Statistics/Data Analysis

```
      name:  <unnamed>
       log:  C:\Users\Conor\Documents\Conor\Grad School\TA Work\Econ 103 - Econometric
> s\STATA Work\Week 5\wk5_section_log.smcl
  log type:  smcl
 opened on:   5 Feb 2018, 12:19:11

. 
. // Demonstration STATA code for week 5
. // Principles of Econometrics 4th Edition
. // Covered Problems: 5.19
. 
. set more off

. clear all

. use cps4_small.dta, clear

. 
. ////////////////////////////////////////\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
> //////////////////////////////// Question 5.19 \\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
> ////////////////////////////////////////\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
> 
. ******************************************************************************
. *Setup: Estimate the wage equation.
. * For parts (A)-(C) use:
. *    ln(WAGE) = beta1 + beta2*EDUC + beta3*EXPER + beta4*HRSWK + e
. * and for parts (D)-(I) use:
. *    ln(WAGE) = beta1 + beta2*EDUC + beta3*EXPER + beta4*HRSWK
. *                  + beta5*(EDUC x EXPER) + beta6*(EDUC^2) + beta7*(EXPER^2) + e
. *
. * Parts (A) - (I)
. ******************************************************************************
. 
. ******************************************************************************
. *5.19 Part A: Report the results. Interpret the estimate for beta2, beta3, and
. * beta4. Are these estimates significantly different from zero?
. ******************************************************************************
. 
. gen ln_wage = log(wage)

. reg ln_wage educ exper hrswk

      Source |       SS           df       MS      Number of obs   =     1,000
-------------+----------------------------------   F(3, 996)       =     93.46
       Model |  73.9786732         3  24.6595577   Prob > F        =    0.0000
    Residual |  262.802058       996  .263857488   R-squared       =    0.2197
-------------+----------------------------------   Adj R-squared   =    0.2173
       Total |  336.780731       999  .337117849   Root MSE        =    .51367

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        educ |   .0903056   .0060781    14.86   0.000     .0783783    .1022329
       exper |   .0057759   .0012748     4.53   0.000     .0032743    .0082774
       hrswk |   .0089411   .0015813     5.65   0.000     .0058379    .0120442
       _cons |    1.10054   .1095477    10.05   0.000     .8855691    1.315511
------------------------------------------------------------------------------

. 
```

```
30. /* Discussion:
  > Since we have a log-linear model, each of the betas 2 through 4 should be
  > interpreted as indicating that a 1 unit increase in the X# variable leads to a
  > beta#*100 percent change in Wage. Given our estimates, we could say:
  >
  > beta2: 1 additional year of education is expected to raise hourly wages by 9.03%
  > beta3: 1 additional year or experience is expected to raise hourly wages by 0.58%
  > beta4: Working 1 additional hour per week is expected to raise hourly wages by 0.89%
  > */
31.
32. ********************************************************************************
33. *5.19 Part B: Test the hypothesis that an extra year of education increases the
34. * wage rate by at least 10% against the alternative that it is less than 10%.
35. ********************************************************************************
36.
37. scalar alpha = 0.1

38. scalar crit_val_1side_lhs = (-1)*invttail(e(df_r), alpha)

39.
40. scalar tstat = (_b[educ]-0.1)/_se[educ]

41.
42. if tstat < crit_val_1side_lhs {
43.         local testConclusion = "Reject Null"
44. }

45. else {
46.         local testConclusion = "Fail to Reject Null"
47. }

48.
49. disp "Test beta2 (_b[educ]) >= 0.1 (10% effect) versus alternative that beta2<0.1"
  Test beta2 (_b[educ]) >= 0.1 (10% effect) versus alternative that beta2<0.1

50. disp "Confidence Level: " 100*(1-alpha) "%"
  Confidence Level: 90%

51. disp "T-stat: " tstat " v.s. critival value: " crit_val_1side_lhs " --> `testConclus
  > ion'"
  T-stat: -1.5949779 v.s. critival value: -1.2824021 --> Reject Null

52.
53. ********************************************************************************
54. *5.19 Part C: Find a 90% interval estimate for the percentage increase in wage
55. * from working an additional hour per week.
56. ********************************************************************************
57.
58. lincom hrswk, level(`=100*(1-alpha)')

 ( 1)  hrswk = 0

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [90% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   .0089411   .0015813     5.65   0.000     .0063376    .0115446
------------------------------------------------------------------------------

59.
60. scalar crit_val_2side = invttail(e(df_r), alpha/2)
```

```
scalar ci_hrswk_low = _b[hrswk]-crit_val_2side*_se[hrswk]

scalar ci_hrswk_high = _b[hrswk]+crit_val_2side*_se[hrswk]


disp 100*(1-alpha) "% Confidence interval for beta4 (HRSWK): [" ci_hrswk_low ", " ci
> _hrswk_high "]"
90% Confidence interval for beta4 (HRSWK): [.00633759, .01154458]


******************************************************************************
*5.19 Part D: Re-estimate the model with the additional variables EDUC x EXPER,
* EDUC^2 and EXPER^2. Report the results. Are the estimated coefficients
* significantly different from zero?
******************************************************************************

// Regression Input version (1)
// Generate interactions as workspace variables and then use reg
gen educ_exper = educ*exper

gen educ_sqr = educ^2

gen exper_sqr = exper^2

reg ln_wage educ exper hrswk educ_exper educ_sqr exper_sqr

      Source |       SS           df       MS      Number of obs   =     1,000
-------------+----------------------------------   F(6, 993)       =     58.87
       Model |  88.3621958         6  14.7270326   Prob > F        =    0.0000
    Residual |  248.418536       993  .250169724   R-squared       =    0.2624
-------------+----------------------------------   Adj R-squared   =    0.2579
       Total |  336.780731       999  .337117849   Root MSE        =    .50017

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        educ |   .0490281   .0366258     1.34   0.181    -.0228447    .1209009
       exper |   .0527446   .0097493     5.41   0.000     .0336131    .0718762
       hrswk |    .006693   .0015681     4.27   0.000     .0036158    .0097702
  educ_exper |  -.0009238   .0005054    -1.83   0.068    -.0019155    .0000679
    educ_sqr |   .0023649   .0011048     2.14   0.033      .000197    .0045328
   exper_sqr |  -.0006287   .0000888    -7.08   0.000     -.000803   -.0004545
       _cons |   .9266082   .3404072     2.72   0.007     .2586081    1.594608
------------------------------------------------------------------------------


// Store the results from this regression (will use for "hand" calculations later)
matrix betaEst = e(b)

matrix vcvEst = e(V)


// Regression Input version (2)
// Use the "interaction" notation, where # indicates multiplication
reg ln_wage educ exper hrswk c.educ#c.exper c.educ#c.educ c.exper#c.exper

      Source |       SS           df       MS      Number of obs   =     1,000
-------------+----------------------------------   F(6, 993)       =     58.87
       Model |  88.3621958         6  14.7270326   Prob > F        =    0.0000
    Residual |  248.418536       993  .250169724   R-squared       =    0.2624
-------------+----------------------------------   Adj R-squared   =    0.2579
       Total |  336.780731       999  .337117849   Root MSE        =    .50017
```

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	.0490281	.0366258	1.34	0.181	-.0228447	.1209009
exper	.0527446	.0097493	5.41	0.000	.0336131	.0718762
hrswk	.006693	.0015681	4.27	0.000	.0036158	.0097702
c.educ#c.exper	-.0009238	.0005054	-1.83	0.068	-.0019155	.0000679
c.educ#c.educ	.0023649	.0011048	2.14	0.033	.000197	.0045328
c.exper#c.exper	-.0006287	.0000888	-7.08	0.000	-.000803	-.0004545
_cons	.9266082	.3404072	2.72	0.007	.2586081	1.594608

```
86.
87. ********************************************************************************
88. *5.19 Part E: For the new model, find expressions for the marginal effects
89. * d ln(WAGE)/d EDUC and d ln(WAGE)/d EXPER
90. ********************************************************************************
91.
92. /* Discussion:
  > Recall that we are using the following regression model:
  >
  >         ln(WAGE) = beta1 + beta2*EDUC + beta3*EXPER + beta4*HRSWK +
  >                  beta5*(EXPER*EDUC) + beta6*(EDUC^2) + beta7*(EXPER^2) + e
  >
  > Taking the derivative with respect to EDUC, we have:
  >
  >         d ln(WAGE)/d EDUC = beta2 + beta5*EXPER + 2*beta6*EDUC
  >
  > and taking the derivative with respect to EXPER, we have:
  >
  >         d ln(WAGE)/d EXPER = beta3 + beta5*EDUC + 2*beta7*EXPER
  >
  > */
93.
94. ********************************************************************************
95. *5.19 Part F: Estimate the marginal effect d ln(WAGE)/d EDUC for two workers
96. * Jill and Wendy; Jill has 16 years of education and 10 years of experience,
97. * while Wendy has 12 years of education and 10 years of experience. What can you
98. * say about the marginal effect of education as education increases?
99. ********************************************************************************
100
101 /* Discussion
  >
  > Since beta6 (the beta for educ^2) is positive, if experience is constant then
  > each additional year of eduction leads to a larger increase in wages than earlier
  > years of education.
  >
  > */
102
103 /* STATA Technical Note: margins command
  >
  > Recall that in order to get the correct output using the margins command, we had
  > to use the interaction syntax in the reg command earlier. The "interaction"
  > syntax refers to inputting EDUC*EXPER as c.educ#c.exper rather than generating
  > a variable separate from the regression command.
  > */
```

```
/* STATA Technical Note: Names for accessing stored beta and standard error values
>
> In STATA, the beta estimate for a single variable can be accessed by using
> _b[NAME]. When the beta corresponds to a workspace variable, the NAME to put in
> is for the workspace variable. In addition, when we used the interaction notation
> in the reg command, we can access the beta associated with that term by using
> the same notation.
>
> For example, the beta estimate for c.educ#c.educ can be accessed by using
> _b[c.educ#c.educ]
>
> The same logic applies to finding standard error values.
> */

// Calculate marginal effect of eduction for Jill:

// Calculation Option (1): margins

margins, dydx(educ) at(educ = 16 exper = 10)
```

```
Average marginal effects                          Number of obs     =      1,000
Model VCE    : OLS

Expression   : Linear prediction, predict()
dy/dx w.r.t. : educ
at           : educ            =          16
               exper           =          10
```

	dy/dx	Delta-method Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ	**.1154664**	**.0107609**	**10.73**	**0.000**	**.0943496**	**.1365831**

```
// Calculation Option (2): lincom

lincom _b[educ] + 10*_b[c.educ#c.exper] + 2*16*_b[c.educ#c.educ]
```

(1) **educ + 10*c.educ#c.exper + 32*c.educ#c.educ = 0**

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1)	**.1154664**	**.0107609**	**10.73**	**0.000**	**.0943496**	**.1365831**

```
// Calculation Option (3): Calculate point estimate and standard error
// by hand using output beta and vcv matricies

scalar margeff_jill = betaEst[1,2-1] + 10*betaEst[1,5-1] + 2*16*betaEst[1,6-1]

scalar margeff_se_jill = sqrt(vcvEst[2-1,2-1] + 10^2*vcvEst[5-1,5-1] + (2*16)^2*vcvE
> st[6-1,6-1] + ///
>                                                                2*(1)*10*vcvEst[2-1,
> 5-1] + 2*(1)*(2*16)*vcvEst[2-1,6-1] + 2*10*(2*16)*vcvEst[5-1,6-1])
```

```

// Report results of "hand" estimate
disp "Marginal Effect (Std Error) of Educ for Jill: " margeff_jill " (" margeff_se_j
> ill ")"
Marginal Effect (Std Error) of Educ for Jill: .11546635 (.01076093)


// Calculate effects for Wendy:

// Calculation Option (1): margins

margins, dydx(educ) at(educ = 12 exper = 10)

Average marginal effects                        Number of obs     =      1,000
Model VCE    : OLS

Expression   : Linear prediction, predict()
dy/dx w.r.t. : educ
at           : educ            =          12
               exper           =          10

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        educ |   .0965473    .011875     8.13   0.000     .0732444    .1198502
------------------------------------------------------------------------------


// Calculation Option (2): lincom

lincom _b[educ] + 10*_b[c.educ#c.exper] + 2*12*_b[c.educ#c.educ]

 ( 1)  educ + 10*c.educ#c.exper + 24*c.educ#c.educ = 0

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   .0965473    .011875     8.13   0.000     .0732444    .1198502
------------------------------------------------------------------------------


// Calculation Option (3): Calculate point estimate and standard error
// by hand using output beta and vcv matricies

matrix margeff_wendy_mat = betaEst[1,"educ"] + 10*betaEst[1,"educ_exper"] + 2*12*bet
> aEst[1,"educ_sqr"]



matrix margeff_var_wendy_mat = vcvEst["educ","educ"] + 10^2*vcvEst["educ_exper","edu
> c_exper"] + (2*12)^2*vcvEst["educ_sqr","educ_sqr"] + ///
>                                                               2*(1)*10*vcvEst["edu
> c","educ_exper"] + 2*(1)*(2*12)*vcvEst["educ","educ_sqr"] + 2*10*(2*12)*vcvEst["educ
> _exper","educ_sqr"]


// Convert 1-by-1 matricies to scalars (see technical note below)
>
scalar margeff_wendy = margeff_wendy_mat[1,1]
```

```
scalar margeff_se_wendy = sqrt(margeff_var_wendy_mat[1,1])

disp "Marginal Effect (Std Error) of Educ for Wendy: " margeff_wendy " (" margeff_se
> _wendy ")"
Marginal Effect (Std Error) of Educ for Wendy: .09654733 (.01187496)

/* STATA Technical Note: matrix subscripting - numbers versus variable names
>
> The matricies e(b) for betas (a 1-by-k row matrix) and e(V) for the variance-
> covariance matrix (a k-by-k symmetric square matrix) are automatically given
> row and column names that match the order of variables entered into the reg command.
> We can then use STATA's string index for matricies to find the values that go with
> each of the variables. Note that since I stored betaEst and vcvEst after running
>
>    reg ln_wage educ exper hrswk educ_exper educ_sqr exper_sqr
>
> the matricies have column and row names that match the names from this command.
>
> Using the variable names as an index (e.g. "educ" and "educ_exper"), as we did
> above for generating the Wendy values, means that STATA will return a matrix
> (in this case a 1-by-1 matrix), while using numbers as indexes (as we did in the
> Jill section) means that STATA automatically converts the 1-by-1 submatrix into
> a scalar. In the section where we did the calculations for Wendy, we converted
> the 1-by-1 matricies to scalars by using the number index [1,1]
>
> Despite the potential nuisance caused by adding an extra step converting from a
> 1-by-1 matrix to a scalar, the advantage of using the name index is that we do
> not have to remember what order the variables were put into the regression in
> order to extract the correct values. As you can see, in the numeric index we
> used #-1 to find the beta# value, since STATA automatically puts the constant
> as the last variable versus our notation where the constant is beta1.
>
> */

********************************************************************************
*5.19 Part G: Test, as an alternative hypothesis, that Jill's marginal effect of
* eduction is greater than that of Wendy. Use a 5% significance level.
********************************************************************************


/* Discussion:
>
>  ME(Jill) - ME(Wendy) = beta3-beta3 + beta5*(EXPER_Jill - EXPER_Wendy) + 2*beta6*(ED
> UC_Jill - EDUC_Wendy)
>
> Right away, we see that the beta3 terms will cancel out. In addition, since
> EXPER_Jill = EXPER_Wendy, this leaves us with:
>
>  ME(Jill) - ME(Wendy) = 2*beta6*(EDUC_Jill - EDUC_Wendy)
>
> Since our alternative is that Jill's marginal effect is greater than Wendy's, we
> are doing a right-hand side test with a null of ME(Jill) - ME(Wendy) <= 0 and
> an alternative that ME(Jill) - ME(Wendy) > 0.
>
> Since this boils down to evaluating a beta estimate times a constant, and our
> null is 0, this question becomes the same as evaluating whether beta6
> (beta for educ^2) is significantly different from 0. Notice that the t-stat we
> calculate below is the same as the t-stat for c.educ#c.educ in the regression
> output.
>
> */
```

```
// Calculation option (1): lincom
// --> Reminder: since the null we're interested in is 0, the t-stat reported by
// STATA is the one that we want to use. However, the p-value is still not the one
// we want to use because STATA assumes a 2-sided alternative while we are
// considering a 1-sided alternative. Since the point estimate is of the correct
// sign for a rejection (positive since we have a RHS test), the p-value for our
// test is 1/2 the p-value reported by lincom.

lincom 2*(16-12)*_b[c.educ#c.educ]
```

(1) 8*c.educ#c.educ = 0

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1)	**.018919**	**.0088381**	**2.14**	**0.033**	**.0015756**	**.0362624**

```
// Calculation option (2): calculate by hand
scalar diff_margeff = margeff_jill - margeff_wendy

scalar diff_margeff_se = 2*(16-12)*_se[c.educ#c.educ]

scalar diff_margeff_tstat = diff_margeff/diff_margeff_se


disp "Difference in Jill vs. Wendy Marginal Effects (se) [t]: " diff_margeff " (" di
> ff_margeff_se ") [" diff_margeff_tstat "]"
Difference in Jill vs. Wendy Marginal Effects (se) [t]: .01891902 (.00883806) [2.14063
> 09]


// Generate the appropriate test statistic for the 5% confidence level RHS test
scalar alpha = 0.05

scalar critical_value = invttail(e(df_r), alpha)

scalar pval = 1-t(e(df_r),diff_margeff_tstat)


// Determine test conclusion:
if diff_margeff_tstat > critical_value {
        local testConclusion = "Reject Null"
}

else {
        local testConclusion = "Fail to Reject Null"
}


disp "Test Jill marginal effect of education is less than or equal to Wendy (Alterna
> tive: Jill > Wendy)"
Test Jill marginal effect of education is less than or equal to Wendy (Alternative: Ji
> ll > Wendy)

disp "T-stat: " diff_margeff_tstat " v.s. " 100*(1-alpha) "% critical value: " criti
> cal_value " (p-value = " pval ") --> `testConclusion'"
T-stat: 2.1406309 v.s. 95% critical value: 1.6463896 (p-value = .01627341) --> Reject
> Null
```

```
*******************************************************************************
*5.19 Part H: Estimate the marginal effect d ln(WAGE)/d EXPER for two workers
* Chris and Dave; Chris has 16 years of education and 20 years of experience,
* while Dave has 16 years of education and 30 years of experience. What can you
* say about the marginal effect of experience as experience increases?
*******************************************************************************

/* Discussion:
>
> Recall that earlier we found that:
>
>         d ln(WAGE)/d EXPER = beta3 + beta5*EDUC + 2*beta7*EXPER
>
> In the case of experience, we found a negative point estimate for beta7. This
> means that, holding education fixed, higher experience has a falling marginal
> effect on wages. Given the positive beta3 (and the relatively small beta5),
> higher experience initially leads to higher wages, but the beneficial effect of
> experience declines and eventually turns negative. We will see an exercise
> on when it turns negative in part (I).
>
> Given the results that we calculate below for Dave, given 16 years of education
> there is still not an expected marginal decline in wages after reaching 30 years
> of experience.
> */

// Estimated marginal effect of EXPER for Chris

// Calculation option (1): margins

margins, dydx(exper) at(educ = 16 exper = 20)
```

```
Average marginal effects                        Number of obs     =      1,000
Model VCE    : OLS

Expression   : Linear prediction, predict()
dy/dx w.r.t. : exper
at           : educ            =          16
               exper           =          20
```

	dy/dx	Delta-method Std. Err.	t	P>|t|	[95% Conf.	Interval]
exper	.012815	.0019196	6.68	0.000	.0090481	.0165818

```
// Calculation option (2): lincom

lincom _b[exper] + 16*_b[c.educ#c.exper] + 2*20*_b[c.exper#c.exper]

 ( 1)  exper + 16*c.educ#c.exper + 40*c.exper#c.exper = 0
```

ln_wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
(1)	.012815	.0019196	6.68	0.000	.0090481	.0165818

```

// Calculation Option (3): Calculate point estimate and standard error
// by hand using output beta and vcv matricies

scalar margeff_chris = betaEst[1,3-1] + 16*betaEst[1,5-1] + 2*20*betaEst[1,7-1]


scalar margeff_se_chris = sqrt(vcvEst[3-1,3-1] + 16^2*vcvEst[5-1,5-1] + (2*20)^2*vcv
> Est[7-1,7-1] + ///
>                                                              2*(1)*16*vcvEst[3-1,
> 5-1] + 2*(1)*(2*20)*vcvEst[3-1,7-1] + 2*16*(2*20)*vcvEst[5-1,7-1])


// Report results of "hand" estimate
disp "Marginal Effect (Std Error) of Exper for Chris: " margeff_chris " (" margeff_s
> e_chris ")"
Marginal Effect (Std Error) of Exper for Chris: .01281497 (.00191955)



// Estimated marginal effect of EXPER for Dave

// Calculation option (1): margins

margins, dydx(exper) at(educ = 16 exper = 30)

Average marginal effects                        Number of obs     =      1,000
Model VCE    : OLS

Expression   : Linear prediction, predict()
dy/dx w.r.t. : exper
at           : educ            =          16
               exper           =          30

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       exper |   .0002404   .0018911     0.13   0.899    -.0034706    .0039514
------------------------------------------------------------------------------


// Calculation option (2): lincom

lincom _b[exper] + 16*_b[c.educ#c.exper] + 2*30*_b[c.exper#c.exper]

 ( 1)  exper + 16*c.educ#c.exper + 60*c.exper#c.exper = 0

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   .0002404   .0018911     0.13   0.899    -.0034706    .0039514
------------------------------------------------------------------------------


// Calculation option (3): Calculate point estimate and standard error by hand
// using output beta and vcv matricies

matrix margeff_dave_mat = betaEst[1,"exper"] + 16*betaEst[1,"educ_exper"] + 2*30*bet
> aEst[1,"exper_sqr"]
```

```
matrix margeff_var_dave_mat = vcvEst["exper","exper"] + 16^2*vcvEst["educ_exper","ed
> uc_exper"] + (2*30)^2*vcvEst["exper_sqr","exper_sqr"] + ///
>                                                              2*(1)*16*vcvEst["exp
> er","educ_exper"] + 2*(1)*(2*30)*vcvEst["exper","exper_sqr"] + 2*16*(2*30)*vcvEst["e
> duc_exper","exper_sqr"]


// Convert 1-by-1 matricies to scalars (see technical note at end of Part F)
>
scalar margeff_dave = margeff_dave_mat[1,1]

scalar margeff_se_dave = sqrt(margeff_var_dave_mat[1,1])


// Report results of "hand" estimate
disp "Marginal Effect (Std Error) of Exper for Dave: " margeff_dave " (" margeff_se_
> dave ")"
Marginal Effect (Std Error) of Exper for Dave: .00024038 (.00189109)


*****************************************************************************
*5.19 Part I: For someone with 16 years of education, find a 95% interval
* interval estimate for the number of years of experience after which the
* marginal effect of experience becomes negative.
*****************************************************************************

/* Discussion
>
> As mentioned earlier, given the negative beta7 there will be some level of
> experience where wages start to decline. We can find the tipping point by
> setting the marginal effect equal to zero:
>
> beta3 + beta5*EDUC + 2*beta7*EXPER_TIP = 0
> --> EXPER_TIP = (beta3 + beta5*EDUC)/(-2*beta7)
>
> Next, to calculate the confidence interval for this, we will need to use the
> delta method. This will mean compiling the following partial deriviatives:
> d EXPER_TIP/d beta3 = prtl_b3 = 1/(-2*beta7)
> d EXPER_TIP/d beta5 = prtl_b5 = EDUC/(-2*beta7)
> d EXPER_TIP/d beta7 = prtl_b7 = (-1)*(beta3 + beta5*EDUC)/(-2*beta7^2)
>                                       = (-1)*EXPER_TIP/beta7
>
> Next, we can plug these partial derivatives into the equation:
>
> Var(EXPER_TIP) = (prtl_b3^2)*var(b3) + (prtl_b5^2)*var(b5) + (prtl_b7^2)*var(b7)
>                    + 2*prtl_b3*prtl_b5*cov(b3,b5) + 2*prtl_b3*prtl_b7*cov(b3,b7)
>                                    + 2*prtl_b5*prtl_b7*cov(b5,b7)
>
> And then s.e.(EXPER_TIP) = sqrt[ Var(EXPER_TIP) ]
>
> Finally, since we are using the delta method, we choose our critical value by
> going to the normal distribution.
>
> */

// Calculation option (1): nlcom
nlcom (_b[exper]+16*_b[c.educ#c.exper])/(-2*_b[c.exper#c.exper])

       _nl_1:  (_b[exper]+16*_b[c.educ#c.exper])/(-2*_b[c.exper#c.exper])
```

ln_wage	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_nl_1	**30.19116**	**1.516336**	**19.91**	**0.000**	**27.2192**	**33.16313**

```
// Calculation option (2): calculate by hand
scalar exper_tip = (_b[exper]+16*_b[c.educ#c.exper])/(-2*_b[c.exper#c.exper])

scalar prtl_b3 = 1/(-2*_b[c.exper#c.exper])

scalar prtl_b5 = 16/(-2*_b[c.exper#c.exper])

scalar prtl_b7 = (-1)*exper_tip/_b[c.exper#c.exper]

scalar exper_tip_se = sqrt(prtl_b3^2*vcvEst[3-1,3-1] + prtl_b5^2*vcvEst[5-1,5-1] + p
> rtl_b7^2*vcvEst[7-1,7-1] + ///
>                                 2*prtl_b3*prtl_b5*vcvEst[3-1,5-1] + 2*prtl_b3*prtl_b
> 7*vcvEst[3-1,7-1] + 2*prtl_b5*prtl_b7*vcvEst[5-1,7-1])


scalar alpha = 0.05

scalar critical_value = invnormal(1-(alpha/2))

scalar exper_tip_cilow = exper_tip - critical_value*exper_tip_se

scalar exper_tip_cihigh = exper_tip + critical_value*exper_tip_se


disp "Experience Tipping Point - Point Estimate (Std Error): " exper_tip " (" exper_
> tip_se ")"
Experience Tipping Point - Point Estimate (Std Error): 30.191163 (1.5163361)

disp "Experience Tipping Point - Confidence Interval: [" exper_tip_cilow ", " exper_
> tip_cihigh "]"
Experience Tipping Point - Confidence Interval: [27.219199, 33.163127]



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