Title

stata.com

mlogit postestimation — Postestimation tools for mlogit

Description

The following postestimation commands are available after `mlogit`:

Command	Description
`contrast`	contrasts and ANOVA-style joint tests of estimates
`estat ic`	Akaike's and Schwarz's Bayesian information criteria (AIC 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
`forecast`[1]	dynamic forecasts and simulations
`hausman`	Hausman's specification test
`lincom`	point estimates, standard errors, testing, and inference for linear combinations of coefficients
`lrtest`[2]	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`	predictions, residuals, influence statistics, and other diagnostic measures
`predictnl`	point estimates, standard errors, testing, and inference for generalized predictions
`pwcompare`	pairwise comparisons of estimates
`suest`	seemingly unrelated estimation
`test`	Wald tests of simple and composite linear hypotheses
`testnl`	Wald tests of nonlinear hypotheses

[1] `forecast` is not appropriate with `mi` or `svy` estimation results.
[2] `lrtest` is not appropriate with `svy` estimation results.

Syntax for predict

predict [*type*] { *stub** | *newvar* | *newvarlist* } [*if*] [*in*] [, *statistic* outcome(*outcome*)]

predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*], scores

statistic	Description
Main	
pr	probability of a positive outcome; the default
xb	linear prediction
stdp	standard error of the linear prediction
stddp	standard error of the difference in two linear predictions

If you do not specify outcome(), pr (with one new variable specified), xb, and stdp assume outcome(#1). You must specify outcome() with the stddp option.

You specify one or k new variables with pr, where k is the number of outcomes.

You specify one new variable with xb, stdp, and stddp.

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

Menu for predict

Statistics > Postestimation > Predictions, residuals, etc.

Options for predict

Main

pr, the default, calculates the probability of each of the categories of the dependent variable or the probability of the level specified in outcome(*outcome*). If you specify the outcome(*outcome*) option, you need to specify only one new variable; otherwise, you must specify a new variable for each category of the dependent variable.

xb calculates the linear prediction. You must also specify the outcome(*outcome*) option.

stdp calculates the standard error of the linear prediction. You must also specify the outcome(*outcome*) option.

stddp calculates the standard error of the difference in two linear predictions. You must specify the outcome(*outcome*) option, and here you specify the two particular outcomes of interest inside the parentheses, for example, predict sed, stddp outcome(1,3).

outcome(*outcome*) specifies the outcome for which the statistic is to be calculated. equation() is a synonym for outcome(): it does not matter which you use. outcome() or equation() can be specified using

#1, #2, ..., where #1 means the first category of the dependent variable, #2 means the second category, etc.;

the values of the dependent variable; or

the value labels of the dependent variable if they exist.

`scores` calculates equation-level score variables. The number of score variables created will be one less than the number of outcomes in the model. If the number of outcomes in the model were k, then

the first new variable will contain $\partial \ln L/\partial(\mathbf{x}_j\boldsymbol{\beta}_1)$;

the second new variable will contain $\partial \ln L/\partial(\mathbf{x}_j\boldsymbol{\beta}_2)$;

...

the $(k-1)$th new variable will contain $\partial \ln L/\partial(\mathbf{x}_j\boldsymbol{\beta}_{k-1})$.

Remarks and examples

stata.com

Remarks are presented under the following headings:

Obtaining predicted values

▷ Example 1: Obtaining predicted probabilities

After estimation, we can use `predict` to obtain predicted probabilities, index values, and standard errors of the index, or differences in the index. For instance, in example 4 of [R] **mlogit**, we fit a model of insurance choice on various characteristics. We can obtain the predicted probabilities for outcome 1 by typing

```
. use http://www.stata-press.com/data/r13/sysdsn1
(Health insurance data)
. mlogit insure age i.male i.nonwhite i.site
  (output omitted)
. predict p1 if e(sample), outcome(1)
(option pr assumed; predicted probability)
(29 missing values generated)
. summarize p1

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
          p1 |       615    .4764228    .1032279   .1698142     .71939
```

We added the `i.` prefix to the `male`, `nonwhite`, and `site` variables to explicitly identify them as factor variables. That makes no difference in the estimated results, but we will take advantage of it in later examples. We also included `if e(sample)` to restrict the calculation to the estimation sample. In example 4 of [R] **mlogit**, the multinomial logit model was fit on 615 observations, so there must be missing values in our dataset.

Although we typed `outcome(1)`, specifying `1` for the indemnity outcome, we could have typed `outcome(Indemnity)`. For instance, to obtain the probabilities for prepaid, we could type

```
. predict p2 if e(sample), outcome(Prepaid)
(option pr assumed; predicted probability)
(29 missing values generated)
. summarize p2

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
          p2 |       615    .4504065    .1125962   .1964103   .7885724
```

We must specify the label exactly as it appears in the underlying value label (or how it appears in the mlogit output), including capitalization.

Here we have used predict to obtain probabilities for the same sample on which we estimated. That is not necessary. We could use another dataset that had the independent variables defined (in our example, age, male, nonwhite, and site) and use predict to obtain predicted probabilities; here, we would not specify if e(sample).

◁

▷ Example 2: Obtaining index values

predict can also be used to obtain the index values—the $\sum x_i \widehat{\beta}_i^{(k)}$—as well as the probabilities:

```
. predict idx1, outcome(Indemnity) xb
(1 missing value generated)

. summarize idx1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        idx1 |        643           0           0          0          0
```

The indemnity outcome was our base outcome—the outcome for which all the coefficients were set to 0—so the index is always 0. For the prepaid and uninsured outcomes, we type

```
. predict idx2, outcome(Prepaid) xb
(1 missing value generated)

. predict idx3, outcome(Uninsure) xb
(1 missing value generated)

. summarize idx2 idx3

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        idx2 |        643   -.0566113     .4962973  -1.298198   1.700719
        idx3 |        643   -1.980747     .6018139  -3.112741  -.8258458
```

We can obtain the standard error of the index by specifying the stdp option:

```
. predict se2, outcome(Prepaid) stdp
(1 missing value generated)

. list p2 idx2 se2 in 1/5

     +-----------------------------------+
     |       p2         idx2        se2  |
     |-----------------------------------|
  1. | .3709022   -.4831167    .2437772  |
  2. | .4977667     .055111    .1694686  |
  3. | .4113073   -.1712106    .1793498  |
  4. | .5424927    .3788345    .2513701  |
  5. |        .   -.0925817    .1452616  |
     +-----------------------------------+
```

We obtained the probability, p2, in the previous example.

Finally, `predict` can calculate the standard error of the difference in the index values between two outcomes with the `stddp` option:

```
. predict se_2_3, outcome(Prepaid,Uninsure) stddp
(1 missing value generated)

. list idx2 idx3 se_2_3 in 1/5

     +----------------------------------+
     |      idx2        idx3     se_2_3 |
     |----------------------------------|
  1. | -.4831167   -3.073253   .5469354 |
  2. |   .055111   -2.715986   .4331918 |
  3. | -.1712106   -1.579621   .3053815 |
  4. |  .3788345   -1.462007   .4492552 |
  5. | -.0925817   -2.814022   .4024784 |
     +----------------------------------+
```

In the first observation, the difference in the indexes is $-0.483 - (-3.073) = 2.59$. The standard error of that difference is 0.547.

◁

▷ Example 3: Interpreting results using predictive margins

It is more difficult to interpret the results from `mlogit` than those from `clogit` or `logit` because there are multiple equations. For example, suppose that one of the independent variables in our model takes on the values 0 and 1, and we are attempting to understand the effect of this variable. Assume that the coefficient on this variable for the second outcome, $\beta^{(2)}$, is positive. We might then be tempted to reason that the probability of the second outcome is higher if the variable is 1 rather than 0. Most of the time, that will be true, but occasionally we will be surprised. The probability of some other outcome could increase even more (say, $\beta^{(3)} > \beta^{(2)}$), and thus the probability of outcome 2 would actually fall relative to that outcome. We can use `predict` to help interpret such results.

Continuing with our previously fit insurance-choice model, we wish to describe the model's predictions by race. For this purpose, we can use the method of predictive margins (also known as recycled predictions), in which we vary characteristics of interest across the whole dataset and average the predictions. That is, we have data on both whites and nonwhites, and our individuals have other characteristics as well. We will first pretend that all the people in our data are white but hold their other characteristics constant. We then calculate the probabilities of each outcome. Next we will pretend that all the people in our data are nonwhite, still holding their other characteristics constant. Again we calculate the probabilities of each outcome. The difference in those two sets of calculated probabilities, then, is the difference due to race, holding other characteristics constant.

```
. gen byte nonwhold=nonwhite              // save real race

. replace nonwhite=0                      // make everyone white
(126 real changes made)

. predict wpind, outcome(Indemnity)       // predict probabilities
(option pr assumed; predicted probability)
(1 missing value generated)

. predict wpp, outcome(Prepaid)
(option pr assumed; predicted probability)
(1 missing value generated)

. predict wpnoi, outcome(Uninsure)
(option pr assumed; predicted probability)
(1 missing value generated)

. replace nonwhite=1                      // make everyone nonwhite
(644 real changes made)
```

```
. predict nwpind, outcome(Indemnity)
(option pr assumed; predicted probability)
(1 missing value generated)

. predict nwpp, outcome(Prepaid)
(option pr assumed; predicted probability)
(1 missing value generated)

. predict nwpnoi, outcome(Uninsure)
(option pr assumed; predicted probability)
(1 missing value generated)

. replace nonwhite=nonwhold              // restore real race
(518 real changes made)

. summarize wp* nwp*, sep(3)
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       wpind |       643    .5141673    .0872679   .3092903     .71939
         wpp |       643    .4082052    .0993286   .1964103   .6502247
       wpnoi |       643    .0776275    .0360283   .0273596   .1302816
-------------+--------------------------------------------------------
      nwpind |       643    .3112809    .0817693   .1511329    .535021
        nwpp |       643     .630078    .0979976   .3871782   .8278881
      nwpnoi |       643    .0586411    .0287185   .0209648   .0933874
```

In example 1 of [R] **mlogit**, we presented a cross-tabulation of insurance type and race. Those values were unadjusted. The means reported above are the values adjusted for age, sex, and site. Combining the results gives

	Unadjusted		Adjusted	
	white	nonwhite	white	nonwhite
Indemnity	0.51	0.36	0.51	0.31
Prepaid	0.42	0.57	0.41	0.63
Uninsured	0.07	0.07	0.08	0.06

We find, for instance, after adjusting for age, sex, and site, that although 57% of nonwhites in our data had prepaid plans, 63% of nonwhites chose prepaid plans.

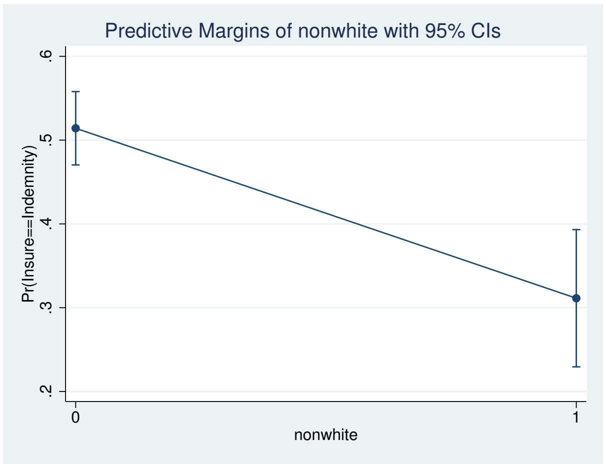
Computing predictive margins by hand was instructive, but we can compute these values more easily using the `margins` command (see [R] **margins**). The two margins for the indemnity outcome can be estimated by typing

```
. margins nonwhite, predict(outcome(Indemnity)) noesample

Predictive margins                              Number of obs   =        643
Model VCE    : OIM

Expression   : Pr(insure==Indemnity), predict(outcome(Indemnity))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    nonwhite |
          0  |   .5141673   .0223485    23.01   0.000      .470365    .5579695
          1  |   .3112809   .0418049     7.45   0.000     .2293448     .393217
------------------------------------------------------------------------------
```

`margins` also estimates the standard errors and confidence intervals of the margins. By default, `margins` uses only the estimation sample. We added the `noesample` option so that `margins` would use the entire sample and produce results comparable to our earlier analysis.

We can use `marginsplot` to graph the results from `margins`:

```
. marginsplot
  Variables that uniquely identify margins: nonwhite
```



The margins for the other two outcomes can be computed by typing

```
. margins nonwhite, predict(outcome(Prepaid)) noesample
 (output omitted)
. margins nonwhite, predict(outcome(Uninsure)) noesample
 (output omitted)
```

◁

❏ Technical note

You can use `predict` to classify predicted values and compare them with the observed outcomes to interpret a multinomial logit model. This is a variation on the notions of sensitivity and specificity for logistic regression. Here we will classify indemnity and prepaid as definitely predicting indemnity, definitely predicting prepaid, and ambiguous.

```
. predict indem, outcome(Indemnity) index            // obtain indexes
(1 missing value generated)
. predict prepaid, outcome(Prepaid) index
(1 missing value generated)
. gen diff = prepaid-indem                           // obtain difference
(1 missing value generated)
. predict sediff, outcome(Indemnity,Prepaid) stddp   // & its standard error
(1 missing value generated)
. gen type = 1 if diff/sediff < -1.96                // definitely indemnity
(504 missing values generated)
. replace type = 3 if diff/sediff > 1.96             // definitely prepaid
(100 real changes made)
. replace type = 2 if type>=. & diff/sediff < .      // ambiguous
(404 real changes made)
. label def type 1 "Def Ind" 2 "Ambiguous" 3 "Def Prep"
. label values type type                             // label results
. tabulate insure type

           |               type
    insure |   Def Ind  Ambiguous   Def Prep |     Total
-----------+---------------------------------+----------
 Indemnity |        78        183         33 |       294 
   Prepaid |        44        177         56 |       277 
  Uninsure |        12         28          5 |        45 
-----------+---------------------------------+----------
     Total |       134        388         94 |       616 
```

We can see that the predictive power of this model is modest. There are many misclassifications in both directions, though there are more correctly classified observations than misclassified observations.

Also the uninsured look overwhelmingly as though they might have come from the indemnity system rather than from the prepaid system.

❑

Calculating marginal effects

▷ Example 4

We have already noted that the coefficients from multinomial logit can be difficult to interpret because they are relative to the base outcome. Another way to evaluate the effect of covariates is to examine the marginal effect of changing their values on the probability of observing an outcome.

The `margins` command can be used for this too. We can estimate the marginal effect of each covariate on the probability of observing the first outcome—indemnity insurance—by typing

```
. margins, dydx(*) predict(outcome(Indemnity))
Average marginal effects                          Number of obs   =        615
Model VCE    : OIM

Expression   : Pr(insure==Indemnity), predict(outcome(Indemnity))
dy/dx w.r.t. : age 1.male 1.nonwhite 2.site 3.site

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0026655    .001399     1.91   0.057    -.0000765    .0054074
      1.male |  -.1295734   .0450945    -2.87   0.004    -.2179571   -.0411898
  1.nonwhite |  -.2032404   .0482554    -4.21   0.000    -.2978192   -.1086616
             |
        site |
          2  |   .0070995   .0479993     0.15   0.882    -.0869775    .1011765
          3  |   .1216165   .0505833     2.40   0.016      .022475     .220758
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

By default, `margins` estimates the average marginal effect over the estimation sample, and that is what we see above. Being male decreases the average probability of having indemnity insurance by 0.130. We also see, from the note at the bottom of the table, that the marginal effect was computed as a discrete change in the probability of being male rather than female. That is why we made `male` a factor variable when fitting the model.

The `dydx(*)` option requested that `margins` estimate the marginal effect for each regressor, `dydx(age)` would have produced estimates only for the effect of `age`. `margins` has many options for controlling how the marginal effect is computed, including the ability to average over subgroups or to compute estimates for specified values of the regressors; see [R] **margins**.

We could evaluate the marginal effects on the other two outcomes by typing

```
. margins, dydx(*) predict(outcome(Prepaid))
  (output omitted)
. margins, dydx(*) predict(outcome(Uninsure))
  (output omitted)
```

◁

Testing hypotheses about coefficients

▷ Example 5

`test` tests hypotheses about the coefficients just as after any estimation command; see [R] **test**. Note, however, `test`'s syntax for dealing with multiple-equation models. Because `test` bases its results on the estimated covariance matrix, we might prefer a likelihood-ratio test; see example 5 in [R] **mlogit** for an example of `lrtest`.

If we simply list variables after the `test` command, we are testing that the corresponding coefficients are zero across all equations:

```
. test 2.site 3.site

 ( 1)  [Indemnity]2o.site = 0
 ( 2)  [Prepaid]2.site = 0
 ( 3)  [Uninsure]2.site = 0
 ( 4)  [Indemnity]3o.site = 0
 ( 5)  [Prepaid]3.site = 0
 ( 6)  [Uninsure]3.site = 0
       Constraint 1 dropped
       Constraint 4 dropped

           chi2(  4) =   19.74
         Prob > chi2 =    0.0006
```

We can test that all the coefficients (except the constant) in an equation are zero by simply typing the outcome in square brackets:

```
. test [Uninsure]

 ( 1)  [Uninsure]age = 0
 ( 2)  [Uninsure]0b.male = 0
 ( 3)  [Uninsure]1.male = 0
 ( 4)  [Uninsure]0b.nonwhite = 0
 ( 5)  [Uninsure]1.nonwhite = 0
 ( 6)  [Uninsure]1b.site = 0
 ( 7)  [Uninsure]2.site = 0
 ( 8)  [Uninsure]3.site = 0
       Constraint 2 dropped
       Constraint 4 dropped
       Constraint 6 dropped

           chi2(  5) =    9.31
         Prob > chi2 =    0.0973
```

We specify the outcome just as we do with `predict`; we can specify the label if the outcome variable is labeled, or we can specify the numeric value of the outcome. We would have obtained the same test as above if we had typed `test [3]` because 3 is the value of `insure` for the outcome uninsured.

We can combine the two syntaxes. To test that the coefficients on the site variables are 0 in the equation corresponding to the outcome prepaid, we can type

```
. test [Prepaid]: 2.site 3.site

 ( 1)  [Prepaid]2.site = 0
 ( 2)  [Prepaid]3.site = 0

           chi2(  2) =   10.78
         Prob > chi2 =    0.0046
```

We specified the outcome and then followed that with a colon and the variables we wanted to test.

We can also test that coefficients are equal across equations. To test that all coefficients except the constant are equal for the prepaid and uninsured outcomes, we can type

```
. test [Prepaid=Uninsure]

 ( 1)  [Prepaid]age - [Uninsure]age = 0
 ( 2)  [Prepaid]0b.male - [Uninsure]0b.male = 0
 ( 3)  [Prepaid]1.male - [Uninsure]1.male = 0
 ( 4)  [Prepaid]0b.nonwhite - [Uninsure]0b.nonwhite = 0
 ( 5)  [Prepaid]1.nonwhite - [Uninsure]1.nonwhite = 0
 ( 6)  [Prepaid]1b.site - [Uninsure]1b.site = 0
 ( 7)  [Prepaid]2.site - [Uninsure]2.site = 0
 ( 8)  [Prepaid]3.site - [Uninsure]3.site = 0
       Constraint 2 dropped
       Constraint 4 dropped
       Constraint 6 dropped

           chi2(  5) =   13.80
         Prob > chi2 =    0.0169
```

To test that only the site variables are equal, we can type

```
. test [Prepaid=Uninsure]: 2.site 3.site

 ( 1)  [Prepaid]2.site - [Uninsure]2.site = 0
 ( 2)  [Prepaid]3.site - [Uninsure]3.site = 0

           chi2(  2) =   12.68
         Prob > chi2 =    0.0018
```

Finally, we can test any arbitrary constraint by simply entering the equation and specifying the coefficients as described in [U] **13.5 Accessing coefficients and standard errors**. The following hypothesis is senseless but illustrates the point:

```
. test ([Prepaid]age+[Uninsure]2.site)/2 = 2-[Uninsure]1.nonwhite

 ( 1)  .5*[Prepaid]age + [Uninsure]1.nonwhite + .5*[Uninsure]2.site = 2

           chi2(  1) =   22.45
         Prob > chi2 =    0.0000
```

See [R] **test** for more information about `test`. The information there about combining hypotheses across `test` commands (the `accumulate` option) also applies after `mlogit`.

◁

Reference

Fagerland, M. W., and D. W. Hosmer, Jr. 2012. A generalized HosmerLemeshow goodness-of-fit test for multinomial logistic regression models. *Stata Journal* 12: 447–453.

Also see

[R] **mlogit** — Multinomial (polytomous) logistic regression

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