Sociology 704: Topics in Multivariate Statistics
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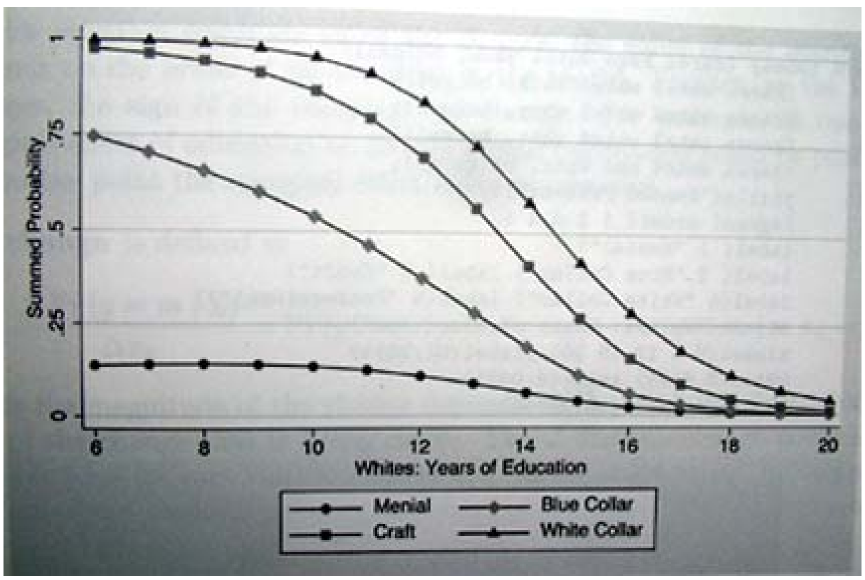
Multinomial logit

We use multinomial logit models when we have multiple categories but cannot order them (or we can, but the parallel regression assumption does not hold). Here the order of categories is unimportant. Multinomial logit model is equivalent to simultaneous estimation of multiple logits where each of the categories is compared to one selected so-called base category. But if we would estimate them separately, we would lose information, as each logit would be estimated on a different sample (selected category plus base category, with all other categories omitted from analyses). To avoid that, we use multinomial logit.

Multinomial logit does not assume parallel slopes – so if we estimate it for ordinal level variable and then plot cumulative probabilities, we would see something like this (note the variation in slope!):



Let's estimate a multinomial logit model for the same variable we used above:

```
. mlogit natarmsy age sex childs educ born
Iteration 0:   log likelihood = -1410.9409
Iteration 1:   log likelihood =  -1388.298
Iteration 2:   log likelihood = -1387.8458
Iteration 3:   log likelihood = -1387.8455
Multinomial logistic regression                   Number of obs   =       1337
                                                  LR chi2(10)     =      46.19
                                                  Prob > chi2     =     0.0000
Log likelihood = -1387.8455                       Pseudo R2       =     0.0164
------------------------------------------------------------------------------
    natarmsy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
too little   |
         age |     .00548   .0039204     1.40   0.162    -.0022039    .0131639
         sex |  -.1919798   .1251455    -1.53   0.125    -.4372605    .0533009
      childs |  -.0194531   .0411446    -0.47   0.636     -.100095    .0611887
        educ |  -.0102552   .0210369    -0.49   0.626    -.0514869    .0309764
        born |  -.8933259   .2685336    -3.33   0.001    -1.419642   -.3670098
       _cons |   .9484196   .4877274     1.94   0.052    -.0075085    1.904348
-------------+----------------------------------------------------------------
```

```
too much     |
         age |  -.0135326   .0049789    -2.72   0.007     -.023291   -.0037742
         sex |   .0420268   .1485803     0.28   0.777    -.2491853    .3332389
      childs |  -.0128663   .0519464    -0.25   0.804    -.1146793    .0889467
        educ |   .0475599   .0257811     1.84   0.065    -.0029701      .09809
        born |   .1980986   .2326138     0.85   0.394    -.2578161    .6540133
       _cons |  -1.054006   .5377872    -1.96   0.050     -2.10805    .0000375
------------------------------------------------------------------------------
(Outcome natarmsy==about right is the comparison group)
```

Model Interpretation

1. Coefficients and Odds Ratios

Note that we now have two sets of coefficients to interpret. So here, we can see that variable born differentiates between categories "too little" and "about right" while variable age differentiates between "too much" and "about right."

Also note that it automatically omitted the category "about right" -- it usually omits the category with the largest number of observations unless you specify otherwise. Here's how we change that:

```
. mlogit natarmsy age sex childs educ born, b(1)
Multinomial logistic regression                   Number of obs   =       1337
                                                  LR chi2(10)     =      46.19
                                                  Prob > chi2     =     0.0000
Log likelihood = -1387.8455                       Pseudo R2       =     0.0164
------------------------------------------------------------------------------
    natarmsy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
about right  |
         age |    -.00548   .0039204    -1.40   0.162    -.0131639    .0022039
         sex |   .1919798   .1251455     1.53   0.125    -.0533009    .4372605
      childs |   .0194531   .0411446     0.47   0.636    -.0611887     .100095
        educ |   .0102552   .0210369     0.49   0.626    -.0309764    .0514869
        born |   .8933259   .2685336     3.33   0.001     .3670098    1.419642
       _cons |  -.9484196   .4877274    -1.94   0.052    -1.904348    .0075085
-------------+----------------------------------------------------------------
too much     |
         age |  -.0190126   .0051423    -3.70   0.000    -.0290914   -.0089338
         sex |   .2340065   .1550509     1.51   0.131    -.0698876    .5379007
      childs |   .0065869   .0537937     0.12   0.903    -.0988468    .1120205
        educ |   .0578152   .0270313     2.14   0.032     .0048347    .1107956
        born |   1.091425   .2962101     3.68   0.000     .5108634    1.671986
       _cons |  -2.002426   .5858732    -3.42   0.001    -3.150716   -.8541352
------------------------------------------------------------------------------
(Outcome natarmsy==too little is the comparison group)
```

This allows us to see that variables age, educ and born differentiate between categories too much and too little. Variables sex and childs appear not to be able to differentiate between any categories.

Interpretation of results is again very similar. Since we cannot interpret sizes of regular coefficients, let's examine odds ratios. To obtain odds ratios in multinomial logit models, we use option rrr rather than or.

```
. mlogit natarmsy age sex childs educ born, rrr
Multinomial logistic regression                   Number of obs   =       1337
                                                  LR chi2(10)     =      46.19
                                                  Prob > chi2     =     0.0000
Log likelihood = -1387.8455                       Pseudo R2       =     0.0164
------------------------------------------------------------------------------
    natarmsy |        RRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
too little   |
         age |   1.005495    .003942     1.40   0.162     .9977986    1.013251
         sex |   .8253236   .1032855    -1.53   0.125     .6458032    1.054747
      childs |   .9807349   .0403519    -0.47   0.636     .9047515      1.0631
        educ |   .9897972   .0208223    -0.49   0.626     .9498161    1.031461
        born |   .4092922   .1099087    -3.33   0.001     .2418006    .6928028
-------------+----------------------------------------------------------------
too much     |
         age |   .9865586   .0049119    -2.72   0.007     .9769782    .9962329
         sex |   1.042922   .1549578     0.28   0.777     .7794355    1.395481
      childs |   .9872161   .0512823    -0.25   0.804      .891652    1.093022
        educ |   1.048709   .0270369     1.84   0.065     .9970343    1.103062
        born |   1.219083   .2835754     0.85   0.394     .7727374    1.923244
------------------------------------------------------------------------------
(Outcome natarmsy==about right is the comparison group)
```

Here we can, for example, say that being foreign born decreases one's odds of saying that the U.S. spends too little versus that the U.S. spends "about right" on national defense by approximately 60%.

We can also use listcoef which generates odds ratios for all possible models group comparisons -- one table per variable:

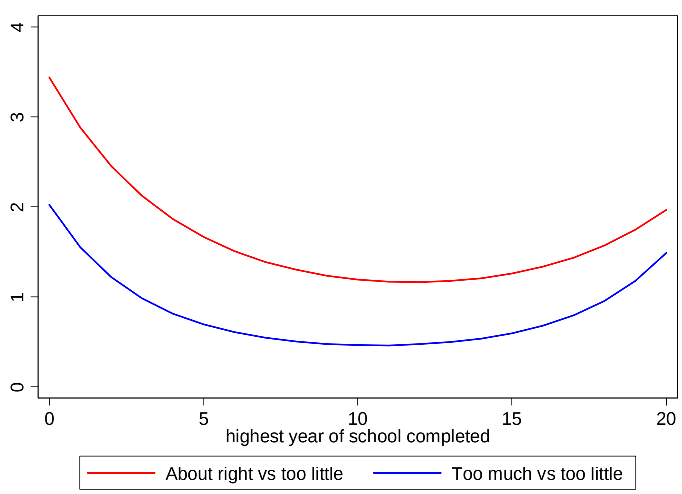
```
. listcoef
mlogit (N=1337): Factor Change in the Odds of natarmsy

Variable: age (sd=      17)
    Odds comparing|
Group 1 vs Group 2|      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
about_ri-too_much |   0.01353    2.718   0.007   1.0136   1.2654
about_ri-too_litt |  -0.00548   -1.398   0.162   0.9945   0.9091
too_much-about_ri |  -0.01353   -2.718   0.007   0.9866   0.7902
too_much-too_litt |  -0.01901   -3.697   0.000   0.9812   0.7184
too_litt-about_ri |   0.00548    1.398   0.162   1.0055   1.1000
too_litt-too_much |   0.01901    3.697   0.000   1.0192   1.3920
----------------------------------------------------------------

Variable: sex (sd=      .5)
    Odds comparing|
Group 1 vs Group 2|      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
about_ri-too_much |  -0.04203   -0.283   0.777   0.9588   0.9793
about_ri-too_litt |   0.19198    1.534   0.125   1.2116   1.1003
too_much-about_ri |   0.04203    0.283   0.777   1.0429   1.0212
too_much-too_litt |   0.23401    1.509   0.131   1.2637   1.1236
too_litt-about_ri |  -0.19198   -1.534   0.125   0.8253   0.9088
too_litt-too_much |  -0.23401   -1.509   0.131   0.7914   0.8900
----------------------------------------------------------------

Variable: childs (sd=     1.7)
    Odds comparing|
Group 1 vs Group 2|      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
about_ri-too_much |   0.01287    0.248   0.804   1.0129   1.0221
about_ri-too_litt |   0.01945    0.473   0.636   1.0196   1.0336
too_much-about_ri |  -0.01287   -0.248   0.804   0.9872   0.9784
too_much-too_litt |   0.00659    0.122   0.903   1.0066   1.0112
too_litt-about_ri |  -0.01945   -0.473   0.636   0.9807   0.9675
too_litt-too_much |  -0.00659   -0.122   0.903   0.9934   0.9889
----------------------------------------------------------------

Variable: educ (sd=       3)
    Odds comparing|
```

```
Group 1 vs Group 2|       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
about_ri-too_much |  -0.04756   -1.845   0.065   0.9536   0.8653
about_ri-too_litt |   0.01026    0.487   0.626   1.0103   1.0317
too_much-about_ri |   0.04756    1.845   0.065   1.0487   1.1557
too_much-too_litt |   0.05782    2.139   0.032   1.0595   1.1923
too_litt-about_ri |  -0.01026   -0.487   0.626   0.9898   0.9693
too_litt-too_much |  -0.05782   -2.139   0.032   0.9438   0.8387
----------------------------------------------------------------

Variable: born (sd=     .28)
    Odds comparing|
Group 1 vs Group 2|       b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
about_ri-too_much |  -0.19810   -0.852   0.394   0.8203   0.9468
about_ri-too_litt |   0.89333    3.327   0.001   2.4432   1.2796
too_much-about_ri |   0.19810    0.852   0.394   1.2191   1.0562
too_much-too_litt |   1.09142    3.685   0.000   2.9785   1.3516
too_litt-about_ri |  -0.89333   -3.327   0.001   0.4093   0.7815
too_litt-too_much |  -1.09142   -3.685   0.000   0.3357   0.7399
----------------------------------------------------------------
```

We can also use all the same options with listcoef that we used with binary logit. Your book also describes mlogview and mlogplot commands that can assist you in interpreting all these sets of odds ratios (pp. 257-272).

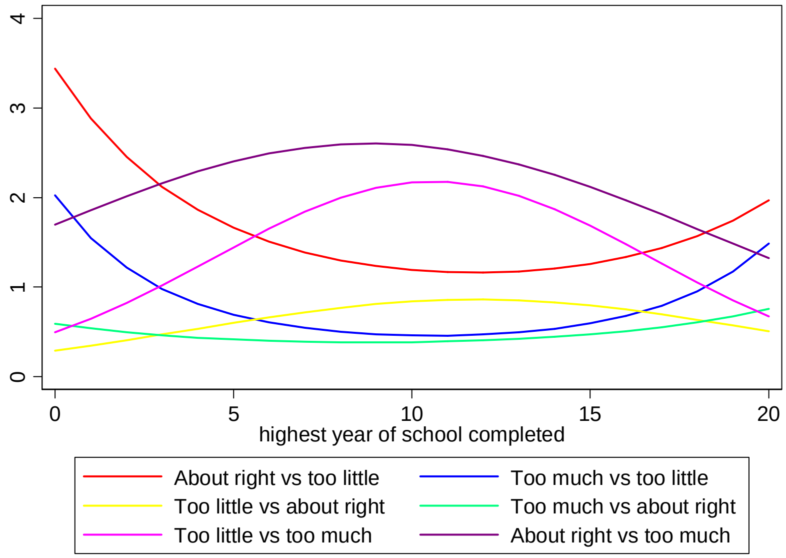
We can also use adjust to create graphs of odds. For mlogit, we need to be aware of multiple equations – need a separate prediction and separate graph for each equation (and remember that these are the odds compared to the omitted category).

```
. qui sum educ
. gen educmean=educ-r(mean)
. gen educ2=educmean^2
. qui mlogit natarmsy age sex childs born educmean educ2, b(1)
. qui adjust age sex childs born if e(sample), gen(odds1) exp eq(about right)
. qui adjust age sex childs born if e(sample), gen(odds2) exp eq(too much)
. qui lab var odds1 "About right vs too little"
. qui lab var odds2 "Too much vs too little
. line odds1 odds2 educ, sort lcolor(red blue)
```



We could also change the base category and generate similar graphs for various combinations and graph all of them:

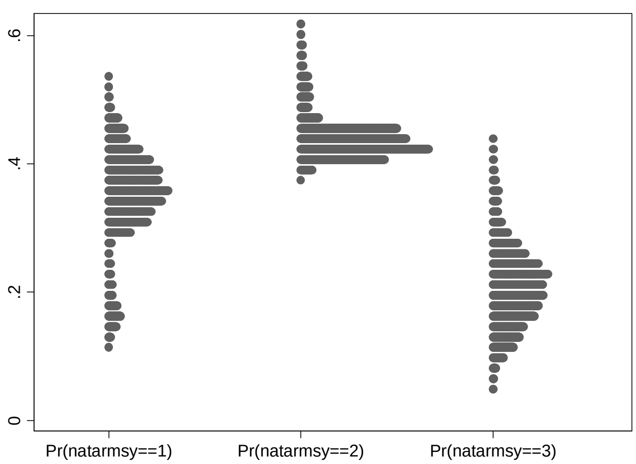
```
qui mlogit natarmsy age sex childs born educmean educ2, b(2)
qui adjust age sex childs born if e(sample), gen(odds3) exp eq(too little)
qui adjust age sex childs born if e(sample), gen(odds4) exp eq(too much)
qui lab var odds3 "Too little vs about right"
qui lab var odds4 "Too much vs about right

qui mlogit natarmsy age sex childs born educmean educ2, b(3)
qui adjust age sex childs born if e(sample), gen(odds5) exp eq(too little)
qui adjust age sex childs born if e(sample), gen(odds6) exp eq(about right)
qui lab var odds5 "Too little vs too much"
qui lab var odds6 "About right vs too much"
line odds1 odds2 odds3 odds4 odds5 odds6 educ, sort lcolor(red blue yellow mint
magenta purple)
```



2. Predicted probabilities and changes in predicted probabilities.

We can also examine predicted probabilities or changes in predicted probabilities. That is, we can use prvalue, prtab and prgen, and prchange just like we did for ordered logit.

```
. predict pm1 pm2 pm3
(option p assumed; predicted probabilities)
(26 missing values generated)

. dotplot pm1 pm2 pm3
```



```
. prvalue
mlogit: Predictions for natarmsy
Confidence intervals by delta method
                                95% Conf. Interval
  Pr(y=too_litt|x):   0.3523   [ 0.3262,    0.3785]
  Pr(y=about_ri|x):   0.4456   [ 0.4185,    0.4727]
  Pr(y=too_much|x):   0.2021   [ 0.1799,    0.2242]
          age        sex     childs       born       educ
x=  46.367988  1.5459985   1.854899  1.0830217  13.352281
```

Measures of Fit and Hypotheses Testing:

We can obtain fit statistics using fitstat like we did for binary and ordered logit.

Although we can use test and lrtest with ordered logit to test hypotheses just like we did with binary logit (test conducts Wald tests and lrtest conducts likelihood ratio tests), for multinomial logit hypotheses tests become more complicated. Here, if we want to drop a variable from the model, we want to test that it is not significant across all outcome categories (regardless of which one we omit). For that we use mlogtest command (we could also use test or lrtest but it would be more difficult).

```
. mlogtest, lr

**** Likelihood-ratio tests for independent variables

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

    natarmsy |       chi2   df   P>chi2
-------------+-------------------------
         age |     14.266    2    0.001
         sex |      3.186    2    0.203
      childs |      0.231    2    0.891
        educ |      4.935    2    0.085
        born |     17.322    2    0.000
---------------------------------------
```

We conclude that variables sex, childs, and educ are not statistically significant across equations and could potentially be dropped (although we saw that educ was significant on .05 level in one of the models, when we join the results across categories it appears to be not significant). We can do the same with Wald test; the results look very similar:

```
. mlogtest, wald
**** Wald tests for independent variables
 Ho: All coefficients associated with given variable(s) are 0.
    natarmsy |       chi2   df   P>chi2
-------------+-------------------------
         age |     13.702    2    0.001
         sex |      3.185    2    0.203
      childs |      0.231    2    0.891
        educ |      4.849    2    0.089
        born |     14.956    2    0.001
---------------------------------------
```

We can also test jointly whether these three variables are statistically significant as a set – i.e.. we can check if it makes sense to drop all three variables, sex, childs, and educ:

```
. mlogtest, lr set(sex childs educ)
**** Likelihood-ratio tests for independent variables
 Ho: All coefficients associated with given variable(s) are 0.
```

```
    natarmsy |       chi2   df   P>chi2
-------------+-------------------------
         age |     14.266    2    0.001
         sex |      3.186    2    0.203
      childs |      0.231    2    0.891
        educ |      4.935    2    0.085
        born |     17.322    2    0.000
-------------+-------------------------
      set_1: |      8.812    6    0.184
         sex |
      childs |
        educ |
---------------------------------------

. mlogtest, wald set(sex childs educ)
**** Wald tests for independent variables
 Ho: All coefficients associated with given variable(s) are 0.
    natarmsy |       chi2   df   P>chi2
-------------+-------------------------
         age |     13.702    2    0.001
         sex |      3.185    2    0.203
      childs |      0.231    2    0.891
        educ |      4.849    2    0.089
        born |     14.956    2    0.001
-------------+-------------------------
      set_1: |      8.678    6    0.193
         sex |
      childs |
        educ |
---------------------------------------
```

Both tests indicate that we can drop all three (we interpret the probability for set_1).

Another test that we might want to do is to test whether it makes sense to combine some categories of our dependent variable – e.g. whether it makes sense to combine “too little” and “about right.” We can combine them if all of our independent variables jointly do not differentiate between the two categories – nothing predicts that they are different.

```
. mlogtest, lrcomb
**** LR tests for combining outcome categories
 Ho: All coefficients except intercepts associated with given pair
     of outcomes are 0 (i.e., categories can be collapsed).
Categories tested |      chi2   df   P>chi2
------------------+------------------------
about_ri-too_much |    16.204    5    0.006
about_ri-too_litt |    16.993    5    0.005
too_much-too_litt |    41.557    5    0.000
-------------------------------------------

. mlogtest, combine
**** Wald tests for combining outcome categories
 Ho: All coefficients except intercepts associated with given pair
     of outcomes are 0 (i.e., categories can be collapsed).
Categories tested |      chi2   df   P>chi2
------------------+------------------------
about_ri-too_much |    15.496    5    0.008
about_ri-too_litt |    15.604    5    0.008
too_much-too_litt |    38.826    5    0.000
-------------------------------------------
```

LR test and Wald test produce similar results - for all combinations of categories, we reject the hypotheses that our variables do not differentiate between categories. So we cannot combine any.

Diagnostics

1. Independence of Irrelevant Alternatives (IIA) assumption

This similarity can only happen if another important assumption of multinomial logit holds: the assumption of Independence of Irrelevant Alternatives (IIA). Therefore, you want to test that assumption before doing other diagnostics.

Multinomial logit models assume that odds for each specific pair of outcomes do not depend on other outcomes available (deleting outcomes should not affect the odds among the remaining outcomes). It is often described with an example of red bus/blue bus. If people select means of transportation and half of them choose car and half choose red bus, the red bus to car odds are 1:1. According to this assumption, they should remain 1:1 if a blue bus is added to the mix. In a real world, we understand that blue bus would take half of the customers of the red bus, so the new odds for car versus red bus will become 2:1. But in the world of multinomial logit, if we add many multicolor buses, the odds that you take a car should be become very very small.

In fact, it is usually not a problem if we can add such a "dependent" alternative to the model – we can come up with such "blue buses" for almost any set of choices. It is more important that the model is not affected if we OMIT one of the existing alternatives.

There were three tests implemented in Stata to assess this assumption -- Hausman test, suest-based Hausman test, and Small-Hsiao test. The results of Hausman test and Small-Hsiao test are typically inconclusive or contradictory – see pp. 243-246 in Long and Freese for discussion of this. Small-Hsiao test, in particular, produces different results every time you run it, as it is based on splitting the sample into two halves. Sometimes the results are drastically different from one execution of it to another, and sometimes it doesn't work at all. Hausman test also produces different results depending on what category is the base category and often doesn't work either. Therefore, I would advise that you rely on suest-based Hausman test when evaluating this assumption.

In Stata 10, there seems to be a problem with execution of these tests if your dependent variable has long value labels. So you might want to create a temporary variable without the labels to run this portion of the analysis.

```
. gen test=natarmsy
(1417 missing values generated)
. mlogit test age sex childs educ born
Multinomial logistic regression                   Number of obs   =       1337
                                                  LR chi2(10)     =      46.19
                                                  Prob > chi2     =     0.0000
Log likelihood = -1387.8455                       Pseudo R2       =     0.0164
------------------------------------------------------------------------------
        test |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
         age |     .00548   .0039204     1.40   0.162    -.0022039    .0131639
         sex |  -.1919798   .1251455    -1.53   0.125    -.4372605    .0533009
      childs |  -.0194531   .0411446    -0.47   0.636     -.100095    .0611887
        educ |  -.0102552   .0210369    -0.49   0.626    -.0514869    .0309764
        born |  -.8933259   .2685336    -3.33   0.001    -1.419642   -.3670098
       _cons |   .9484196   .4877274     1.94   0.052    -.0075085    1.904348
-------------+----------------------------------------------------------------
3            |
         age |  -.0135326   .0049789    -2.72   0.007     -.023291   -.0037742
         sex |   .0420268   .1485803     0.28   0.777    -.2491853    .3332389
      childs |  -.0128663   .0519464    -0.25   0.804    -.1146793    .0889467
        educ |   .0475599   .0257811     1.84   0.065    -.0029701      .09809
        born |   .1980986   .2326138     0.85   0.394    -.2578161    .6540133
       _cons |  -1.054006   .5377872    -1.96   0.050     -2.10805    .0000375
------------------------------------------------------------------------------
(test==2 is the base outcome)
```

```
. mlogtest, iia base
**** Hausman tests of IIA assumption (N=1337)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |      chi2   df   P>chi2   evidence
---------+------------------------------------
       1 |    -1.260    6     ---    ---
       3 |    -0.264    6     ---    ---
       2 |     5.821    6    0.443   for Ho
----------------------------------------------
 Note: If chi2<0, the estimated model does not
 meet asymptotic assumptions of the test.

**** suest-based Hausman tests of IIA assumption (N=1337)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |      chi2   df   P>chi2   evidence
---------+------------------------------------
       1 |     6.923    6    0.328   for Ho
       3 |     4.753    6    0.576   for Ho
       2 |     7.230    6    0.300   for Ho
----------------------------------------------

**** Small-Hsiao tests of IIA assumption (N=1337)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |  lnL(full)  lnL(omit)    chi2   df   P>chi2   evidence
---------+---------------------------------------------------------
       1 |   -277.968   -273.664   8.607    6    0.197   for Ho
       3 |   -351.326   -347.968   6.716    6    0.348   for Ho
       2 |   -235.719   -228.263  14.913    6    0.021   against Ho
-------------------------------------------------------------------
```

Focusing on suest-based test, we can conclude that the null hypothesis of independent alternatives cannot be rejected. If you find a problem with IIA, respecifying the model might help. To do that, you should pinpoint the problem by running the model with each category omitted and compare to the original – if you note any large differences in coefficients, you will see which variables are responsible. For example:

```
. tab affrmact
  favor preference in |
        hiring blacks |      Freq.     Percent        Cum.
----------------------+-----------------------------------
strongly support pref |         84        9.51        9.51
         support pref |         58        6.57       16.08
          oppose pref |        249       28.20       44.28
 strongly oppose pref |        492       55.72      100.00
----------------------+-----------------------------------
                Total |        883      100.00
. gen test2=affrmact
(1882 missing values generated)
. xi:  mlogit test2 age sex childs i.marital i.hhrace
i.marital         _Imarital_1-5       (naturally coded; _Imarital_1 omitted)
i.hhrace          _Ihhrace_1-5        (naturally coded; _Ihhrace_1 omitted)
Iteration 0:   log likelihood = -948.72821
... [Output Omitted]
Iteration 24:  log likelihood = -863.96312
Multinomial logistic regression                   Number of obs   =        876
                                                  LR chi2(33)     =     169.53
                                                  Prob > chi2     =     0.0000
Log likelihood = -863.96312                       Pseudo R2       =     0.0893
------------------------------------------------------------------------------
       test2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
         age |   .0153307   .0103638     1.48   0.139    -.0049819    .0356433
```

```
         sex |   .127623   .2750164     0.46   0.643    -.4113991    .6666452
      childs |   .0914568    .081667     1.12   0.263    -.0686076    .2515212
  _Imarital_2 |   .2375485   .5259401     0.45   0.652    -.7932752    1.268372
  _Imarital_3 |   .0067687   .4447657     0.02   0.988    -.8649561    .8784936
  _Imarital_4 |   .6272958   .6274078     1.00   0.317    -.6024008    1.856992
  _Imarital_5 |   .8868586   .3816766     2.32   0.020     .1387862    1.634931
   _Ihhrace_2 |   2.810721   .3145544     8.94   0.000     2.194206    3.427237
   _Ihhrace_3 |   2.799152    1.44715     1.93   0.053    -.0372097    5.635514
   _Ihhrace_4 |   2.690154   .8063353     3.34   0.001     1.109766    4.270542
   _Ihhrace_5 |   2.085318   .5088164     4.10   0.000     1.088056     3.08258
        _cons |  -4.171851   .7346331    -5.68   0.000    -5.611706   -2.731997
-------------+----------------------------------------------------------------
2            |
         age |   .0021839   .0112815     0.19   0.847    -.0199273    .0242952
         sex |  -.6522365   .3030374    -2.15   0.031    -1.246179   -.0582941
      childs |   .1153213   .0905491     1.27   0.203    -.0621516    .2927943
  _Imarital_2 |   .8113829   .5264184     1.54   0.123    -.2203783    1.843144
  _Imarital_3 |  -.6210244   .5691675    -1.09   0.275    -1.736572    .4945234
  _Imarital_4 |   .8012122   .6138342     1.31   0.192    -.4018807    2.004305
  _Imarital_5 |   .2053164   .4231079     0.49   0.627    -.6239597    1.034593
   _Ihhrace_2 |   1.240227   .4054687     3.06   0.002     .4455226    2.034931
   _Ihhrace_3 |  -33.87909   1.01e+08    -0.00   1.000    -1.98e+08    1.98e+08
   _Ihhrace_4 |   2.620388   .7472531     3.51   0.000     1.155799    4.084977
   _Ihhrace_5 |   1.374765   .5595134     2.46   0.014     .2781388    2.471391
        _cons |  -1.984545   .7423338    -2.67   0.008    -3.439492   -.5295975
-------------+----------------------------------------------------------------
3            |
         age |   .0179628   .0058175     3.09   0.002     .0065606    .0293649
         sex |   .2428758   .1629963     1.49   0.136    -.0765911    .5623427
      childs |  -.0334237   .0547558    -0.61   0.542     -.140743    .0738957
  _Imarital_2 |  -.3085248   .3229562    -0.96   0.339    -.9415074    .3244578
  _Imarital_3 |  -.2243995   .2444331    -0.92   0.359    -.7034796    .2546806
  _Imarital_4 |  -.6237182   .5259484    -1.19   0.236    -1.654558    .4071217
  _Imarital_5 |   .2391751   .2255807     1.06   0.289     -.202955    .6813052
   _Ihhrace_2 |   .7711707   .2608954     2.96   0.003     .2598251    1.282516
   _Ihhrace_3 |  -34.70005   4.86e+07    -0.00   1.000    -9.53e+07    9.53e+07
   _Ihhrace_4 |   .2260227   .8742244     0.26   0.796    -1.487426    1.939471
   _Ihhrace_5 |   .8891223    .376266     2.36   0.018     .1516545     1.62659
        _cons |  -1.953449   .4116147    -4.75   0.000    -2.760199   -1.146699
------------------------------------------------------------------------------
(test2==4 is the base outcome)
. mlogtest, iia base
**** Hausman tests of IIA assumption (N=876)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |      chi2   df   P>chi2   evidence
---------+------------------------------------
       1 |    -0.000    2     ---    ---
       2 |    -0.000    1     ---    ---
       3 |    -0.000    1     ---    ---
       4 |     0.000    1    1.000   for Ho
----------------------------------------------
 Note: If chi2<0, the estimated model does not
 meet asymptotic assumptions of the test.

**** suest-based Hausman tests of IIA assumption (N=876)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |      chi2   df   P>chi2   evidence
---------+------------------------------------
       1 |  3126.170   24    0.000   against Ho
       2 |   3.9e+08   24    0.000   against Ho
       3 |   3.6e+06   24    0.000   against Ho
       4 |   462.165   24    0.000   against Ho
----------------------------------------------
```

```
**** Small-Hsiao tests of IIA assumption (N=876)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |  lnL(full)  lnL(omit)    chi2   df   P>chi2   evidence
---------+-----------------------------------------------------
       1 |   -446.534   -325.117 242.835   22    0.000   against Ho
       2 |   -448.469   -309.574 277.790   24    0.000   against Ho
       3 |   -191.974   -162.549  58.850   24    0.000   against Ho
       4 |   -214.816   -135.774 158.083   24    0.000   against Ho
```

```
*Suest test indicates a problem. Let's omit categories one by one:

. qui xi:  mlogit test2 age sex childs i.marital i.hhrace
. est store full

. qui xi:  mlogit test2 age sex childs i.marital i.hhrace if test2~=1
. est store drop1

. qui xi:  mlogit test2 age sex childs i.marital i.hhrace if test2~=2
. est store drop2

. qui xi: mlogit test2 age sex childs i.marital i.hhrace if test2~=3
. est store drop3

. est table full drop1 drop2 drop3
-----------------------------------------------------------------
    Variable |    full        drop1        drop2        drop3
-------------+---------------------------------------------------
1            |
         age |   .0153307                 .01472615    .02070928
         sex |  .12762301                 .15882882    .11544375
      childs |  .09145679                  .0922736     .0850332
 _Imarital_2 |  .23754847                 .21510493    .04048313
 _Imarital_3 |  .00676871                 .10725132    .02622092
 _Imarital_4 |  .62729582                 .59384189    .62849184
 _Imarital_5 |  .88685865                  .8914914    .90067504
  _Ihhrace_2 |  2.8107214                  2.788965    2.8695328
  _Ihhrace_3 |  2.7991523                 2.7870629    2.8390566
  _Ihhrace_4 |  2.6901537                 2.7009729    2.7217418
  _Ihhrace_5 |  2.0853179                 2.1239666     2.083009
       _cons | -4.1718511                -4.2023336   -4.3922676
-------------+---------------------------------------------------
2            |
         age |  .00218393    .00203868                 .00454722
         sex | -.65223653   -.62790591                 -.6734499
      childs |  .11532131    .11734368                 .09535341
 _Imarital_2 |  .81138292    .76427802                 .75428227
 _Imarital_3 | -.62102443   -.64975772                -.61644615
 _Imarital_4 |  .80121222    .80263237                 .82745781
 _Imarital_5 |  .20531642    .20092336                 .17396716
  _Ihhrace_2 |  1.2402267    1.2351053                 1.2668539
  _Ihhrace_3 | -33.879087   -29.457203                -32.048022
  _Ihhrace_4 |  2.6203882    2.6111518                 2.7040764
  _Ihhrace_5 |  1.3747649    1.3453995                 1.3515568
       _cons |  -1.984545   -2.0046142                 -2.014668
-------------+---------------------------------------------------
3            |
         age |  .01796278    .01740244    .01802241
         sex |   .2428758    .23767733    .25447095
      childs | -.03342367   -.03736422   -.03094094
 _Imarital_2 | -.30852481   -.28572923   -.31060192
 _Imarital_3 |  -.2243995   -.24292323   -.20797225
 _Imarital_4 | -.62371824   -.60176465   -.63467656
 _Imarital_5 |  .23917513    .23094031    .24950962
```

```
  _Ihhrace_2 |  .77117075    .74845578    .75962479
  _Ihhrace_3 | -34.700053   -30.292659   -31.026633
  _Ihhrace_4 |  .22602272    .24361779    .21618095
  _Ihhrace_5 |  .88912232    .88572906    .92468621
       _cons | -1.9534491   -1.9072182   -1.9839445
------------------------------------------------------------------
```

We note the huge coefficient and substantial fluctuations for _Ihhrace)3. Let's look into that variable:

```
. tab hhrace if e(sample)
race of household |      Freq.     Percent        Cum.
------------------+-----------------------------------
            white |        689       78.65       78.65
            black |        129       14.73       93.38
      amer indian |          2        0.23       93.61
asiatic, oriental |         13        1.48       95.09
     other, mixed |         43        4.91      100.00
------------------+-----------------------------------
            Total |        876      100.00
```

There we have it – there are only 2 people in that group! Let's recode hhrace to have a more acceptable category distribution:

```
. recode hhrace (3/5=3), gen(hhrace3)
(200 differences between hhrace and hhrace3)
. tab hhrace3 if e(sample)
  RECODE of |
     hhrace |
   (race of |
 household) |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |        689       78.65       78.65
          2 |        129       14.73       93.38
          3 |         58        6.62      100.00
------------+-----------------------------------
      Total |        876      100.00
```

Much better. Let's try our mlogit model.

```
. xi:  mlogit test2 age sex childs i.marital i.hhrace3
i.marital         _Imarital_1-5       (naturally coded; _Imarital_1 omitted)
i.hhrace3         _Ihhrace3_1-3       (naturally coded; _Ihhrace3_1 omitted)
Iteration 0:   log likelihood = -948.72821
Iteration 1:   log likelihood = -897.10827
Iteration 2:   log likelihood = -868.02319
Iteration 3:   log likelihood = -867.36068
Iteration 4:   log likelihood = -867.35988
Multinomial logistic regression                   Number of obs   =        876
                                                  LR chi2(27)     =     162.74
                                                  Prob > chi2     =     0.0000
Log likelihood = -867.35988                       Pseudo R2       =     0.0858
------------------------------------------------------------------------------
       test2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
         age |   .0155303   .0103278     1.50   0.133    -.0047119    .0357725
         sex |   .1407728   .2735739     0.51   0.607    -.3954222    .6769678
      childs |    .087027   .0814665     1.07   0.285    -.0726443    .2466983
 _Imarital_2 |   .2213172   .5249781     0.42   0.673     -.807621    1.250255
 _Imarital_3 |  -.0244227   .4426918    -0.06   0.956    -.8920828    .8432373
 _Imarital_4 |   .6099481   .6269465     0.97   0.331    -.6188445    1.838741
 _Imarital_5 |   .8792547   .3804179     2.31   0.021     .1336493     1.62486
 _Ihhrace3_2 |   2.814086   .3147167     8.94   0.000     2.197253     3.43092
 _Ihhrace3_3 |   2.277384   .4377921     5.20   0.000     1.419328    3.135441
```

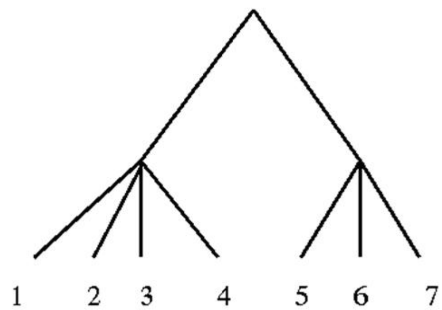
```
       _cons |  -4.184655   .7315309    -5.72   0.000     -5.61843   -2.750881
-------------+----------------------------------------------------------------
2            |
         age |   .0025737   .0112145     0.23   0.818    -.0194064    .0245538
         sex |  -.6593543    .301151    -2.19   0.029    -1.249599   -.0691092
      childs |   .1050154   .0903734     1.16   0.245    -.0721133    .2821441
 _Imarital_2 |   .7808888   .5247843     1.49   0.137    -.2476695    1.809447
 _Imarital_3 |   -.675004   .5673385    -1.19   0.234    -1.786967    .4369591
 _Imarital_4 |   .7710688   .6132029     1.26   0.209    -.4307867    1.972924
 _Imarital_5 |   .1775124   .4203233     0.42   0.673     -.646306    1.001331
 _Ihhrace3_2 |   1.253918   .4054017     3.09   0.002     .4593453    2.048491
 _Ihhrace3_3 |   1.728979   .4529444     3.82   0.000     .8412239    2.616734
       _cons |  -1.953793   .7356396    -2.66   0.008     -3.39562   -.5119657
-------------+----------------------------------------------------------------
3            |
         age |   .0178654   .0058183     3.07   0.002     .0064618     .029269
         sex |   .2379156   .1628584     1.46   0.144     -.081281    .5571122
      childs |  -.0312925   .0546871    -0.57   0.567    -.1384771    .0758922
 _Imarital_2 |  -.3001936   .3228967    -0.93   0.353    -.9330595    .3326722
 _Imarital_3 |  -.2112982   .2439783    -0.87   0.386     -.689487    .2668905
 _Imarital_4 |  -.6143016    .525753    -1.17   0.243    -1.644759    .4161553
 _Imarital_5 |   .2416129   .2254549     1.07   0.284    -.2002707    .6834964
 _Ihhrace3_2 |   .7698931   .2608357     2.95   0.003     .2586644    1.281122
 _Ihhrace3_3 |   .7236144   .3438067     2.10   0.035     .0497657    1.397463
       _cons |  -1.947955   .4115944    -4.73   0.000    -2.754665   -1.141245
------------------------------------------------------------------------------
(test2==4 is the base outcome)
```

Note that it took much fewer iterations to estimate this model than the previous one!

```
. mlogtest, iia base

**** Hausman tests of IIA assumption (N=876)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |      chi2   df   P>chi2   evidence
---------+------------------------------------
       1 |     6.715   20    0.998   for Ho
       2 |     1.550   19    1.000   for Ho
       3 |    -0.688   20     ---    ---
       4 |     2.697   20    1.000   for Ho
----------------------------------------------
 Note: If chi2<0, the estimated model does not
 meet asymptotic assumptions of the test.

**** suest-based Hausman tests of IIA assumption (N=876)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |      chi2   df   P>chi2   evidence
---------+------------------------------------
       1 |    10.836   20    0.950   for Ho
       2 |     9.382   20    0.978   for Ho
       3 |     8.216   20    0.990   for Ho
       4 |     9.947   20    0.969   for Ho
----------------------------------------------

**** Small-Hsiao tests of IIA assumption (N=876)
 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.
 Omitted |  lnL(full)  lnL(omit)    chi2   df   P>chi2   evidence
---------+---------------------------------------------------------
       1 |   -317.738   -306.449  22.578   20    0.310   for Ho
       2 |   -332.564   -323.061  19.005   20    0.521   for Ho
       3 |   -159.750   -153.830  11.838   20    0.922   for Ho
       4 |   -140.806   -128.628  24.355   20    0.227   for Ho
-------------------------------------------------------------------
```

Problem solved! But respecifying the model doesn't always help. The alternatives may be genuinely non-independent. So in addition to implementing the test, users of multinomial logit should think carefully about the model – multinomial logit should be used when outcome categories can be plausibly assumed distinct and weighed independently in the eyes of each decision maker.

If IIA indeed assumption does not hold, one alternative that allows partial relaxation of that assumption is a nested model, i.e. a model in which some categories are considered to share a nest together. IIA holds within a nest but not across nests.



The commands in Stata that you'd want to look into are nlogit and nlogitrum, but the data would have to be restructured with each alternative being a separate observation (separate line in the dataset) – see chapter 7 in Long and Freese as well as the following paper:
http://www.mea.uni-mannheim.de/mea_neu/pages/files/nopage_pubs/dp16.pdf

2. Multicollinearity.
As was the case for binary and ordered logit, we can test for multicollinearity by running OLS model instead of multinomial logit and using vif.

3. Linearity and Additivity.
As usual, you should start the process by examining the univariate distributions and the bivariate relationships. Like in ordered logit, in order to examine bivariate relationships as well as to conduct many diagnostics, we should create the dichotomies corresponding to each equation:

```
. gen natarmsy1=(natarmsy==1) if (natarmsy==1 | natarmsy==3)
(2008 missing values generated)
. gen natarmsy2=(natarmsy==2) if (natarmsy==2 | natarmsy==3)
(1894 missing values generated)
```

For each of these dichotomous variables, we can then obtain lowess plots, just like we did for ordered logit. We can then use these dichotomies to run binary logits and conduct various multivariate diagnostics.

```
. logit natarmsy1 age sex childs educ born
Logistic regression                               Number of obs   =        751
                                                  LR chi2(5)      =      42.34
                                                  Prob > chi2     =     0.0000
Log likelihood = -473.24011                       Pseudo R2       =     0.0428
------------------------------------------------------------------------------
   natarmsy1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |    .020441   .0052802     3.87   0.000      .010092      .03079
         sex |   -.257952    .157136    -1.64   0.101    -.5659329     .050029
      childs |  -.0009124   .0532109    -0.02   0.986    -.1052039    .1033791
        educ |  -.0584523   .0282196    -2.07   0.038    -.1137618   -.0031428
        born |  -1.038649   .3007153    -3.45   0.001     -1.62804   -.4492576
       _cons |    1.91543   .5894602     3.25   0.001     .7601091     3.07075
------------------------------------------------------------------------------
```

```
. logit natarmsy2 age sex childs educ born
Logistic regression                               Number of obs   =        863
                                                  LR chi2(5)      =      15.22
                                                  Prob > chi2     =     0.0095
Log likelihood = -534.01018                       Pseudo R2       =     0.0140
------------------------------------------------------------------------------
   natarmsy2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .0128336   .0049079     2.61   0.009     .0032143    .0224529
         sex |  -.0536544   .1496431    -0.36   0.720    -.3469494    .2396406
      childs |   .0114876   .0522925     0.22   0.826    -.0910039    .1139791
        educ |  -.0426433   .0247853    -1.72   0.085    -.0912217     .005935
        born |  -.2192112    .232668    -0.94   0.346     -.675232    .2368097
       _cons |   1.062732   .5271903     2.02   0.044     .0294579    2.096006
------------------------------------------------------------------------------
```

Note that in order for this approach to work, each binary model should look similar to the corresponding equation of the multinomial model. That will typically be the case if the IIA assumption holds. But let's compare:

```
. mlogit natarmsy age sex childs educ born, b(3)
Multinomial logistic regression                   Number of obs   =       1337
                                                  LR chi2(10)     =      46.19
                                                  Prob > chi2     =     0.0000
Log likelihood = -1387.8455                       Pseudo R2       =     0.0164
------------------------------------------------------------------------------
    natarmsy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
too little   |
         age |   .0190126   .0051423     3.70   0.000     .0089338    .0290914
         sex |  -.2340065   .1550509    -1.51   0.131    -.5379007    .0698876
      childs |  -.0065869   .0537937    -0.12   0.903    -.1120205    .0988468
        educ |  -.0578152   .0270313    -2.14   0.032    -.1107956   -.0048347
        born |  -1.091425   .2962101    -3.68   0.000    -1.671986   -.5108634
       _cons |   2.002426   .5858732     3.42   0.001     .8541352    3.150716
-------------+----------------------------------------------------------------
about right  |
         age |   .0135326   .0049789     2.72   0.007     .0037742     .023291
         sex |  -.0420268   .1485803    -0.28   0.777    -.3332389    .2491853
      childs |   .0128663   .0519464     0.25   0.804    -.0889467    .1146793
        educ |  -.0475599   .0257811    -1.84   0.065      -.09809    .0029701
        born |  -.1980986   .2326138    -0.85   0.394    -.6540133    .2578161
       _cons |   1.054006   .5377872     1.96   0.050    -.0000375     2.10805
------------------------------------------------------------------------------
(natarmsy==too much is the base outcome)
```

Looks similar. For each of these binary models, you can do the full range of linearity diagnostics that are appropriate for binary models – i.e., run Box-Tidwell test, etc. Like with ordered logit, you should be aware of the possibility that you might find different patterns for different binary models; in that case, you'll have to figure out how to reconcile them in mlogit.

You can also use fitint for these binary models (fitint does not work with mlogit), although keep in mind the warnings regarding interpreting interactions mentioned in the discussion of binary logit.

4. Outliers and Influential Observations

In order to do unusual data diagnostics for multinomial logit, we should also rely on separate binary models we've used in previous steps. All the same methods we discussed for binary logit apply here as well, and like in ordered logit, the fact that you'll have to do a separate search for unusual data for each binary model may complicate things if they suggest that different observations are influential. Make sure that you test the potential effects of these influential observations on your mlogit model (rather than just on individual binary logits).

5. Error term distribution

Like we did for binary and ordered logit, we can obtain robust standard errors for the multinomial logit model in order to check whether our assumptions about error distribution hold (compare with the model on pp.1-2):

```
. mlogit natarmsy age sex childs educ born, robust
Multinomial logistic regression                   Number of obs   =       1337
                                                  Wald chi2(10)   =      40.85
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -1387.8455                 Pseudo R2       =     0.0164
------------------------------------------------------------------------------
             |               Robust
    natarmsy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
too little   |
         age |     .00548   .0039155     1.40   0.162    -.0021943    .0131543
         sex |  -.1919798   .1254863    -1.53   0.126    -.4379285    .0539689
      childs |  -.0194531   .0405578    -0.48   0.631    -.0989449    .0600386
        educ |  -.0102552    .019935    -0.51   0.607     -.049327    .0288166
        born |  -.8933259   .2701132    -3.31   0.001    -1.422738   -.3639138
       _cons |   .9484196   .4706752     2.02   0.044     .0259132    1.870926
-------------+----------------------------------------------------------------
too much     |
         age |  -.0135326   .0050701    -2.67   0.008    -.0234697   -.0035955
         sex |   .0420268   .1482007     0.28   0.777    -.2484413    .3324949
      childs |  -.0128663   .0534559    -0.24   0.810     -.117638    .0919054
        educ |   .0475599   .0278666     1.71   0.088    -.0070576    .1021775
        born |   .1980986   .2302914     0.86   0.390    -.2532642    .6494614
       _cons |  -1.054006   .5745375    -1.83   0.067    -2.180079    .0720669
------------------------------------------------------------------------------
(natarmsy==about right is the base outcome)
```

Example of multinomial logit:

Reynolds, Jeremy. 2004. "When Too Much Is Not Enough: Actual and Preferred Work Hours in the United States and Abroad." *Sociological Forum, 19*: 89-120.

Questions to answer about the article:

1. What are the dependent and the independent variables in this analysis?
2. What is reported in Table IV? How can we interpret these results? How do the authors discuss these results in the text?
3. What is presented in Figures 1-3? How can we interpret these results?
4. In addition to what the authors chose to present, how else could they have presented their results?
5. What measures of model fit and model diagnostics are presented? What diagnostics and potential problems did the authors not address?