Week 8. Logistic Regression 2

This handout is heavily indebted on the following two references:
- Powers, Daniel A. and Yu Xie. 2000. *Statistical Methods for Categorical Data Analysis.* Academic Press.
- Mize, Trenton D. 2019. "Best Practices for Estimating, Interpreting, and Presenting Nonlinear Interaction Effects." *Sociological Science* 6: 81-117.

Install `spost13_ado.pkg` in your machine. Type `net install spost13_ado.pkg` in Stata. `spost13_ado.pkg` is a user-written program developed by Scott Long at Indiana University.

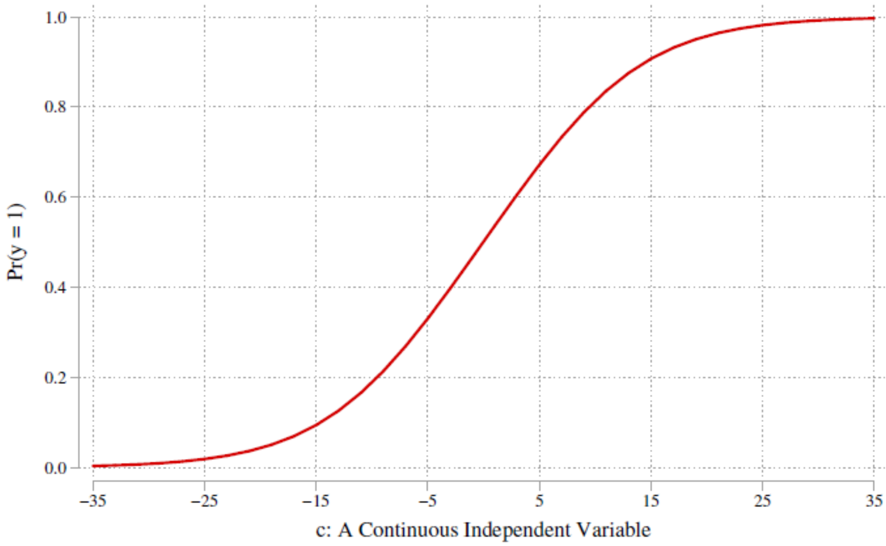
Logit

1. Recall that logit = log odds = $\log \frac{P_A}{1-P_A}$
2. logit $= b_0 + b_1 x_1 + b_2 x_2$,
3. exp(log odds) = odds $= e^{b_0+b_1x_1+b_2x_2}$
4. odds $= e^{b_0} e^{b_1 x_1} e^{b_2 x_2}$
5. Thus, as x_1 increases by 1 unit, odds of event A increases by $\exp(b_1)$ times, net of x_2.
6. $\exp(b_1)$ is called odds ratio.
7. Compared to the reference group (or as x_1 increases by 1 unit), the likelihood of event A is $\exp(b_1)$ times more likely. (Note that here likelihood implies odds.)
8. If you would like to discuss the effect of x on P_A rather than the effect of x on the odds of A, you should report marginal effects.

Logit: Interaction effects without interaction terms

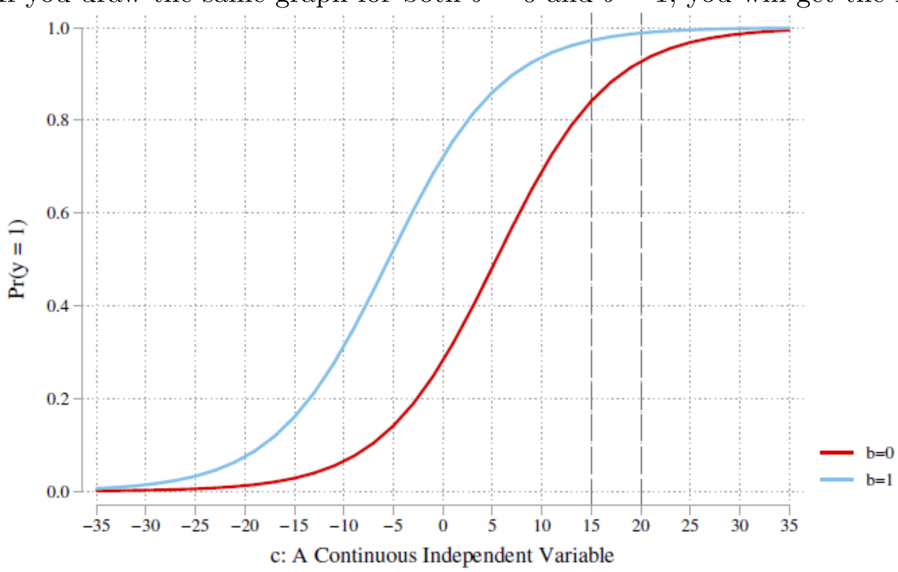
1. The effects of independent variables are linear on logit (= log odds).
2. Because all logit functions are multiplicative, the effect of independent variable on P are nonlinear even though there is no interaction effects. That is, the effect of x on P varies across x.
3. Suppose you have the following result:
   log odds = -1 + 0.2 c + 2 b
   where "c" is a continuous variable and "b" is a binary dummy variable. No interaction terms are added.

4. When you draw the cdf of the continuous variable, you will get the following graph:



5. As you see, the effect of "c" on P varies across "c". At c=-25, the slope of c (or 1st derivative or the effect of c) is small (or very flat), but at c=0, the slope of c is quite steep.

6. If you draw the same graph for both $b = 0$ and $b = 1$, you will get the following graph:



7. The effect of "b" varies across "c". In the middle of the distribution c, the effect of b is substantial, while the effect of b is tiny at the both ends of the distribution c.

8. The ceiling and flooring effects of logit (and probit) is called "compression." In essence, the effect of independent variables on P is always interactive even without interaction terms.

9. The effect of "c" differs between $b = 0$ and $b = 1$ depending on "c". In the middle, the slopes of c are basically the same between $d = 0$ and $d = 1$. At the high end, the slope of c is steep for $b = 0$ while it is flat for $b = 1$.

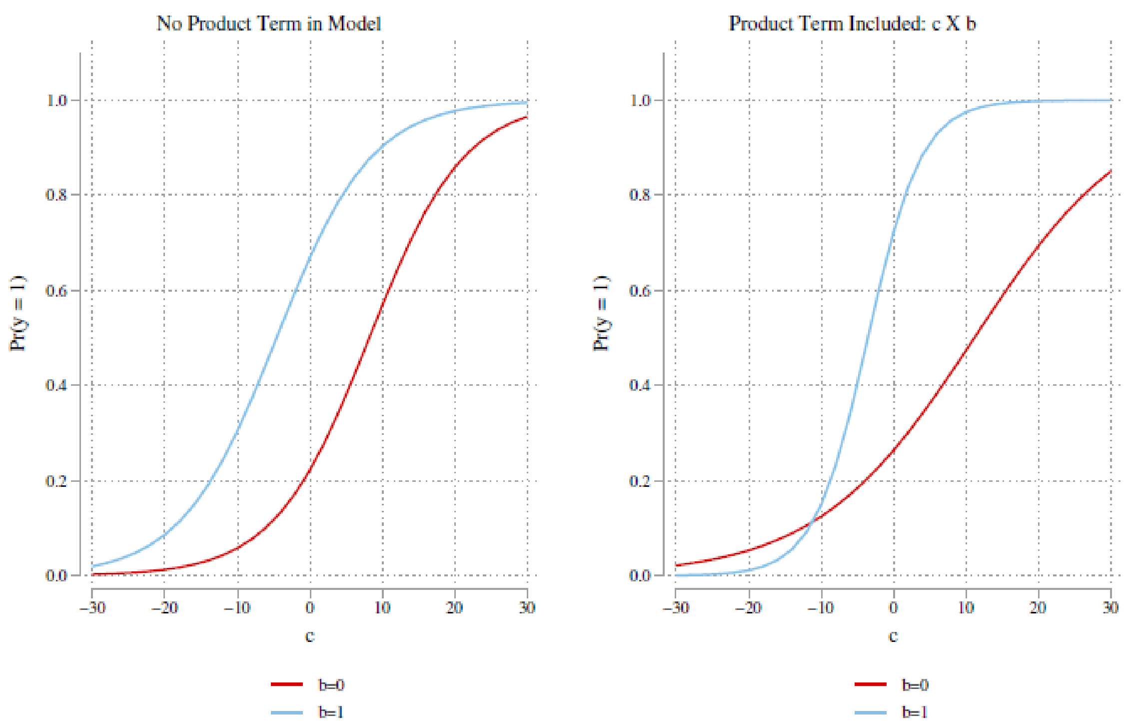
10. Solution 1: Report marginal effects using the `margins` command which is an average effect.

11. Solution 2: Draw a graph.

12. Solution 3: Compute the marginal effects at different points of interest, using the `margins` and `lincom` (and `mlincom`) command.
```
margins if b==0, at(c=5)
margins if b==1, at(c=5)
mlincome 2-1
```

Logit: Interaction effects with interaction terms

1. Now we add an interaction term on the logit model and get the following coefficients:
   log odds $= -1 + 0.2c + 2b + 0.2(c \times b)$

2. 

3. The significance of the coefficient estimated for the interaction term does not necessarily indicate whether the interaction is statistically significant. The statistical significance of the interaction term varies across independent variables.

4. Solution 1: The best way to do is to present a graph.

5. Solution 2: Compute the marginal effects at different points of interest, using the `margins` and `lincom` (and `mlincom`) command.

Example:

- Dependent variable: Having a managerial or professional occupation.
- Independent variable: female, education(BA+), racial minority, and age

```
. logit profmanag minority female ba age age2 [pw=perwt]

Logistic regression                               Number of obs   =      22256
                                                  Wald chi2(5)    =    1980.90
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -429223.45                 Pseudo R2       =     0.1288

------------------------------------------------------------------------------
             |               Robust
   profmanag |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    minority |  -.5967156   .0423213   -14.10   0.000    -.6796638   -.5137674
      female |   .1127462   .0378161     2.98   0.003      .038628    .1868644
          ba |   2.430903   .0561393    43.30   0.000     2.320872    2.540934
         age |  -.1344215   .2073944    -0.65   0.517     -.540907     .272064
        age2 |   .0015181   .0026189     0.58   0.562    -.0036149     .006651
       _cons |   2.093365   4.089812     0.51   0.609    -5.922518    10.10925
------------------------------------------------------------------------------
```

Non-significant interaction effect: minority * female

```
. logit profmanag i.minority##i.female ba age age2 [pw=perwt]


Logistic regression                               Number of obs   =      22256
                                                  Wald chi2(6)    =    1985.82
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -429194.32                 Pseudo R2       =     0.1288

---------------------------------------------------------------------------------
                |               Robust
      profmanag |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
     1.minority |  -.5514066   .0617447    -8.93   0.000    -.6724239   -.4303892
       1.female |   .1387856   .0444581     3.12   0.002     .0516493    .2259219
                |
minority#female |
           1 1  |  -.0882374   .0844265    -1.05   0.296    -.2537102    .0772354
                |
             ba |   2.431258   .0561342    43.31   0.000     2.321237    2.541279
            age |  -.1343862   .2074167    -0.65   0.517    -.5409154    .2721431
```

```
         age2 |   .0015159   .0026192     0.58   0.563    -.0036176    .0066495
        _cons |   2.082047   4.090049     0.51   0.611    -5.934301     10.0984
------------------------------------------------------------------------------------
```

Significant interaction effect: minority * ba

```
. logit profmanag i.minority##i.ba female age age2 [pw=perwt]

Logistic regression                                Number of obs   =      22256
                                                   Wald chi2(6)    =    2072.96
                                                   Prob > chi2     =     0.0000
Log pseudolikelihood = -428973.94                  Pseudo R2       =     0.1293

------------------------------------------------------------------------------
             |               Robust
   profmanag |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  1.minority | -.6460647    .046621   -13.86   0.000    -.7374402   -.5546892
        1.ba |  2.300923   .0665198    34.59   0.000     2.170547      2.4313
             |
 minority#ba |
        1 1  |  .3935145    .119472     3.29   0.001     .1593537    .6276754
             |
      female |   .112484   .0378229     2.97   0.003     .0383524    .1866156
         age | -.1390151    .207292    -0.67   0.502        -.5453    .2672698
        age2 |  .0015759   .0026176     0.60   0.547    -.0035545    .0067062
       _cons |  2.198296    4.08792     0.54   0.591     -5.81388    10.21047
------------------------------------------------------------------------------
```

Computing marginal effects (or predicted probabilities)

```
. margins minority#ba

Predictive margins                                 Number of obs   =      22256
Model VCE    : Robust

Expression   : Pr(profmanag), predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
 minority#ba |
        0 0  |   .3176858   .0050686    62.68   0.000     .3077515    .3276202
        0 1  |    .822589   .0090821    90.57   0.000     .8047885    .8403895
        1 0  |   .1962522   .0063493    30.91   0.000     .1838079    .2086966
        1 1  |   .7827279   .0154165    50.77   0.000     .7525121    .8129438
------------------------------------------------------------------------------
```

Testing the difference between majority BA (2nd line) and minority BA (4th line)

```
. mlincom (4-2)

             |   lincom    pvalue        ll        ul
-------------+--------------------------------------
           1 |   -2.188     0.000    -2.339    -2.038
```

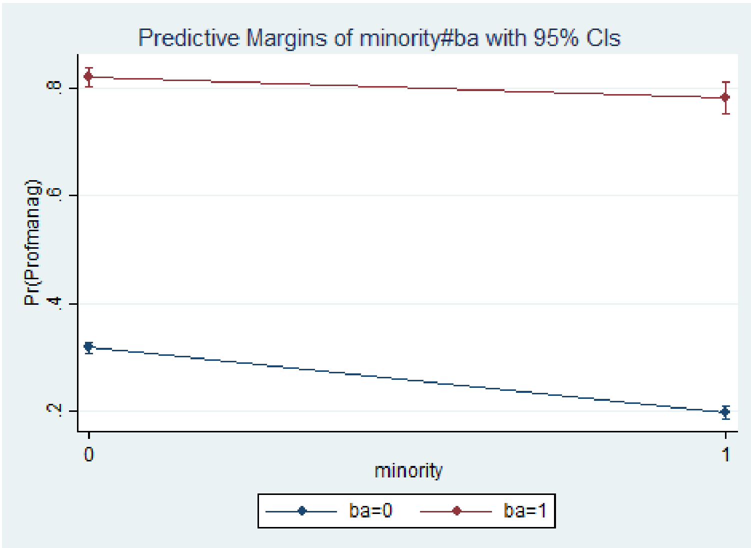
Testing the difference between (A) majority BA (2nd line) and minority BA (4th line) and (B) majority non-BA (1st line) and minority non-BA (3rd line).

```
. mlincom (4-2)-(3-1)

             |   lincom    pvalue        ll        ul
-------------+--------------------------------------
           1 |   -3.228     0.000    -3.480    -2.977
```

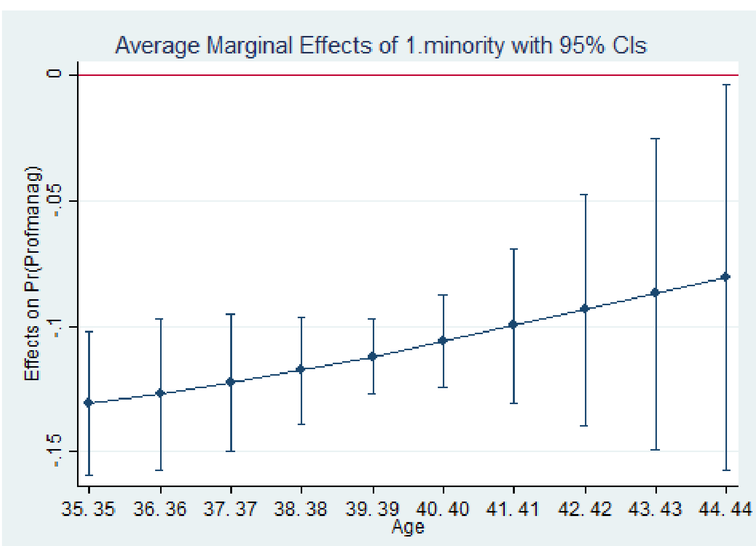
Drawing a graph about the interaction effect between minority and BA+

```
margins minority#ba
marginsplot
```



Drawing a graph on the marginal effect of being minority over age

```
margins, dydx(minority) at(age=(35(1)44))
marginsplot, yline(0)
```



Multinomial Logit

1. Multinomial Logit models (`mlogit`) can be used when your outcome is multinomial (= 3 or more discrete choices).

2. For logit models, the probability distribution of the event A given the total n follows the binomial distribution. For multinomial logit, the probability distribution of the count Y_j given the total n follows the multinomial distribution.

3. Suppose there are 3 possible outcomes: Y_1, Y_2, and Y_3. (more generally, we can say that there are J possible outcomes Y_1, Y_2, ... and Y_J).

4. Then, we can estimate the log odds of event j compared to the reference point J as follows:

$$\log \frac{P_j}{P_J} = \alpha_j + x\prime\beta_j$$

Note that $\frac{P_j}{P_J}$ is the odds of Y_1 compared to Y_3. In logit, $\frac{P_A}{1-P_A}$ is the odds of event A compared to event not-A. Thus, logit is a special case of multinomial logit.

If we set Y_3 as a reference event, we can estimate the following two models:

$$\log \frac{P_1}{P_3} = \alpha_1 + x\prime\beta_1$$
$$\log \frac{P_2}{P_3} = \alpha_2 + x\prime\beta_2$$

Each coefficient estimated quantifies the change in log odds of Y_j compared to Y_J when x increases by 1 unit. Put differently, $\exp(\beta)$ indicates the odds ratio of Y_j compared to Y_J when x increases by 1 unit. As x increases by 1 unit, the likelihood of Y_j compared to Y_J increases by $\exp(\beta)$ times.

5. The estimation of $\log \frac{P_1}{P_2}$ is not necessary because all coefficients for $\log \frac{P_1}{P_2}$ can be computed from the previous 2 models.

$$\log \frac{P_1}{P_3} - \log \frac{P_2}{P_3} = (\log P_1 - \log P_3) - (\log P_2 - \log P_3) = \log P_1 - \log P_2 = \log \frac{P_1}{P_2}$$

thus,

$$\log \frac{P_1}{P_2} = (\alpha_1 - \alpha_2) + x\prime(\beta_1 - \beta_2)$$

6. Estimation of the parameters of this model by maximum likelihood proceeds by maximization of the multinomial likelihood with the probabilities P_j viewed as functions of the α_j and β_j parameters.

Multinomial Logit Example

- Dependent Variable: Employment Status = (1) Employed, (2) Unemployed, (3) Not in Labor Force.

```
. mlogit empstat i.edu female minority age age2 [pw=perwt]

Multinomial logistic regression                   Number of obs   =      22256
                                                  Wald chi2(16)   =    1421.83
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -403878.38                 Pseudo R2       =     0.0978

------------------------------------------------------------------------------------
                   |               Robust
           empstat |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
1__Employed        |  (base outcome)
-------------------+----------------------------------------------------------------
2__Unemployed      |
               edu |
                 2 |  -.2816744   .1293254    -2.18   0.029    -.5351475   -.0282013
                 3 |  -.5087672   .1303798    -3.90   0.000    -.7643069   -.2532274
                 4 |  -1.216158    .143058    -8.50   0.000    -1.496547   -.9357697
                 5 |  -1.692009   .1765734    -9.58   0.000    -2.038086   -1.345931
                   |
            female |   .2232413   .0794099     2.81   0.005     .0676006    .3788819
          minority |   .4576939   .0842396     5.43   0.000     .2925873    .6228005
               age |     -.6087   .4206603    -1.45   0.148    -1.433179    .2157791
              age2 |   .0076419   .0053096     1.44   0.150    -.0027648    .0180486
             _cons |   9.629997   8.300133     1.16   0.246    -6.637965    25.89796
-------------------+----------------------------------------------------------------
3__Not_in_labor_~e |
               edu |
                 2 |  -.6377104   .0944152    -6.75   0.000    -.8227608     -.45266
                 3 |  -1.040515   .0909344   -11.44   0.000    -1.218743   -.8622865
                 4 |  -1.089392   .0942667   -11.56   0.000    -1.274151   -.9046326
                 5 |  -1.718559   .1094104   -15.71   0.000    -1.932999   -1.504119
                   |
            female |   2.011937   .0643168    31.28   0.000     1.885878    2.137995
          minority |  -.0446437   .0568998    -0.78   0.433    -.1561653    .0668779
               age |   .1359571   .2787946     0.49   0.626    -.4104703    .6823844
              age2 |  -.0017603   .0035227    -0.50   0.617    -.0086647    .0051441
             _cons |  -4.806532   5.497639    -0.87   0.382    -15.58171    5.968642
------------------------------------------------------------------------------------
```

Computing the probability of employment by education.

```
. margins edu, atmeans

Adjusted predictions                            Number of obs     =     22,256
Model VCE    : Robust

1._predict   : Pr(empstat==1__Employed), predict(pr outcome(1))
2._predict   : Pr(empstat==2__Unemployed), predict(pr outcome(2))
3._predict   : Pr(empstat==3__Not_in_labor_force), predict(pr outcome(3))
at           : 1.edu           =    .0918028 (mean)
               2.edu           =    .2230475 (mean)
               3.edu           =    .2969211 (mean)
               4.edu           =    .2437092 (mean)
               5.edu           =    .1445194 (mean)
               0.female        =    .4966023 (mean)
               1.female        =    .5033977 (mean)
               0.minority      =    .6600245 (mean)
               1.minority      =    .3399755 (mean)
               age             =    39.54809 (mean)
               age2            =    1572.167 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_predict#edu |
        1 1  |   .7059303   .0142476    49.55   0.000     .6780054    .7338551
        1 2  |   .8024339   .0075069   106.89   0.000     .7877206    .8171472
        1 3  |    .850526   .0055411   153.49   0.000     .8396656    .8613864
        1 4  |   .8806488   .0050144   175.62   0.000     .8708207    .8904769
        1 5  |   .9300099   .0045712   203.45   0.000     .9210505    .9389694
        2 1  |   .0813647   .0080513    10.11   0.000     .0655845    .0971449
        2 2  |   .0697837   .0047661    14.64   0.000     .0604423     .079125
        2 3  |   .0589396   .0038759    15.21   0.000     .0513429    .0665362
        2 4  |    .030082   .0026606    11.31   0.000     .0248672    .0352967
        2 5  |   .0197393   .0027065     7.29   0.000     .0144347    .0250439
        3 1  |    .212705   .0129952    16.37   0.000      .187235    .2381751
        3 2  |   .1277824   .0062557    20.43   0.000     .1155215    .1400433
        3 3  |   .0905344   .0042333    21.39   0.000     .0822373    .0988316
        3 4  |   .0892692   .0043666    20.44   0.000     .0807109    .0978275
        3 5  |   .0502508   .0037632    13.35   0.000      .042875    .0576266
------------------------------------------------------------------------------
```

Gender comparison across the probabilities of three outcomes.

```
. margins edu, predict() over(i.female) atmeans
```

```
Adjusted predictions                            Number of obs     =     22,256
Model VCE    : Robust

over         : female
1._predict   : Pr(empstat==1__Employed), predict(pr outcome(1))
2._predict   : Pr(empstat==2__Unemployed), predict(pr outcome(2))
3._predict   : Pr(empstat==3__Not_in_labor_force), predict(pr outcome(3))
at           : 0.female
                   1.edu           =    .1029445 (mean)
                   2.edu           =    .2354108 (mean)
                   3.edu           =    .2854081 (mean)
                   4.edu           =     .235196 (mean)
                   5.edu           =    .1410406 (mean)
                   female          =           0
                   0.minority      =    .6620612 (mean)
                   1.minority      =    .3379388 (mean)
                   age             =    39.54567 (mean)
                   age2            =    1572.055 (mean)
               1.female
                   1.edu           =    .0808115 (mean)
                   2.edu           =    .2108511 (mean)
                   3.edu           =    .3082787 (mean)
                   4.edu           =    .2521074 (mean)
                   5.edu           =    .1479512 (mean)
                   female          =           1
                   0.minority      =    .6580153 (mean)
                   1.minority      =    .3419847 (mean)
                   age             =    39.55048 (mean)
                   age2            =    1572.278 (mean)

------------------------------------------------------------------------------------
                    |            Delta-method
                    |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
_predict#female#edu |
              1 0 1 |   .8248057   .0109713    75.18   0.000     .8033024     .846309
              1 0 2 |   .8806449    .006263   140.61   0.000     .8683697    .8929202
              1 0 3 |   .9086188   .0049485   183.62   0.000     .8989199    .9183176
              1 0 4 |   .9369143   .0036388   257.48   0.000     .9297823    .9440463
              1 0 5 |   .9628471   .0031045   310.15   0.000     .9567624    .9689318
              1 1 1 |    .513562   .0183012    28.06   0.000     .4776924    .5494316
              1 1 2 |   .6537221   .0110446    59.19   0.000     .6320751    .6753692
              1 1 3 |    .731767   .0083771    87.35   0.000     .7153481    .7481858
              1 1 4 |   .7613286    .008998    84.61   0.000     .7436928    .7789644
              1 1 5 |   .8543542   .0087141    98.04   0.000     .8372749    .8714334
              2 0 1 |   .0849345   .0085949     9.88   0.000     .0680888    .1017801
              2 0 2 |   .0684232    .005294    12.92   0.000     .0580472    .0787992
              2 0 3 |   .0562547   .0043786    12.85   0.000     .0476728    .0648367
              2 0 4 |   .0285931   .0027867    10.26   0.000     .0231313    .0340549
              2 0 5 |   .0182583   .0025854     7.06   0.000      .013191    .0233255
              2 1 1 |   .0661529   .0074037     8.94   0.000      .051642    .0806639
              2 1 2 |    .063536   .0049815    12.75   0.000     .0537725    .0732995
              2 1 3 |   .0566727   .0041721    13.58   0.000     .0484956    .0648499
```

```
             2 1 4  |   .0290641    .002782    10.45   0.000     .0236115    .0345168
             2 1 5  |   .0202658   .0029099     6.96   0.000     .0145626    .0259691
             3 0 1  |   .0902598   .0073401    12.30   0.000     .0758734    .1046462
             3 0 2  |   .0509319   .0035917    14.18   0.000     .0438923    .0579714
             3 0 3  |   .0351265     .00243    14.46   0.000     .0303637    .0398893
             3 0 4  |   .0344926   .0023514    14.67   0.000      .029884    .0391012
             3 0 5  |   .0188947   .0017217    10.97   0.000     .0155203    .0222691
             3 1 1  |   .4202851   .0190743    22.03   0.000     .3829002    .4576699
             3 1 2  |   .2827419   .0108342    26.10   0.000     .2615073    .3039765
             3 1 3  |   .2115603   .0078637    26.90   0.000     .1961478    .2269728
             3 1 4  |   .2096072   .0088578    23.66   0.000     .1922463    .2269682
             3 1 5  |     .12538   .0084167    14.90   0.000     .1088836    .1418765
------------------------------------------------------------------------------------


. margins i.edu, dydx(i.female) atmeans

Conditional marginal effects                    Number of obs     =     22,256
Model VCE    : Robust

dy/dx w.r.t. : 1.female
1._predict   : Pr(empstat==1__Employed), predict(pr outcome(1))
2._predict   : Pr(empstat==2__Unemployed), predict(pr outcome(2))
3._predict   : Pr(empstat==3__Not_in_labor_force), predict(pr outcome(3))
at           : 1.edu           =    .0918028 (mean)
               2.edu           =    .2230475 (mean)
               3.edu           =    .2969211 (mean)
               4.edu           =    .2437092 (mean)
               5.edu           =    .1445194 (mean)
               0.female        =    .4966023 (mean)
               1.female        =    .5033977 (mean)
               0.minority      =    .6600245 (mean)
               1.minority      =    .3399755 (mean)
               age             =    39.54809 (mean)
               age2            =    1572.167 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
0.female     |  (base outcome)
-------------+----------------------------------------------------------------
1.female     |
_predict#edu |
        1 1  |  -.3111994   .0140035   -22.22   0.000    -.3386457   -.2837532
        1 2  |  -.2268817   .0098033   -23.14   0.000    -.2460957   -.2076676
        1 3  |  -.1768153   .0077511   -22.81   0.000    -.1920073   -.1616233
        1 4  |  -.1755627   .0080303   -21.86   0.000    -.1913018   -.1598236
        1 5  |  -.1084769   .0072672   -14.93   0.000    -.1227204   -.0942334
        2 1  |  -.0188237   .0058193    -3.23   0.001    -.0302294   -.0074181
        2 2  |  -.0049249   .0049082    -1.00   0.316    -.0145447    .0046949
        2 3  |   .0003853   .0042242     0.09   0.927    -.0078941    .0086646
        2 4  |   .0004538   .0022263     0.20   0.838    -.0039097    .0048173
        2 5  |   .0019959   .0015355     1.30   0.194    -.0010137    .0050054
```

```
        3 1  |   .3300231   .0147675    22.35   0.000     .3010794    .3589669
        3 2  |   .2318066   .0094055    24.65   0.000     .2133722    .2502409
        3 3  |     .17643   .0070254    25.11   0.000     .1626606    .1901995
        3 4  |   .1751088   .0079644    21.99   0.000     .1594989    .1907188
        3 5  |   .1064811   .0072558    14.68   0.000       .09226    .1207022
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

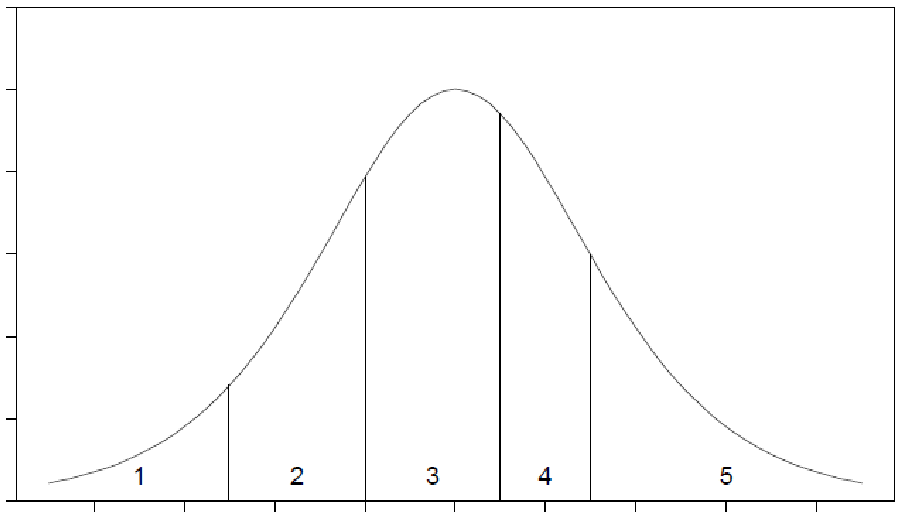
If you would like to change the base outcome to (2) Unemployed, estimate the following command.

```
mlogit empstat i.edu female minority age age2 mar[pw=perwt], baseoutcome(2)
```

Ordinal Logit or Ordered Logit

1. Ordered Logit models (`ologit`) can be used when your outcome variable is ordered (for example, high=3, medium=2, and low=1; for another example, strongly agree=4, somewhat agree=3, somewhat disagree=2, strongly disagree=1).

2. These models can also be interpreted in terms of a latent variable. Specifically, suppose that the manifest response Y_i results from grouping an underlying continuous variable Y_i^* using cut-points $\theta_1 < \theta_2 ... < \theta_{J-1}$, so that Y_i takes the value 1 if Y_i^* is below θ_1, the value 2 if Y_i^* is between θ_1 and θ_2, and so on, taking the value J if Y_i^* is above θ_{J-1}.



3. Thus, Ordered Logit estimates the effect of independent variables as a function of cumulative probabilities. Because it is a cumulative probability function, Ordered Logit estimates one coefficient for each independent variable and compute

4. The cumulative probability C_{ij} for individual i up to response level j,

$$C_{ij} = Pr(y_j \leq j) = Pr(y_i \leq j|x) = Pr(x\prime\beta + \epsilon \leq \theta_j),$$

Rearrange terms, we find that:

$$C_{ij} = Pr(\epsilon \leq \theta_j - x\prime\beta) = F(\theta_j - x\prime\beta)$$

Thus, the probability of $y_j = j$ given x is,

$$Pr(y_i = j|X_i) = \begin{cases} F(\theta_1 - x\prime\beta), & j = 1 \\ F(\theta_j - x\prime\beta) - F(\theta_{j-1} - x\prime\beta), & 1 < j \leq J - 1 \\ 1 - F(\theta_{J-1} - x\prime\beta), & j = J \end{cases}$$

In Stata, θ_j are cut points. Note that only one set of β's are estimated.

5. The probability of C_{ij} can be estimated as follows:

$$C_{ij} = \frac{\exp(\theta_j + x\prime\beta)}{1 + \exp(\theta_j + x\prime\beta)}$$

6. Interpretation: Conditional on the other covariates, the odds that Y_j is less than or equal to a given level j versus greater than j is estimated to be $\exp(\beta)$ times greater as x increases by 1 unit.

Ordered logit: dep variable = Subjective Well-being (5= high, 1=low)

```
. ologit SWB SSS c.age##c.age female yrsch [pw=weight]

Iteration 0:   log pseudolikelihood = -13331.542
Iteration 1:   log pseudolikelihood = -12972.818
Iteration 2:   log pseudolikelihood = -12969.055
Iteration 3:   log pseudolikelihood = -12969.053
Iteration 4:   log pseudolikelihood = -12969.053

Ordered logistic regression                     Number of obs     =     11,001
                                                Wald chi2(5)      =     535.31
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -12969.053               Pseudo R2         =     0.0272

------------------------------------------------------------------------------
             |               Robust
         SWB |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         SSS |    .288463   .0133989    21.53   0.000     .2622015    .3147244
         age |  -.0197745   .0068535    -2.89   0.004    -.0332072   -.0063418
             |
 c.age#c.age |   .0001688   .0000676     2.50   0.013     .0000362    .0003013
             |
      female |  -.0299368   .0400124    -0.75   0.454    -.1083596     .048486
       yrsch |   .0028191   .0050849     0.55   0.579    -.0071471    .0127854
-------------+----------------------------------------------------------------
       /cut1 |  -3.373698   .2013347                     -3.768307   -2.979089
       /cut2 |   -1.68202   .1899033                     -2.054223   -1.309816
       /cut3 |  -.2022073   .1863877                     -.5675205    .1631058
       /cut4 |   2.366788   .1875696                      1.999158    2.734417
------------------------------------------------------------------------------
```

Estimating the probabilities of 5 Likert-scale outcomes.

```
. margins

Predictive margins                              Number of obs     =     11,001
Model VCE    : Robust
```

```
1._predict   : Pr(SWB==1), predict(pr outcome(1))
2._predict   : Pr(SWB==2), predict(pr outcome(2))
3._predict   : Pr(SWB==3), predict(pr outcome(3))
4._predict   : Pr(SWB==4), predict(pr outcome(4))
5._predict   : Pr(SWB==5), predict(pr outcome(5))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    _predict |
          1  |   .0168795   .0013263    12.73   0.000       .01428    .0194789
          2  |   .0668575   .0025816    25.90   0.000     .0617977    .0719173
          3  |   .1920383   .0039601    48.49   0.000     .1842766    .1998001
          4  |   .5374719    .005133   104.71   0.000     .5274114    .5475323
          5  |   .1867528   .0039678    47.07   0.000     .1789761    .1945296
------------------------------------------------------------------------------
```

Comparing the probabilities of 5 Likert-scale outcomes by Subjective Social Standing

```
. margins, at(SSS=(1(3)10))

Predictive margins                              Number of obs     =     11,001
Model VCE    : Robust

1._predict   : Pr(SWB==1), predict(pr outcome(1))
2._predict   : Pr(SWB==2), predict(pr outcome(2))
3._predict   : Pr(SWB==3), predict(pr outcome(3))
4._predict   : Pr(SWB==4), predict(pr outcome(4))
5._predict   : Pr(SWB==5), predict(pr outcome(5))

1._at        : SSS             =           1

2._at        : SSS             =           4

3._at        : SSS             =           7

4._at        : SSS             =          10

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_predict#_at |
        1 1  |   .0405484   .0035615    11.39   0.000     .0335681    .0475288
        1 2  |   .0174791   .0013727    12.73   0.000     .0147887    .0201694
        1 3  |   .0074324   .0006443    11.54   0.000     .0061696    .0086951
```

```
        1 4  |   .0031418   .0003445     9.12   0.000     .0024667     .003817
        2 1  |   .1459302   .0071279    20.47   0.000     .1319598    .1599006
        2 2  |   .0705568   .0027353    25.79   0.000     .0651958    .0759179
        2 3  |   .0316223   .0016948    18.66   0.000     .0283005     .034944
        2 4  |   .0136784    .001178    11.61   0.000     .0113695    .0159872
        3 1  |   .3147249   .0074074    42.49   0.000     .3002068    .3292431
        3 2  |   .2094484   .0043884    47.73   0.000     .2008473    .2180494
        3 3  |   .1123264   .0041648    26.97   0.000     .1041636    .1204891
        3 4  |   .0530482   .0039051    13.58   0.000     .0453944     .060702
        4 1  |   .4277687   .0095175    44.95   0.000     .4091147    .4464227
        4 2  |   .5488553   .0052543   104.46   0.000      .538557    .5591537
        4 3  |   .5474551   .0058007    94.38   0.000     .5360859    .5588242
        4 4  |   .4245533   .0136385    31.13   0.000     .3978223    .4512842
        5 1  |   .0710278   .0039199    18.12   0.000     .0633448    .0787107
        5 2  |   .1536604   .0038903    39.50   0.000     .1460356    .1612852
        5 3  |   .3011639   .0081255    37.06   0.000     .2852381    .3170897
        5 4  |   .5055784   .0182223    27.75   0.000     .4698633    .5412934
------------------------------------------------------------------------------
```