Maximization of \( L(\beta, \Sigma) \) is performed with respect to \((\beta, \sigma^2)\), where \( \sigma^2 \) is a vector comprising the unique elements of \( \Sigma \). Parameter estimates are stored in \( e(b) \) as \( (\hat{\beta}, \hat{\sigma}^2) \), with the corresponding variance–covariance matrix stored in \( e(V) \). In the presence of auxiliary parameters, their estimates and standard errors are included in \( e(b) \) and \( e(V) \), respectively.

**Survey data**

In the presence of sampling weights, following Rabe-Hesketh and Skrondal (2006), the weighted log pseudolikelihood for a two-level model is given as

\[ L(\beta, \Sigma) = \sum_{j=1}^M w_j \log \int_{-\infty}^{\infty} \exp \left\{ \sum_{i=1}^{n_j} w_{ij} \log f(y_{ij}|\eta_{ij}) \right\} \phi(v_{j1}) \, dv_{j1} \]

where \( w_j \) is the inverse of the probability of selection for the \( j \)th cluster; \( w_{ij} \) is the inverse of the conditional probability of selection of individual \( i \), given the selection of cluster \( j \); \( f(\cdot) \) is as defined previously; and \( \phi(\cdot) \) is the standard multivariate normal density.

Weighted estimation is achieved through the direct application of \( w_j \) and \( w_{ij} \) into the likelihood calculations as detailed above to reflect replicated clusters for \( w_j \) and replicated observations within clusters for \( w_{ij} \). Because this estimation is based on replicated clusters and observations, frequency weights are handled similarly.

Weights are not allowed with crossed models or the Laplacian approximation.

**References**


Cameron, A. C., and P. K. Trivedi. 2022. *Microeconometrics Using Stata*. 2nd ed. College Station, TX: Stata Press.


Also see

[ME] *meglm postestimation* — Postestimation tools for *meglm*

[ME] *mixed* — Multilevel mixed-effects linear regression

[ME] *menl* — Nonlinear mixed-effects regression

[ME] *me* — Introduction to multilevel mixed-effects models

[BAYES] *bayes: meglm* — Bayesian multilevel generalized linear model

[R] *glm* — Generalized linear models

[SEM] *Intro 5* — Tour of models (*Multilevel mixed-effects models*)

[SVY] *svy estimation* — Estimation commands for survey data

[U] *20 Estimation and postestimation commands*