Post-Estimation Commands for MLogit

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These notes borrow heavily (sometimes verbatim) from Long & Freese, 2014 Regression Models for Categorical Dependent Variables Using Stata, 3rd Edition.

Many/most of the Stata & `spost13` post-estimation commands work pretty much the same way for `mlogit` as they do for `logit` and/or `ologit`. We'll therefore concentrate primarily on the commands that are somewhat unique.

Making comparisons across categories. By default, `mlogit` sets the base category to the outcome with the most observations. You can change this with the `basecategory` option. `mlogit` reports coefficients for the effect of each independent variable on each category relative to the base category. Hence, you can easily see whether, say, yr89 significantly affects the likelihood of your being in the SD versus the SA category; but you can't easily tell whether yr89 significantly affects the likelihood of your being in, say, SD versus D, when neither is the base. You could just keep rerunning models with different base categories; but `listcoef` makes things easier by presenting estimates for all combinations of outcome categories.

```
. use https://www3.nd.edu/~rwilliam/statafiles/ordwarm2.dta
(77 & 89 General Social Survey)
. mlogit  warm i.yr89 i.male i.white age ed prst, b(4) nolog

Multinomial logistic regression                 Number of obs     =       2293
                                                LR chi2(18)       =     349.54
                                                Prob > chi2       =     0.0000
Log likelihood = -2820.9982                     Pseudo R2         =     0.0583

------------------------------------------------------------------------------
        warm |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
SD           |
        yr89 |
       1989  |  -1.160197   .1810497    -6.41   0.000    -1.515048   -.8053457
             |
        male |
        Men  |   1.226454    .167691     7.31   0.000     .8977855    1.555122
             |
       white |
      White  |    .834226   .2641771     3.16   0.002     .3164484    1.352004
         age |   .0316763   .0052183     6.07   0.000     .0214487     .041904
          ed |  -.1435798   .0337793    -4.25   0.000     -.209786   -.0773736
        prst |  -.0041656   .0070026    -0.59   0.552    -.0178904    .0095592
       _cons |  -.7221679   .4928708    -1.47   0.143    -1.688177    .2438411
-------------+----------------------------------------------------------------
D            |
        yr89 |
       1989  |  -.4255712   .1318065    -3.23   0.001    -.6839071   -.1672352
             |
        male |
        Men  |   1.326716    .137554     9.65   0.000     1.057115    1.596317
             |
       white |
      White  |   .4126344   .1872718     2.20   0.028     .0455885    .7796804
         age |   .0292275   .0042574     6.87   0.000     .0208832    .0375718
          ed |  -.0513285   .0283399    -1.81   0.070    -.1068737    .0042167
        prst |  -.0130318   .0055446    -2.35   0.019     -.023899   -.0021645
       _cons |  -.3088357   .3938354    -0.78   0.433    -1.080739    .4630676
-------------+----------------------------------------------------------------
```

```
A            |
        yr89 |
       1989  |  -.0625534   .1228908    -0.51   0.611    -.3034149    .1783082
             |
        male |
        Men  |   .8666833   .1310965     6.61   0.000     .6097389    1.123628
             |
       white |
      White  |   .3002409   .1710551     1.76   0.079    -.0350211    .6355028
         age |   .0066719   .0041053     1.63   0.104    -.0013744    .0147181
          ed |  -.0330137   .0274376    -1.20   0.229    -.0867904     .020763
        prst |  -.0017323   .0052199    -0.33   0.740    -.0119631    .0084985
       _cons |   .3932277   .3740361     1.05   0.293    -.3398697    1.126325
-------------+----------------------------------------------------------------
SA           |  (base outcome)
------------------------------------------------------------------------------

. listcoef 1.yr89, help

mlogit (N=2293): Factor change in the odds of warm

Variable: 1.yr89 (sd=0.490)
-------------------------------------------------------------------------------
                             |          b        z     P>|z|       e^b   e^bStdX
-----------------------------+-------------------------------------------------
SD          vs D             |    -0.7346   -4.434    0.000     0.480     0.698
SD          vs A             |    -1.0976   -6.705    0.000     0.334     0.584
SD          vs SA            |    -1.1602   -6.408    0.000     0.313     0.567
D           vs SD            |     0.7346    4.434    0.000     2.085     1.433
D           vs A             |    -0.3630   -3.395    0.001     0.696     0.837
D           vs SA            |    -0.4256   -3.229    0.001     0.653     0.812
A           vs SD            |     1.0976    6.705    0.000     2.997     1.712
A           vs D             |     0.3630    3.395    0.001     1.438     1.195
A           vs SA            |    -0.0626   -0.509    0.611     0.939     0.970
SA          vs SD            |     1.1602    6.408    0.000     3.191     1.765
SA          vs D             |     0.4256    3.229    0.001     1.530     1.232
SA          vs A             |     0.0626    0.509    0.611     1.065     1.031
-------------------------------------------------------------------------------
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in odds for unit increase in X
 e^bStdX = exp(b*SD of X) = change in odds for SD increase in X
```

Based on the above, we see that yr89 has little effect on strongly agreeing versus agreeing. In every other contrast though, the difference is significant.

It is possible to get overwhelmed with output, at least if you do this for all variables. The `pvalue` option can limit the output to differences which are significant. Also, the `positive` option only shows the positive differences (if you flip the comparison the coefficient will go negative.)

```
. listcoef , help pvalue(.01) positive

mlogit (N=2293): Factor change in the odds of warm (P<0.01)

Variable: 1.yr89 (sd=0.490)
-------------------------------------------------------------------------------
                             |          b         z     P>|z|       e^b   e^bStdX
-----------------------------+-------------------------------------------------
D            vs SD           |     0.7346     4.434     0.000     2.085     1.433
A            vs SD           |     1.0976     6.705     0.000     2.997     1.712
A            vs D            |     0.3630     3.395     0.001     1.438     1.195
SA           vs SD           |     1.1602     6.408     0.000     3.191     1.765
SA           vs D            |     0.4256     3.229     0.001     1.530     1.232
-------------------------------------------------------------------------------

Variable: 1.male (sd=0.499)
-------------------------------------------------------------------------------
                             |          b         z     P>|z|       e^b   e^bStdX
-----------------------------+-------------------------------------------------
SD           vs SA           |     1.2265     7.314     0.000     3.409     1.844
D            vs A            |     0.4600     4.403     0.000     1.584     1.258
D            vs SA           |     1.3267     9.645     0.000     3.769     1.938
A            vs SA           |     0.8667     6.611     0.000     2.379     1.541
-------------------------------------------------------------------------------

Variable: 1.white (sd=0.329)
-------------------------------------------------------------------------------
                             |          b         z     P>|z|       e^b   e^bStdX
-----------------------------+-------------------------------------------------
SD           vs SA           |     0.8342     3.158     0.002     2.303     1.316
-------------------------------------------------------------------------------

Variable: age (sd=16.779)
-------------------------------------------------------------------------------
                             |          b         z     P>|z|       e^b   e^bStdX
-----------------------------+-------------------------------------------------
SD           vs A            |     0.0250     5.578     0.000     1.025     1.521
SD           vs SA           |     0.0317     6.070     0.000     1.032     1.701
D            vs A            |     0.0226     6.789     0.000     1.023     1.460
D            vs SA           |     0.0292     6.865     0.000     1.030     1.633
-------------------------------------------------------------------------------

Variable: ed (sd=3.161)
-------------------------------------------------------------------------------
                             |          b         z     P>|z|       e^b   e^bStdX
-----------------------------+-------------------------------------------------
D            vs SD           |     0.0923     3.374     0.001     1.097     1.339
A            vs SD           |     0.1106     3.945     0.000     1.117     1.418
SA           vs SD           |     0.1436     4.251     0.000     1.154     1.574
-------------------------------------------------------------------------------

Variable: prst (sd=14.492)
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in odds for unit increase in X
 e^bStdX = exp(b*SD of X) = change in odds for SD increase in X
```

Using the .01 level of significance (which may be wise given the many comparisons that are being done) we see that white only clearly distinguished between those who strongly agree and those who strongly disagree. prst does not have any significant effects.

Using mlogtest for tests of the Multinomial Logistic Model.

The `mlogtest` command provides a convenient means for testing various hypotheses of interest. Incidentally, keep in mind that `mlogit` can also estimate a logistic regression model; ergo you might sometimes want to use `mlogit` instead of `logit` so you can take advantage of the `mlogtest` command.

Tests of independent variables. `mlogtest` can provide likelihood-ratio tests for each variable in the model. To do this yourself, you would have to estimate a series of models, store the results, and then use the `lrtest` command. `mlogtest` can automate this process.

```
. mlogtest, lr

LR tests for independent variables (N=2293)

  Ho: All coefficients associated with given variable(s) are 0

                 |      chi2    df   P>chi2
-----------------+-------------------------
         1.yr89 |    58.853     3    0.000
         1.male |   106.199     3    0.000
        1.white |    11.152     3    0.011
            age |    83.119     3    0.000
             ed |    21.087     3    0.000
           prst |     8.412     3    0.038
```

From the above, we can see that each variable’s effects are significant at the .05 level.

If you happen to have a very large data set or a very complicated model, LR tests can take a long time. It may be sufficient to simply use Wald tests in such cases. Remember, a Wald test only requires the estimation of the constrained model. In Stata, we could just do this with a series of `test` commands. Again, `mlogtest`, using the `wald` parameter, can automate the process and also present results more succinctly:

```
. mlogtest, wald

Wald tests for independent variables (N=2293)

  Ho: All coefficients associated with given variable(s) are 0

                 |      chi2    df   P>chi2
-----------------+-------------------------
         1.yr89 |    53.812     3    0.000
         1.male |    97.773     3    0.000
        1.white |    10.783     3    0.013
            age |    79.925     3    0.000
             ed |    20.903     3    0.000
           prst |     8.369     3    0.039
```

We see that both tests lead to very similar conclusions in this case. That is fairly common; it seems they are most likely to differ in borderline cases.

You can also use `mlogtest` to test sets of variables, e.g.

```
. mlogtest, lr set(1.white prst \ 1.white ed \ 1.yr89 1.male )

LR tests for independent variables (N=2293)

  Ho: All coefficients associated with given variable(s) are 0

                 |      chi2    df   P>chi2
-----------------+-------------------------
          1.yr89 |    58.853     3    0.000
          1.male |   106.199     3    0.000
         1.white |    11.152     3    0.011
             age |    83.119     3    0.000
              ed |    21.087     3    0.000
            prst |     8.412     3    0.038
           set_1 |    19.282     6    0.004
           set_2 |    30.334     6    0.000
           set_3 |   167.621     6    0.000

   set_1 contains: 1.white prst
   set_2 contains: 1.white ed
   set_3 contains: 1.yr89 1.male
```

Tests for combining dependent categories. If none of the IVs significantly affects the odds of outcome m versus outcome n, we say that m and n are indistinguishable with respect to the variables in the model. If two outcomes are indistinguishable with respect to the variables in the model, you can obtain more efficient estimates by combining them. I often use this command to see if I can combine categories, even if, say, I am using a command like ologit. Again, you can use both Stata or spost13 commands, and you can do LR or Wald tests.

```
. mlogtest, lrcomb

LR tests for combining alternatives (N=2293)

  Ho: All coefficients except intercepts associated with a given pair
      of alternatives are 0 (i.e., alternatives can be collapsed)

                         |      chi2    df   P>chi2
-------------------------+-------------------------
                 SD & D  |    43.864     6    0.000
                 SD & A  |   153.130     6    0.000
                 SD & SA |   215.033     6    0.000
                  D & A  |    98.857     6    0.000
                  D & SA |   191.730     6    0.000
                  A & SA |    54.469     6    0.000
```

Based on the above, we see that no categories should be combined. Doing the same thing with Wald tests,

```
. mlogtest, combine

Wald tests for combining alternatives (N=2293)

  Ho: All coefficients except intercepts associated with a given pair
      of alternatives are 0 (i.e., alternatives can be combined)

                 |      chi2    df   P>chi2
-----------------+------------------------
          SD & D |    41.018     6    0.000
          SD & A |   135.960     6    0.000
         SD & SA |   183.910     6    0.000
           D & A |    93.183     6    0.000
          D & SA |   167.439     6    0.000
          A & SA |    51.441     6    0.000
```

Independence of Irrelevant Alternatives (IIA) Tests. The Stata 12 Reference Manual (P. 710) explains the IIA assumption this way:

> A stringent assumption of multinomial and conditional logit models is that outcome categories for the model have the property of independence of irrelevant alternatives (IIA). Stated simply, this assumption requires that the inclusion or exclusion of categories does not affect the relative risks associated with the regressors in the remaining categories. One classic example of a situation in which this assumption would be violated involves the choice of transportation mode; see McFadden (1974). For simplicity, postulate a transportation model with the four possible outcomes: rides a train to work, takes a bus to work, drives the Ford to work, and drives the Chevrolet to work. Clearly, "drives the Ford" is a closer substitute to "drives the Chevrolet" than it is to "rides a train" (at least for most people). This means that excluding "drives the Ford" from the model could be expected to affect the relative risks of the remaining options and that the model would not obey the IIA assumption.

The 3rd edition of Long & Freese (section 8.4, pp. 407-411) explains the assumption further, and also explains ways of testing it. Long & Freese include tests for IIA in their programs but do NOT encourage their use. They note that these tests often provide conflicting results (e.g. some tests reject the null while others do not) and that various simulation studies have shown that these tests are not useful for assessing violations of the IIA assumption. They further argue that the multinomial logit model works best when the alternatives are dissimilar and not just substitutes for one another (e.g. if your choices were take your car to work, take a blue bus, or take a red bus, the two bus alternatives would be very similar and the IIA assumption would likely be violated, whether the tests showed it or not).

Paul Allison has also raised concerns about the IIA tests; see his blog entry at http://www.statisticalhorizons.com/iia.

But, if some reviewer says you need to test the IIA assumption, here is how you can do it with `mlogtest`.

```
. mlogtest, iia

Hausman tests of IIA assumption (N=2293)

  Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

                 |      chi2    df   P>chi2
-----------------+-------------------------
              SD |    -0.177    14        .
               D |   -10.884    14        .
               A |    -3.009    13        .
              SA |    -1.606    14        .

  Note: A significant test is evidence against Ho.
  Note: If chi2<0, the estimated model does not meet asymptotic assumptions.

suest-based Hausman tests of IIA assumption (N=2293)

  Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

                 |      chi2    df   P>chi2
-----------------+-------------------------
              SD |    18.651    14    0.179
               D |    20.289    14    0.121
               A |    23.480    14    0.053
              SA |    11.381    14    0.656

  Note: A significant test is evidence against Ho.

Small-Hsiao tests of IIA assumption (N=2293)

  Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

                 | lnL(full)  lnL(omit)       chi2    df   P>chi2
-----------------+---------------------------------------------
              SD | -1025.061  -1018.448     13.226    14    0.509
               D |  -718.007   -711.796     12.422    14    0.572
               A |  -678.789   -673.072     11.433    14    0.652
              SA |  -936.474   -928.840     15.268    14    0.360

  Note: A significant test is evidence against Ho.
```

In this example the tests say IIA has not been violated. Long & Freese give examples of where different tests reach different conclusions with the same set of data.

Measures of Fit. The `fitstat` command can be used the same as before, e.g.

```
. quietly mlogit  warm i.yr89 i.male i.white age ed prst, b(4) nolog
. quietly fitstat, save
. * Now drop prst, white & ed, the three least significant vars
. quietly mlogit  warm i.yr89 i.male age , b(4) nolog
. fitstat, dif

                         |     Current        Saved   Difference
-------------------------+---------------------------------------
Log-likelihood           |
                   Model |   -2848.592    -2820.998      -27.594
          Intercept-only |   -2995.770    -2995.770        0.000
-------------------------+---------------------------------------
Chi-square               |
      D (df=2281/2272/9) |    5697.184     5641.996       55.188
         LR (df=9/18/-9) |     294.357      349.544      -55.188
                 p-value |       0.000        0.000        0.000
-------------------------+---------------------------------------
R2                       |
                McFadden |       0.049        0.058       -0.009
     McFadden (adjusted) |       0.045        0.051       -0.006
           Cox-Snell/ML |       0.120        0.141       -0.021
  Cragg-Uhler/Nagelkerke |       0.130        0.153       -0.023
                   Count |       0.412        0.424       -0.013
        Count (adjusted) |       0.061        0.081       -0.020
-------------------------+---------------------------------------
IC                       |
                     AIC |    5721.184     5683.996       37.188
       AIC divided by N |       2.495        2.479        0.016
       BIC (df=12/21/-9) |    5790.035     5804.486      -14.451

Note: Likelihood-ratio test assumes current model nested in saved model.

Difference of   14.451 in BIC provides very strong support for current model.
```

Incidentally, note that the chi-square and AIC tests favor the full model; however, the BIC test prefers the model that drops the least significant variables, prst, white & ed. As we have seen before, the BIC test tends to lead to more parsimonious models, especially when the sample size is large.

Outliers. The `leastlikely` command can be used to identify the cases where the observed value was farthest from the predicted value. You might want to check such cases for coding errors or think if there are ways to modify the model so these cases are not so discrepant.

```
. quietly mlogit  warm i.yr89 i.male i.white age ed prst, b(4) nolog
. leastlikely warm yr89 male white age ed prst

Outcome: 1 (SD)

      +--------------------------------------------------------------+
      |     Prob   warm   yr89    male      white   age   ed   prst |
      |--------------------------------------------------------------|
 112. | .0389264     SD   1989   Women      White    46   16     57 |
 167. | .0355258     SD   1989   Women      White    37   15     61 |
 212. | .0423206     SD   1989   Women      White    50   16     62 |
 271. | .0352297     SD   1989   Women      White    20   12     31 |
 286. | .0407416     SD   1989   Women   NotWhite    54   12     34 |
      +--------------------------------------------------------------+
```

```
Outcome: 2 (D)

      +--------------------------------------------------------------+
      |     Prob   warm   yr89    male      white   age   ed   prst |
      |--------------------------------------------------------------|
 414. | .1286143      D   1989   Women      White    19   12     50 |
 563. | .1175782      D   1989   Women   NotWhite    41   18     69 |
 675. | .1322747      D   1989   Women      White    25   16     50 |
 803. |  .107113      D   1989   Women   NotWhite    30   16     60 |
1001. | .1288399      D   1989   Women      White    32   18     62 |
      +--------------------------------------------------------------+

Outcome: 3 (A)

      +----------------------------------------------------------+
      |     Prob   warm   yr89   male   white   age   ed   prst |
      |----------------------------------------------------------|
1305. | .1621244      A   1977    Men   White    79    8     41 |
1344. | .1575535      A   1977    Men   White    72    7     22 |
1404. | .1625481      A   1977    Men   White    74    8     26 |
1449. | .1398363      A   1977    Men   White    71    4     23 |
1729. | .1303623      A   1977    Men   White    81    5     36 |
      +----------------------------------------------------------+

Outcome: 4 (SA)

      +----------------------------------------------------------+
      |     Prob   warm   yr89   male   white   age   ed   prst |
      |----------------------------------------------------------|
1963. | .0313339     SA   1977    Men   White    64    6     26 |
2093. | .0372785     SA   1977    Men   White    48    4     17 |
2107. |  .034017     SA   1977    Men   White    69    8     33 |
2119. | .0345335     SA   1977    Men   White    58    4     41 |
2138. | .0316978     SA   1977    Men   White    57    3     37 |
      +----------------------------------------------------------+
```

Aids to Interpretation. These are much the same as we talked about before. Standardized coefficients, however, are a noteworthy exception:

```
. listcoef, std
option std not allowed after mlogit
```

This is because the y* rationale does not hold in a multinomial logit model, i.e. there is no underlying latent variable. (As we saw earlier, however, the `listcoef` command will still do X-standardization.)

Other commands, however, behave identically or almost identically to what we have seen before. For example, we can use the `predict` command to come up with predicted probabilities:

```
. quietly mlogit  warm i.yr89 i.male i.white age ed prst, b(4) nolog
. predict SDlogit Dlogit Alogit SAlogit
(option pr assumed; predicted probabilities)
```

```
. list warm yr89 male white age ed prst SDlogit Dlogit Alogit SAlogit in 1/10, clean

       warm   yr89    male   white   age   ed   prst    SDlogit     Dlogit     Alogit    SAlogit
  1.     SD   1977   Women   White    33   10     31     .14696   .2569168    .375222   .2209013
  2.     SD   1977     Men   White    74   16     50   .1931719   .4962518   .2510405   .0595358
  3.     SD   1989     Men   White    36   12     41    .074012   .3257731   .4686748   .1315401
  4.     SD   1977   Women   White    73    9     36    .277139    .383207   .2358743   .1037797
  5.     SD   1977   Women   White    59   11     62   .2066857   .2824558   .3317693   .1790893
  6.     SD   1989     Men   White    33    4     17   .1461631    .383301   .3885765   .0819594
  7.     SD   1977   Women   White    43    7     40   .2276894   .2719278   .3321202   .1682626
  8.     SD   1977   Women   White    48   12     48   .1571982   .2740046    .358632   .2101651
  9.     SD   1977     Men   White    27   17     69   .0970773    .259278    .477971   .1656736
 10.     SD   1977     Men   White    46   12     50   .1997817   .3800453   .3360028   .0841702
```

The extremes (use findit extremes) command helps you to see who is most likely and least likely to be predicted to strongly disagree:

```
. extremes  SDlogit warm yr89 male white age ed prst

  +----------------------------------------------------------------------+
  |  obs:    SDlogit   warm   yr89    male      white   age   ed    prst |
  |----------------------------------------------------------------------|
  | 1214.   .0078837      A   1989   Women   NotWhite    27   20      68 |
  | 2048.    .011555     SA   1989   Women   NotWhite    26   17      52 |
  | 2241.   .0127511     SA   1989   Women   NotWhite    21   15      61 |
  | 1855.   .0131329      A   1989   Women   NotWhite    25   16      36 |
  |  803.   .0142298      D   1989   Women   NotWhite    30   16      60 |
  +----------------------------------------------------------------------+

  +-------------------------------------------------------------+
  | 612.   .4276913      D   1977    Men   White    80    5     45 |
  | 171.   .4289597     SD   1977    Men   White    67    3     32 |
  | 282.   .4378463     SD   1977    Men   White    68    3     37 |
  |  87.   .4426529     SD   1977    Men   White    83    5     51 |
  | 863.    .479314      D   1977    Men   White    54    0     40 |
  +-------------------------------------------------------------+
```

Based on the results, we see that fairly young white women in 1989 with high levels of education and occupational prestige were predicted to be the least likely to strongly disagree. Conversely, nonwhite elderly males in 1977 with low levels of education and generally low levels of occupational prestige had almost a 50% predicted probability of strongly disagreeing.

Other comments. See Long and Freese for detailed explanations of how different commands are working, e.g. they often show you how the same things could be done in Stata without their commands (albeit in a much more tedious process). They also offer detailed advice on graphing results.