What is this text about?

How to use Long & Freese routines in multinomial logit problems.
Demonstrated with the example of chapter 6 of Long & Freese's textbook[1] .
This text is a summarization of the Long & Freese chapter.

Whom is this text for?

Who urgently need these routines but do not have the textbook or time to read it.

Contents

[1] Long JS, Freese J (2006) Regression for Categorical Dependent Variables Using Stata. Stata Press

Reinstall SPOST

You might have to reinstall the Long & Freese routines SPOST.
The problems for STATA 10 are now fixed.

See: http://www.indiana.edu/~jslsoc/web_spost/sp_news.htm

How to reinstall SPOST (for STATA 9 and STATA 10):

net from http://www.indiana.edu/~jslsoc/stata/
net install spost9_ado, replace

The model [2]

$$\pi_j(x) := P(Y = j \mid x)$$

$$\text{Baseline - category logit}: \left(\frac{\pi_j(x)}{\pi_J(x)}\right) \text{for } j = 1,\ldots,J$$

The multinomial logit model (MNLM) = polytomous logit model = discrete choice model is:

$$\ln\left(\frac{\pi_j(x)}{\pi_J(x)}\right) = \alpha_j + ß_j^{'}x \quad \text{for } j = 1,\ldots,J-1$$

where **J is the baseline category**.

The model simultaneously describes the effect of x on J-1 baseline category logits

Other pairs of response categories can be derived since:

$$\ln\left(\frac{\pi_a(x)}{\pi_b(x)}\right) = \ln\left(\frac{\pi_a(x)}{\pi_J(x)}\right) - \ln\left(\frac{\pi_b(x)}{\pi_J(x)}\right)$$

Response probabilities are derived as

$$\pi_j(x) = \frac{\exp(\alpha_j + ß_j^{'}x)}{1 + \sum_{h=1}^{J-1} \exp(\alpha_h + ß_h^{'}x)} = \frac{\exp(y_j)}{1 + \sum_{h=1}^{J-1} \exp(y_h)}$$

The odds ratio of outcome Y=j versus outcome Y=J for x=a versus x=b is

$$OR_{j,J}(a,b) = \frac{\dfrac{P(Y = j \mid a)}{P(Y = J \mid a)}}{\dfrac{P(Y = j \mid b)}{P(Y = J \mid b)}} = \frac{\dfrac{\pi_j(a)}{\pi_J(a)}}{\dfrac{\pi_j(b)}{\pi_J(b)}}$$

[2] Agresti A (2002) Categorical data analysis. Wiley, New York, pp. 268

The example file in Long & Freese consists of 337 cases from the 1982 General Social Survey (GSS)
http://www.stata-press.com/data/lf2/nomocc2

Variable	**Label**	**Value labels**
occ	Occupation	1=Menial 2=BlueCol 3=Craft 4=WhiteCol 5=Prof
white	Race: 1=white 0=nonwhite	
ed	Years of education	
exper	Years of work experience	

Input data file

```
open the file

use http://www.stata-press.com/data/lf2/nomocc2,clear
```

do some labeling

```
label def lbwhite 0 NonWhite 1 White
label val white lbwhite
label variable white Race
```

creating a new variable occ3 which has 3 categories of types of work instead of the original 5 categories for variable occ:

```
recode occ (1/3=1 "Manual" ) (4=2 "WhiteCol") (5=3 "Prof"), gen(occ3) label (lbocc3) test
label variable occ3 "Occupation simplified into 3 classes"
```

save the file

```
save "nomocc2_own.dta"
```

Variable	**Label**	**Value labels**
occ	Occupation	1=Menial 2=BlueCol 3=Craft 4=WhiteCol 5=Prof
white	Race	1 = white 0=nonwhite
ed	Years of education	
exper	Years of work experience	
occ3	Occupation simplified into 3 classes	1=Manual 2=WhiteCol 3=Prof

Multinomial regression: OCC3 = white

mlogit occ3 white

```
Multinomial logistic regression                   Number of obs   =        337
                                                  LR chi2(2)      =       2.33
                                                  Prob > chi2     =     0.3119
Log likelihood = -319.92643                       Pseudo R2       =     0.0036

------------------------------------------------------------------------------
        occ3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
WhiteCol     |
       white |    .808908    .7644154     1.06   0.290    -.6893187    2.307135
       _cons |  -2.251292    .7433904    -3.03   0.002     -3.70831   -.7942734
-------------+----------------------------------------------------------------
Prof         |
       white |   .5465437     .459427     1.19   0.234    -.3539167    1.447004
       _cons |  -.9985288    .4421411    -2.26   0.024     -1.86511   -.1319481
------------------------------------------------------------------------------
(occ3==Manual is the base outcome)
```

now with the option "relative risk" ~ Odds ratio:

mlogit occ3 white,rrr

```
Multinomial logistic regression                   Number of obs   =        337
                                                  LR chi2(2)      =       2.33
                                                  Prob > chi2     =     0.3119
Log likelihood = -319.92643                       Pseudo R2       =     0.0036

------------------------------------------------------------------------------
        occ3 |        RRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
WhiteCol     |
       white |   2.245455     1.71646     1.06   0.290     .5019179     10.0456
-------------+----------------------------------------------------------------
Prof         |
       white |   1.727273    .7935558     1.19   0.234     .7019334    4.250362
------------------------------------------------------------------------------
(occ3==Manual is the base outcome)
```

With listcoef you will get an overview of all coefficients and odds ratios for all comparisons

listcoef

```
mlogit (N=337): Factor Change in the Odds of occ3

Variable: white (sd=.27642268)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
WhiteCol-Prof     |   0.26236    0.319   0.750   1.3000   1.0752
WhiteCol-Manual   |   0.80891    1.058   0.290   2.2455   1.2506
Prof    -WhiteCol |  -0.26236   -0.319   0.750   0.7692   0.9300
Prof    -Manual   |   0.54654    1.190   0.234   1.7273   1.1631
Manual  -WhiteCol |  -0.80891   -1.058   0.290   0.4453   0.7996
Manual  -Prof     |  -0.54654   -1.190   0.234   0.5789   0.8598
----------------------------------------------------------------
```

Example to read:

The Odds ratio of a "White Collar job" against a "Manual work job" is 2.246 times higher for white persons than for black people.

Now lets recalculate this Odds ratio with probabilities

With "prtab" we can find the probabilities and recalculate the odds ratio from listcoef above:

For "white"	we have Odd for "White collar"/"Manual"	= 0.1262 / 0.5340	= 0.2363
For "non white"	we have Odd for "White collar"/"Manual"	= 0.0714 / 0.6786	= 0.1052
The odds ratio	0.2363 / 0.1052 = 2.246		

prtab white

```
mlogit: Predicted probabilities for occ3

Predicted probability of outcome 2 (WhiteCol)

----------------------
     Race | Prediction
----------+-----------
 NonWhite |     0.0714
    White |     0.1262
----------------------

Predicted probability of outcome 3 (Prof)

----------------------
     Race | Prediction
----------+-----------
 NonWhite |     0.2500
    White |     0.3398
----------------------

Predicted probability of outcome 1 (Manual)

----------------------
     Race | Prediction
----------+-----------
 NonWhite |     0.6786
    White |     0.5340
----------------------

        white
x=  .91691395
```

You can also find this probabilities in this example by using the cross table

tab2 white occ3, row

```
           |   Occupation simplified into 3
           |             classes
      Race |    Manual   WhiteCol        Prof |     Total
-----------+---------------------------------+----------
  NonWhite |        19          2           7 |        28
           |     67.86       7.14       25.00 |    100.00
-----------+---------------------------------+----------
     White |       165         39         105 |       309
           |     53.40      12.62       33.98 |    100.00
-----------+---------------------------------+----------
     Total |       184         41         112 |       337
           |     54.60      12.17       33.23 |    100.00
```

After these demonstrations of how to read and interpret odds ratios it is quite obvious why people prefer ordinary probabilities to interpret and present results.

Long & Freese developed the routines "mlogview" (menu) or "mlogplot" (direct input) to produce graphical results in multinomial logistic regression.

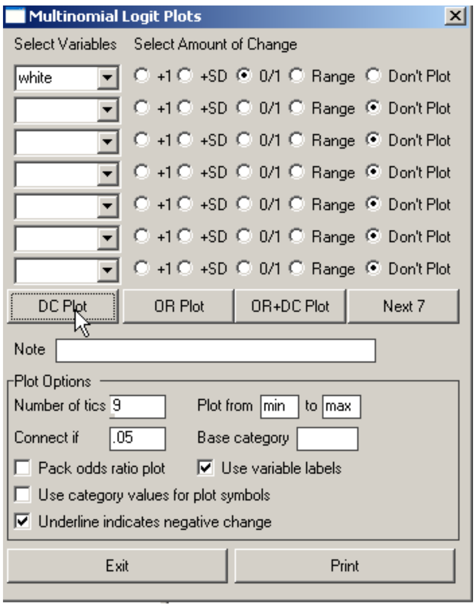
Before you can call this routine you have to call "prchange" so that "mlogview" can use its internal results.

prchange

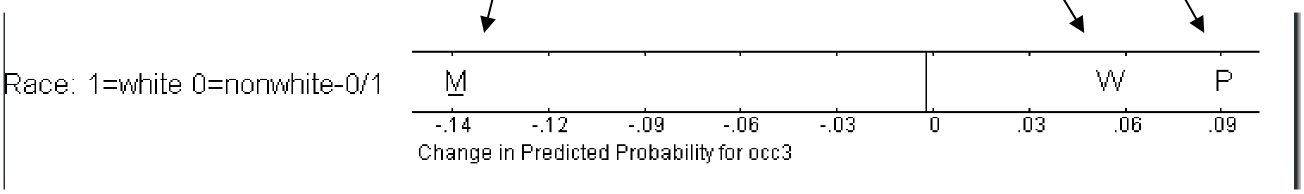
```
mlogit: Changes in Probabilities for occ3
white
           Avg|Chg|    WhiteCol        Prof      Manual
    0->1  .09639388   .05478502   .08980581  -.1445908
          WhiteCol        Prof      Manual
Pr(y|x)  .12082359   .33246318   .54671323
          white
    x=   .916914
sd(x)=   .276423
```

mlogview

Now, we choose DC Plot = Discrete change Plot

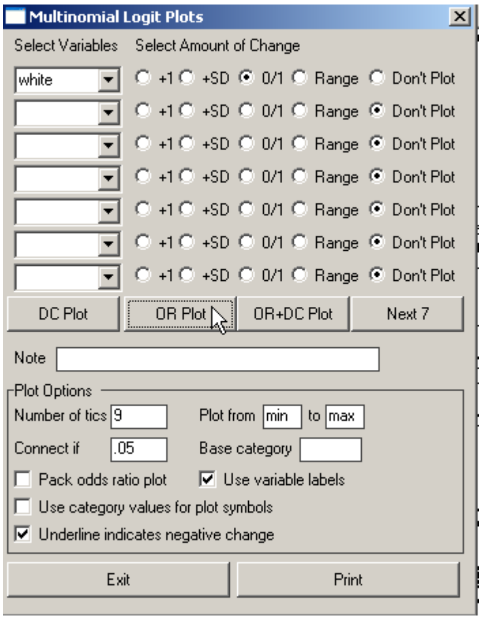


alternative direct: `mlogplot white, std(0) p(.05) dc labels sign ntics(9)`

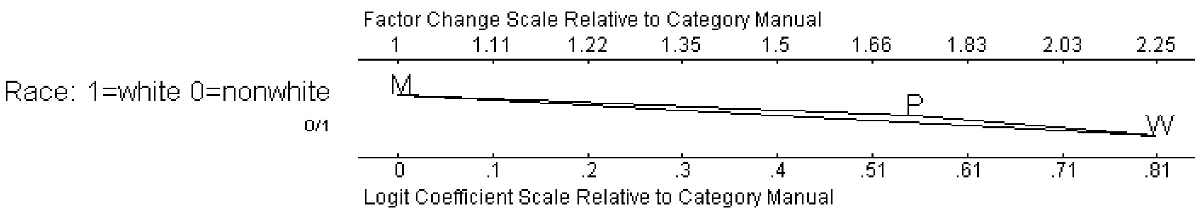


You can also plot the odds ratios:

```
mlogview
```



alternative direct: `mlogplot white, std(0) p(.05) or labels sign ntics(9)`



Where

$W = OR_{WhiteCol,Manual}$ (white, nonwhite)

$P = OR_{Prof,Manual}$ (white, nonwhite)

$M = OR_{Manual,Manual}$ (white, nonwhite)=1

A line between two categories indicates: "**not** a significant difference"

Multinomial regression: OCC3 = white + education + experience

mlogit occ3 white ed exper

```
Multinomial logistic regression                   Number of obs   =        337
                                                  LR chi2(6)      =     154.22
                                                  Prob > chi2     =     0.0000
Log likelihood = -243.98352                       Pseudo R2       =     0.2401

------------------------------------------------------------------------------
        occ3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
WhiteCol     |
       white |   1.018823   .7930599     1.28   0.199    -.5355457    2.573192
          ed |   .3390136    .087539     3.87   0.000     .1674402    .5105869
       exper |   .0188215   .0128899     1.46   0.144    -.0064423    .0440852
       _cons |  -7.060006   1.515697    -4.66   0.000    -10.03072   -4.089295
-------------+----------------------------------------------------------------
Prof         |
       white |   1.240769   .6196045     2.00   0.045     .0263662    2.455171
          ed |    .761776   .0844286     9.02   0.000      .596299     .927253
       exper |   .0194976   .0116698     1.67   0.095    -.0033748    .0423701
       _cons |  -12.30889    1.44883    -8.50   0.000    -15.14855   -9.469237
------------------------------------------------------------------------------
(occ3==Manual is the base outcome)
```

estimates store full

mlogit occ3 white ed

```
Multinomial logistic regression                   Number of obs   =        337
                                                  LR chi2(4)      =     150.43
                                                  Prob > chi2     =     0.0000
Log likelihood = -245.87455                       Pseudo R2       =     0.2343

------------------------------------------------------------------------------
        occ3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
WhiteCol     |
       white |   .9570256   .7910705     1.21   0.226     -.593444    2.507495
          ed |   .3127784   .0866336     3.61   0.000     .1429796    .4825771
       _cons |  -6.283392   1.421957    -4.42   0.000    -9.070375   -3.496408
-------------+----------------------------------------------------------------
Prof         |
       white |   1.191351   .6175922     1.93   0.054    -.0191072     2.40181
          ed |   .7392936   .0827332     8.94   0.000     .5771395    .9014478
       _cons |  -11.58107   1.363245    -8.50   0.000    -14.25298   -8.909155
------------------------------------------------------------------------------
(occ3==Manual is the base outcome)
```

estimates store short

lrtest full short

```
Likelihood-ratio test                                 LR chi2(2)  =      3.78
(Assumption: short nested in full)                    Prob > chi2 =    0.1509
```

Just to check whether STATA is able to detect the full model itself:

lrtest short full

```
Likelihood-ratio test                                 LR chi2(2)  =      3.78
(Assumption: short nested in full)                    Prob > chi2 =    0.1509
```

mlogit occ3 white ed exper

```
Multinomial logistic regression                   Number of obs   =        337
                                                  LR chi2(6)      =     154.22
                                                  Prob > chi2     =     0.0000
Log likelihood = -243.98352                       Pseudo R2       =     0.2401

------------------------------------------------------------------------------
        occ3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
WhiteCol     |
       white |   1.018823   .7930599     1.28   0.199    -.5355457    2.573192
          ed |   .3390136    .087539     3.87   0.000     .1674402    .5105869
       exper |   .0188215   .0128899     1.46   0.144    -.0064423    .0440852
       _cons |  -7.060006   1.515697    -4.66   0.000    -10.03072   -4.089295
-------------+----------------------------------------------------------------
Prof         |
       white |   1.240769   .6196045     2.00   0.045     .0263662    2.455171
          ed |    .761776   .0844286     9.02   0.000      .596299     .927253
       exper |   .0194976   .0116698     1.67   0.095    -.0033748    .0423701
       _cons |  -12.30889    1.44883    -8.50   0.000    -15.14855   -9.469237
------------------------------------------------------------------------------
(occ3==Manual is the base outcome)
```

mlogtest, lr

```
**** Likelihood-ratio tests for independent variables (N=337)

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

             |      chi2   df   P>chi2
-------------+-------------------------
       white |     4.949    2    0.084
          ed |   150.523    2    0.000
       exper |     3.782    2    0.151
---------------------------------------
```

This alternative to lrtest is preferred by Long & Freese because it "automatically computes the tests for all variables by making repeated calls to rltest" (p.236).

Later we will see another application of this test: Combining categories

Now let's see the result for listcoef, prtab, prchange and mlogview

listcoef white, help

```
mlogit (N=337): Factor Change in the Odds of occ3

Variable: white (sd=.27642268)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
WhiteCol-Prof     |  -0.23433   -0.270   0.787   0.7911   0.9373
WhiteCol-Manual   |   0.95703    1.210   0.226   2.6039   1.3028
Prof    -WhiteCol |   0.23433    0.270   0.787   1.2641   1.0669
Prof    -Manual   |   1.19135    1.929   0.054   3.2915   1.3900
Manual  -WhiteCol |  -0.95703   -1.210   0.226   0.3840   0.7676
Manual  -Prof     |  -1.19135   -1.929   0.054   0.3038   0.7194
----------------------------------------------------------------
       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
```

listcoef white, pvalue(0.1)

```
mlogit (N=337): Factor Change in the Odds of occ3 when P>|z| < 0.10

Variable: white (sd=.27642268)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
Prof    -Manual   |   1.19135    1.929   0.054   3.2915   1.3900
Manual  -Prof     |  -1.19135   -1.929   0.054   0.3038   0.7194
----------------------------------------------------------------
```

listcoef ed

```
mlogit (N=337): Factor Change in the Odds of occ3

Variable: ed (sd=2.9464271)

Odds comparing    |
Alternative 1     |
to Alternative 2  |      b         z     P>|z|     e^b   e^bStdX
------------------+---------------------------------------------
WhiteCol-Prof     |  -0.42652   -4.710   0.000   0.6528   0.2846
WhiteCol-Manual   |   0.31278    3.610   0.000   1.3672   2.5133
Prof    -WhiteCol |   0.42652    4.710   0.000   1.5319   3.5138
Prof    -Manual   |   0.73929    8.936   0.000   2.0945   8.8311
Manual  -WhiteCol |  -0.31278   -3.610   0.000   0.7314   0.3979
Manual  -Prof     |  -0.73929   -8.936   0.000   0.4775   0.1132
----------------------------------------------------------------
```

prtab ed white, outcome(1)

```
mlogit: Predicted probabilities of outcome 1 (Manual) for occ3
------------------------------
          |   Race: 1=white
Years of  |     0=nonwhite
education | NonWhite     White
----------+-------------------
        3 |   0.9952    0.9875
        6 |   0.9872    0.9668
        7 |   0.9820    0.9534
        8 |   0.9744    0.9339
        9 |   0.9630    0.9050
       10 |   0.9454    0.8614
       11 |   0.9174    0.7960
       12 |   0.8724    0.7010
       13 |   0.8011    0.5739
       14 |   0.6940    0.4257
       15 |   0.5509    0.2822
       16 |   0.3907    0.1683
       17 |   0.2461    0.0924
       18 |   0.1401    0.0480
       19 |   0.0742    0.0240
       20 |   0.0376    0.0118
------------------------------
        white         ed
x=  .91691395  13.094955
```

prtab ed white, outcome(2)

```
mlogit: Predicted probabilities of outcome 2 (WhiteCol) for occ3
------------------------------
          |   Race: 1=white
Years of  |     0=nonwhite
education | NonWhite     White
----------+-------------------
        3 |   0.0047    0.0123
        6 |   0.0120    0.0307
        7 |   0.0164    0.0414
        8 |   0.0222    0.0554
        9 |   0.0300    0.0734
       10 |   0.0403    0.0956
       11 |   0.0534    0.1208
       12 |   0.0695    0.1454
       13 |   0.0872    0.1627
       14 |   0.1033    0.1651
       15 |   0.1122    0.1496
       16 |   0.1088    0.1220
       17 |   0.0936    0.0916
       18 |   0.0729    0.0650
       19 |   0.0528    0.0445
       20 |   0.0365    0.0299
------------------------------
        white         ed
x=  .91691395  13.094955
```

prtab ed white, outcome(3)

```
mlogit: Predicted probabilities of outcome 3 (Prof) for occ3
------------------------------
          |   Race: 1=white
Years of  |     0=nonwhite
education | NonWhite     White
----------+-------------------
        3 |   0.0001    0.0003
        6 |   0.0008    0.0025
        7 |   0.0016    0.0052
        8 |   0.0034    0.0106
        9 |   0.0070    0.0216
       10 |   0.0143    0.0430
       11 |   0.0292    0.0833
       12 |   0.0581    0.1536
       13 |   0.1117    0.2634
       14 |   0.2027    0.4092
       15 |   0.3369    0.5682
       16 |   0.5005    0.7097
       17 |   0.6603    0.8160
       18 |   0.7871    0.8871
       19 |   0.8731    0.9314
       20 |   0.9259    0.9583
------------------------------

        white         ed
x=  .91691395  13.094955
```

Now let's plot the probabilities

First, we have to calculate all probabilities we wanted to plot

prgen ed, x(white=1) from(6) to (20) generate(white) ncases(15)
prgen ed, x(white=0) from(6) to (20) generate(nowhite) ncases(15)

These two commands generate each 7 variables with values

variable	Label
white**x**	Years of education ← **this is the x axes for the plot**
white**p2**	pr(WhiteCol)=Pr(2)
white**p3**	pr(Prof)=Pr(3)
white**p1**	pr(Manual)=Pr(1)
whites2	pr(y<=2)
whites3	pr(y<=3)
whites1	pr(y<=1)
nowhite**x**	Years of education ← **this is the x axes for the plot (same values like the one above)**
nowhite**p2**	pr(WhiteCol)=Pr(2)
nowhite**p3**	pr(Prof)=Pr(3)
nowhite**p1**	pr(Manual)=Pr(1)
nowhites2	pr(y<=2)
nowhites3	pr(y<=3)
nowhites1	pr(y<=1)

From these new variables we need

- the variables ending in …**p2** …**p3** …**p1** they contain the probabilities for the three choices
- one of variables ending in …**x** they contain the values for the x axes (years of education)

We do not need the new variables ending in …s2 …s3 …s1 because they contain the sum of probabilities (used in ordinal logit models).

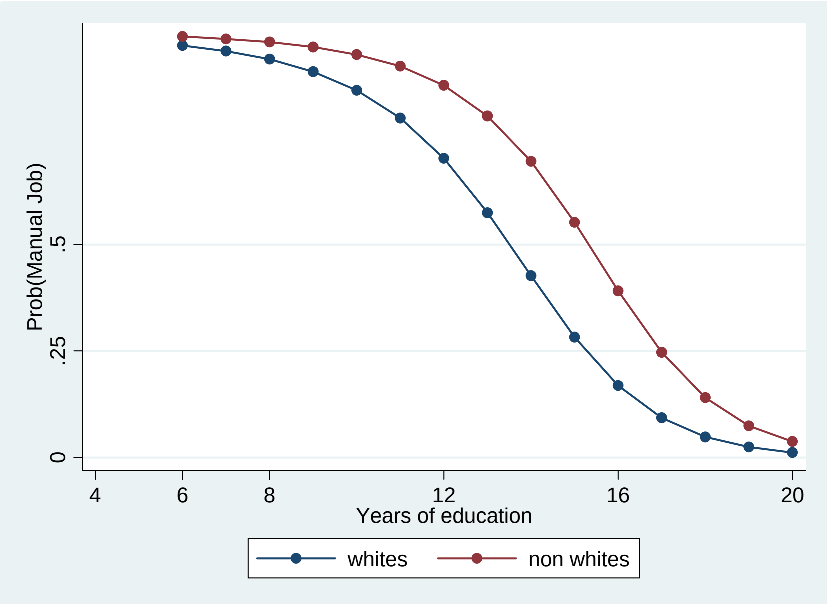
First we label the variables … p1 …p2 …p3 so that the legend of our plot is automatically OK

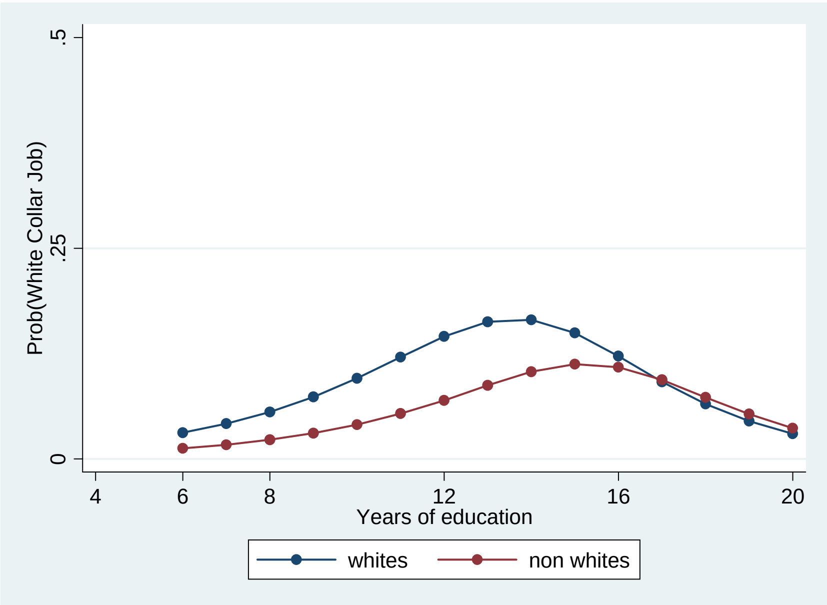
NOTE: Remember (record) the meaning of the variables described in the label !!!

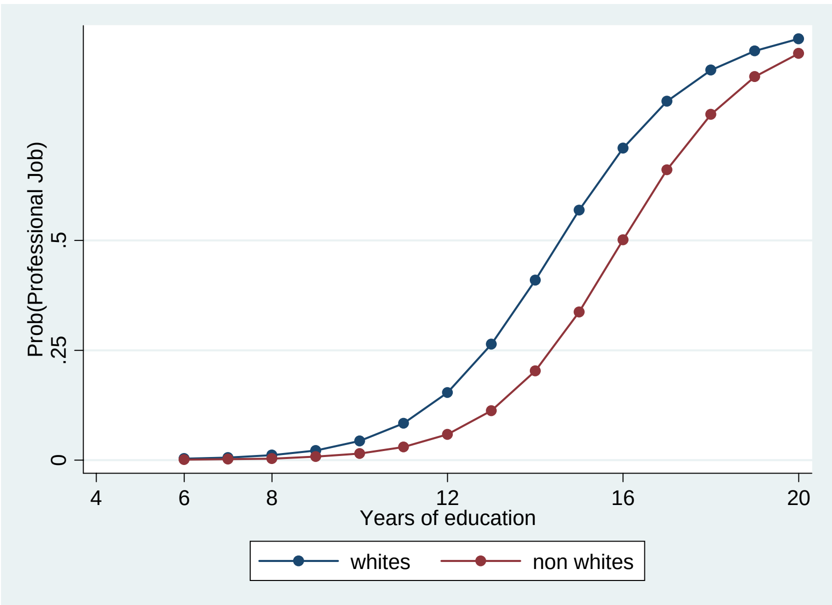
label var whitep1 "whites"
label var whitep2 "whites"
label var whitep3 "whites"
label var nowhitep1 "non whites"
label var nowhitep2 "non whites"
label var nowhitep3 "non whites"

```
graph twoway connected  whitep1 nowhitep1 whitex ,
xtitle("Years of education")
ytitle("Prob(Manual Job)")
ylabel(0 (0.25) 0.5)
xlabel(4 6 8 12 16 20)

graph twoway connected  whitep2 nowhitep2 whitex ,
xtitle("Years of education")
ytitle("Prob(White Collar Job)")
ylabel(0 (0.25) 0.5)
xlabel(4 6 8 12 16 20)

graph twoway connected  whitep3 nowhitep3 whitex ,
xtitle("Years of education")
ytitle("Prob(Professional Job)")
ylabel(0 (0.25) 0.5)
xlabel(4 6 8 12 16 20)
```

graph twoway (see commands above)







Checking the variables on the right side of the model

This can be done via lrtest see above
or easier via mlogtest, lr see above

Checking the categories (choices) on the left side of the model (indistinguishable)

To test, whether we can use a model with combined alternatives (choices) for the left side variable (dependent) Which is a test that alternatives are indistinguishable in respect to variables in the model.

```
mlogit occ white ed exper, baseoutcome(5) nolog  /* base category is 5 (Prof) */
```

1. Wald test to test all J*(J-1) pairs of categories "mlogtest, combine"

mlogtest, combine

```
**** Wald tests for combining alternatives (N=337)

 Ho: All coefficients except intercepts associated with a given pair
     of alternatives are 0 (i.e., alternatives can be combined).
Alternatives tested|     chi2   df   P>chi2
-------------------+------------------------
  Menial- BlueCol  |    3.994    3    0.262
  Menial-   Craft  |    3.203    3    0.361
  Menial-WhiteCol  |   11.951    3    0.008
  Menial-    Prof  |   48.190    3    0.000
 BlueCol-   Craft  |    8.441    3    0.038
 BlueCol-WhiteCol  |   20.055    3    0.000
 BlueCol-    Prof  |   76.393    3    0.000
   Craft-WhiteCol  |    8.892    3    0.031
   Craft-    Prof  |   60.583    3    0.000
WhiteCol-    Prof  |   22.203    3    0.000
--------------------------------------------
```

2. Wald test to test a specific alternative against the base category "test [category]"

test [Menial]

```
 ( 1)  [Menial]white = 0
 ( 2)  [Menial]ed = 0
 ( 3)  [Menial]exper = 0

           chi2(  3) =   48.19
         Prob > chi2 =    0.0000
Is "Menial" undistinguishable from the base category "Prof" (the same as line Menial-Prof above)
```

3. Wald test to test any alternative against any other "test [category1=category2]"

test [Menial=Craft]

```
 ( 1)  [Menial]white - [Craft]white = 0
 ( 2)  [Menial]ed - [Craft]ed = 0
 ( 3)  [Menial]exper - [Craft]exper = 0

           chi2(  3) =    3.20
         Prob > chi2 =    0.3614
```

4. Likelihood-ratio test (LR) to test all J*(J-1) pairs of categories "mlogtest, lrcomb"

mlogtest, lrcomb

```
**** LR tests for combining alternatives (N=337)

 Ho: All coefficients except intercepts associated with a given pair
     of alternatives are 0 (i.e., alternatives can be collapsed).
Alternatives tested|     chi2   df   P>chi2
-------------------+------------------------
  Menial- BlueCol  |    4.095    3    0.251
  Menial-   Craft  |    3.376    3    0.337
  Menial-WhiteCol  |   13.223    3    0.004
  Menial-    Prof  |   64.607    3    0.000
 BlueCol-   Craft  |    9.176    3    0.027
 BlueCol-WhiteCol  |   22.803    3    0.000
 BlueCol-    Prof  |  125.699    3    0.000
   Craft-WhiteCol  |    9.992    3    0.019
   Craft-    Prof  |   95.889    3    0.000
WhiteCol-    Prof  |   26.736    3    0.000
--------------------------------------------
```

Assumption: Independence of irrelevant alternatives (I I A)

Not-binary logit models do have additional assumptions[3].

In case of multinomial logit model (MNLM) and conditional logit models it is the assumption "independence of irrelevant alternatives = IIA).

The idea of that assumption is, that the odds for a decision are not depending on other categories.
E.g. one could think of a situation where the odd for a decision would become smaller and smaller the more alternatives are possible - that should be excluded by the IIA assumption.

Unfortunately there seems to be no reliable test available to test whether the assumption is violated.

Long and Freese discuss the often used tests Hausman-McFadden and Small-Hsui and come to the conclusion "we do not encourage their use." (p. 244)[4]

They suggest:

"It appears that the best advice regarding IIA goes back to an early statement by McFadden (1973), who wrote that multinominal and conditional logit models should be used only in cases where the alternatives can 'plausibly be assumed to be distinct and weighted independently in the eyes of the decision maker'."

---

[3] In case of ordered models it is the "parallel regression assumption" or the "proportional odds assumption"
[4] Whereas two tests (an approximate LR-Test <omodel> and a Wald test by Brant <brant>) are available to test the parallel regression assumption in ordered models (p.199).