CDA Lab Guide for ICPSR | 2014

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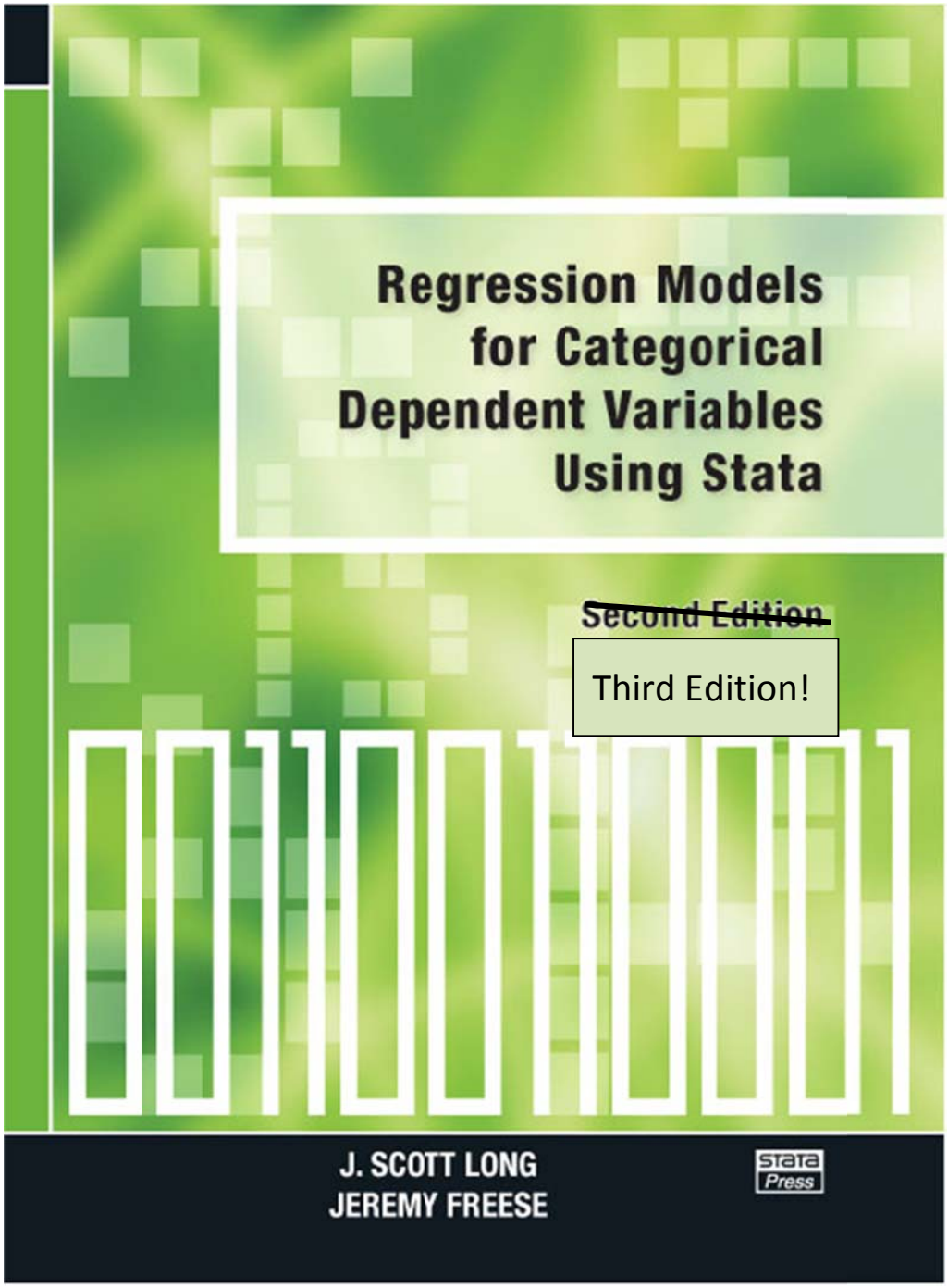

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1: INTRODUCTION TO LAB GUIDE

The lab guide presents tools and exercises for categorical data analysis that corresponds to the lectures. It is designed to let you quickly learn the basics of the SPost commands. It does not necessarily show you the best way to do things. So, use the guide as a starting point to learn Stata and SPost, then use the lecture notes for planning your more detailed analyses.

If you are unfamiliar with Stata or would just like a quick review, please refer to *Getting Started Using Stata*.

1. The guide is divided into parts corresponding to lectures. Each part includes a **review** which everyone should complete and an **exercise** to encourage you to work creatively with the commands. *As you do the exercises, feel free to skip questions and explore commands on your own.*
2. Sections marked [optional] are considered less critical either because they are not used very often in practice, they require more advanced understanding, or we don't think they are generally as important as other topics for the purposes of this course. If, however, you need these methods for you work, please treat them as [not-optional]!
3. Each part has an accompanying do-file with the Stata commands from the guide (e.g., cda14lab-brm-review.do). Exercises in the guide have corresponding do-files that you can use (e.g., cda14lab-brm-exercise.do). You can open the do-file in the Stata do-file editor so that you don't need to move from Stata to Word and back while you work through exercises.
4. We provide data sets for the exercises. For ICPSR, these datasets are named icpsr_nes4.dta, icpsr_science4.dta, icpsr_hsb4.dta, icpsr_addhealth4.dta, and hrssvy01.dta. Versions of the datasets without the "icpsr_" prefix require more data cleaning. Codebooks are at the end of this guide; hrssvy01.dta does not have a codebook since it has so few variables. The codebooks include suggestions for variables to use in the exercises. This will save you time, giving you more time to try the statistical methods.
5. Stata commands and output are in this `font`. Commands are often preceded by "`.`" or sometimes "`>`". When you work in a do-file, make sure you do not put "`.`" or "`>`" in front of the command.
6. We provide examples of interpretation that are in boxes.
7. If you want feedback on interpretation, write a paragraph or two and give this to us along with the relevant output from your log-file.
8. Although the command window can be used for exploring new commands, exercises should be completed using do-files. If you are not sure how to use a do-file see the *Getting Started with Stata Guide* for help.

2: CONTINUOUS OUTCOMES

The commands from this section are in **`cda14lab-lrm-review.do`**.

2.0) Set-up your do-file

Be sure to put today's date inside the quotation marks, replacing the text **`"<insert date>"`** and put your name inside the quotation marks, replacing **`"<your-name>"`**. Later parts of the lab guide will not show this step.

```
capture log close
log using cda14lab-lrm-review, replace text

version 13.1
clear all
set linesize 80
macro drop _all
set scheme s2color

//  task:    Linear Regression Example
//  project: ICPSR CDA
local pgm "cda14lab-lrm-review"
local dte "<insert date>"
local who "<your-name>"
local tag "`pgm'.do `who' `dte'"
```

2.1) Load the Data

```
sysuse icpsr_scireview4, clear
```

2.2) Examine the Data and Select Variables

Begin by using the command **`codebook, compact`** to list variables, their labels, and summary statistics.

```
. codebook, compact

Variable   Obs Unique      Mean    Min    Max  Label
-------------------------------------------------------------------------------
id         264    264  58556.74  57001  62420  ID Number.
cit1       264     48  11.33333      0    130  Citations: PhD yr -1 to 1.
cit3       264     54  14.68561      0    196  Citations: PhD yr 1 to 3.
cit6       264     59  17.58712      0    143  Citations: PhD yr 4 to 6.
cit9       264     67  19.92803      0    214  Citations: PhD yr 7 to  9.
enroll     264      9  5.530303      3     14  Years from BA to PhD.
fel        264     96  3.191098      1   4.69  Fellow or PhD prestige.
felclass   264      4  2.700758      1      4  Fellow or PhD prestige class.
fellow     264      2  .4128788      0      1  Postdoctoral fellow? (1=yes)
female     264      2   .344697      0      1  Female? (1=yes)
jobimp     264    180  2.864109   1.01   4.69  Prestige of 1st univ job/Imputed.
jobprst    264      4  2.348485      1      4  Rankings of University Job.
mcit3      264     59  20.71591      0    129  Mentor's 3 yr citation.
mcitt      264     81  43.45076      0    223  Mentor's total citations.
mmale      264      2  .9848485      0      1  Was mentor a male? (1=yes)
mnas       264      2  .0833333      0      1  Was mentor in NAS? (1=yes)
mpub3      264     35  11.11364      0     48  Mentor's 3 year publications.
nopub1     264      2  .2537879      0      1  No pubs PhD yr -1 to 1? (1=yes)
nopub3     264      2  .1931818      0      1  No pubs PhD yr 1 to 3? (1=yes)
nopub6     264      2  .1969697      0      1  No pubs PhD yr 4 to 6? (1=yes)
nopub9     264      2  .1931818      0      1  No pubs PhD yr 7 to 9? (1=yes)
phd        264     79  3.181894      1   4.66  Prestige of Ph.D. department.
phdclass   264      4  2.681818      1      4  Prestige class of Ph.D. dept.
pub1       264     14   2.32197      0     19  Publications: PhD yr -1 to 1.
pub3       264     16  2.939394      0     27  Publications: PhD yr 1 to 3.
pub6       264     23  3.878788      0     29  Publications: PhD yr 4 to 6.
```

```
pub9       264      25  4.253788      0     27  Publications: PhD yr 7 to 9.
pubtot     264      42  11.07197      0     73  Total Pubs in 9 Yrs post-Ph.D.
work       264       5  2.045455      1      5  Type of first job.
workadmn   264       2  .0795455      0      1  Administration? (1=yes)
workfac    264       2  .5340909      0      1  Faculty in Univ? (1=yes)
worktch    264       2      .625      0      1  Teaching? (1=yes)
workuniv   264       2  .7045455      0      1  University work? (1=yes)
-------------------------------------------------------------------------------
```

Next, use **keep** to select the dependent variable **pubtot** and the three independent variables, **workfac**, **enrol**, and **phd**, which we use in the regression models later.

```
. keep pubtot workfac enrol phd
```

2.3) Regression

Specifying a model is simple, with the dependent variable listed *first* followed by independent variables. Prefacing an independent variable with **i.** indicates that it is a factor variable (i.e., a binary or categorical variable). By default, the category with the lowest value (in this case workfac=0) is the reference category. Prefacing a variable with **c.** indicates that a variable is continuous. If no prefix is specified, Stata assumes the variable is continuous.

```
. regress pubtot i.workfac c.enrol c.phd
```

```
      Source |       SS       df       MS              Number of obs =     264
-------------+------------------------------           F(  3,   260) =   10.77
       Model |  3519.43579     3  1173.14526           Prob > F      =  0.0000
    Residual |  28326.1968   260  108.946911           R-squared     =  0.1105
-------------+------------------------------           Adj R-squared =  0.1003
       Total |  31845.6326   263  121.086055           Root MSE      =  10.438

------------------------------------------------------------------------------
      pubtot |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     workfac |
      1_Yes  |   5.227261   1.297375     4.03   0.000     2.672561     7.78196
      enroll |  -1.174879   .4465778    -2.63   0.009    -2.054249   -.2955094
         phd |   1.506904   .6442493     2.34   0.020     .2382931    2.775514
       _cons |   9.982767    3.33341     2.99   0.003     3.418849    16.54668
------------------------------------------------------------------------------
```

2.4) Compute Standardized Coefficients

listcoef displays the estimated coefficients along with standardized coefficients. The **help** option provides details on the meaning of each coefficient.

```
. listcoef, help

regress (N=264): Unstandardized and standardized estimates

  Observed SD: 11.0039
  SD of error: 10.4378

------------------------------------------------------------------------------
             |          b        t    P>|t|    bStdX    bStdY   bStdXY     SDofX
-------------+----------------------------------------------------------------
     workfac |
      1_Yes  |     5.2273    4.029    0.000    2.613    0.475    0.237     0.500
      enroll |    -1.1749   -2.631    0.009   -1.696   -0.107   -0.154     1.443
         phd |     1.5069    2.339    0.020    1.515    0.137    0.138     1.005
    constant |     9.9828    2.995    0.003        .        .        .         .
------------------------------------------------------------------------------
       b = raw coefficient
       t = t-score for test of b=0
```

```
   P>|t| = p-value for t-test
   bStdX = x-standardized coefficient
   bStdY = y-standardized coefficient
  bStdXY = fully standardized coefficient
   SDofX = standard deviation of X
```

2.5) Interpretation

For a unit increase in the prestige of the doctoral department, the number of total publication is expected to increase by 1.5, holding other variables constant (p<0.05, two-tailed test).

For a standard deviation increase in the length of time between enrollment and graduation, about 1.5 years, the number of total publication is expected to decrease by 1.7, holding other variables constant (p<0.01, two-tailed test).

On average, scientists who take faculty positions have about a half a standard deviation more publications than scientists who do not take faculty positions (p<0.001, two-tailed test).

2.6) Close log and exit program

```
log close
exit
```

2: Continuous outcomes exercise

`cda14lab-lrm-exercise.do` contains an outline of this exercise. For this and later exercises you can use any of the datasets we provide.

1) Load the data.

2) Examine the data and select variables. Choose a continuous dependent variable and at least three independent variables (make sure one is binary and one is continuous) to use in a regression analysis.

3) Run an OLS regression.

4) Compute x-standardized, y-standardized, and fully standardized coefficients.

5) Interpretation the results as you would in a research paper.

6a) Interpret at least one unstandardized coefficient.

6b) Interpret at least one x-standardized, one y-standardized and one fully standardized coefficient.

3: BINARY OUTCOMES

The commands for this section are in **`cda14lab-brm-review.do`**.

3.1) Load the data

```
sysuse icpsr_scireview4, clear
```

3.2) Examine data, select variables, and verify

```
codebook, compact
keep workfac fellow phd mcit3 mnas
tab1 fellow mnas workfac, miss
codebook, compact
```

3.3) Binary logit model

The dependent variable is listed first. A probit model is run by changing **`logit`** to **`probit`**.

```
. logit workfac i.fellow c.phd c.mcit3 i.mnas, nolog

Logistic regression                                     Number of obs   =        264
                                                        LR chi2(4)      =      37.64
                                                        Prob > chi2     =     0.0000
Log likelihood = -163.55534                             Pseudo R2       =     0.1032

------------------------------------------------------------------------------
     workfac |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      fellow |
      1_Yes  |   1.250155   .2767966     4.52   0.000     .7076434    1.792666
         phd |  -.0637186   .1471307    -0.43   0.665    -.3520894    .2246522
       mcit3 |   .0206156   .0071255     2.89   0.004     .0066498    .0345814
             |
        mnas |
      1_Yes  |   .3639082   .5571229     0.65   0.514    -.7280327    1.455849
       _cons |  -.5806031   .4498847    -1.29   0.197    -1.462361    .3011547
------------------------------------------------------------------------------
```

3.4) Store the estimation results

It is sometimes necessary to store estimation results to restore later (e.g., when posting with **`margins`**). You do this using **`estimates store`**. Here we store the estimates with the name **`estlogit`**.

```
estimates store estlogit
```

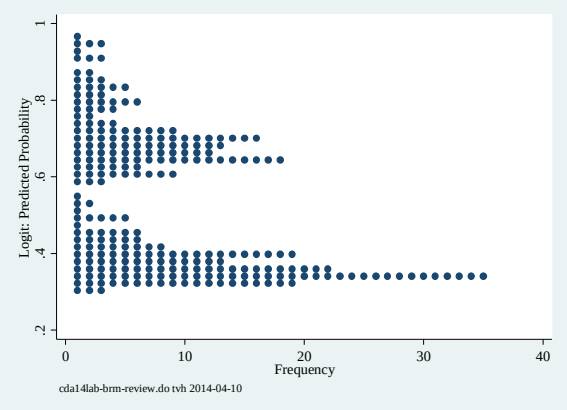
3.5) Predicted probabilities for each observation

We can compute and plot predicted probabilities for each observations. We pick the name **`prlogit`** for the new variable that contains predictions.

```
. predict prlogit
(option pr assumed; Pr(workfac))

. label var prlogit "Logit: Predicted Probability"

. sum prlogit

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
     prlogit |       264    .5340909    .1828654   .3035647   .9665072
```

The **`dotplot`** command is used to plot the distribution:

```
. dotplot prlogit
. graph export cda14lab-brm-review-fig1.emf, replace
```



3.6) Predict specific probabilities

mtable computes a predictions and saves them in a table. Here we focus on the probability of our dependent variable for given values of the independent variables. The **at()** option sets the values where predictions are made. The **atmeans** option sets the other independent variables at their means.

- **predict** creates a new variable that contains predictions for each case in the sample.
- **mtable** computes predictions at specified values of the regressors and does not create a new variable.

We predict the probability of working as a faculty member for someone who has a postdoctoral fellowship and whose mentor was a member of the National Academy of sciences with other regressors held at their means:

```
. mtable, at(fellow=1 mnas=1) stat(ci) atmeans

Expression: Pr(workfac), predict()

   Pr(y)        ll        ul
------------------------------
   0.779     0.593     0.964

Specified values of covariates

           |   fellow       phd     mcit3      mnas
 ----------+-----------------------------------------
   Current |        1      3.18      20.7         1
```

The predicted probability of obtaining a faculty position is 0.78 (95% CI: 0.59, 0.96) for an average scientist who began his career with a postdoctoral fellow after studying with a mentor who is in National Academies of Sciences.

3.7) Table of probabilities

mtable can make a table of predicted probabilities for combinations of values of independent variables.

```
. mtable, at(fellow=(0 1) mnas=(0 1)) stat(ci) atmeans

Expression: Pr(workfac), predict()

           |   fellow      mnas     Pr(y)        ll        ul
 ----------+-------------------------------------------------
         1 |        0         0     0.412     0.330     0.494
         2 |        0         1     0.502     0.232     0.771
         3 |        1         0     0.710     0.619     0.801
         4 |        1         1     0.779     0.593     0.964

Specified values of covariates

           |      phd     mcit3
 ----------+------------------
   Current |     3.18      20.7
```

The same predictions can be obtained using **margins** which produces more output. The SPost **m*** commands are "wrappers" that make it easier to work with **margins**.

```
. margins, at(fellow=(0 1) mnas=(0 1)) atmeans

Adjusted predictions                              Number of obs   =        264
Model VCE    : OIM

Expression   : Pr(workfac), predict()
```

```
1._at        : fellow          =           0
               phd             =    3.181894 (mean)
               mcit3           =    20.71591 (mean)
               mnas            =           0

2._at        : fellow          =           0
               phd             =    3.181894 (mean)
               mcit3           =    20.71591 (mean)
               mnas            =           1

3._at        : fellow          =           1
               phd             =    3.181894 (mean)
               mcit3           =    20.71591 (mean)
               mnas            =           0

4._at        : fellow          =           1
               phd             =    3.181894 (mean)
               mcit3           =    20.71591 (mean)
               mnas            =           1

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _at |
          1  |   .4118608   .0417942     9.85   0.000     .3299457    .4937759
          2  |   .5019075   .1374789     3.65   0.000     .2324539    .7713612
          3  |   .7096895    .046453    15.28   0.000     .6186433    .8007358
          4  |   .7786445   .0946714     8.22   0.000     .5930921     .964197
------------------------------------------------------------------------------
```

3.8) Discrete change at means with mlincom

`mtable` with the **`post`** option can be used to compute discrete changes. First, **`mtable`** computes the probabilities at the start and end values of the discrete change. With the **`post`** the predictions are left in memory for **`mlincom`** to use.

```
. mtable, at(fellow=(0 1)) atmeans post

Expression: Pr(workfac), predict()

           |   fellow     Pr(y)
 ----------+--------------------
         1 |        0     0.419
         2 |        1     0.716

Specified values of covariates

           |                              1.
           |      phd     mcit3      mnas
 ----------+------------------------------
   Current |     3.18      20.7     .0833
```

`mlincom` computes the change in probability, that is, the discrete change. The numbers after **`mlincom`** refer to the numbered rows from **`mtable`** (e.g., row 2 minus row 1):

```
. mlincom 2-1, stats(all)

             |   lincom        se    zvalue    pvalue        ll        ul
-------------+------------------------------------------------------------
           1 |    0.297     0.061     4.888     0.000     0.178     0.416
```

A scientist who receives a post-doctoral fellowship has a .30 higher probability of being on faculty at a university than a scientist who does not receive a fellowship, holding other variables at their means (p<0.001, two-tailed test).

3.9) Discrete change at means using dydx()

Restoring estimates: After using **`mtable`** or **`margins`** with the **`post`** option, the logit results are no longer in memory since they have been replaced by the estimates from **`margins`**. To put the logit results back in memory, we use **`estimate restore`**.

```
. estimates restore estlogit
(results estlogit are active now)
```

Using dydx(): Now we can compute additional predictions using these estimates. The results from the example using **`mlincom`** can be duplicated using the **`dydx()`** option with **`mtable`**. For binary variables with an **`i.`** prefix, **`dydx()`** computes a change from 0 to 1. For variables with a **`c.`** prefix or no prefix, **`dydx()`** computes the marginal change. Be careful since it is easy to compute incorrect results if you did not correctly specify the prefix for the independent variables in your regression model. Here we compute the discrete change for the variable fellow, which match the results above.

```
. mtable, dydx(fellow) atmeans stat(ci p)

Expression: Pr(workfac), predict()

 d Pr(y)        ll        ul         p
------------------------------------------
   0.297     0.178     0.416     0.000

Specified values of covariates

           |        1.                              1.
           |   fellow       phd     mcit3      mnas
 ----------+-----------------------------------------
   Current |     .413      3.18      20.7     .0833
```

3.10) Average discrete change with mchange

`mchange` computes the discrete change for some or all independent variables. Independent variables can be held at specific values using **`at()`** or at the means with **`atmeans`**. By default, however, the average discrete change is computed along with the p-value for a test that the marginal effect is 0.

```
. mchange, amount(one sd)

logit: Changes in Pr(y) | Number of obs = 264

Expression: Pr(workfac), predict(pr)

               |    Change    p-value
---------------+----------------------
fellow         |
 1 Yes vs 0 No |     0.285      0.000
phd            |
       +1 cntr |    -0.014      0.665
      +SD cntr |    -0.014      0.665
mcit3          |
       +1 cntr |     0.004      0.002
      +SD cntr |     0.113      0.002
mnas           |
 1 Yes vs 0 No |     0.078      0.509

Average predictions
```

```
             |      0_No      1_Yes
-------------+----------------------
  Pr(y|base) |     0.466      0.534
```

The discrete change for fellow is different than in the examples above since **mchange** is computing the Average Marginal Effect (AME), whereas the first two discrete changes computed the Marginal Effect at the Mean (MEM). In the following interpretations, note the subtle yet crucial difference in wording for a discrete change computed using AME versus the wording of the earlier discrete change using MEM.

On average having a post-doctoral fellowship increases the probability of being a faculty at a university by .28 (p<0.001, two-tailed test).

On average, a standard deviation increase in the mentor's citations, about 25, is expected to increases the probability of being a faculty member by 0.11 (p<0.01, two-tailed test)

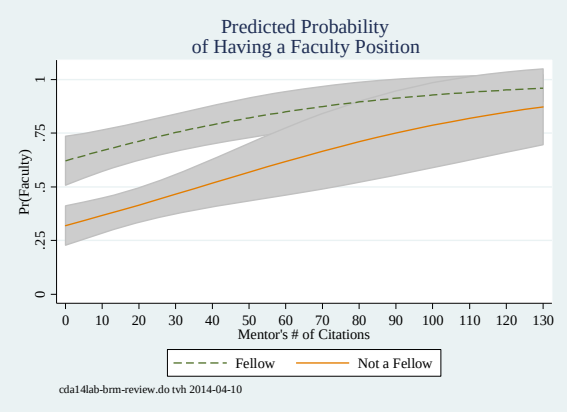
3.11) Plotting predicted probabilities

You might want to compute predicted probabilities across the range of a continuous variable for two groups and then plot these. **mgen** generates new variables containing predicted values and confidence intervals. These variables begin with the stem specified with **stub()**. The **predlabel()** option allows you to name what is being predicted.

```
. mgen, at(fellow=1 mcit3=(0(5)130)) atmeans stub(fel1) predlabel(Fellow)

Predictions from: margins, at(fellow=1 mcit3=(0(5)130)) atmeans predict(pr)

Variable   Obs Unique      Mean       Min       Max  Label
------------------------------------------------------------------------------
fel1pr1     27     27  .8361422   .621785  .9599656  Fellow
fel1ll1     27     27   .748555  .5078947  .8969149  95% lower limit
fel1ul1     27     27  .9237294  .7356753  1.023016  95% upper limit
fel1mcit3   27     27        65         0       130  Mentor's 3 yr citation.
------------------------------------------------------------------------------

. mgen, at(fellow=0 mcit3=(0(5)130)) atmeans stub(fel0) predlabel(Not a Fellow)

:: Output deleted ::
```

After creating the variables with **mgen**, the following commands create the graph.

```
. graph twoway ///
>     (rarea fel1ul fel1ll fel1mcit3, col(gs10)) ///
>     (rarea fel0ul fel0ll fel1mcit3, col(gs10)) ///
>     (connected fel1pr fel1mcit, lpat(dash)  msym(i)) ///
>     (connected fel0pr fel1mcit, lpat(solid) msym(i)), ///
>     legend(on order(3 4)) ///
>     ylab(0(.25)1) ytitle("Pr(Faculty)") ///
>     xlab(0(10)130) xtitle("Mentor's # of Citations") ///
>     title("Predicted Probability of Having a Faculty Position")
. graph export cda14lab-BRMexample-fig2.emf , replace
```



For an average scientist, receiving a fellowship increases the probability of being employed as a faculty member. The advantage for fellows is nearly .30 for those with mentors who have not been cited and decreases gradually to about .10 for those with highly cited mentor.

You **cannot** use overlapping confidence intervals to determine if the differences in probabilities for fellows and non-fellows are significant. For this, you need to compute discrete changes as illustrated in the lecture notes.

3.12) Computing Odds Ratios

The factor change in the odds and the standardized factor change are obtained with **`listcoef`**. **`listcoef`** can run after a probit model where it will compute standardized beta coefficients instead.

```
. listcoef, help

logit (N=264): Factor change in odds

  Odds of: 1_Yes vs 0_No

------------------------------------------------------------------------------
             |          b         z     P>|z|       e^b   e^bStdX     SDofX
-------------+----------------------------------------------------------------
      fellow |
      1_Yes  |     1.2502     4.517     0.000     3.491     1.853     0.493
         phd |    -0.0637    -0.433     0.665     0.938     0.938     1.005
       mcit3 |     0.0206     2.893     0.004     1.021     1.690    25.445
             |
        mnas |
      1_Yes  |     0.3639     0.653     0.514     1.439     1.106     0.277
    constant |    -0.5806    -1.291     0.197         .         .         .
------------------------------------------------------------------------------
       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
   SDofX = standard deviation of X
```

Obtaining a post-doctoral fellowship increases the odds of obtaining a faculty position by a factor of 3.5, holding other variables constant (p<0.001, two-tailed test). A standard deviation increase in mentor's citations, about 25, increases the odds of a faculty position by a factor of 1.7 (p<0.01, two-tailed test).

3.13) [optional] Comparing the coefficients from Logit and Probit

Here we run a probit model using the same variables and store the results. We use **`estimates table`** to list the logit and probit estimates side-by-side. The logit estimates are around 1.7 times as large as the probit estimates. Why is this?

```
. probit workfac i.fellow c.phd c.mcit3 i.mnas, nolog

Probit regression                                 Number of obs   =        264
                                                  LR chi2(4)      =      37.28
                                                  Prob > chi2     =     0.0000
Log likelihood = -163.73838                       Pseudo R2       =     0.1022

------------------------------------------------------------------------------
     workfac |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      fellow |
      1_Yes  |    .763915   .1675688     4.56   0.000     .4354862    1.092344
         phd |  -.0392676   .0897915    -0.44   0.662    -.2152556    .1367204
       mcit3 |   .0118642    .003994     2.97   0.003     .0040361    .0196922
             |
        mnas |
      1_Yes  |   .2299521   .3252356     0.71   0.480    -.4074981    .8674022
       _cons |  -.3450294   .2743016    -1.26   0.208    -.8826507     .192592
------------------------------------------------------------------------------

. estimates store estprobit

. estimates table estlogit estprobit, b(%7.2f) t(%7.2f) stats(N) modelwidth(10)

---------------------------------------
    Variable |  estlogit    estprobit
-------------+-------------------------
      fellow |
      1_Yes  |       1.25         0.76
             |       4.52         4.56
             |
         phd |      -0.06        -0.04
             |      -0.43        -0.44
       mcit3 |       0.02         0.01
             |       2.89         2.97
             |
        mnas |
      1_Yes  |       0.36         0.23
             |       0.65         0.71
             |
       _cons |      -0.58        -0.35
             |      -1.29        -1.26
-------------+-------------------------
           N |        264          264
---------------------------------------
                           legend: b/t
```

3.14) Close log and exit program

```
log close
exit
```

3: Binary outcomes exercise

The file **`cda14lab-brm-exercise.do`** contains an outline of this exercise.

1) Load the data

2) Examine the data and select your variables. Choose one binary dependent variable and at least three independent variables (make sure one is binary and one is continuous). Verify.

3) Estimate a binary logit model

4) Store the results of the logistic regression.

5) [optional] Predict probabilities for each observation using **`predict`**. Plot the distribution of these probabilities using **`dotplot`**. Make sure to label the new variable created by predict.

6) Use **`mtable`** to compute the predicted probability at some specific value of the independent variables. Interpret this.

7) Use **`mtable`** to create a table of predicted probabilities with two variables held at multiple values and the rest held at their means.

8) [optional] Use **`mtable, post`** and **`mlincom`** to calculate a discrete change for a binary variable. Interpret this.

9) [optional] Use **`mtable, dydx`** to reproduce the same discrete change in **3.8**.

10) Use **`mchange`** to calculate discrete changes for all variables using AME. Interpret the discrete change of both a binary and a continuous variable.

11) Use **`mgen`** to plot the predicted probabilities over the range of a continuous variable for the two levels of a binary variable. Interpret this.

12) [optional] Use **`mgen`** to plot the difference (i.e., discrete change) for the two groups. Interpret this.

13) Obtain the factor change coefficients using **`listcoef, help`**. Interpret at least one of the unstandardized and one the standardized factor change coefficients.

4: HYPOTHESIS TESTING

The file **`cda14lab-test-review.do`** contains these Stata commands.

4.1) Load the Data

```
sysuse icpsr_scireview4, clear
```

4.2) Examine data, select variables, and verify

```
codebook, compact
keep workfac female fellow phd mcit3 mnas
tab1 workfac female fellow mnas, miss
codebook, compact
```

4.3) Computing a z-test

z-scores are produced with the standard ML estimation commands. The z-scores are in the 4th column, labeled "z". Estimation results are stored with **`estimates store`** using the name **`base`**.

```
. logit workfac i.female i.fellow c.phd c.mcit3 i.mnas, nolog

Logistic regression                                     Number of obs   =        264
                                                        LR chi2(5)      =      41.72
                                                        Prob > chi2     =     0.0000
Log likelihood = -161.51514                             Pseudo R2       =     0.1144

------------------------------------------------------------------------------
     workfac |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
      female |
      1_Yes  |  -.5869003   .2911944    -2.02   0.044    -1.157631   -.0161698
             |
      fellow |
      1_Yes  |   1.118336   .2844612     3.93   0.000     .5608027     1.67587
         phd |    .002004   .1521298     0.01   0.989    -.2961648    .3001729
       mcit3 |   .0190813   .0072584     2.63   0.009     .0048551    .0333075
             |
        mnas |
      1_Yes  |   .3537104   .5652778     0.63   0.531    -.7542137    1.461635
       _cons |  -.5004836   .4539085    -1.10   0.270    -1.390128    .3891607
------------------------------------------------------------------------------

. estimates store base
```

4.4) Single Coefficient Wald Test

The **`test`** command computes a Wald test that a single coefficient is equal to zero. Note that the name **`1.female`** exactly matches the output from the logit output. Entering "female" or "i.female" will result in an error. This can be confusing when working with factor variables.

```
. test 1.female

 ( 1)  [workfac]1.female = 0

           chi2(  1) =    4.06
         Prob > chi2 =    0.0439
```

The effect of being female is significant at the .05 level (X^2=4.06, *df*=1, *p*=0.04).

4.5) Multiple Coefficients Wald Test

We can also test if multiple coefficients are simultaneously equal to zero.

```
. test mcit3 1.mnas

 ( 1)  [workfac]mcit3 = 0
 ( 2)  [workfac]1.mnas = 0

           chi2(  2) =    7.78
         Prob > chi2 =    0.0204
```

The hypothesis that the effects of mentor's citations and mentor's membership in the NAS are simultaneously equal to zero can be rejected at the .05 level (X^2=7.78, *df*=2, *p*=0.02).

4.6) Equal Coefficients Wald Test

We can test whether the magnitude of the effect of being female equals the effect of having a fellowship. Since female and fellow have opposite signs, we multiple fellow by -1.

```
. test 1.female = -1*1.fellow

 ( 1)  [workfac]1.female + [workfac]1.fellow = 0

           chi2(  1) =    1.42
         Prob > chi2 =    0.2331
```

The magnitude of the effects of being a female and having a postdoctoral fellowship are not significantly different (X^2=1.42, *df*=1, *p*=0.23).

4.7) [optional] Single Coefficient LR Test

To test that the effect of female is zero, run the base model without **`female`** and compare it with the full model, stored earlier as **`base`**, using **`lrtest`** *estname1 estname2*.

```
. logit workfac i.fellow c.phd c.mcit3 i.mnas, nolog
:: output deleted ::
. estimates store dropfemale

. lrtest base dropfemale

Likelihood-ratio test                                 LR chi2(1)  =      4.08
(Assumption: dropfemale nested in base)               Prob > chi2 =    0.0434
```

The effect of being female is significant at the .05 level (LRX^2=4.08, *df*=1, *p*=0.04).

4.8) [optional] Multiple Coefficients LR Test

To test if the effects of **`mcit3`** and **`mnas`** are jointly zero, run the comparison model without these variables, store using **`estimates store`**, and then compare models using **`lrtest`**.

```
. logit workfac i.female i.fellow c.phd
:: output deleted ::
. estimates store dropmcit3mnas

. lrtest base dropmcit3mnas

Likelihood-ratio test                                 LR chi2(2)  =      9.19
(Assumption: dropmcit3mnas nested in base)            Prob > chi2 =    0.0101
```

The hypothesis that the effects of mentor's citations and mentor's status in the NAS are simultaneously equal to zero can be rejected at the .05 level (LRX^2=9.19, *df*=2, *p*<0.05).

4.9) LR Test All Coefficients are Zero

To test that all of the regression coefficients are zero, we estimate the model with only an intercept, store the results, and compare the models using **`lrtest`**. This test statistic is identical to the one at the top of the estimation output for the full model shown in **4.3**.

```
. logit workfac
:: output deleted ::
. estimates store intercept

. lrtest base intercept

Likelihood-ratio test                                 LR chi2(5)  =     41.72
(Assumption: intercept nested in base)                Prob > chi2 =    0.0000
```

We can reject the hypothesis that all coefficients except the intercept are zero at the .01 level (LRX^2=41.72, *df*=5, *p*<0.01).

4.10) Close log and exit program

```
log close
exit
```

4: Hypothesis testing exercise

The file **cda14lab-test-exercise.do** contains an outline of this Exercise.

4.1) Load a dataset.

4.2) Examine the data and select one binary dependent variable and at least three independent variables. Include at least one binary and one continuous independent variable. Drop cases with missing data and verify.

4.3) Run a logit on the full model. Test the hypothesis that the effect of one of your independent variables is zero using the z-statistic. What is your conclusion? Use **estimates store** to store estimation results.

4.4) Use **test** to conduct a Wald test of the same hypothesis in **4.3**. How is the specific value of the Wald test related to the z-test in **4.3**?

4.5) Test the hypothesis that the effects of two of your independent variables are simultaneously equal to zero using the Wald test. What is your conclusion?

4.6) Test the hypothesis that the effects of two of your independent variables are equal. Why do these results differ from **4.5**?

4.7) [optional] Use the likelihood ratio test for the same hypothesis in **4.3**.

4.8) [optional] Now use the likelihood ratio test for the same hypothesis in **4.5**.

4.9) Close log & exit.

5: [optional] INTERNAL FIT AND SCALAR MEASURES OF FIT

The file **cda14lab-fit-review.do** contains these Stata commands. For ICPSR, I suggest you skip this exercise unless there are specific techniques you want to learn for your research.

5.1) Load the Data

```
sysuse icpsr_scireview4, clear
```

5.2) Examine data, select variables, and verify

```
codebook, compact
keep workfac female fellow phd mcit3 mnas

tab1 workfac female fellow mnas, miss
codebook, compact
```

5.3) Fit Statistics

fitstat computes measures of fit for your model. The **save** option saves the measures for subsequent comparisons. **dif** compares the measures for the current model with those of the saved model. Here we compare the base model to the model without **mcit3** and **mnas**.

```
. logit workfac i.female i.fellow c.phd c.mcit3 i.mnas
:: output deleted ::

. fitstat, save

                           |       logit
---------------------------+-------------
Log-likelihood             |
                     Model |    -161.515
          Intercept-only   |    -182.377
---------------------------+-------------
Chi-square                 |
```

```
       Deviance (df=258) |     323.030
              LR (df=5) |      41.723
                p-value |       0.000
------------------------+-------------
R2                      |
               McFadden |       0.114
:: output deleted – see below ::

. logit workfac i.female i.fellow c.phd
:: output deleted ::

. fitstat, dif

                        |     Current        Saved   Difference
------------------------+-------------------------------------
Log-likelihood          |
                  Model |    -166.112     -161.515       -4.596
          Intercept-only |    -182.377     -182.377        0.000
------------------------+-------------------------------------
Chi-square              |
        D (df=260/258/2) |     332.223      323.030        9.193
          LR (df=3/5/-2) |      32.530       41.723       -9.193
                 p-value |       0.000        0.000        0.010
------------------------+-------------------------------------
R2                      |
               McFadden |       0.089        0.114       -0.025
     McFadden (adjusted) |       0.067        0.081       -0.014
      McKelvey & Zavoina |       0.145        0.201       -0.055
           Cox-Snell/ML |       0.116        0.146       -0.030
  Cragg-Uhler/Nagelkerke |       0.155        0.195       -0.040
                   Efron |       0.120        0.151       -0.031
               Tjur's D |       0.119        0.150       -0.030
                  Count |       0.659        0.678       -0.019
        Count (adjusted) |       0.268        0.309       -0.041
------------------------+-------------------------------------
IC                      |
                    AIC |     340.223      335.030        5.193
        AIC divided by N |       1.289        1.269        0.020
         BIC (df=4/6/-2) |     354.527      356.486       -1.959
------------------------+-------------------------------------
Variance of             |
                      e |       3.290        3.290        0.000
                  y-star |       3.850        4.116       -0.266

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

Difference of    1.959 in BIC provides weak support for current model.
```

5.4) Fit Statistics, Information measures only

`fitstat` with the **`ic`** option presents only information measures BIC and AIC. **`ic`** can be combined with the **`save`** and **`dif`** options.

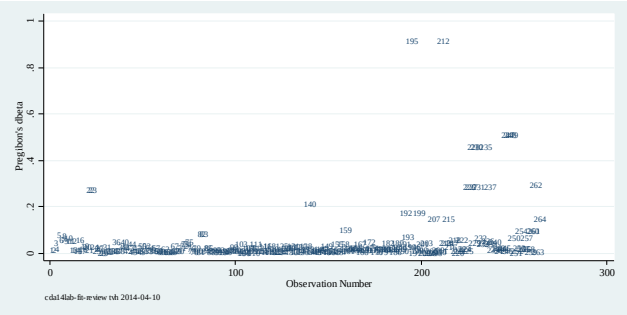
```
. quietly logit workfac i.female i.fellow c.phd c.mcit3 c.mnas

. fitstat, ic

                        |       logit
------------------------+-------------
AIC                     |
                    AIC |     335.030
          (divided by N) |       1.269
------------------------+-------------
BIC                     |
              BIC (df=6) |     356.486
```

```
 BIC (based on deviance) |    -1115.565
    BIC' (based on LRX2) |     -13.843
```

5.5) Plotting Influential Cases Using dbeta

We compute influence using the command **`predict, dbeta`**. Then we sort our data in some meaningful way (here we choose to sort by **phd**). Next we generate the variable **`index`** whose values correspond to the rank order of **phd** (because of the way the data are sorted). Finally we plot the dbeta distance against the rank order of **phd**. You can also plot residuals as shown in the lecture notes.

```
. twoway scatter dbeta index, ysiz(1) xsiz(2) ///
>         xlab(0(100)300) ylab(0(.2)1., grid) ///
>         xscale(range(0, 300)) yscale(range(0, 1.)) ///
>         xtitle("Observation Number") ///
>         msym(none) mlab(index) mlabposition(0)
. graph export cda14lab-fit-review-fig1.emf, replace
```



5.6) Close log and exit program

```
log close
exit
```

5: [optional] Internal fit and scalar measures of fit exercise

The file **`cda14lab-fit-exercise.do`** contains an outline of this Exercise.

5.1) Load your data

5.2) Examine the data and select your variables. Select one binary dependent variable and at least three independent variables. Again be sure to include at least one binary and one continuous independent variable. Drop cases with missing data and verify.

5.3) Run two or more logit models with the same outcome but change the measures on the right hand side.

5.4) Use **`fitstat`** to compare two of your models. Which model do you prefer and why?

5.5) Using your preferred model, use methods for detecting outliers and influential observations to evaluate weaknesses in your model. Based on what you find as extreme and/or influential cases, revise your model. Evaluate the revised model in terms of outliers and influential observations. Did things change?

5.6) Close log & exit.

6: COMPLEX SAMPLING AND NONLINEARITIES ON THE RHS

The file **`cda14lab-brm-complications-review.do`** contains these commands.

6.1) Load the Data.

```
sysuse hrssvy01, clear
```

6.2) Examine data, select variables, and verify.

```
codebook, compact
keep arthritis kage female ed11less ed12 ed1315 ed15more secu kwgtr stratum
tab1 arthritis female ed11less ed12 ed1315 ed15more, miss
codebook, compact
```

6.3) Prepare Stata for svy commands

Always double check variables related to survey design to avoid careless mistakes.

```
. nmlab secu kwgtr stratum

secu     sampling error computation unit
kwgtr    2006 weight: respondent level
stratum  stratum id
```

Then declare that you are using a complex sampling design.

```
svyset secu [pweight=kwgtr], strata(stratum) vce(linearized) singleunit(missing)
```

6.4) Examine Descriptive Statistics with and without Survey Variables

Next, look at descriptive statistics without survey adjustments and note how the survey adjustments affect variables. First we examine the mean and standard deviation without accounting for survey complexities.

```
. mean arthritis female kage ed11less ed12 ed1315 ed15more
:: Output deleted ::

. estat sd

------------------------------------
             |       Mean   Std. Dev.
-------------+----------------------
   arthritis |   .5985473    .4902055
      female |   .5892238     .491988
        kage |   68.48726    11.12583
    ed11less |   .2419775    .4282923
        ed12 |   .3322853    .4710455
      ed1315 |   .2081526    .4059976
    ed15more |   .2117845     .408584
------------------------------------
```

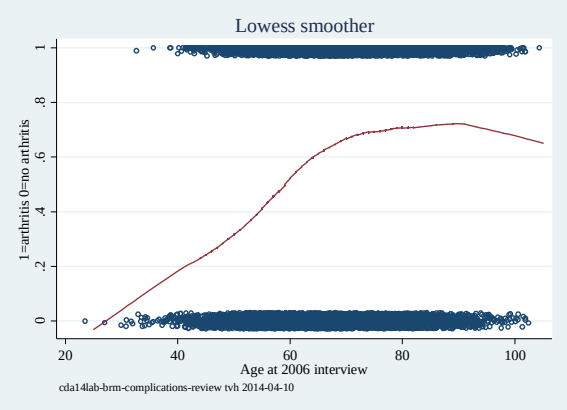
We compare these results to statistics accounting for survey complexities by adding **`svy:`** before **`mean`**.

```
. svy: mean arthritis female kage ed11less ed12 ed1315 ed15more
(running mean on estimation sample)
:: Output deleted ::

. estat sd

------------------------------------
             |       Mean   Std. Dev.
-------------+----------------------
   arthritis |   .5685845    .4952884
      female |    .543871    .4980863
        kage |   66.49795    10.37758
    ed11less |   .1947895    .3960502
        ed12 |   .3259713    .4687504
      ed1315 |   .2241667    .4170446
    ed15more |    .249774    .4328949
------------------------------------
```

6.5) Lowess plot

Now that we've set up our survey data, we can analyze nonlinearities in the right hand side of the model. A lowess plot shows a moving average of y as x changes. For key variables, a lowess plot can be a valuable first step in determining potential nonlinearities. Stata typically takes longer to produce lowess plots than other kinds of plots, so be patient. **`lowess`** does not support **`svy:`**, so these results are simply exploratory.

```
. lowess arthritis kage, bwidth(0.4) jitter(4) msym(oh)
. graph export cda14lab-brm-complications-review-fig1.emf, replace
```



6.6) Logit Models with Age, Age-squared, and Age-Cubed

Since the lowess plot suggests age has a nonlinear association with arthritis, we'll examine this more formally. We'll begin by estimating a model with age, then a model with age and age-squared, and finally a model that adds age-cubed. After each regression, we compute a Wald test determining whether the age terms are simultaneously equal to zero. **`logit`** is preceded by **`svy:`** which means that the models are fit taking into account the complex survey design. A squared term is added by including the factor notation **`c.kage##c.kage`** as an independent. ## indicates that both age and age-squared are to be included in the model. To see independent variable names for Wald tests, include the command **`logit, coeflegend`** after running a logistic regression. First for the model with only age:

```
. * aM1: kage
. svy: logit arthritis female ed11less ed1315 ed15more kage
(running logit on estimation sample)
:: Output deleted ::
. estimates store aM1

. test kage

Adjusted Wald test

 ( 1)  [arthritis]kage = 0

       F(  1,    56) =  516.05
            Prob > F =    0.0000
```

Adding age-squared:

```
. * aM2: kage + kage^2
. svy: logit arthritis female ed11less ed1315 ed15more c.kage##c.kage
(running logit on estimation sample)
:: Output deleted ::
. estimates store aM2

. test kage c.kage#c.kage
```

```
Adjusted Wald test

 ( 1)  [arthritis]kage = 0
 ( 2)  [arthritis]c.kage#c.kage = 0

       F(  2,    55) =  295.18
            Prob > F =    0.0000
```

Adding age-cubed:

```
. *aM3: kage + kage^2 + kage^3
. svy: logit arthritis female ed11less ed1315 ed15more ///
> c.kage c.kage#c.kage c.kage#c.kage#c.kage
(running logit on estimation sample)
:: Output deleted ::
. estimates store aM3

. test kage c.kage#c.kage c.kage#c.kage#c.kage

Adjusted Wald test

 ( 1)  [arthritis]kage = 0
 ( 2)  [arthritis]c.kage#c.kage = 0
 ( 3)  [arthritis]c.kage#c.kage#c.kage = 0

       F(  3,    54) =  190.27
            Prob > F =    0.0000
```

The **`estimates table`** command provides a concise way to view the three regression models.

```
. estimates table aM1 aM2 aM3, title(Arthritis) ///
>     eform b(%9.3f) t(%9.2f) stats(N)

Arthritis

-----------------------------------------------
    Variable |    aM1         aM2         aM3
-------------+---------------------------------
      female |     1.781       1.814       1.815
             |     12.90       13.02       13.04
    ed11less |     1.219       1.228       1.228
             |      3.29        3.43        3.42
      ed1315 |     0.948       0.975       0.976
             |     -0.97       -0.44       -0.43
    ed15more |     0.646       0.658       0.658
             |     -8.20       -7.81       -7.80
        kage |     1.049       1.366       2.301
             |     22.72       12.44        3.40
             |
      c.kage#|
      c.kage |                 0.998       0.991
             |                -10.84       -2.73
             |
      c.kage#|
      c.kage#|
      c.kage |                             1.000
             |                              2.21
             |
       _cons |     0.045       0.000       0.000
             |    -20.30      -13.60       -4.17
-------------+---------------------------------
           N |     18448       18448       18448
-----------------------------------------------
                                   legend: b/t
```

6.7) A closer look at the probabilities

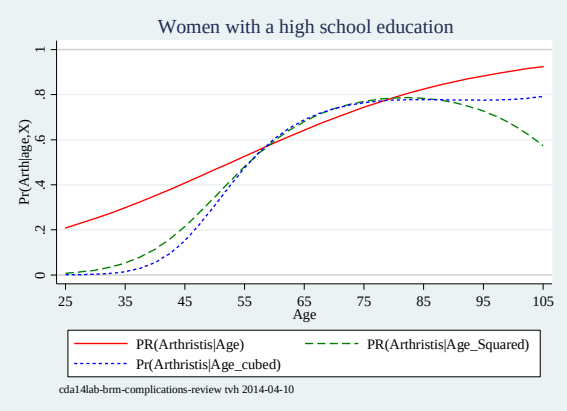
After determining that age, age-squared, and age-cubed are all significant, it is time to graph the predicted probabilities. We use **mgen** to create variables with predictions.

```
. estimates restore aM1
(results aM1 are active now)

. mgen, at(kage=(25(2.5)105) female=1 ed11less=0 ed1315=0 ed15more=0) ///
>         stub(aM1) noci predlabel(PR(Arthristis|Age))
:: Output deleted ::

. estimates restore aM2
(results aM2 are active now)

. mgen, at(kage=(25(2.5)105) female=1 ed11less=0 ed1315=0 ed15more=0) ///
>         stub(aM2) noci predlabel(PR(Arthristis|Age_Squared))
:: Output deleted ::

. estimates restore aM3
(results aM3 are active now)

. mgen, at(kage=(25(2.5)105) female=1 ed11less=0 ed1315=0 ed15more=0) ///
>         stub(aM3) noci predlabel(Pr(Arthristis|Age_cubed))
:: Output deleted ::
```

6.8) Graph the probabilities

Now that we've created variables for the predicted probabilities with **mgen**, we can to make the graph below.

```
. graph twoway ///
>     (connected aM1pr aM1kage, msym(i) lcol(red)   lpat(solid)) ///
>     (connected aM2pr aM2kage, msym(i) lcol(green) lpat(dash)) ///
>     (connected aM3pr aM3kage, msym(i) lcol(blue)  lpat(shortdash)), ///
>     title("Women with a high school education") xtitle("Age") ///
>     ytitle("Pr(Arth|age,X)") xlabel(25(10)105) ylabel(0(.2)1, grid) ///
>     yline(0 1, lcol(gs13))
. graph export cda14lab-brm-complications-review-fig2.emf, replace
```



6.9) Close log and exit program

```
log close
exit
```

6: Complex sampling and nonlinearities on the RHS exercise

The file **cda14lab-brm-complications-exercise.do** contains an outline of this Exercise.

6.1) Load your data

6.2) Load the hrssvy01 data. Examine the data and select your variables as in previous exercises.

6.3) Declare a survey design using the **svyset** command.

6.4) Compare descriptive statistics with and without svy. Do survey adjustments have any effect?

6.5) Create a lowess plot of your dependent variable and your continuous variable. Describe the relationship between these two variables.

6.6) Create a squared term for your continuous variable and rerun your logit model. Test whether the squared term is significant.

6.7) Use **mgen** to estimate predicted probabilities over a range of your continuous variable for both logit models with and without the squared term.

6.8) Plot the probabilities generated in #7 in a single graph, and save the graph. How does the addition of a squared term change your interpretation of the association between your dependent and continuous variable?

6.9) Close log & exit.

PART 7: NOMINAL OUTCOMES

The file **cda14lab-nrm-review.do** contains these Stata commands. The lab guide does not have exercise associated with Part 9 of the lecture.

7.1) Load the Data

```
sysuse icpsr_scireview4, clear
```

7.2) Examine data, select variables, and verify

Make sure to pay special attention to the distribution of the outcome variable **jobprst**.

```
codebook, compact
keep jobprst pub1 phd female
tab1 pub1 female, miss
codebook, compact
```

7.3) Multinomial Logit

mlogit estimates the multinomial logit model. The option **baseoutcome()** allows you to set the comparison category. **estimates store** stores estimation results for model comparison.

```
. mlogit jobprst c.pub1 c.phd i.female, baseoutcome(4) nolog

Multinomial logistic regression                 Number of obs   =        264
                                                LR chi2(9)      =     108.80
                                                Prob > chi2     =     0.0000
Log likelihood = -240.45919                     Pseudo R2       =     0.1845

------------------------------------------------------------------------------
     jobprst |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1_Adeq       |
        pub1 |  -.1577122   .1164937    -1.35   0.176    -.3860356    .0706112
         phd |  -2.227522   .5717459    -3.90   0.000    -3.348123   -1.106921
```

```
             |
      female |
      1_Yes  |   2.016045   1.168225     1.73   0.084    -.2736336    4.305724
       _cons |   8.952493   2.312129     3.87   0.000     4.420802    13.48418
-------------+----------------------------------------------------------------
2_Good       |
        pub1 |  -.2360238   .1027013    -2.30   0.022    -.4373146   -.0347329
         phd |  -2.473911   .5486436    -4.51   0.000    -3.549233   -1.398589
             |
      female |
      1_Yes  |   2.957967   1.104288     2.68   0.007     .7936018    5.122331
       _cons |    10.9781   2.257877     4.86   0.000     6.552745    15.40346
-------------+----------------------------------------------------------------
3_Strong     |
        pub1 |  -.1196281   .0831959    -1.44   0.150    -.2826891    .0434329
         phd |  -1.080595   .5279581    -2.05   0.041    -2.115374   -.0458166
             |
      female |
      1_Yes  |    1.76863   1.082655     1.63   0.102    -.3533356    3.890596
       _cons |   6.285116   2.216631     2.84   0.005     1.940598    10.62963
-------------+----------------------------------------------------------------
4_Dist       |  (base outcome)
------------------------------------------------------------------------------

. estimates store base
```

7.4) [optional] Single Variable LR Test

In the MNLM, testing that a variable has no effect requires a test that *J*-1 coefficients are simultaneously equal to zero. For example, the effect of **`i.female`** involves three coefficients. We can use an LR test to test that all three are simultaneously equal to zero. First, we save the base model (which we did above); second, we estimate the model without **`i.female`** and store the estimation results; and third, we compare the two models using **`lrtest`** *estname1 estname2.*

```
. quietly mlogit jobprst c.pub1 c.phd, baseoutcome(4)
. estimates store dropfemale

. lrtest base dropfemale

Likelihood-ratio test                                 LR chi2(3)  =     19.17
(Assumption: dropfemale nested in base)               Prob > chi2 =    0.0003
```

The effect of gender on job prestige is significant at the .001 level (LRX^2=19.17, *df*=3, *p*=<.001).

Another way to do this is to use the command **`mlogtest`** after running the base model. This saves you the step of having to re-estimate the model minus the variable whose effect you want to test.

```
. estimates restore base
(results base are active now)

. mlogtest, lr

Likelihood-ratio tests for independent variables (N=264)

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

             |       chi2   df   P>chi2
-------------+--------------------------
        pub1 |      5.600    3    0.133
         phd |     87.236    3    0.000
    1.female |     19.168    3    0.000
-------------------------------------
```

7.5) Single Coefficient Wald Test

Wald tests can also be computed using the **test** command. For factor variables, you must enter the variable exactly as it is shown in the regression output, in this case **1.female**.

```
. test 1.female

 ( 1)  [1_Adeq]1.female = 0
 ( 2)  [2_Good]1.female = 0
 ( 3)  [3_Strong]1.female = 0
 ( 4)  [4_Dist]1o.female = 0
       Constraint 4 dropped

           chi2(  3) =   15.75
         Prob > chi2 =    0.0013
```

Again you can automate this process using **mlogtest**.

```
. mlogtest, wald

Wald tests for independent variables (N=264)

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

             |       chi2   df   P>chi2
-------------+--------------------------
        pub1 |      5.421    3    0.143
         phd |     56.559    3    0.000
    1.female |     15.748    3    0.001
-------------------------------------
```

The effect of gender on job prestige is significant at the .001 level (X^2=15.7, *df*=3, *p*=<.001).

7.6) [optional] Combining Outcomes Test (low priority unless you need this test)

test can also compute a Wald test that two outcomes can be combined. Recall, that the coefficients for category **1_Adeq** were in comparison to the category **4_Dist**. Therefore, we are testing whether we can combine **1_Adeq** and **4_Dist**. Note that **[1_Adeq]** is necessary in specifying the test across categories and that **[1_Adeq]** does not equal **[1_adeq]** since syntax in Stata is case sensitive.

```
. test [1_Adeq]

 ( 1)  [1_Adeq]pub1 = 0
 ( 2)  [1_Adeq]phd = 0
 ( 3)  [1_Adeq]0b.female = 0
 ( 4)  [1_Adeq]1.female = 0
       Constraint 3 dropped

           chi2(  3) =   19.01
         Prob > chi2 =    0.0003
```

We can reject the hypothesis that *adequate* and *distinguished* are indistinguishable (X^2=19.0, *df*=3, *p*<.001) and therefore conclude that these two categories cannot be combined.

This test could be done for combining other categories as well. For example we could test whether we can combine categories Adequate and Good by typing **test [1_Adeq=2_Good]**. But the easier way is to use **mlogtest**.

```
. mlogtest, combine

Wald tests for combining alternatives (N=264)
```

```
  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
-------------------+------------------------
  1_Adeq-  2_Good  |    5.189    3    0.158
  1_Adeq-3_Strong  |   19.884    3    0.000
  1_Adeq-  4_Dist  |   19.015    3    0.000
  2_Good-3_Strong  |   51.717    3    0.000
  2_Good-  4_Dist  |   31.132    3    0.000
3_Strong-  4_Dist  |    9.173    3    0.027
```

We cannot reject the hypothesis that categories *adequate* and *good* are indistinguishable (X^2=5.2, *df*=3, *p*=0.16).

7.7) [optional] Testing for IIA (low priority unless you need this test)

`mlogtest` can also be used to test the IIA (independence of irrelevant alternatives) assumption. While often recommended, this test is not very useful. Nonetheless, **`mlogtest`** computes both a Hausman and a Small-Hsiao test. Because the Small-Hsiao test requires randomly dividing the data into subsamples, the results will differ with successive calls of the command. To obtain test results that can be replicated, we set the seed used by the random-number generator. You can set the seed to whatever number you like. But when setting seeds in research that will be published, refer to the suggestions made in **`help set seed`**, as some seeds are more trustworthy than others.

```
. set seed 4415906
. mlogtest , iia

Hausman tests of IIA assumption (N=264)

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

                 |      chi2    df   P>chi2
-----------------+------------------------
          1_Adeq |     3.588     8    0.892
          2_Good |    17.887     8    0.022
        3_Strong |   -45.118     8        .
          4_Dist |    -0.222     8        .

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

suest-based Hausman tests of IIA assumption (N=264)

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

                 |      chi2    df   P>chi2
-----------------+------------------------
          1_Adeq |     4.309     8    0.828
          2_Good |     9.915     8    0.271
        3_Strong |    21.271     8    0.006
          4_Dist |     4.377     8    0.822

  Note: A significant test is evidence against Ho.

Small-Hsiao tests of IIA assumption (N=264)

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

                 | lnL(full)  lnL(omit)       chi2    df   P>chi2
```

```
----------------+--------------------------------------------
          1_Adeq |   -83.512    -72.740     21.543     8    0.006
          2_Good |   -70.925    -55.187     31.476     8    0.000
        3_Strong |   -76.846    -56.081     41.531     8    0.000
          4_Dist |  -112.991   -104.306     17.369     8    0.026

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

As is often the case with IIA tests, the evidence is mixed.

7.8) Predicted Probabilities

`mtable` computes predicted probabilities for values of the independent variables. By default, **`mtable`** shows predicted probabilities for each outcome category. If you only want to list certain outcome categories, use the **`outcome()`** option.

```
. mtable, atmeans stat(ci)

Expression: Pr(jobprst), predict(outcome())

           |   1_Adeq    2_Good  3_Strong    4_Dist
 ----------+---------------------------------------
     Pr(y) |    0.128     0.513     0.344     0.014
        ll |    0.081     0.440     0.274    -0.004
        ul |    0.176     0.587     0.415     0.032

Specified values of covariates

           |                            1.
           |     pub1       phd    female
 ----------+-----------------------------
   Current |     2.32      3.18      .345
```

For an average scientist, the probability of being employed in a department rated as "Good" is about 0.50 (95% CI: 0.44, 0.59).

7.9) Marginal and Discrete Change

We can use **`mchange`** to calculate marginal and discrete change. By default, these are AME's. We only consider discrete changes.

```
. mchange, amount(one sd)

mlogit: Changes in Pr(y) | Number of obs = 264

Expression: Pr(jobprst), predict(outcome())

               |    1 Adeq     2 Good   3 Strong     4 Dist
---------------+--------------------------------------------
pub1           |
       +1 cntr |     0.003     -0.021      0.012      0.006
       p-value |     0.720      0.080      0.277      0.071
      +SD cntr |     0.007     -0.054      0.030      0.016
       p-value |     0.720      0.080      0.277      0.071
phd            |
       +1 cntr |    -0.031     -0.202      0.169      0.064
       p-value |     0.049      0.000      0.000      0.005
      +SD cntr |    -0.031     -0.203      0.170      0.064
       p-value |     0.049      0.000      0.000      0.005
female         |
 1 Yes vs 0 No |    -0.043      0.224     -0.116     -0.065
       p-value |     0.267      0.000      0.032      0.005
```

```
Average predictions

             |    1_Adeq     2_Good   3_Strong     4_Dist
-------------+----------------------------------------------
  Pr(y|base) |     0.110      0.485      0.352      0.053
```

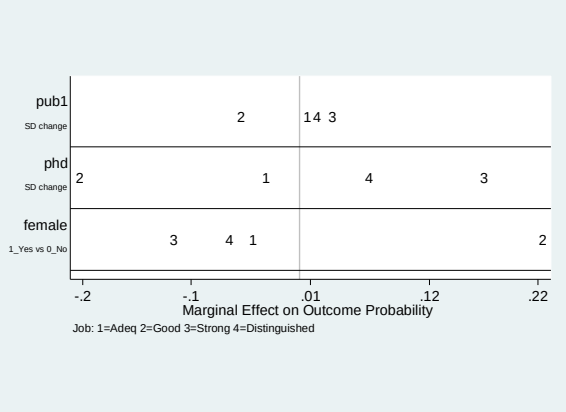
On average, being a female scientists is expected to decrease the probability of a job in a strong department by 0.12 (p<0.05, two-tailed test) and a decrease of 0.07 of being in a distinguished department (p<0.01, two-tailed test).

On average, increasing PhD prestige by one level increases the probability on having a distinguished job by 0.06 (p<0.01, two-tailed test).

7.10) Plot Discrete Change

One difficulty with nominal outcomes is the many coefficients that need to be considered. To help you sort out the information, discrete change coefficients can be plotted using **`mchangeplot`**. We recommend adding a **`note`** to the plot that includes the values and value labels. **`mchangeplot`** must be run after **`mchange`**. We use **`aspect(.4)`** to change the vertical spacing of the graph.

```
. mchangeplot pub1 phd 1.female aspect(.4) ///
>         note(Job: 1=Adeq 2=Good 3=Strong 4=Distinguished)
. graph export cda14lab-nrm-review-fig1.emf, replace
```



The average marginal effects of a standard deviation change in PhD prestige and of being female are larger than the effects of a standard deviation change in publications. On average, a standard deviation increase in PhD prestige increases the probability of being in a *strong* (3) job and decreases the probability of being in *good* (2) job by about .20. Being female increases the probability of being in a *good* (2) job by .22 and decreases the probability of being in a *strong* (3) job by .12.

7.11) Odds Ratios

`listcoef` computes the factor change coefficients for each of the comparisons. The output is arranged by the independent variables.

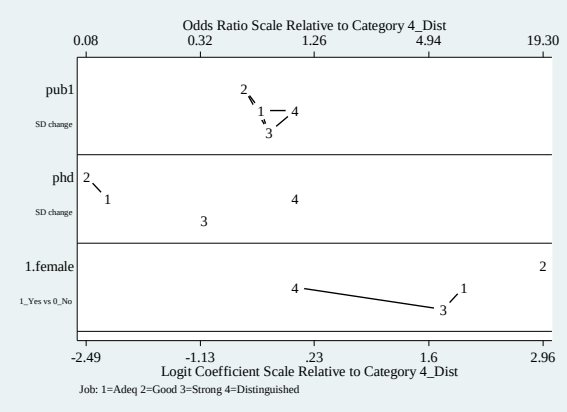
```
. listcoef, help

mlogit (N=264): Factor change in the odds of jobprst

Variable: pub1 (sd=2.581)
------------------------------------------------------------------------------
                            |          b        z    P>|z|       e^b   e^bStdX
```

```
-----------------------------+-------------------------------------------------
1_Adeq       vs 2_Good       |     0.0783    0.879    0.379     1.081     1.224
1_Adeq       vs 3_Strong     |    -0.0381   -0.412    0.680     0.963     0.906
1_Adeq       vs 4_Dist       |    -0.1577   -1.354    0.176     0.854     0.666
2_Good       vs 1_Adeq       |    -0.0783   -0.879    0.379     0.925     0.817
2_Good       vs 3_Strong     |    -0.1164   -1.623    0.105     0.890     0.741
2_Good       vs 4_Dist       |    -0.2360   -2.298    0.022     0.790     0.544
3_Strong     vs 1_Adeq       |     0.0381    0.412    0.680     1.039     1.103
3_Strong     vs 2_Good       |     0.1164    1.623    0.105     1.123     1.350
3_Strong     vs 4_Dist       |    -0.1196   -1.438    0.150     0.887     0.734
4_Dist       vs 1_Adeq       |     0.1577    1.354    0.176     1.171     1.502
4_Dist       vs 2_Good       |     0.2360    2.298    0.022     1.266     1.839
4_Dist       vs 3_Strong     |     0.1196    1.438    0.150     1.127     1.362
-------------------------------------------------------------------------------

:: Output deleted ::
```

7.12) Plot Odds Ratios

The odds ratios can be plotted in much the same way as the discrete changes by using the **`mlogitplot`** command. In the plot, a solid line indicates that the coefficient cannot differentiate between the two outcomes that are connected (i.e., the odds ratio is not significant). The significance level of the line is set with **`linep()`**.

```
. mlogitplot pub1 phd 1.female ///
>         note(Job: 1=Adeq 2=Good 3=Strong 4=Distinguished) linep(.1)
. graph export cda14lab-nrm-review-fig2.emf , replace
```

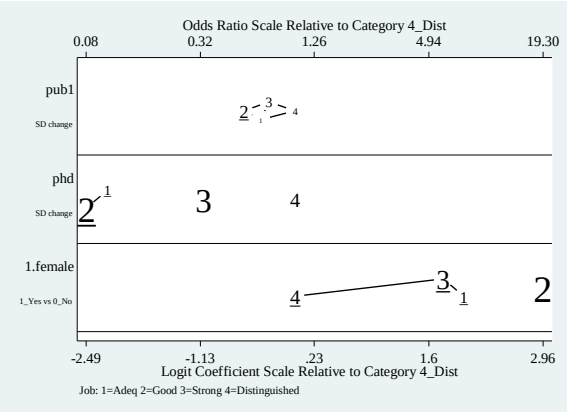


Here are the general patterns of effects. The effects of publications are smallest, with the overall magnitude of effects of doctoral origin and being female being roughly equal. While doctoral prestige does not significantly affect the odds of jobs in adequate compared to good departments, it significantly increases the odds of strong and distinguished job placement. Overall, being female increases the odds of less prestigious placements.

7.13) Adding Discrete Change to OR Plot

Information about the discrete change can be incorporated in the odds-ratio plot by using **`mlogitplot, meffect`**. Whereas the factor change in the odds is constant across the levels of all variables, the discrete change gets larger or smaller at different values of the independent variables. In the plot below, the discrete change is indicated by the size of the numbers with the area of the number proportional to the size of the discrete change. A number is underlined to indicate a negative discrete change. The **`offsetlist`** and **`msizefactor`** options "tweak" the graph to make it look better. Try experimenting with them. Try **`help mlogitplot`** for details.

```
. mlogitplot pub1 phd 1.female, ///
>         note(Job: 1=Adeq 2=Good 3=Strong 4=Distinguished) linep(.1) meffect ///
>         offsetlist(-1 0 1 0 1 -1 0 0 -1 0 1 -1) msizefactor(1.4)
. graph export cda14lab-nrm-review-fig3.emf , replace
```



7.14) Close log and exit program

```
log close
exit
```

7: Nominal outcomes exercise

The file **`cda14lab-nrm-exercise.do`** contains an outline of this exercise.

7.1) Load your data

7.2) Examine the data and select your variables. Select one nominal dependent variable and at least three independent variables. Make sure on is binary and one is continuous. Drop cases with missing data and verify. Make sure to look at the distribution of your outcome variable.

7.3) Estimate a multinomial logit model.

7.4) Use **`mlogtest`** to compute the Wald test for each independent variable. Write your conclusion for at least one variable.

7.5) [optional] Use **`mlogtest`** to compute the LR test that categories of the dependent variable can be combined. What do you find?

7.6) Compute the predicted probabilities for all outcomes at a theoretically interesting combination of your independent variables using **`mtable`**. Feel free to apply some of the options used in **`mtable`** from earlier sections of the lab guide.

7.7) Compute discrete changes and marginal effects using **`mchange`**. Be sure to indicate in your interpretation whether you compute these changes using AME or MEM.

7.8) Use **`mchangeplot`** to plot the discrete changes. Write up an interpretation as if it were part of a publishable research paper. Note that you can use the output from **7.7** to determine the specific values.

7.9) Use **`listcoef, help`** to compute the factor change coefficients.

7.10) Use **`mlogitplot`** to plot the odds ratios. Write up an interpretation as if it were part of a publishable research paper. Note that you can use the output from **7.9** to determine the specific values.

7.11) Now add discrete change to the odds ratio plot using **`mlogitplot, dc`**. Do you see how discrete change and odds ratios give you different pieces of information?

7.12) Close log and exit do-file

PART 8: ORDINAL OUTCOMES

The file **cda14lab-orm-review.do** contains these Stata commands.

8.1) Load the Data

```
sysuse icpsr_scireview4, clear
```

8.2) Examine data, select variables, and verify

Make sure to look at the distribution of the outcome variable, in this case **jobprst**.

```
codebook, compact
keep jobprst pub1 phd female
tab1 jobprst female, miss
codebook, compact
```

8.3) Ordered Logit

ologit and **oprobit** work in the same way. We only show **ologit**, but you could use **oprobit**.

```
. ologit jobprst c.pub1 c.phd i.female, nolog

Ordered logistic regression                     Number of obs   =        264
                                                LR chi2(3)      =      80.69
                                                Prob > chi2     =     0.0000
Log likelihood = -254.51518                     Pseudo R2       =     0.1368

------------------------------------------------------------------------------
     jobprst |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        pub1 |   .1078786   .0481107     2.24   0.025     .0135833    .2021738
         phd |   1.130028   .1444046     7.83   0.000     .8470003    1.413056
             |
      female |
      1_Yes  |  -.6973579   .2617103    -2.66   0.008    -1.210301   -.1844152
-------------+----------------------------------------------------------------
       /cut1 |   .9274554   .4268201                      .0909033    1.764007
       /cut2 |   4.003182   .4996639                      3.023859    4.982506
       /cut3 |   7.034637   .6296717                      5.800503     8.26877
------------------------------------------------------------------------------

. estimates store ologit
```

8.4) [optional] Predicted Probabilities in Sample

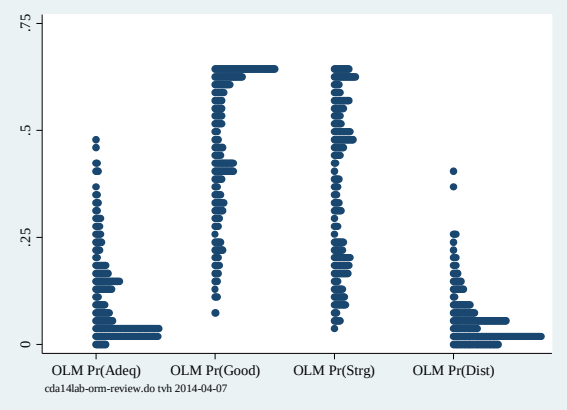
predict computes predicted probabilities after **ologit** or **oprobit**. It creates as many new variables as there are categories of the outcome variable so you will need to provide variable names that correspond to the four outcome categories. The first variable contains the probability associated with the lowest outcome; the second the probability associated with the second outcome; and so on. Remember to label the newly created variables.

```
predict jpad jpgo jpst jpdi
label var jpad "OLM Pr(Adeq)"
label var jpgo "OLM Pr(Good)"
label var jpst "OLM Pr(Strg)"
label var jpdi "OLM Pr(Dist)"
```

An easy way to see the range of predictions is with the command **dotplot**.

```
. dotplot jpad jpgo jpst jpdi, ylabel(0(.25).75)
```

```
. graph export cda14lab-orm-review-fig1.emf, replace
```



8.5) Predict Specific Probabilities

`mtable` computes the predicted value for a set of values for the independent variables. Use the **`at()`** and **`atmeans`** options to set the values at which the variables will be examined.

```
. mtable, at(female=1 phd=4) atmeans stat(ci)

Expression: Pr(jobprst), predict(outcome())

           |   1_Adeq    2_Good  3_Strong    4_Dist
 ----------+-------------------------------------
     Pr(y) |    0.041     0.441     0.468     0.049
        ll |    0.017     0.344     0.369     0.018
        ul |    0.065     0.539     0.568     0.080

Specified values of covariates

           |     pub1       phd    female
 ----------+----------------------------
   Current |     2.32         4         1
```

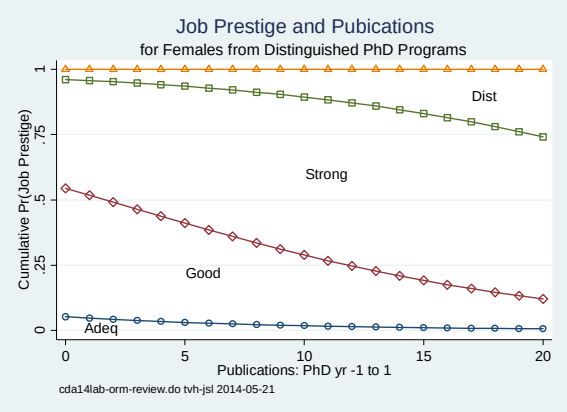
For a female from a distinguished university who is otherwise average, the probability of obtaining a distinguished job is .05 (95% CI: 0.02, 0.08).

8.6) Graph Predicted Probabilities

Graphing predictions as a continuous variable changes is a useful way to examine the effect of the variable. **`mgen`** creates variables for graphing. We consider women from distinguished PhD programs **`(phd=4)`** and show how predicted probabilities are influenced by publications. **`mgen`** creates variables of both the predicted probabilities and the cumulative probabilities. We plot the cumulative probabilities below.

```
. mgen, at(female=1 phd=4 pub1=(0(1)20)) atmeans stub(pub)

Predictions from: margins, at(female=1 phd=4 pub1=(0(1)20)) atmeans predict(outc
> ome())

Variable   Obs Unique       Mean        Min       Max  Label
-------------------------------------------------------------------------------
pubpr1      21     21   .0223568   .0063504  .0523864  pr(y=1_Adeq) from margins
publl1      21     21   .0036257  -.0053376  .0215249  95% lower limit
pubul1      21     21   .0410879   .0180384   .083248  95% upper limit
pubpub1     21     21         10          0        20  Publications: PhD yr -...
pubCpr1     21     21   .0223568   .0063504  .0523864  pr(y<=1_Adeq)
pubpr2      21     21   .2839126   .1152733  .4925985  pr(y=2_Good) from margins
```

```
publl2      21     21   .1313544  -.0629369  .3922909  95% lower limit
pubul2      21     21   .4364709   .2934835  .5929062  95% upper limit
pubCpr2     21     21   .3062694   .1216237   .544985  pr(y<=2_Good)
pubpr3      21     21   .5720646    .416294  .6397324  pr(y=3_Strong) from ma...
publl3      21     21   .4590643   .3121963  .5507059  95% lower limit
pubul3      21     21   .6850648   .5203917  .7909892  95% upper limit
pubCpr3     21     21    .878334   .7416018   .961279  pr(y<=3_Strong)
pubpr4      21     21    .121666    .038721  .2583981  pr(y=4_Dist) from margins
publl4      21     21  -.0032969  -.0789567  .0229574  95% lower limit
pubul4      21     21    .246629   .0650923   .595753  95% upper limit
pubCpr4     21      2          1   .9999999         1  pr(y<=4_Dist)
------------------------------------------------------------------------------

. graph twoway (connected pubCpr1 pubCpr2 pubCpr3 pubCpr4 pubpub1, ///
>         title("Job Prestige and Publications") ///
>         subtitle("for Females from Distinguished PhD Programs") ///
>         ytitle("Cumulative Pr(Job Prestige)") ///
>         xtitle("Publications: PhD yr -1 to 1") ///
>         xlabel(0(5)20) ylabel(0(.25)1, grid) ///
>         msymbol(Oh Dh Sh Th) name(tmp2, replace) ///
>         text(.01 .75 "Adeq", place(e)) text(.22 5 "Good", place(e)) ///
>         text(.60 10 "Strong", place(e))text(.90 17 "Dist", place(e))), legend(off)
. graph export cda14lab-orm-review-fig2.emf , replace
```



The plot shows many things. First, the probability of obtaining a job in the least prestigious category adequate is low for women scientists from distinguished universities regardless of the number of publications. Second, the probability of obtaining a strong or distinguished job is much larger, increasing as the number of publications increase. With twenty publications, over 80% of these women are predicted to be in these types of positions. Third, the increase in strong and distinguished jobs is offset by a corresponding decreases in good jobs.

8.8) Discrete Change

mchange computes marginal and discrete change at specific values of the independent variables. Values for specific independent variables can be set using the **at()**. The below results are computed using AME.

```
. mchange, amount(one sd)

ologit: Changes in Pr(y) | Number of obs = 264

Expression: Pr(jobprst), predict(outcome())

               |    1 Adeq     2 Good   3 Strong     4 Dist
---------------+----------------------------------------
pub1           |
```

```
       +1 cntr |    -0.009     -0.011      0.015      0.005
       p-value |     0.032      0.024      0.025      0.039
      +SD cntr |    -0.023     -0.029      0.038      0.013
       p-value |     0.032      0.024      0.025      0.040
phd            |
       +1 cntr |    -0.094     -0.114      0.152      0.056
       p-value |     0.000      0.000      0.000      0.000
      +SD cntr |    -0.095     -0.115      0.153      0.056
       p-value |     0.000      0.000      0.000      0.000
female         |
 1 Yes vs 0 No |     0.062      0.066     -0.097     -0.031
       p-value |     0.014      0.006      0.008      0.015

Average predictions

             |    1_Adeq     2_Good   3_Strong     4_Dist
-------------+--------------------------------------------
  Pr(y|base) |     0.104      0.470      0.371      0.055
```

On average, being a female scientist decreases the probability of adequate and good job placements by .06 ($p<0.05$ and $p<0.01$ respectively, two-tailed test), and decreases the probability of strong jobs by .10 ($p<0.01$, two-tailed test) and distinguished jobs by .03 ($p<0.05$, two-tailed test).

If we wanted to compute predictions for women from distinguished departments who are average on other characteristics (i.e. MEM):

```
. mchange, at(female=1 phd=4) atmeans

ologit: Changes in Pr(y) | Number of obs = 264

Expression: Pr(jobprst), predict(outcome())

               |    1 Adeq     2 Good   3 Strong     4 Dist
---------------+--------------------------------------------
pub1           |
       +1 cntr |    -0.004     -0.023      0.022      0.005
       p-value |     0.044      0.028      0.028      0.058
      +SD cntr |    -0.011     -0.058      0.056      0.013
       p-value |     0.045      0.027      0.027      0.058
phd            |
       +1 cntr |    -0.047     -0.228      0.220      0.055
       p-value |     0.000      0.000      0.000      0.002
      +SD cntr |    -0.047     -0.229      0.221      0.055
       p-value |     0.000      0.000      0.000      0.002
female         |
 1 Yes vs 0 No |     0.020      0.145     -0.121     -0.045
       p-value |     0.029      0.007      0.012      0.018

Predictions at base value

             |    1_Adeq     2_Good   3_Strong     4_Dist
-------------+--------------------------------------------
  Pr(y|base) |     0.041      0.441      0.468      0.049

Base values of regressors

             |      pub1        phd     female
-------------+--------------------------------
          at |      2.32          4          1

1: Estimates with margins option atmeans.
```

8.9) [optional] Odds Ratios

The factor change in the odds can be computed for the ordinal logit model. Again we do this with the command **`listcoef`**. The **`help`** option presents a "key" to interpreting the headings of the output.

```
. listcoef, help

ologit (N=264): Factor change in odds

  Odds of: >m vs <=m

------------------------------------------------------------------------------
             |          b        z    P>|z|       e^b   e^bStdX     SDofX
-------------+----------------------------------------------------------------
        pub1 |     0.1079    2.242    0.025     1.114     1.321     2.581
         phd |     1.1300    7.825    0.000     3.096     3.114     1.005
             |
      female |
      1_Yes  |    -0.6974   -2.665    0.008     0.498     0.717     0.476
   constant1 |     0.9275    2.173    0.030         .         .         .
   constant2 |     4.0032    8.012    0.000         .         .         .
   constant3 |     7.0346   11.172    0.000         .         .         .
   constant4 |          .        .        .         .         .         .
------------------------------------------------------------------------------
       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
   SDofX = standard deviation of X
```

The odds of receiving a higher ranked job are .50 times smaller for women than men, holding other variables constant (p<0.01, two-tailed test).

For a standard deviation increase in publications, about 2.6, the odds of receiving a higher ranked job increase by a factor of 1.3, holding other variables constant (p<0.05, two-tailed test).

8.10) [optional] Testing the Parallel Regression Assumption

`brant` performs a Brant test of the parallel regressions assumptions for the ordered logit model.

```
. brant, detail

:: Output deleted ::

Brant Test of Parallel Regression Assumption

    Variable |      chi2   p>chi2    df
-------------+--------------------------
         All |     38.88    0.000     6
-------------+--------------------------
        pub1 |      2.76    0.252     2
         phd |     22.68    0.000     2
    1.female |     11.26    0.004     2
---------------------------------------

A significant test statistic provides evidence that the parallel
regression assumption has been violated.
```

There is strong evidence that the parallel regression assumption is violated (p<.001).

8.11) Close log and exit program

```
log close
exit
```

8: Ordinal outcomes exercise

The file **cda14lab-orm-exercise.do** contains an outline of this Exercise

8.1) Load your data

8.2) Examine the data and select your variables. Select one ordinal dependent variable. Select at least three independent variables (make sure on is binary and one is continuous). Drop cases with missing data and verify. Make sure to look at the distribution of your outcome variable.

8.3) Estimate an ordered logit model.

8.4) [optional] Predict probabilities for each observation. Make sure to label the new variables created by **predict**.

8.5) [optional] Graph the probabilities from **8.4** using **dotplot**. What does this tell you?

8.6) Use **mtable** to compute the predicted probability at some specific value of the independent variables. Interpret this.

8.6) Use **mgen** to plot the predicted probabilities over the range of a continuous variable. Interpret this.

8.7) Use **mchange** to calculate the discrete changes, using either AME or MEM. Interpret a couple of these.

8.8) [optional] Obtain the factor change coefficients using **listcoef, help**. Interpret at least one unstandardized and one standardized factor change coefficient.

8.9) [optional] Use **brant** to test the parallel regression assumption. What is your conclusion?

8.10) Close log and exit do-file.

PART 9: COUNT OUTCOMES

The file **cda14lab-crm-review.do** contains these Stata commands.

9.1) Load the Data

```
use icpsr_scireview4, clear
```

9.2) Examine data, select variables, and verify

Make sure to look at the distribution of the outcome variable, in this case, **pub6**.

```
codebook, compact
keep pub6 female phd enrol
tab1 pub6 female, miss
codebook, compact
```

9.3) Estimate the Negative Binomial Regression Model

```
. nbreg pub6 i.female c.phd c.enrol, nolog

Negative binomial regression                    Number of obs   =        264
                                                LR chi2(3)      =      20.59
Dispersion     = mean                           Prob > chi2     =     0.0001
Log likelihood = -642.723                       Pseudo R2       =     0.0158

------------------------------------------------------------------------------
```

```
        pub6 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |
      1_Yes  |  -.2822292   .1382637    -2.04   0.041     -.553221   -.0112373
         phd |   .1995909   .0651859     3.06   0.002     .0718288     .327353
      enroll |   -.150895   .0480431    -3.14   0.002    -.2450578   -.0567322
       _cons |   1.607418   .3379749     4.76   0.000     .9449989    2.269836
-------------+----------------------------------------------------------------
    /lnalpha |   -.203673   .1255831                     -.4498113    .0424654
-------------+----------------------------------------------------------------
       alpha |   .8157291   .1024418                      .6377485     1.04338
------------------------------------------------------------------------------
Likelihood-ratio test of alpha=0:  chibar2(01) =  394.12 Prob>=chibar2 = 0.000
```

Because there is significant evidence of overdispersion (G^2=394.12, p< .001), the negative binomial regression model is preferred to the Poisson regression model.

9.4) Factor Changes

`listcoef` computes the factor change coefficients.

```
. listcoef, help

nbreg (N=264): Factor change in expected count

  Observed SD:  4.3103

------------------------------------------------------------------------------
             |          b        z    P>|z|       e^b   e^bStdX     SDofX
-------------+----------------------------------------------------------------
      female |
      1_Yes  |    -0.2822   -2.041    0.041     0.754     0.874     0.476
         phd |     0.1996    3.062    0.002     1.221     1.222     1.005
      enroll |    -0.1509   -3.141    0.002     0.860     0.804     1.443
    constant |     1.6074    4.756    0.000         .         .         .
-------------+----------------------------------------------------------------
alpha        |
     lnalpha |    -0.2037        .        .         .         .         .
       alpha |     0.8157        .        .         .         .         .
------------------------------------------------------------------------------
  LR test of alpha=0: 394.12   Prob>=LRX2 = 0.000
       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 expected count for unit increase in X
 e^bStdX = exp(b*SD of X) = change in expected count for SD increase in X
   SDofX = standard deviation of X
```

Being a female scientist decreases the expected number of publications by a factor of .75, holding other variables constant (p<0.05, two-tailed test).

A standard deviation increase in the number of years from enrollment to completion of the PhD, about 1.4 years, decreases the expected number of publications by 14%, holding other variables constant (p<0.01, two-tailed test).

9.5) Discrete Change

`mchange` computes the discrete change in the expected count/rate. The changes below are AME's. To compute them using MEM, simply add the option **`atmeans`**.

```
. mchange, amount(one sd)

nbreg: Changes in mu | Number of obs = 264

Expression: Predicted number of pub6, predict()

               |    Change    p-value
---------------+----------------------
female         |
 1 Yes vs 0 No |    -1.048      0.036
phd            |
       +1 cntr |     0.779      0.004
      +SD cntr |     0.783      0.004
enroll         |
       +1 cntr |    -0.588      0.003
      +SD cntr |    -0.850      0.003

Average prediction

    3.896
```

On average, being a female scientist is expected to decrease productivity by 1.0 publication (p<0.05, two-tailed test).

On average, the effect of an additional year in graduate schools is to decreases the rate of productivity by -0.59 (p<0.01, two-tailed test).

9.6 Expected Count

Use **`mtable`** to compute the expected count of publications for average men and average women. **`mtable`** is run 3 times, with the option **`below`** stacking the current **`mtable`** results below the previous **`mtable`** results. Note that **`rowname()`** is used to label each of the rows.

```
. quietly mtable, at(female=0) stat(ci) atmeans rowname(Men)
. quietly mtable, at(female=1) stat(ci) atmeans rowname(Women) below
. mtable, dydx(female) stat(ci) atmeans rowname(Change) below

Expression: Predicted number of pub6, predict()

           |       mu        ll        ul
 ----------+-----------------------------
       Men |    4.088     3.456     4.719
     Women |    3.083     2.399     3.766
    Change |   -1.005    -1.939    -0.072

Specified values of covariates

           |                                      1.
           |   female       phd    enroll    female
 ----------+---------------------------------------
     Set 1 |        0      3.18      5.53         .
     Set 2 |        1      3.18      5.53         .
   Current |        .      3.18      5.53      .345
```

For scientists who are average on other characteristics, women are expected to have about 1.0 fewer publications than men (95% CI: -1.94, -0.07).

9.7) Predicted Rate and Probabilities

mtable can also calculate the predicted probabilities for specific levels of the outcome variable, as well as the discrete change in the probabilities. This is done using the **pr()** option. The option **roweq** is used to name the different sections of the table rows.

```
. quietly mtable, at(female=0) atmeans  ///
>     roweq(Men_) pr(0(1)5)
. quietly mtable, at(female=1) atmeans ///
>     roweq(Women_) pr(0(1)5) below
. mtable, dydx(female) stat(est pvalue) atmeans ///
>     roweq(Change) pr(0(1)5) below

Expression: Marginal effect of Pr(pub), predict(pr(5))

           |        0         1         2         3         4         5
 ----------+------------------------------------------------------------
 Men       |
         1 |    0.166     0.156     0.134     0.111     0.090     0.072
 Women     |
         1 |    0.214     0.188     0.150     0.115     0.087     0.065
 Change    |
   d Pr(y) |    0.049     0.032     0.016     0.004    -0.003    -0.007
         p |    0.049     0.043     0.036     0.053     0.261     0.093

Specified values of covariates

           |                                      1.
           |   female       phd    enroll    female
 ----------+---------------------------------------
     Set 1 |        0      3.18      5.53         .
     Set 2 |        1      3.18      5.53         .
   Current |        .      3.18      5.53      .345
```

For scientists who are average on all other characteristics, women have a higher probability than men of having zero publications (p<0.05, two-tailed test), while men have a higher probability of having five publications (p<0.01, two-tailed test).

9.8) [optional] ZIP Model

The **zip** command with the **inf(*indvars*)** option estimates a Zero-Inflated Poisson Regression Model. You can "inflate" the same set of variables that are used in the PRM portion of the model or an entirely different set of variables. Here we "inflate" the variable **phd**.

```
. zip pub6 i.female c.phd c.enrol, inf(c.phd) nolog

Zero-inflated Poisson regression                Number of obs   =        264
                                                Nonzero obs     =        212
                                                Zero obs        =         52

Inflation model = logit                         LR chi2(3)      =      48.74
Log likelihood  = -758.0032                     Prob > chi2     =     0.0000

------------------------------------------------------------------------------
        pub6 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
pub6         |
      female |
      1_Yes  |  -.1210631   .0710846    -1.70   0.089    -.2603864    .0182602
         phd |   .1400257   .0334849     4.18   0.000     .0743964     .205655
      enroll |  -.1306837   .0250179    -5.22   0.000    -.1797178   -.0816496
       _cons |   1.838966   .1749225    10.51   0.000     1.496124    2.181808
```

```
-------------+----------------------------------------------------------------
inflate      |
         phd |  -.2383082   .1657934    -1.44   0.151    -.5632572    .0866408
       _cons |  -.7539084   .5332584    -1.41   0.157    -1.799076     .291259
------------------------------------------------------------------------------
```

9.9)) [optional] ZINB Model

We can use the same types of commands for the ZINB. The results are stored using **`estimates store`**.

```
. zinb pub6 i.female c.phd c.enrol, inf(c.phd) nolog

Zero-inflated negative binomial regression        Number of obs   =        264
                                                  Nonzero obs     =        212
                                                  Zero obs        =         52

Inflation model = logit                           LR chi2(3)      =      18.91
Log likelihood  = -642.2026                       Prob > chi2     =     0.0003

------------------------------------------------------------------------------
        pub6 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
pub6         |
      female |
      1_Yes  |  -.2708994   .1371918    -1.97   0.048    -.5397905   -.0020084
         phd |   .1745669   .0695427     2.51   0.012     .0382657    .3108682
      enroll |  -.1527173    .047032    -3.25   0.001    -.2448984   -.0605362
       _cons |   1.739814   .3498874     4.97   0.000     1.054047     2.42558
-------------+----------------------------------------------------------------
inflate      |
         phd |  -.5440498   .8665119    -0.63   0.530    -2.242382    1.154282
       _cons |  -1.456929   2.082817    -0.70   0.484    -5.539175    2.625316
-------------+----------------------------------------------------------------
    /lnalpha |  -.3514184   .2107589    -1.67   0.095    -.7644982    .0616614
-------------+----------------------------------------------------------------
       alpha |   .7036893   .1483088                      .4655675    1.063602
------------------------------------------------------------------------------

. estimates store estzinb
```

9.10) Factor Change

Factor change coefficients can be computed after estimating the ZIP or ZINB models using **`listcoef`**. Since the output is similar, we show only the output for ZINB. The top half of the output, labeled Count Equation, contains coefficients for the factor change in the expected count for those in the Not Always Zero group. The bottom half, labeled Binary Equation, contains coefficients for the factor change in the odds of being in the Always Zero group compared with the Not Always Zero group.

```
. listcoef, help

zinb (N=264): Factor change in expected count

  Observed SD:  4.3103

Count equation: Factor change in expected count for those not always 0

------------------------------------------------------------------------------
             |          b        z    P>|z|       e^b   e^bStdX     SDofX
-------------+----------------------------------------------------------------
      female |
      1_Yes  |    -0.2709   -1.975    0.048     0.763     0.879     0.476
         phd |     0.1746    2.510    0.012     1.191     1.192     1.005
      enroll |    -0.1527   -3.247    0.001     0.858     0.802     1.443
    constant |     1.7398    4.972    0.000         .         .         .
```

```
-------------+------------------------------------------------------------
alpha        |
     lnalpha |    -0.3514        .        .         .         .         .
       alpha |     0.7037        .        .         .         .         .
------------------------------------------------------------------------------
       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 expected count for unit increase in X
 e^bStdX = exp(b*SD of X) = change in expected count for SD increase in X
   SDofX = standard deviation of X

Binary equation: factor change in odds of always 0
------------------------------------------------------------------------------
             |          b        z    P>|z|       e^b   e^bStdX     SDofX
-------------+----------------------------------------------------------------
         phd |    -0.5440   -0.628    0.530     0.580     0.579     1.005
    constant |    -1.4569   -0.699    0.484         .         .         .
------------------------------------------------------------------------------
       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
   SDofX = standard deviation of X
```

Among those who have the opportunity to publish, a standard deviation increase PhD prestige increases the expected rate of publication by a factor of 1.2, holding other variables constant (p<0.05, two-tailed test).

A standard deviation increase in PhD prestige decreases the odds of not having the opportunity to publish by a factor of 0.58, although this is not significant (z=-0.63, p=0.53).

9.11) Predicted Probabilities and Expected Count

The ZINB model has 3 types of post-estimation results we are interested in: the expected count, the probability of always being zero, and the predicted probability of various levels of the outcome. By default **`mtable`** computes the expected count. To compute the probability of being always zero, include the **`predict(pr)`** option. To compute the predicted probability of various levels of the outcome variable, include the **`pr()`** option.

```
. quietly mtable, at(phd=(1 4)) atmeans long stat(ci)
. quietly mtable, at(phd=(1 4)) atmeans long stat(ci) noatvar right ///
>     estname(Always0) predict(pr)
. mtable, at(phd=(1 4)) atmeans long stat(ci) noatvar colstub(pr) ///
>     right pr(0 1 9)

Expression: Pr(pub), predict(pr(9))

           |      phd        mu   Always0       pr0       pr1       pr9
 ----------+------------------------------------------------------------
        mu |        1     2.339     0.119     0.316     0.182     0.012
        ll |        1     1.470    -0.166     0.111     0.102     0.004
        ul |        1     3.208     0.404     0.521     0.262     0.021
        mu |        4     4.367     0.026     0.155     0.139     0.032
        ll |        4     3.692    -0.068     0.099     0.102     0.026
        ul |        4     5.042     0.120     0.210     0.176     0.038

Specified values of covariates

           |        1.
           |   female    enroll
 ----------+-------------------
```

```
     Set 1 |      .345      5.53
     Set 2 |      .345      5.53
   Current |      .345      5.53
```

An average scientist from a distinguished university is expected to have slightly over 4 publications (95% CI: 3.69, 5.04), while an average scientist from an adequate university is expected to have slightly over 2 publications (95% CI: 1.47, 3.21).

For an average scientist from an adequate university, the probability of having no publications because the scientist does not have the opportunity to publish is 0.12 (95% CI: -0.17, 0.40). Thus most of the 0's for average scientists are for those who are "potential publishers."

For an average scientist from a low prestige university, the probability of having no publications, either because the scientist does not have the opportunity to publish or because the scientist is a potential publisher who by chance did not publish, is 0.32 (95% CI: 0.11, 0.52).

For an average scientist from a high prestige university, the probability of having 9 publications is 0.03 (95% CI: 0.026, 0.038).

9.12) Discrete Change for Predicted Probabilities and Expected Counts

To compute the discrete change of the different types of predicted values above, we can use **`margins, post`** followed by **`mlincom`**. The results are stacked into an easy to read table with **`mlincom`** by specifying the **`add`** option. Note that estimation results need to be restored before each **`margins, post`** by using **`estimates restore`**.

```
. quietly margins, at(phd=(1 4)) atmeans post
. quietly mlincom 2-1, rowname(Expected_y) stat(all) estname(Change)
. estimates restore estzinb

. quietly margins, at(phd=(1 4)) atmeans predict(pr) post
. quietly mlincom 2-1, rowname(Always_0) stat(all) estname(Change) add
. estimates restore estzinb

. quietly margins, at(phd=(1 4)) atmeans predict(pr(0)) post
. quietly mlincom 2-1, rowname(Pr_y=0) stat(all) estname(Change) add
. estimates restore estzinb

. quietly margins, at(phd=(1 4)) atmeans predict(pr(1)) post
. quietly mlincom 2-1, rowname(Pr_y=1) stat(all) estname(Change) add
. estimates restore estzinb

. quietly margins, at(phd=(1 4)) atmeans predict(pr(9)) post
. mlincom 2-1, rowname(Pr_y=9) stat(all) estname(Change) add
. estimates restore estzinb
```

```
             |   Change        se    zvalue    pvalue        ll        ul
-------------+------------------------------------------------------------
  Expected_y |    2.028     0.619     3.278     0.001     0.816     3.241
    Always_0 |   -0.093     0.163    -0.573     0.566    -0.412     0.226
      Pr_y=0 |   -0.162     0.120    -1.343     0.179    -0.398     0.074
      Pr_y=1 |   -0.043     0.046    -0.941     0.347    -0.134     0.047
      Pr_y=9 |    0.020     0.006     3.354     0.001     0.008     0.031
```

For an average scientist, attending a distinguished university compared to an adequate university is expected to increase productivity by slightly over two publications (p<0.01, two-tailed test).

For an average scientist, attending a distinguished university compared to an adequate university does not affect the probability of having no publications because the scientist does not have the opportunity to publish (z=-0.573, p=0.566).

For an average scientist, attending a high prestige university compared to a low prestige university increases the probability of having 9 publications (95% CI: 0.008, 0.031).

9.14) Compare models

`countfit` compares the fit of PRM, NBRM, ZIP, and ZINB, optionally generating a table of estimates, a table of differences between observed and average estimated probabilities, a graph of these differences, and various tests and measures of fit.

```
. countfit pub6 i.female c.phd c.enrol, inf(c.phd) ///
>     graphexport(`pgm'-fig1.emf, replace)
```

Variable	PRM	NBRM	ZIP	ZINB
pub6				
female				
1_Yes	0.786	0.754	0.895	0.836
	-3.49	-2.04	-1.57	-1.19
Prestige of Ph.D. department.	1.207	1.221	1.151	1.231
	5.85	3.06	4.19	3.19
Years from BA to P..	0.876	0.860	0.879	0.871
	-5.51	-3.14	-5.14	-2.82
Constant	4.630	4.990	6.213	4.532
	9.02	4.76	10.44	4.45
lnalpha				
Constant		0.816		0.735
		-1.62		-2.14
inflate				
female				
1_Yes			2.006	2.60e+06
			2.04	0.02
Prestige of Ph.D. department.			0.759	1.430
			-1.66	0.49
Years from BA to P..			1.028	1.370
			0.23	0.68
Constant			0.351	0.000
			-1.24	-0.02
Statistics				
alpha		0.816		
N	264	264	264	264
ll	-839.781	-642.723	-755.914	-641.263
bic	1701.865	1313.326	1556.436	1332.709
aic	1687.561	1295.446	1527.828	1300.526

legend: b/t

```
Comparison of Mean Observed and Predicted Count
```

Model	Maximum Difference	At Value	Mean |Diff|
PRM	0.163	0	0.051
NBRM	0.038	6	0.015
ZIP	0.100	1	0.033
ZINB	0.037	6	0.012

PRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.197	0.034	0.163	205.490
1	0.144	0.100	0.044	4.992
2	0.129	0.161	0.032	1.688
3	0.121	0.185	0.064	5.777
4	0.095	0.170	0.075	8.815
5	0.053	0.133	0.080	12.712
6	0.091	0.092	0.001	0.003
7	0.023	0.057	0.035	5.546
8	0.042	0.033	0.009	0.589
9	0.023	0.018	0.005	0.371
Sum	0.917	0.983	0.507	245.982

NBRM: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.197	0.187	0.010	0.142
1	0.144	0.167	0.023	0.834
2	0.129	0.136	0.008	0.115
3	0.121	0.109	0.013	0.382
4	0.095	0.086	0.009	0.255
5	0.053	0.067	0.014	0.781
6	0.091	0.053	0.038	7.394
7	0.023	0.041	0.018	2.176
8	0.042	0.032	0.009	0.728
9	0.023	0.025	0.003	0.069
Sum	0.917	0.903	0.145	12.875

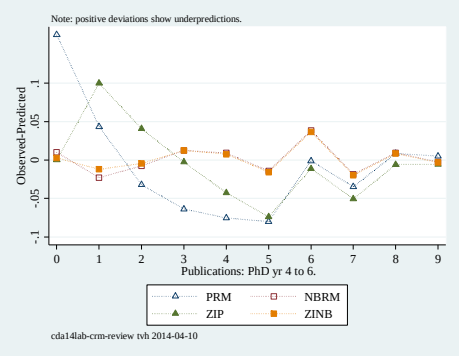
ZIP: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.197	0.197	0.000	0.000
1	0.144	0.044	0.100	59.264
2	0.129	0.088	0.041	4.940
3	0.121	0.124	0.003	0.016
4	0.095	0.137	0.042	3.465
5	0.053	0.127	0.074	11.353
6	0.091	0.102	0.011	0.320
7	0.023	0.073	0.050	9.169
8	0.042	0.048	0.006	0.193
9	0.023	0.028	0.006	0.306
Sum	0.917	0.969	0.332	89.027

ZINB: Predicted and actual probabilities

Count	Actual	Predicted	|Diff|	Pearson
0	0.197	0.194	0.003	0.010
1	0.144	0.156	0.012	0.247
2	0.129	0.133	0.004	0.040
3	0.121	0.109	0.012	0.373
4	0.095	0.087	0.008	0.179
5	0.053	0.069	0.016	0.958
6	0.091	0.054	0.037	6.598
7	0.023	0.042	0.020	2.416
8	0.042	0.033	0.008	0.567

```
9        0.023       0.026      0.003     0.109
-------------------------------------------------
Sum      0.917       0.904      0.123    11.496

Tests and Fit Statistics

PRM             BIC=  1701.865  AIC=  1687.561  Prefer  Over  Evidence
-----------------------------------------------------------------------
  vs NBRM       BIC=  1313.326  dif=   388.539  NBRM    PRM   Very strong
                AIC=  1295.446  dif=   392.115  NBRM    PRM
                LRX2=  394.115  prob=    0.000  NBRM    PRM   p=0.000
-----------------------------------------------------------------------
  vs ZIP        BIC=  1556.436  dif=   145.429  ZIP     PRM   Very strong
                AIC=  1527.828  dif=   159.733  ZIP     PRM
                Vuong=   4.358  prob=    0.000  ZIP     PRM   p=0.000
-----------------------------------------------------------------------
  vs ZINB       BIC=  1332.709  dif=   369.155  ZINB    PRM   Very strong
                AIC=  1300.526  dif=   387.035  ZINB    PRM
-----------------------------------------------------------------------
NBRM            BIC=  1313.326  AIC=  1295.446  Prefer  Over  Evidence
-----------------------------------------------------------------------
  vs ZIP        BIC=  1556.436  dif=  -243.110  NBRM    ZIP   Very strong
                AIC=  1527.828  dif=  -232.382  NBRM    ZIP
-----------------------------------------------------------------------
  vs ZINB       BIC=  1332.709  dif=   -19.384  NBRM    ZINB  Very strong
                AIC=  1300.526  dif=    -5.080  NBRM    ZINB
                Vuong=   0.834  prob=    0.202  ZINB    NBRM  p=0.202
-----------------------------------------------------------------------
ZIP             BIC=  1556.436  AIC=  1527.828  Prefer  Over  Evidence
-----------------------------------------------------------------------
  vs ZINB       BIC=  1332.709  dif=   223.726  ZINB    ZIP   Very strong
                AIC=  1300.526  dif=   227.302  ZINB    ZIP
                LRX2=  229.302  prob=    0.000  ZINB    ZIP   p=0.000
-----------------------------------------------------------------------
```



9.15) Close log and exit program

```
log close
exit
```

PART 9: Count outcomes exercise

The file **`cda14lab-crm-exercise.do`** contains an outline of this exercise.

9.1) Load your data.

9.2) Examine the data and select your variables. Choose one count dependent variable and at least three independent variables (make sure on is binary and one is continuous). Drop cases with missing data and verify. Make sure to look at the distribution of your outcome variable.

9.3) Estimate a NBRM. Store results

9.4) List the factor change coefficients using **`listcoef, help`**. Interpret a few of the unstandardized and standardized factor change coefficients.

9.5) Use **`mchange`** to calculate a discrete change. Interpret this.

9.6) Use **`mtable`** to compute the expected count for both values of your binary variable, as well as the discrete change. Interpret this.

9.7) Using the same binary variable in 9.6, use **`mtable`** to compute predicted probabilities and discrete change over a range of values for your outcome variables. Interpret results.

9.8) Test NBRM against PRM and write up the results as though it were part of a research paper. (Hint: use the LR test results at the end of the NBRM output)

9.9) [optional] Estimate the same model using **`zip.`**

9.10) [optional] Estimate the same model using **`zinb`**.

9.11) [optional] List the factor change coefficients using **`listcoef, help`** for either the ZIP or ZINB model. Interpret a few of the unstandardized and standardized factor change coefficients.

9.12) [optional] Use **`mtable`** to compute the expected count, the probability of being Always zero, and predicted probabilities over a range of values for your outcome variable. Interpret this.

9.13) [optional] Use **`margins, post`** and **`mlincom`** to compute discrete changes for the probabilities and values estimated in 9.12 at two levels of your continuous variable. Interpret this.

9.14) [optional] Use **`countfit`** to compare count models. Which model do you prefer and why?

9.15) Close log and exit do-file.

Datasets for CDA Workshop

There are the datasets that we provide for exercises.

icpsr_science4 (icpsr_scireview4) contains information on the careers of 308 Ph.D. biochemists. (Note that icpsr_scireview4 has dropped missing cases and therefore contains information on 264 scientists.) This data set is based on data collected by Scott Long with funding from the National Science Foundation. Please note that some variables have been modified.

icpsr_hsb4 contains 1647 observations on 68 variables from the 1983 High School and Beyond Study.

icpsr_nes4 contain 2487 observations on 45 variables from the 1992 National Election Study.

icpsr_addhealth4 contains 2146 observations on 126 variables. It is an extract from the 1994-95 wave of the Add Health public use dataset, and contains information on the hobbies and activities of students aged 12-21, including delinquent behavior and drug/alcohol use. The dataset also includes information about the relationships between the respondents and their parents

The codebooks and data are like those you will encounter in the real world. They attempt to be accurate, but they probably are not. That means that it is up to you to make sure that the descriptions correspond to the distribution of the data in the file. As always in such things, *caveat emptor.*

icpsr_science4.dta (icpsr_scireview4): Codebook for Science Data

id	ID number of scientist.
cit#	Number of citations over 3-year period ending in career year # (for #=1, 3, 6, 9)
enrol	Number of years it took to get a Ph.D. after receipt of B.A.
fel	Prestige of Ph.D. if scientist is not a fellow; prestige of fellowship department if a fellow. Ranges from 0.75 to 5.00. See **phd** for details on scores.
fellow	Postdoctoral fellow? 0: No 1: Yes
felclass	Fellow or Ph.D. prestige class. 1: adequate 2: good 3: strong 4: distinguished
female	Female? 0: No 1: Yes
job	Prestige of first job if first job is as a university faculty member. Ranges from 0.75 to 5.00. See **phd** for details on prestige scores.
jobclass	Prestige class of 1st job. 1: adequate 2: good 3: strong 4: distinguished
mcit3	Mentor's # of citations for 3 year period ending the year of the student's Ph.D.
mcitt	Mentor's total # of citations in 1961.
mmale	Was mentor a male? 0: No 1: Yes
mnas	Was mentor in National Academy of Science? 0: No 1: Yes
mpub3	Mentor's # of articles in 3 year period ending year of the student's Ph.D.

nopub# No articles in 3 year period ending year # after Ph.D. (for #=1, 3, 6, 9)
0: No 1: Yes

phd Prestige of Ph.D department. Ranges from 0.75 to 5.00. All prestige variables can be broken into categories as follows: 0.75-1.99 is adequate; 2.00-2.99 is good; 3.00-3.99 is strong; and 4.00-5.00 is distinguished.

phdclass Prestige class of Ph.D. department.
1: adequate 2: good 3: strong 4: distinguished

pub# Number of publications over 3-year period ending # (for #=1, 3, 6, 9)

pubtot Total Pubs in 9 Yrs post-Ph.D.

work Type of first job
1: Faculty in university 2: Academic research 3: College teacher
4: Industrial research 5: Administration

workfac Faculty in a college or university? 0: No 1: Yes

workadmn Work in administration? 0: No 1: Yes

worktch Work in teaching? 0: No 1: Yes

workuniv Work in university? 0: No 1: Yes

Suggestions for variable sets by model:

Linear Regression Model: Y: totcit (created in the Stata Guide)
C: fel D: mnas X: enroll

Binary Regression Model: Y: nopub3
C: phd D: female X: enroll

Multinomial Logit Model: Y: work
C: pub1 D: female X: phd

Count Model: Y: pub9
C: mcit3 D: workuniv X: fellow

icpsr_hsb4.dta: Codebook for 1983 High School and Beyond Study

id: ID number of respondent

sex 1: male 2: female

male 0: no 1: yes

female 0: no 1: yes

region 1: New England 2: Mid Atlantic 3: South Atlantic
4: East South Central 5: West South Central 6: East North Central
7: West North Central 8: Mountain 9: Pacific

hsprog: High School program.
1: general 2: academic 3: agricultural 4: business
5: distributive educ. 6: health 7: home economics 8: technical
9: trade/industrial

algebra2, **geometry**, **trig**, **calc**, **physics**, **chem**: Did you take ...?
0: no 1: yes

hsgrades: What are your grades in HS?

1: Mostly below D's 2: Mostly D's 3: Mostly C's & D's 4: Mostly C's
5: Mostly B's & C's 6: Mostly B's 7: Mostly A's & B's 8: Mostly A's

mathabs: Are your math grades mostly A's and B's? 0: no 1: yes

englabs: Are your English grades mostly A's and B's? 0: no 1: yes

busiabs: Are your business grades mostly A's and B's? 0: no 1: yes

remengl: Have you taken remedial English? **remmath**: Have you taken remedial math?

advengl: Have you taken advanced English? **advmath**: Have you taken advanced math?

0: no 1: yes

hmwktime: How much time do you spend on homework each week?

1: None is assigned 2: Don't do any 3: Less than 1 hour 4: 1 to 3 hours
5: 3 to 5 hours 6: 5 to 10 hours 7: 10 or more hours

workage: Age you first worked.

1: age 11 or less 2 to 9: ages 12 to 19 respectively 11: never worked

hrswork: Hours worked last week. **hrslstyr**: Hours worked per week last year

1: none 2: 1 to 4 3: 5 to 14 4: 15 to 21
5: 22 to 29 6: 30 to 34 7: 35 or more

varsport: Did you participate in varsity sports?

pepclub: In pep club, cheerleading, or other activity?

1: non participant 2: participant 3: leader/officer

livealon: Did you live alone while attending HS? **livedad**: With your father while attending HS?
livemale: With other male guardian? **livemom**: With mother?
livfemal: With other female guardian? **livsibs**: With any brothers or sisters?
livgrand: With your grandparent(s)?

0: no 1: yes

momwork: Did your mother work while you were in HS?
elmomwrk: Did your mother work while you were in elementary school?
premomwk: Did your mother work before you were in elementary school?

1: no paid work 2: part time work 3: full time work
4: DK 5: NA

dadocc: Father's occupation. **momocc**: Mother's occupation.

1: not living with father	2: clerical	3: craftsman
4: farmer	5: homemaker	6: laborer
7: manager/admin	8: military	9: operative
10: professional	11: advanced professional	12: proprietor
13: protective service	14: sales	15: school teacher
16: service	17: technical	18: never worked
19: DK		

daded: Father's education level. **momed**: Mother's education level.

1: not living with father	2: less than HS degree	3: HS or equivalent degree
4: vocational less than 2 years	5: vocational 2 or more years	6: college less than 2 years
7: college 2 or more years	8: college graduate	9: masters degree
10: PhD/MD advanced degree	11: DK	

dadhsgrd: Dad graduate high school? **momhsgrd:** Mom graduate high school?
dadcoll: Dad graduate college? **momcoll:** Mom graduate college?

0: no 1:yes

mommonit: Mother monitors your school work? **dadmonit**: Father monitors your school work?

1: yes 2: no 3: NA

talkpar: How often do you talk to your parents?

1: rarely or never 2: less than *once* a week
3: once or twice a week 4: almost every day

dadplans: How much did your father influence your HS plans? **momplans**: your mother?

1: not at all 2: somewhat 3: a great deal

edattain: What educational level do you expect to attain?

momatain: What educational level does your mother expect you to attain?

lowed: What is the lowest educational level you would be satisfied with?

1: Less than HS 2: HS graduate 3: vocational < 2 years
4: vocational 2+ years 5: college < 2 years 6: college 2+years
7: college graduate 8: masters degree 9: PhD/MD degree
10: DK

compserv: Which would you chose if forced into compulsory service?

1: military 2: public service
3: undecided 4: avoid both

earnings: How much have you made this year?

1: None 2: <$1K 3: $1K-$3K 4: $3K-$5K
5: $5K-$7K 6: $7K-$9K 7: $9K-$11K 8: $11K-$13K
9: $13K-$15K 10: $15K+

expenses: How many expenses do you have?

1: None, at home 2: None: other 3: Less than $1K 4: $1K-$2K
5: $2K-$3K 6: $3K-$4K 7: $4K-$5K 8: $5K-$7K
9: $7K-$10K 10: $10K+

netearn: Net earnings this year **sumearn**: Net earnings from last year.

1: none 2: less than $200 3: $300-$600
4: $600-$1,200 5: $1,200-$2,000 6: $2,000+

agewed: Age you expect to be married. **agekid**: ...to have your first child.

agejob: ...to have your first full time job. **agehome**: ...to move out on your own.

ageeduc: ...to finish your education.

1: Don't expect to 2: already am 3: under 18 4: 19
5: 20 6: 21 7: 22 8: 23
9: 24 10: 25 11: 26 12: 27
13: 28 14: 29 15: 30 16: over 30

age: 15 to 20 is actual years; 21 = 21 years and older.

race: Respondent's race

1: Black 2: White 3: American Indian 4: Asian/Pacific Islander
5: Other

white: White? **black:** Black? **amerind:** American Indian?
asian: Asian? **othrace:** Other race?

0: no 1: yes

origin: Respondent's national origin/country of origin

1: Mexican	2: Cuban	3: Puerto Rican	4: Latin American
5: Afro-American	6: West Indian	7: Alaskan	8: American Indian
9: Chinese	10: Filipino	11: Indian: other	12: Japanese
13: Korean	14: Vietnamese	15: Pacific Islander	16: Asian: other
17: English/Welsh	18: French	19: German	20: Greek
21: Irish	22: Italian	23: Polish	24: Portuguese
25: Russian	26: Scottish	27: Europe-other	28: Fr. Canadian
29: Canadian	30: USA.	31: Other	

religion:

1: Baptist	2: Methodist	3: Lutheran	4: Presbyterian
5: Episcopalian	6: Other Protestant	7: Catholic	8: Other Christian
9: Jewish	10: Other	11: None	

relProt: Protestant? **relCath:** Catholic? **relJew:** Jewish?
relOth: Other religion? **relNone:** No religion?

0: no 1: yes

religper: Do you consider yourself a religious person?

1: not at all 2: somewhat 3: very much

politics: Political ideology

1: conservative	2: moderate	3: liberal
4: radical liberal	5: none	6: DK

fincome: Family income

1: Under $7K	2: $7-$12K	3: $12-$16K	4: $16-$20K
5: $20-$25K	6: $25-38K	7: >$38K	

college: Type of college you plan to attend

1: four year college 2: two year college

pubpriv: Do you plan to attend a public or private college?

1: public college 2: private college

instate: Do you plan to attend a college in your state?

1: home state 2: another state

ses: Socioeconomic status

1: low 2: medium 3: high

Suggestions for variable sets by model:

Binary Regression Model	Y: dadmonit; C: hsgrades; D: chem; X: ses
Ordinal Logit Model:	Y: talkpar; C: agehome; D: female; X: dadplans
Multinomial Logit Model:	Y: talkpar; C: agehome; D: female; X: dadplans
	Y: varsport; C: edattain; D: male; X: momplans

icpsr_nes4.dta: Codebook for 1992 National Election Study

caseid: ID number of respondent

prebush, **preclint**, **preperot**: Feelings about each candidate prior to the 1992 presidential election.

postbush, **postclin**, **postpero**: Feelings about each candidate after the 1992 presidential election.

(NOTE: Feeling thermometers range from 0 to 100. The higher the score, the more favorable the view of the candidate. 50 is a neutral score.)

partyid: Political party identification

1: Strong Democrat	2: Weak Democrat	3: Indep-leaning Democrat
4: Independent	5: Indep-leaning Republican	6: Weak Republican
7: Strong Republican	8: Other minor party	

abortion: View on abortion

1: Abortion never permitted by law	2: Only if rape, incest, or life threatening
3: Only if need is established	4: Abortion as personal choice
5: Law should not be involved	6: Other

election: Who do you think you will vote for?

1: Bush	2: Clinton	3: Perot	7: Other

religion: Religious affiliation

1: Protestant	2: Catholic	3: Jewish	4: Other

relProt: Protestant? **relCath:** Catholic? **relJew:** Jewish? **relOth:** Other religion?

0: no 1: yes

age: 17-90 is actual years; 91 = 91 years and older.

marital:Marital status

1: Married and living with spouse	2: Never married	3: Divorced
4: Separated	5: Widowed	6: Unmarried partners

married: Married?

0: no 1: yes

educatio: Education level.

1: 8th grade or less	2: 9th-11th grades	3: High school
4: More than 12 years	5: Jr. college degree	6: BA level degrees
7: Advanced degree		

collgrad: College graduate? **hsgrad:** High School graduate?

0: no 1:yes

occup: Occupational code.

1: Executive, administrative and managerial	8: Service except protective & household
2: Professional specialty occupations	9: Farming, forestry, and fishing occup.
3: Technicians and related support occup.	10: Precision production, craft and repair
4: Sales occupations	11: Machine operators, assemblers, inspectors
5: Administrative support, including clerical	12: Transport &material moving occup.
6: Private household	13: Handlers, equipment cleaners, laborers
7: Protective service	14: Member of the armed forces

fincome: Family income.

1: <3K	2: 3-5K	3: 5-7K	4: 7-9K
5: 9-10K	6: 10-11K	7: 11-12K	8: 12-13K
9: 13-14K	10: 14-15K	11: 15-17K	12: 17-20K
13: 20-22K	14: 22-25K	15: 25-30K	16: 30-35K
17: 35-40K	18: 40-45K	19: 45-50K	20: 50-60K
21: 60-75K	22: 75-90K	23: 90-105K	24: >105K
66: Below 25K but NA	77: Above 25K but NA		

income: Income, recoded to midpoints of fincome (66 and 77 = missing)

sex: Respondent's sex

1: Male	2: Female

male: Male?	**female:** Female?
0: no	1:yes

race: Respondent's race

1: White	2: Black
3: American Indian/Alaskan	4: Asian/Pacific Islander

white: White?	**black:** Black?	**amerind:** American Indian?	**asian:** Asian?
0: no		1: yes	

didvote: Did you vote this November?	**regvote**: Were you registered to vote?

0: No	1: Yes	6: Not required

presvote: Presidential vote.	**prefvote**: Did not vote, but preferred

1: Bush	2: Clinton	3: Perot	7: Other

canparty: Which party(ies) did the candidate you contributed to belong to?

whichpar: To which party did you give money?

1: Republican	2: Both	3: Democratic	7: Other

campaign*: Did you talk to people about voting for or against a party or candidate?

contact: Were you contacted by any person intent on showing you who to vote for?

support*: Did you wear or display a campaign button, sticker, or sign?

attend*: Did you attend any political meetings, rallies etc. in support of a candidate?

enlist: Did anyone enlist you to attend a political rally, meeting, speech, or dinner?

partywrk*: Did you do any work for one of the parties or candidates?

askwork: Did anyone ask you to do any work for one of the parties or candidates?

taxretur*: Did you make a political contribution on your income tax return this year?

fundcam:* Did you give any money to an individual candidate running for public office?

fundpart*: Did you give any money to a political party during this election year?

fundgrp*: Did you give money to any other group that supported or opposed candidates?

contvote: This year, did anyone talk to you about registering or getting out to vote?

mailfund: Did you receive any mail requests asking you to contribute to a party/candidate?

contmail: Did you contribute any money because of the mail you received?

phonfund: Did you receive any phone requests asking you to contribute to a party/candidate?

contphon: Did you contribute any money because of the phone calls you received?

persfund: Did you receive any personal requests asking you to contribute to a party/candidate?

contpers: Did you contribute any money because of the personal contacts you received?

0: no 1: yes

*these variables are used to create **polacts**; the code for creating this variable is in the Stata Guide provided by the instructor.

alotmail: How many mail requests for contributions to a candidate/party did you receive?

alotphon: How many phone requests for contributions to a candidate/party did you receive?

persalot: How many personal requests for contributions to a candidate/party did you receive?

1: not very many 5: quite a few

Suggestions for variable sets by model:

Linear Regression Model Y: preclint; C: age; D: hsgrad; X: fundcam

Binary Regression Model Y: campaign; C: income; D: male; X: age

Ordinal Logit Model Y: partyid (recoded to fewer categories); C: income; D: relProt; X: educatio

Multinomial Logit Model Y: partyid (recoded to fewer categories); C: income; D: relProt; X: education

MNLM 2nd Outcome Y: abortion; C: income; D: relProt; X: partyid

Count Model Y: polacts (created in the Stata Guide); C: prebush; D: collgrad; X:married

icpsr_addhealth4: Codebook for 1994-95 Add Health Public Data extract

Note: missing values for all variables are as follows:

.d:Don't know .n: Not applicable .r: Refused .s: Skip

caseid: Respondent's case ID number

gswgt1: Grand sample weight

cluster2: Sample cluster, stratum 2

Note: the syntax for setting the survey weights is:

```
svyset, clear
svyset [pweight=gswgt1], strata(cluster2)
```

age: Respondent's age (calculation includes months; ranges from 12.4167 to 21.1667).

sex: Respondent's sex 1: Male 2: Female

male: Male? **female:** Female?

0: no 1:yes

hispanic: Are you of Hispanic origin? **hhwhite:** Are you white?

nhblack: Are you Black or African American? **nhasian:** Are you Asian or Pacific Islander?

raceoth: Are you of another race?

0: No 1: Yes

bornus: Born in the United States?

0: No 1: Yes

hobbies: During the past week, how many times did you do hobbies, such as collecting baseball cards, playing a musical instrument, reading, or doing arts and crafts?

videos: During the past week, how many times did you watch television or videos, or play video games?

skating: During the past week, how many times did you go roller-blading, roller-skating, skate-boarding, or bicycling?

sport: During the past week, how many times did you play an active sport, such as baseball, softball, basketball, soccer, swimming, or football?

exercise: During the past week, how many times did you do exercise, such as jogging, walking, karate, jumping rope, gymnastics or dancing?

friends: During the past week, how many times did you just hang out with friends?

0: None 1: 1-2 times 2: 3-4 times 3: 5+ times

hrstv: How many hours a week do you watch television?

hrsvideo: How many hours a week do you watch videos?

hrscomp: How many hours a week do you play video or computer games?

hrsradio: How many hours a week do you listen to the radio?

brthctrl: If you wanted to use birth control, how sure are you that you could stop yourself and use birth control once you were highly aroused or turned on?

1: Very unsure 2: Somewhat unsure 3: Neither sure or unsure
4: Somewhat sure 5: Very sure 6: Never want to use birth control

intlgnce: Compared with other people your age, how intelligent are you?

1: Moderately below average 2: Slightly below average
3: About average 4: Slightly above average
4: Moderately above average 6: Extremely above average

bothered: You were bothered by things that usually don't bother you.

appetite: You didn't feel like eating, your appetite was poor.

blues: You felt that you could not shake off the blues, even with help from your family and your friends.

goodas: You felt that you were just as good as other people.*

minfoc: You had trouble keeping your mind on what you were doing.

depressed: You felt depressed.

hopeful: You felt hopeful about the future.*

fearful: You felt fearful.

talkless: You talked less than usual.

unfrndly: People were unfriendly to you.

sad: You felt sad.

tired: You felt that you were too tired to do things.

failure: You thought your life had been a failure.

happy: You were happy.*

lonely: You felt lonely.

enjlife: You enjoyed life.*

dislike: You felt that people disliked you.

getstart: It was hard to get started doing things.

living: You felt life was not worth living.

0: Never 1: Some 2: A lot 3: Mostly

(Variables marked with an asterisk (*) are coded as follows:

0: Mostly 1: A lot 2: Some 3: Never

depress: Depression scale, above 19 items added together.

momeduc: How far in school did your mom go?

dadeduc: How far in school did your dad go?

1: eighth grade or less 2: more than 8th grade, but not HS grad
3: business/trade/vocational instead of HS 4: high school graduate

5: completed a GED
6: business/trade/vocational after HS
7: went to college, but did not graduate
8: graduated from a college/univ
9: prof. training beyond a 4yr college/univ.
10: Never went to school.
11: Went, but R doesn't know what level.
12: R doesn't know if went to school.

momcoll: Mom graduated from college?
dadcoll: Dad graduated from college?

momhsgrd: Mom graduated from high school?
dadhsgrd: Dad graduated from high school?

0: No
1: Yes

mombrnUS: Was your mom born in the United States?

dadbrnUS: Was your dad born in the United States?

0: No
1: Yes

momcare: How much do you think your mom cares about you?

dadcare: How much do you think your dad cares about you?

1: Not at all
2: Very little
3: Somewhat
4: Quite a bit
5: Very much

Which of the things listed on this card have you done with your mother in the past 4 weeks?

momshop: gone shopping

momsport: played a sport

momrel: gone to a religious service or church-related event

momlife: talked about someone you're dating, or a party you went to

mommovie: gone to a movie, play, museum, concert, or sports event

momprob: had a talk about a personal problem you were having

mombehav: had a serious argument about your behavior

momgrades: talked about your school work or grades

momproj: worked on a project for school

momoth: talked about other things you're doing in school

momnone: none

0: No
1: Yes

actsmom: Number of above activities respondent did with mom, except talk about personal problems, argue about behavior, and talk about grades (range 0-7)

Which of these things have you done with your father in the past 4 weeks?

dadshop: gone shopping

dadsport: played a sport

dadrel: gone to a religious service or church-related event

dadlife: talked about someone you're dating, or a party you went to

dadmovie: gone to a movie, play, museum, concert, or sports event

dadprob: had a talk about a personal problem you were having

dadbehav: had a serious argument about your behavior

dadgrades: talked about your school work or grades

dadproj: worked on a project for school

dadoth: talked about other things you're doing in school

dadnone: none

0: No 1: Yes

actsdad: Number of above activities respondent did with dad, except talk about personal problems, argue about behavior, and talk about grades (range 0-7)

momrshp: Overall, you are satisfied with your relationship with your mother.

dadrshp: Overall, you are satisfied with your relationship with your father.

0: No 1: Yes

goodqual: You have a lot of good qualities.

proud: You have a lot to be proud of.

likeself: You like yourself just the way you are.

doright: You feel like you are doing everything just about right.

accepted: You feel socially accepted.

loved: You feel loved and wanted.

1: Strongly disagree 2: Disagree 3: Neither agree nor disagree
4: Agree 5: Strongly agree

esteem: Self-esteem scale, six above items added together

abpledge: Have you taken a public or written pledge to remain a virgin until marriage?

havesex: Have you ever had sexual intercourse?

0: No 1: Yes

smokereg: Have you ever smoked cigarettes regularly, that is, at least 1 cigarette every day for 30 days?

0: No 1: Yes

dayssmok: During the past 30 days, on how many days did you smoke cigarettes?

numcigs: During the past 30 days, on the days you smoked, how many cigarettes did you smoke each day?

numdrinks: Think of all the times you have had a drink during the past 12 months. How many drinks did you usually have each time?

daysdrink: During the past 12 months, on how many days did you drink alcohol?

drink5: Over the past 12 months, on how many days did you drink five or more drinks in a row?

daysdrunk: Over the past 12 months, on how many days have you gotten drunk or "very, very high" on alcohol?

1: Never 2: 1 to 2 days 3: Once a month
4: A few times a month 5: Once a week 4: A few times a week
7: Daily

potlife: During your life, how many times have you used marijuana?

potlstmo: During the past 30 days, how many times did you use marijuana?

In the past 12 months, how often did you ...

graffiti: paint graffiti or signs on someone else's property or in a public place?

damage: deliberately damage property that didn't belong to you?

lieprnts: lie to your parents or guardians about where you had been or whom you were with?

shoplift: take something from a store without paying for it?

fight: get into a serious physical fight?
injuroth: hurt someone badly enough to need bandages or care from a doctor or nurse?
runaway: run away from home?
stealcar: drive a car without its owner's permission?
stealGT50: steal something worth more than $50?
burglar: go into a house or building to steal something?
weapon: use or threaten to use a weapon to get something from someone?
selldrugs: sell marijuana or other drugs?
stealLT50: steal something worth less than $50?
grpfight: take part in a fight where a group of your friends was against another group?
rowdy: act loud, rowdy, or unruly in a public place?

0: None 1: 1-2 times 2: 3-4 times 3: 5+ times

delinq: Number of the above items respondent did at least once in the last 12 months (range 0-15)
adultcare: How much do you feel that adults care about you?
tchrcare: How much do you feel that your teachers care about you?
prntscare: How much do you feel that your parents care about you?
frndscare: How much do you feel that your friends care about you?
famundrst: How much do you feel that people in your family understand you?
leavehome: How much do you feel that you want to leave home?
famfun: How much do you feel that you and your family have fun together?
famattn: How much do you feel that your family pays attention to you?

1: Not at all 2: Very little 3: Somewhat
4: Quite a bit 5: Very much 6: Does not apply

relig: What is your religion?

0: none	1: Adventist	2: AME, AME Zion, CME
3 Assemblies of God	4: Baptist	5: Christian Church (Disciples of Christ)
6: Christian Science	7: Congregational	8: Episcopal
9: Friends/Quaker	10: Holiness	11: Jehovah's Witness
12: Latter Day Saints (Mormon)	13: Lutheran	14: Methodist
15: National Baptist	16: Pentecostal	17: Presbyterian
18: United Church of Christ	19: other Protestant	20: Baha'i
21: Buddhist	22: Catholic	23: Eastern Orthodox
24: Hindu	25: Islam, Muslim	26: Jewish
27: Unitarian	28: other religion	

relProt: Protestant? **relCath**: Catholic? **relJew:** Jewish?
relOth: Other religion? **relNone:** No religion?

0: No 1: Yes

service: In the past 12 months, how often did you attend religious services?

1: Never 2: Less than once a month
3: Less than once a week 4: Once a week or more

pray: How often do you pray?

1: Never 2: Less than once a month 3: Once a month
4: Once a week 5: Once a day

wantcoll: On a scale of 1 to 5, where 1 is low and 5 is high, how much do you want to go to college?

likelycol: On a scale of 1 to 5, where 1 is low and 5 is high, how likely is it that you will go to college?

1: Low 5: High

AHvocab: Add Health Picture Vocabulary Test standardized score

RAWvocab: Add Health Picture Vocabulary Test raw score

Suggestions for variable sets by model:

Linear Regression Model	Y: AHvocab; C: hrstv; D: dadcoll; X: depress
Binary Regression Model	Y: havesex; C: age; D: dadcoll; X: depress
Ordinal Logit Model	Y: pray; C: actsmom; D: female; X: nhblack
Multinomial Logit Model	Y: momrshp; C: age; D: dadcare; X: goodqual
Count Model	Y: delinq; C: esteem; D: racewhite X: adultcare