Title

> **melogit postestimation** — Postestimation tools for melogit

Postestimation commands

The following postestimation commands are of special interest after `melogit`:

Command	Description
estat group	summarize the composition of the nested groups
estat icc	estimate intraclass correlations
estat sd	display variance components as standard deviations and correlations

The following standard postestimation commands are also available:

Command	Description
contrast	contrasts and ANOVA-style joint tests of estimates
estat ic	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian information criteria (AIC, CAIC, AICc, and BIC)
estat summarize	summary statistics for the estimation sample
estat vce	variance–covariance matrix of the estimators (VCE)
estat (svy)	postestimation statistics for survey data
estimates	cataloging estimation results
etable	table of estimation results
* hausman	Hausman's specification test
lincom	point estimates, standard errors, testing, and inference for linear combinations of coefficients
* lrtest	likelihood-ratio test
margins	marginal means, predictive margins, marginal effects, and average marginal effects
marginsplot	graph the results from margins (profile plots, interaction plots, etc.)
nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients
predict	means, probabilities, densities, REs, residuals, etc.
predictnl	point estimates, standard errors, testing, and inference for generalized predictions
pwcompare	pairwise comparisons of estimates
test	Wald tests of simple and composite linear hypotheses
testnl	Wald tests of nonlinear hypotheses

*`hausman` and `lrtest` are not appropriate with `svy` estimation results.

predict

Description for predict

predict creates a new variable containing predictions such as mean responses; linear predictions; density and distribution functions; standard errors; and Pearson, deviance, and Anscombe residuals.

Menu for predict

Statistics > Postestimation

Syntax for predict

Syntax for obtaining predictions of the outcome and other statistics

> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*] [, *statistic options*]

Syntax for obtaining estimated random effects and their standard errors

> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*], reffects [*re_options*]

Syntax for obtaining ML scores

> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*], <u>sc</u>ores

statistic	Description
Main	
mu	mean response; the default
eta	fitted linear predictor
xb	linear predictor for the fixed portion of the model only
stdp	standard error of the fixed-portion linear prediction
<u>density</u>	predicted density function
<u>distribution</u>	predicted distribution function
<u>pearson</u>	Pearson residuals
<u>deviance</u>	deviance residuals
<u>ans</u>combe	Anscombe residuals

These statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample.

options	Description
Main	
<u>condition</u>al(*[ctype](#)*)	compute *statistic* conditional on estimated random effects; default is conditional(ebmeans)
marginal	compute *statistic* marginally with respect to the random effects
<u>nooff</u>set	make calculation ignoring offset or exposure
Integration	
[int_options](#)	integration options

pearson, deviance, anscombe may not be combined with marginal.

ctype	Description
<u>ebmeans</u>	empirical Bayes means of random effects; the default
<u>ebmodes</u>	empirical Bayes modes of random effects
<u>fixed</u>only	prediction for the fixed portion of the model only

re_options	Description
Main	
<u>ebmeans</u>	use empirical Bayes means of random effects; the default
<u>ebmodes</u>	use empirical Bayes modes of random effects
reses(*stub* *	*[newvarlist](#)*)	calculate standard errors of empirical Bayes estimates
Integration	
[int_options](#)	integration options

int_options	Description
<u>intp</u>oints(*#*)	use *#* quadrature points to compute marginal predictions and empirical Bayes means
<u>iter</u>ate(*#*)	set maximum number of iterations in computing statistics involving empirical Bayes estimators
<u>tol</u>erance(*#*)	set convergence tolerance for computing statistics involving empirical Bayes estimators

Options for predict

> **Main**

mu, the default, calculates the predicted mean, that is, the probability of a positive outcome.

eta, xb, stdp, density, distribution, pearson, deviance, anscombe, scores, conditional(), marginal, and nooffset; see [ME] **meglm postestimation**.

reffects, ebmeans, ebmodes, and reses(); see [ME] **meglm postestimation**.

> **Integration**

intpoints(), iterate(), and tolerance(); see [ME] **meglm postestimation**.

margins

Description for margins

margins estimates margins of response for mean responses and linear predictions.

Menu for margins

Statistics > Postestimation

Syntax for margins

> margins [*marginlist*] [, *options*]
>
> margins [*marginlist*] , <u>predict</u>(*statistic* ...) [<u>predict</u>(*statistic* ...) ...] [*options*]

statistic	Description
mu	mean response; the default
eta	fitted linear predictor
xb	linear predictor for the fixed portion of the model only
stdp	not allowed with margins
<u>dens</u>ity	not allowed with margins
<u>dist</u>ribution	not allowed with margins
<u>pear</u>son	not allowed with margins
<u>dev</u>iance	not allowed with margins
<u>ans</u>combe	not allowed with margins
<u>ref</u>fects	not allowed with margins
scores	not allowed with margins

Options conditional(ebmeans) and conditional(ebmodes) are not allowed with margins.

Option marginal is assumed where applicable if conditional(fixedonly) is not specified.

Statistics not allowed with margins are functions of stochastic quantities other than e(b).

For the full syntax, see [R] **margins**.

Remarks and examples

Various predictions, statistics, and diagnostic measures are available after fitting a logistic mixed-effects model with melogit. For the most part, calculation centers around obtaining estimates of the subject/group-specific random effects. Random effects are not provided as estimates when the model is fit but instead need to be predicted after estimation. Calculation of intraclass correlations, estimating the dependence between latent linear responses for different levels of nesting, may also be of interest.

▷ Example 1: Estimating the intraclass correlation

Following Rabe-Hesketh and Skrondal (2022, chap. 10), we consider a two-level mixed-effects model for onycholysis (separation of toenail plate from nail bed) among those who contract toenail fungus. The data are obtained from De Backer et al. (1998) and were also studied by Lesaffre and Spiessens (2001). The onycholysis outcome is dichotomously coded as 1 (moderate or severe onycholysis) or 0 (none or mild onycholysis). Fixed-effects covariates include treatment (0: itraconazole; 1: terbinafine), the month of measurement, and their interaction.

We fit the two-level model with melogit:

```
. use https://www.stata-press.com/data/r18/toenail
(Onycholysis severity)

. melogit outcome treatment month trt_month || patient:, intpoints(30)
  (iteration log omitted)
```

Mixed-effects logistic regression   Number of obs   =   1,908
Group variable: patient   Number of groups =   294

                                            Obs per group:
                                                          min =   1
                                                          avg =   6.5
                                                          max =   7
Integration method: mvaghermite   Integration pts. =   30

                                            Wald chi2(3)   =   150.61
Log likelihood = -625.38557   Prob > chi2   =   0.0000

outcome	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
treatment	-.1608934	.5802058	-0.28	0.782	-1.298076	.9762891
month	-.3911056	.0443906	-8.81	0.000	-.4781097	-.3041016
trt_month	-.1368286	.0680213	-2.01	0.044	-.2701479	-.0035093
_cons	-1.620355	.4322382	-3.75	0.000	-2.467526	-.7731834
patient						
var(_cons)	16.0841	3.062625			11.07431	23.36021

LR test vs. logistic model: chibar2(01) = 565.24   Prob >= chibar2 = 0.0000

It is of interest to determine the dependence among responses for the same subject (between-subject heterogeneity). Under the latent-linear-response formulation, this dependence can be obtained with the intraclass correlation. Formally, in a two-level random-effects model, the intraclass correlation corresponds to the correlation of latent responses within the same individual and also to the proportion of variance explained by the individual random effect.

We use estat icc to estimate the residual intraclass correlation:

```
. estat icc
```

Residual intraclass correlation

Level	ICC	Std. err.	[95% conf. interval]	
patient	.8301913	.0268433	.7709672	.8765531

In the presence of fixed-effects covariates, estat icc reports the residual intraclass correlation, which is the correlation between latent linear responses conditional on the fixed-effects covariates.

Conditional on treatment and month of treatment, we estimate that latent responses within the same patient have a large correlation of approximately 0.83. Further, 83% of the variance of a latent response is explained by the between-patient variability.

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▷ Example 2: Predicting random effects

In example 3 of [ME] **melogit**, we represented the probability of contraceptive use among Bangladeshi women by using the model (stated with slightly different notation here)

$$\text{logit}(\pi_{ij}) = \beta_0 0.\text{urban}_{ij} + \beta_1 1.\text{urban}_{ij} + \beta_2 \text{age}_{ij} +$$
$$\beta_3 1.\text{children}_{ij} + \beta_4 2.\text{children}_{ij} + \beta_5 3.\text{children}_{ij} +$$
$$a_j 0.\text{urban}_{ij} + b_j 1.\text{urban}_{ij}$$

where π_{ij} is the probability of contraceptive use, $j = 1, \ldots, 60$ districts, $i = 1, \ldots, n_j$ women within each district, and a_j and b_j are normally distributed with mean 0 and variance–covariance matrix

$$\boldsymbol{\Sigma} = \text{Var}\begin{bmatrix} a_j \\ b_j \end{bmatrix} = \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{bmatrix}$$

```
. use https://www.stata-press.com/data/r18/bangladesh
(Bangladesh Fertility Survey, 1989)

. melogit c_use ibn.urban age i.children, noconstant nofvlabel
> || district: ibn.urban, noconstant cov(unstructured)

Fitting fixed-effects model:

  (iteration log omitted)
```

| Mixed-effects logistic regression | | Number of obs | = | 1,934 |
| 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(6)      =     120.24
Log likelihood = -1199.315                Prob > chi2       =     0.0000
 ( 1)  [c_use]_cons = 0
```

c_use	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
urban						
0	-1.711652	.1605617	-10.66	0.000	-2.026347	-1.396956
1	-.8958623	.1704954	-5.25	0.000	-1.230027	-.5616974
age	-.026415	.008023	-3.29	0.001	-.0421398	-.0106903
children						
1	1.13252	.1603285	7.06	0.000	.8182819	1.446758
2	1.357739	.1770522	7.67	0.000	1.010724	1.704755
3	1.353827	.18288	7.40	0.000	.9953883	1.712265
_cons	0	(omitted)				
district						
var(0.urban)	.3897485	.1292403			.2034823	.7465212
var(1.urban)	.2442899	.1450625			.0762871	.7822759
district						
cov(0.urban,						
1.urban)	-.0161411	.1057462	-0.15	0.879	-.2233999	.1911177

```
LR test vs. logistic model: chi2(3) = 58.42          Prob > chi2 = 0.0000

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

The purpose of using this particular model was to allow for district random effects that were specific to the rural and urban areas of that district and that could be interpreted as such. We can obtain predictions of these random effects and their corresponding standard errors,

```
. predict re_rural re_urban, reffects reses(se_rural se_urban)
(calculating posterior means of random effects)
(using 7 quadrature points)
```

The order in which we specified the variables to be generated corresponds to the order in which the variance components are listed in `melogit` output. If in doubt, a simple `describe` will show how these newly generated variables are labeled just to be sure.

Having generated estimated random effects and standard errors, we can now list them for the first 10 districts:

```
. by district, sort: generate tolist = (_n==1)

. list district re_rural se_rural re_urban se_urban if district <= 10 & tolist,
>  sep(0)
```

	district	re_rural	se_rural	re_urban	se_urban
1.	1	-.9432691	.3156852	-.558359	.2332665
118.	2	-.0427011	.3822029	.0017684	.493834
138.	3	-.0149571	.6242161	.2263715	.4698407
140.	4	-.2864846	.3990107	.5869046	.3988538
170.	5	.0688648	.3102899	.0046016	.4685461
209.	6	-.3979315	.2762392	.2761181	.4204175
274.	7	-.1910399	.4046772	.0079117	.4938647
292.	8	.034071	.3180097	.2266263	.4689558
329.	9	-.3737992	.3923573	.0764026	.4569863
352.	10	-.5640147	.4769353	.0233582	.4939753

◁

❑ Technical note

When these data were first introduced in [ME] **melogit**, we noted that not all districts contained both urban and rural areas. This fact is somewhat demonstrated by the random effects that are nearly 0 in the above. A closer examination of the data would reveal that district 3 has no rural areas, and districts 2, 7, and 10 have no urban areas.

The estimated random effects are not exactly 0 in these cases because of the correlation between urban and rural effects. For instance, if a district has no urban areas, it can still yield a nonzero (albeit small) random-effects estimate for a nonexistent urban area because of the correlation with its rural counterpart.

Had we imposed an independent covariance structure in our model, the estimated random effects in the cases in question would be exactly 0.

❑

❑ Technical note

The estimated standard errors produced above with the reses() option are conditional on the values of the estimated model parameters: β and the components of Σ. Their interpretation is therefore not one of standard sample-to-sample variability but instead one that does not incorporate uncertainty in the estimated model parameters; see *Methods and formulas*.

That stated, conditional standard errors can still be used as a measure of relative precision, provided that you keep this caveat in mind.

❑

▷ Example 3: Obtaining predicted probabilities

Continuing with example 2, we can obtain predicted probabilities, the default prediction:

```
. predict p
(option mu assumed)
(predictions based on fixed effects and posterior means of random effects)
(using 7 quadrature points)
```

These predictions are based on a linear predictor that includes both the fixed effects and the random effects due to district. Specifying the conditional(fixedonly) option gives predictions that set the random effects to their prior mean of 0. Below we compare both over the first 20 observations:

```
. predict p_fixed, conditional(fixedonly)
(option mu assumed)

. list c_use p p_fixed age children in 1/20
```

	c_use	p	p_fixed	age	children
1.	No	.3572114	.4927182	18.44	3 or more children
2.	No	.21293	.3210403	-5.56	No children
3.	No	.4664207	.6044016	1.44	2 children
4.	No	.4198625	.5584863	8.44	3 or more children
5.	No	.2504834	.3687281	-13.56	No children
6.	No	.2406963	.3565185	-11.56	No children
7.	No	.3572114	.4927182	18.44	3 or more children
8.	No	.4984106	.6345998	-3.56	3 or more children
9.	No	.4564025	.594723	-5.56	1 child
10.	No	.465447	.6034657	1.44	3 or more children
11.	Yes	.2406963	.3565185	-11.56	No children
12.	No	.1999512	.3040173	-2.56	No children
13.	No	.4498569	.5883406	-4.56	1 child
14.	No	.439278	.5779263	5.44	3 or more children
15.	No	.4786124	.6160359	-0.56	3 or more children
16.	Yes	.4457945	.584356	4.44	3 or more children
17.	No	.21293	.3210403	-5.56	No children
18.	Yes	.4786124	.6160359	-0.56	3 or more children
19.	Yes	.4629632	.6010735	-6.56	1 child
20.	No	.4993888	.6355067	-3.56	2 children

◁

▷ Example 4: Intraclass correlations for higher-level models

Continuing with example 2, we can also compute intraclass correlations for the model using estat icc; see [ME] estat icc.

In the presence of random-effects covariates, the intraclass correlation is no longer constant and depends on the values of the random-effects covariates. In this case, estat icc reports conditional intraclass correlations assuming 0 values for all random-effects covariates. For example, in a two-level model, this conditional correlation represents the correlation of the latent responses for two measurements on the same subject, both of which have random-effects covariates equal to 0. Similarly to the interpretation of intercept variances in random-coefficients models (Rabe-Hesketh and Skrondal 2022, chap. 16), interpretation of this conditional intraclass correlation relies on the usefulness of the 0 baseline values of random-effects covariates. For example, mean centering of the covariates is often used to make a 0 value a useful reference.

Estimation of the conditional intraclass correlation in the Bangladeshi contraceptive study setting of example 2 is of interest. In example 2, the random-effects covariates 0.urban and 1.urban for the random level district are mutually exclusive indicator variables and can never be simultaneously 0. Thus we could not use estat icc to estimate the conditional intraclass correlation for this model, because estat icc requires that the random intercept is included in all random-effects specifications.

   Instead, we consider an alternative model for the Bangladeshi contraceptive study. In example 2 of [ME] **melogit**, we represented the probability of contraceptive use among Bangladeshi women with fixed-effects for urban residence (`urban`), age (`age`), and the number of children (`children`). The random effects for urban and rural residence are represented as a random slope for urban residence and a random intercept at the `district` level.

   We fit the model with `melogit`:

```
. use https://www.stata-press.com/data/r18/bangladesh, clear
(Bangladesh Fertility Survey, 1989)

. melogit c_use i.urban age i.children, nofvlabel
> || district: i.urban, covariance(unstructured)
```

   (*iteration log omitted*)

```
Mixed-effects logistic regression              Number of obs     =      1,934
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)      =      97.50
Log likelihood = -1199.315                     Prob > chi2       =     0.0000
```

c_use	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
1.urban	.8157875	.1715519	4.76	0.000	.4795519	1.152023
age	-.026415	.008023	-3.29	0.001	-.0421398	-.0106902
children						
1	1.13252	.1603285	7.06	0.000	.818282	1.446758
2	1.357739	.1770522	7.67	0.000	1.010723	1.704755
3	1.353827	.1828801	7.40	0.000	.9953882	1.712265
_cons	-1.71165	.1605618	-10.66	0.000	-2.026345	-1.396954
district						
var(1.urban)	.6663237	.3224689			.258074	1.720387
var(_cons)	.3897448	.1292463			.203473	.7465413
district						
cov(1.urban,						
_cons)	-.4058861	.1755414	-2.31	0.021	-.7499408	-.0618313

```
LR test vs. logistic model: chi2(3) = 58.42            Prob > chi2 = 0.0000
Note: LR test is conservative and provided only for reference.
```

   We use `estat icc` to estimate the intraclass correlation conditional on `urban` being equal to 0:

```
. estat icc

Conditional intraclass correlation
```

Level	ICC	Std. err.	[95% conf. interval]	
district	.1059201	.0314045	.058246	.1849518

```
Note: ICC is conditional on zero values of random-effects covariates.
```

   This estimate suggests that the latent responses are not strongly correlated for rural residents (`0.urban`) within the same district, conditional on the fixed-effects covariates.

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▷ Example 5: Estimating the residual intraclass correlation

In example 4 of [ME] **melogit**, we fit a three-level model for the cognitive ability of schizophrenia patients as compared with their relatives and a control. Fixed-effects covariates include the difficulty of the test, difficulty, and an individual's category, group (control, family member of patient, or patient). Family units (family) represent the third nesting level, and individual subjects (subject) represent the second nesting level. Three measurements were taken on all but one subject, one for each difficulty measure.

We fit the model with melogit:

```
. use https://www.stata-press.com/data/r18/towerlondon
(Tower of London data)
. melogit dtlm difficulty i.group || family: || subject:
  (iteration log omitted)
```

Mixed-effects logistic regression   Number of obs   =   677

Grouping information

Group variable	No. of groups	Observations per group Minimum	Average	Maximum
family	118	2	5.7	27
subject	226	2	3.0	3

Integration method: mvaghermite   Integration pts. =   7

Wald chi2(3)   =   74.90

Log likelihood = -305.12041   Prob > chi2   =   0.0000

dtlm	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
difficulty	-1.648505	.1932075	-8.53	0.000	-2.027185	-1.269826
group						
2	-.2486841	.3544076	-0.70	0.483	-.9433102	.445942
3	-1.052306	.3999921	-2.63	0.009	-1.836276	-.2683357
_cons	-1.485863	.2848455	-5.22	0.000	-2.04415	-.9275762
family						
var(_cons)	.5692105	.5215654			.0944757	3.429459
family> subject						
var(_cons)	1.137917	.6854853			.3494165	3.705762

LR test vs. logistic model: chi2(2) = 17.54   Prob > chi2 = 0.0002
Note: LR test is conservative and provided only for reference.

We can use estat icc to estimate the residual intraclass correlation (conditional on the difficulty level and the individual's category) between the latent responses of subjects within the same family or between the latent responses of the same subject and family:

```
. estat icc
```

Residual intraclass correlation

Level	ICC	Std. err.	[95% conf. interval]	
family	.1139105	.0997727	.0181851	.4715289
subject|family	.3416307	.0889471	.192923	.5297291

estat icc reports two intraclass correlations for this three-level nested model. The first is the level-3 intraclass correlation at the family level, the correlation between latent measurements of the cognitive ability in the same family. The second is the level-2 intraclass correlation at the subject-within-family level, the correlation between the latent measurements of cognitive ability in the same subject and family.

There is not a strong correlation between individual realizations of the latent response, even within the same subject.

◁

Methods and formulas

Methods and formulas for predicting random effects and other statistics are given in *Methods and formulas* of [ME] **meglm postestimation**.

References

De Backer, M., C. De Vroey, E. Lesaffre, I. Scheys, and P. De Keyser. 1998. Twelve weeks of continuous oral therapy for toenail onychomycosis caused by dermatophytes: A double-blind comparative trial of terbinafine 250 mg/day versus itraconazole 200 mg/day. *Journal of the American Academy of Dermatology* 38: S57–S63. https://doi.org/10.1016/s0190-9622(98)70486-4.

Lesaffre, E., and B. Spiessens. 2001. On the effect of the number of quadrature points in a logistic random-effects model: An example. *Journal of the Royal Statistical Society, Series C* 50: 325–335. https://doi.org/10.1111/1467-9876.00237.

Rabe-Hesketh, S., and A. Skrondal. 2022. *Multilevel and Longitudinal Modeling Using Stata*. 4th ed. College Station, TX: Stata Press.

Also see

[ME] **melogit** — Multilevel mixed-effects logistic regression

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

[U] **20 Estimation and postestimation commands**