

## 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://academicweb.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   |
| ----- |      |           |           |       |       |                      |



```
. 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 3<sup>rd</sup> 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/iaa>.

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  $\chi^2 < 0$ , 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 SAllogit
(option pr assumed; predicted probabilities)
```

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

|     | warm | yr89 | male  | white | age | ed | prst | SDlogit  | Dlogit   | Alogit   | SAllogit |
|-----|------|------|-------|-------|-----|----|------|----------|----------|----------|----------|
| 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.