```
      name:  main
       log:  C:\Users\Conor\Documents\Conor\Grad School\TA Work\Econ 103 - Econometric
> s\STATA Work\Week 4\wk4_section_log.smcl
  log type:  smcl
 opened on:   5 Feb 2018, 11:55:49

. qui log using wk4_section_simple, name(simple) replace

. 
. // Demonstration STATA code for week 4
. // Principles of Econometrics 4th Edition
. // Covered Problems: 4.15
. 
. set more off

. clear all

. use cps4.dta, clear

. 
. ////////////////////////////////////////\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
> /////////////////////////////// Question 4.15 \\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
> ////////////////////////////////////////\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
> 
. ********************************************************************************
. *Setup: Does the return to education differ by race and gender? In this exercise,
. * we will look at the following subsamples ("partitions") of the data:
. * (i) all males (ii) all females (iii) all whites (iv) all blacks
. * (v) white males (vi) white females (vii) black males (viii) black females
. *
. * Parts (A) - (E)
. ********************************************************************************
. 
. // Most of the work for this problem is repetitive. For that reason, I will
. // use a loop to generate the required results, and then report the output and
. // include some discussion. The "simple" log file will not record the commands
. // or the output from the loop, but will show results that I store. The "main"
. // log file will continuing recording the full do file.
. 
. qui log off simple

. // Note that at the beginning of the file, we had initated 2 log file.
. // log off [name] tells STATA to stop recording using log file [name] where
. // name was set in the name option, and is NOT the name of the .smcl file
. // Since we have 2 log files running, wk4_section_log (name = main) will
. // continuing recording while wk4_section_simple (name = simple) will not
. // document running the loop
. 
. 
. //////////////////// Warning: Advanced STATA Usage Below \\\\\\\\\\\\\\\\\\\\\\\
> /////////////////// Exercise in How to Use Loops in STATA \\\\\\\\\\\\\\\\\\\\\\
> 
. // Set variable for significance level at 5% significance
. // Used for hypothesis test in Part E
. scalar alpha = 0.05

. 
. // Set variable for null for beta where beta = 0.1
. // Used for hypothesis test in Part E
```

```
43. scalar nullBeta = 0.1

44.
45. // Generate log wage
46. gen ln_wage = log(wage)

47.
48. // Use this loop to do all the exercises for the 8 partitions of the data:
49.
50. // Create a column vector of 0s for the values we want to store.
51. // As we go through the loop, we will store values of interest in
52. // the rows of the matrix
53. //
54. // Also, for each matrix, assign a column name to make it clear what value
55. // is being stored
56. //
57. // command: matrix NAME = J(n,k,a) creates an n-by-k matrix, with all entries
58. // set to the value a. A can be a number of ., where . means a missing value
59. matrix store_values = J(8,11,0)

60. matrix colnames store_values = "NumObs" "Wage_mean" "Wage_sd" "Wage_cv" ///
  >                                                                "Beta" "StdError" "R
  > Sqr" "RMSE" ///
  >                                                                "T:Beta=0.1" "TC_95%
  > _2side" "Reject_Null"

61.
62. local starRow "*******************************************************************
  > ***********"

63.
64. gen condition = 0

65.
66. forvalues partition = 1/8 {
    2.         // at the beginning of each iteration, set condition = 0
67.         replace condition = 0
    3.
68.         // What the loop does:
69.         // (1) depending on the value of the loop (1 through 8), set the value of
70.         //     "condition" = 1 for the observations we want to isolate
71.         // (2) add a new "element" to the local setRowNames describing which set of
72.         //     observations is being used. Later, we will use this local to assign
73.         //     names to the rows of the storage matrices.
74.         // (3) Display which loop number in the loop we've reached, and which
75.         //     observations are being used. Useful for troubleshooting as well as
76.         //     reading the output in the log file wk4_section_log
77.         // (4) For each partition, run the commands associated with each question:
78.         //     (a) summary statistics of wage
79.         //     (b) coefficient of variation for wage
80.         //     (c) run OLS for ln_wage = b1 + b2*educ, interpret coefficient
81.         //     (d) evaluate model fit (we use R2 and RMSE)
82.         //     (e) test beta2 = 0.1 at 5% confidence, 2-sided test
83.         if `partition' == 1 { // all men
    4.                 replace condition = 1 if female == 0
    5.                 local setRowNames "men"
    6.                 local conditionName = "all men"
    7.         }
    8.         else if `partition' == 2 { // all women
    9.                 replace condition = 1 if female == 1
   10.                 local setRowNames `setRowNames' "women"
   11.                 local conditionName = "all women"
   12.         }
   13.         else if `partition' == 3 { // all whites
   14.                 replace condition = 1 if white == 1
   15.                 local setRowNames `setRowNames' "white"
   16.                 local conditionName = "all whites"
   17.         }
   18.         else if `partition' == 4 { // all blacks
   19.                 replace condition = 1 if black == 1
   20.                 local setRowNames `setRowNames' "black"
   21.                 local conditionName = "all blacks"
```

```
           }
           else if `partition' == 5 { // white men
                   replace condition = 1 if white == 1 & female == 0
                   local setRowNames `setRowNames' "whtMen"
                   local conditionName = "white men"
           }
           else if `partition' == 6 { // white women
                   replace condition = 1 if white == 1 & female == 1
                   local setRowNames `setRowNames' "whtWomen"
                   local conditionName = "white women"
           }
           else if `partition' == 7 { // black men
                   replace condition = 1 if black == 1 & female == 0
                   local setRowNames `setRowNames' "blkMen"
                   local conditionName "black men"
           }
           else if `partition' == 8 { // black women
                   replace condition = 1 if black == 1 & female == 1
                   local setRowNames `setRowNames' "blkWomen"
                   local conditionName = "black women"
           } // if partition ... else if partition ...

        // Report where in the loop we are to results window
        disp "`starRow'"
           disp "Partition: `partition' - Condition: `conditionName'"
           disp "`starRow'"

        // Part A: Summary statistics for WAGE, by partition
        sum wage if condition == 1
           matrix store_values[`partition',1] = r(N)
           matrix store_values[`partition',2] = r(mean)
           matrix store_values[`partition',3] = r(sd)

        // Part B: Coefficient of Variation for WAGE, by partition
        matrix store_values[`partition',4] = 100*r(sd)/r(mean)

        // Part C: Run regression ln(WAGE) = beta1 + beta2*EDUC + e
        reg ln_wage educ if condition == 1

        // Store beta and standard error for regression
        matrix store_values[`partition',5] = _b[educ]
           matrix store_values[`partition',6] = _se[educ]

        // Part D: Does model fit equally well for each partition?
        // --> To evaluate this, we look at the R2 and RMSE
        matrix store_values[`partition',7] = e(r2)
           matrix store_values[`partition',8] = e(rmse)^2

        // Part E: Test the null hypothesis that the rate of return to education
        // is 10% against the alternative that it is not, using a two-sided test at
        // the 5% level of significance.

        // E-1: Calculte t-statistic for 10% return is equivalent to _b[educ] = 0.1
        // set null beta = 0.1 earlier
        matrix store_values[`partition',9] = (_b[educ]-`=nullBeta')/_se[educ]

        // E-2: Calculate critical value for 2-sided t-test at significance alpha
        // alpha = 0.05 (set above)
        // Since the degrees of freedom will vary from one regression to another, we
        // need to calculate a different critical value for each. Given the large
```

```
        // overall size of the sample, the differences are unlikely to be
        // particularly large, however.
        matrix store_values[`partition',10] = invttail(e(df_r), alpha/2)
  58.
        // E-3: Decide test
        // Store a logical (0 or 1) value, based on whether we reject the null
        // for a given regression. Since this is a 2-sided test, we compare the
        // absolute value to the (positve) critical value
        matrix store_values[`partition',11] = abs(store_values[`partition',9])>store
> _values[`partition',10]
  59.

} // end loop: forvalues partition
(0 real changes made)
(2,395 real changes made)
**************************************************************************
Partition: 1 - Condition: all men
**************************************************************************

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        wage |      2,395    22.25795    13.47253          1        173

      Source |       SS           df       MS      Number of obs   =     2,395
-------------+----------------------------------   F(1, 2393)      =    614.54
       Model |  159.850456         1  159.850456   Prob > F        =    0.0000
    Residual |  622.449238     2,393  .260112511   R-squared       =    0.2043
-------------+----------------------------------   Adj R-squared   =    0.2040
       Total |  782.299694     2,394  .326775144   Root MSE        =    .51001

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        educ |   .0883697   .0035647    24.79   0.000     .0813794    .0953599
       _cons |   1.732617   .0498571    34.75   0.000      1.63485    1.830385
------------------------------------------------------------------------------
(2,395 real changes made)
(2,443 real changes made)
**************************************************************************
Partition: 2 - Condition: all women
**************************************************************************

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        wage |      2,443     18.0538     11.1568       1.14      96.17

      Source |       SS           df       MS      Number of obs   =     2,443
-------------+----------------------------------   F(1, 2441)      =    734.02
       Model |   175.94651         1   175.94651   Prob > F        =    0.0000
    Residual |  585.114023     2,441   .23970259   R-squared       =    0.2312
-------------+----------------------------------   Adj R-squared   =    0.2309
       Total |  761.060533     2,442    .3116546   Root MSE        =    .48959

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        educ |   .1063988   .0039272    27.09   0.000     .0986978    .1140998
       _cons |   1.242679   .0559434    22.21   0.000     1.132977     1.35238
------------------------------------------------------------------------------
(2,443 real changes made)
(4,116 real changes made)
**************************************************************************
Partition: 3 - Condition: all whites
**************************************************************************

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        wage |      4,116    20.48479    12.63815       1.14        173
```

Source	SS	df	MS			
Model	260.04068	1	260.04068	Number of obs	=	4,116
Residual	1091.91738	4,114	.265415017	F(1, 4114)	=	979.75
				Prob > F	=	0.0000
				R-squared	=	0.1923
				Adj R-squared	=	0.1921
Total	1351.95806	4,115	.328543879	Root MSE	=	.51518

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	.0910544	.002909	31.30	0.000	.0853512	.0967577
_cons	1.59244	.0411475	38.70	0.000	1.511769	1.673112

(4,116 real changes made)
(493 real changes made)
****
Partition: 4 - Condition: all blacks
****

Variable	Obs	Mean	Std. Dev.	Min	Max
wage	493	16.44389	10.13587	1	72.13

Source	SS	df	MS			
Model	27.1848402	1	27.1848402	Number of obs	=	493
Residual	106.565497	491	.217037672	F(1, 491)	=	125.25
				Prob > F	=	0.0000
				R-squared	=	0.2033
				Adj R-squared	=	0.2016
Total	133.750337	492	.271850279	Root MSE	=	.46587

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	.1051817	.0093982	11.19	0.000	.0867161	.1236473
_cons	1.245588	.127762	9.75	0.000	.99456	1.496615

(493 real changes made)
(2,065 real changes made)
****
Partition: 5 - Condition: white men
****

Variable	Obs	Mean	Std. Dev.	Min	Max
wage	2,065	22.83416	13.67063	1.5	173

Source	SS	df	MS			
Model	135.920445	1	135.920445	Number of obs	=	2,065
Residual	524.197917	2,063	.254094967	F(1, 2063)	=	534.92
				Prob > F	=	0.0000
				R-squared	=	0.2059
				Adj R-squared	=	0.2055
Total	660.118362	2,064	.319824788	Root MSE	=	.50408

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	.0861452	.0037247	23.13	0.000	.0788407	.0934497
_cons	1.7909	.0521835	34.32	0.000	1.688562	1.893238

(2,065 real changes made)
(2,051 real changes made)
****
Partition: 6 - Condition: white women
****

Variable	Obs	Mean	Std. Dev.	Min	Max
wage	2,051	18.11937	11.01337	1.14	96.17

Source	SS	df	MS			
Model	144.303713	1	144.303713	Number of obs	=	2,051
Residual	493.10938	2,049	.240658555	F(1, 2049)	=	599.62
Total	637.413093	2,050	.310933216	Prob > F	=	0.0000
				R-squared	=	0.2264
				Adj R-squared	=	0.2260
				Root MSE	=	.49057

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	.1057232	.0043175	24.49	0.000	.097256	.1141903
_cons	1.254094	.0616503	20.34	0.000	1.13319	1.374997

(2,051 real changes made)
(214 real changes made)
****
Partition: 7 - Condition: black men
****

Variable	Obs	Mean	Std. Dev.	Min	Max
wage	214	16.21332	9.492562	1	72.13

Source	SS	df	MS			
Model	5.57111511	1	5.57111511	Number of obs	=	214
Residual	51.0759938	212	.240924499	F(1, 212)	=	23.12
Total	56.6471089	213	.265948868	Prob > F	=	0.0000
				R-squared	=	0.0983
				Adj R-squared	=	0.0941
				Root MSE	=	.49084

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	.0761759	.0158412	4.81	0.000	.0449495	.1074022
_cons	1.652099	.2104773	7.85	0.000	1.237203	2.066996

(214 real changes made)
(279 real changes made)
****
Partition: 8 - Condition: black women
****

Variable	Obs	Mean	Std. Dev.	Min	Max
wage	279	16.62075	10.61639	3.75	72.13

Source	SS	df	MS			
Model	23.314309	1	23.314309	Number of obs	=	279
Residual	53.7803451	277	.19415287	F(1, 277)	=	120.08
Total	77.0946541	278	.2773189	Prob > F	=	0.0000
				R-squared	=	0.3024
				Adj R-squared	=	0.2999
				Root MSE	=	.44063

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	.126164	.0115132	10.96	0.000	.1034995	.1488285
_cons	.9395272	.1591768	5.90	0.000	.6261772	1.252877

```

// Assign row names for all the matrices we created earlier
// have STATA report the list of all matrices in a local
local allMatrices : all matrices

// Use foreach ... to loop over the matrices
// Assign each matrix the set of rownames that we created during the loop above
foreach x of local allMatrices {
  2.         matrix rownames `x' = `setRowNames'
  3. }

////////////////////////////// End Advanced STATA Usage \\\\\\\\\\\\\\\\\\\\\\\\\\
> ///////////////////////////////////////\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
> 
// Begin recording with the "simple" log file
qui log on simple

********************************************************************************
*4.15 Part A: For each sample partition, obtain the summary statistics of WAGE.
********************************************************************************

// Extract the columns we want from the store_values matrix using
// number indexing
matrix partA_values = store_values[1...,1..3] // rows 1 and on, columns 1-3

// Have stata report the contents of a matrix using:
// matrix list matName
matrix list partA_values

partA_values[8,3]
              NumObs  Wage_mean    Wage_sd
       men      2395  22.257954  13.472531
     women      2443  18.053799  11.156805
     white      4116  20.484786  12.638152
     black       493  16.443895  10.135868
    whtMen      2065  22.834165  13.670627
  whtWomen      2051  18.119371  11.013366
    blkMen       214  16.213318  9.4925622
  blkWomen       279  16.620753  10.616392

********************************************************************************
*4.15 Part B: A variable's "coefficient of variation" (CV) is 100 times the ratio
* of its sample standard deviation to its sample mean For a variable y, it is:
*
* CV = 100*se(y)/bar(y)
*
* It is a measure of variation that takes into account the size of the variable.
* What is the coefficient of variation for WAGE within each sample partition?
********************************************************************************

// use column name Wage_cv as index to extract the appropriate column of store_value
> s
// store_values[1...,"Wage_cv"] is rows 1 and on, column with name Wage_cv
matrix cvByPartition = store_values[1...,"Wage_cv"]
```

```
matrix list cvByPartition

  cvByPartition[8,1]
              Wage_cv
        men  60.529064
      women  61.797546
      white  61.695306
      black  61.639098
     whtMen  59.869178
   whtWomen  60.782278
     blkMen  58.547932
   blkWomen  63.874313


******************************************************************************
*4.15 Part C: For each sample partition, estimate the log-linear model:
*
* ln(WAGE) = beta1 + beta2*educ + e
*
* What is the approximate percentage return to another year of education for
* each group?
******************************************************************************

// Can join matricies together by having one matrix to the left and one matrix
// to the right by using [mat1, mat2]. Note, this only works if mat1 and mat2
// have the same number of rows
matrix partC_values = [store_values[1...,"Beta"], store_values[1...,"Beta"]*100]

// Reset names of columns in partC_values - useful for display
matrix colnames partC_values = "Beta" "BetaX100"

matrix list partC_values

  partC_values[8,2]
                 Beta   BetaX100
        men  .08836967  8.8369667
      women  .10639878  10.639878
      white  .09105444  9.1054445
      black   .1051817   10.51817
     whtMen  .08614524  8.6145236
   whtWomen  .10572316  10.572316
     blkMen  .07617588   7.617588
   blkWomen  .12616401  12.616401


// Since we have a log-linear regression, i.e. ln(y) = beta1+beta2*x+e
// the interpretation of the b2 coefficient is that a 1 unit increase in x leads
// to a b2*100 percent increase in y

******************************************************************************
*4.15 Part D: Does the model fit the data equally well for each sample
* partition?
******************************************************************************

// store_values[1...,"R2".."RMSE"] = rows 1 and on, columns from R2 to RMSE
// Recall that R2 = 1 - (SSE/TSS) while RMSE = sqrt((1/df_r)*SSE)
matrix partD_values = store_values[1...,"RSqr".."RMSE"]

matrix list partD_values

  partD_values[8,2]
                 RSqr       RMSE
        men  .20433404  .26011251
      women  .23118596  .23970259
      white  .19234375  .26541502
      black  .20325063  .21703767
     whtMen  .20590314  .25409497
   whtWomen  .22638963  .24065856
     blkMen  .09834774   .2409245
   blkWomen  .30241149  .19415287
```

```
/* Discussion:
>
> The data fit in a broadly similar range for all (R^2 of 19-23) for all the models,
> except when we use the two smallest groups: black-by-gender. The model fits
> very poorly for black men but does its best for black women, which netted out
> to an average performance for the black partition as a whole. Notably, the model
> fits somewhat better for white men and white women separately than it does for
> whites as a whole.
>
> */

****************************************************************************
*4.15 Part E: For each sample partition, test the null hypothesis that the rate
* of return to education is 10% against the alternative that it is not, using a
* two-tail test at the 5% level of significance.
****************************************************************************

// One way to get columns 5-6 and 9-11
matrix partE_values = [store_values[1...,5..6], store_values[1...,9..11]]

matrix list partE_values
```

partE_values[8,5]

	Beta	StdError	T: Beta=0.1	TC_95%_2side	Reject_Null
men	.08836967	.00356473	-3.2626106	1.9609558	1
women	.10639878	.0039272	1.6293497	1.9609363	0
white	.09105444	.002909	-3.075134	1.9605408	1
black	.1051817	.00939819	.551351	1.9648072	0
whtMen	.08614524	.00372466	-3.7197368	1.9611146	1
whtWomen	.10572316	.0043175	1.3255746	1.9611224	0
blkMen	.07617588	.01584116	-1.5039381	1.971217	0
blkWomen	.12616401	.0115132	2.2725228	1.968565	1

```
/* Discussion:
>
> The table shows the betas for eduction, along with the standard error, the t-stat
> that the beta shown is equal to 0.1 (10% in decimal terms), the critical value,
> and a column of 1s and 0s where 1 indicates a rejection of the null and 0 a
> failure to reject. We can reject the null of beta = 0.1 to the downside for the
> partitions men, whites, and white men; to the upside we can reject the null of
> beta = 0.1 for black women. For the other four partition (women, black, white women
> and black men) we fail to reject the null.
>
> A few comments: first note that the critical values change slightly from one
> regression to the next. This reflects the changes in the sample size. Notice also
> that the standard errors for black, black men, and black women are much larger,
> again reflecting the small sample sizes for these groups. This leads to differing
> conclusions - for example, the point estimate for black men is lower than the
> point estimate for white men but we fail to reject the null for black men because
> the beta is so imprecisely (large standard error). Comparing black men to black
> women, however, we are able to reject the null because the fit of the model was
> better for black women than for black men (though there are more black women
> observations, the gap is small compared to black men vs. white men in the sample).
>
> */

//Comment: How to think about partitioned regressions
```

```
//
// One way to think of a regression partition is that it is equivalent to
// interacting ALL the right-hand side variables with an indicator variable.
// Below, we show how we get identical point estimates for the betas for male
// vs. female when we partition and when we interact with female.
//
// Note that, while the betas are the same the standard errors are not. The
// standard errors differ because (1) the sigma_hat^2 for the interaction
// regression is a weighted average of the sigma_hat^2 estimates from the separate
// regressions and (2) the interaction regression adjusts the standard errors
// using information about the relationship between the various RHS terms, which
// differs from what OLS uses in the partitioned regressions.

// put a constant in the regression by hand, rather than let STATA do it for us
gen onesCol = 1


reg ln_wage onesCol educ if female == 0, noconstant

      Source |       SS           df       MS      Number of obs   =     2,395
-------------+----------------------------------   F(2, 2393)      =  40134.89
       Model |  20879.1724         2  10439.5862   Prob > F        =    0.0000
    Residual |  622.449238     2,393  .260112511   R-squared       =    0.9711
-------------+----------------------------------   Adj R-squared   =    0.9710
       Total |  21501.6217     2,395   8.9777126   Root MSE        =    .51001

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     onesCol |   1.732617   .0498571    34.75   0.000      1.63485    1.830385
        educ |   .0883697   .0035647    24.79   0.000     .0813794    .0953599
------------------------------------------------------------------------------

reg ln_wage onesCol educ if female == 1, noconstant

      Source |       SS           df       MS      Number of obs   =     2,443
-------------+----------------------------------   F(2, 2441)      =  38468.63
       Model |  18442.0587         2  9221.02933   Prob > F        =    0.0000
    Residual |  585.114023     2,441   .23970259   R-squared       =    0.9692
-------------+----------------------------------   Adj R-squared   =    0.9692
       Total |  19027.1727     2,443  7.78844564   Root MSE        =    .48959

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     onesCol |   1.242679   .0559434    22.21   0.000     1.132977     1.35238
        educ |   .1063988   .0039272    27.09   0.000     .0986978    .1140998
------------------------------------------------------------------------------

reg ln_wage i.female#c.onesCol i.female#c.educ, noconstant

      Source |       SS           df       MS      Number of obs   =     4,838
-------------+----------------------------------   F(4, 4834)      =  39351.73
       Model |  39321.2311         4  9830.30778   Prob > F        =    0.0000
    Residual |  1207.56326     4,834  .249806219   R-squared       =    0.9702
-------------+----------------------------------   Adj R-squared   =    0.9702
       Total |  40528.7944     4,838  8.37717949   Root MSE        =    .49981

----------------------------------------------------------------------------------
         ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
female#c.onesCol |
               0 |   1.732617   .0488593    35.46   0.000     1.636831    1.828404
               1 |   1.242679   .0571103    21.76   0.000     1.130716    1.354641
                 |
   female#c.educ |
               0 |   .0883697   .0034934    25.30   0.000      .081521    .0952183
               1 |   .1063988   .0040091    26.54   0.000     .0985391    .1142585
----------------------------------------------------------------------------------
```

```
//Convert log file (smcl) to pdf
```