

# Problem Set 4 (SOLUTIONS)

This problem set will revisit some of the material covered in Handouts 3 and 4. You will be required to work with a ‘raw’ dataset, downloaded from an online repository. For this reason, you should take care to check how the data is coded.

You will be using a version of the US Current Population Survey (CPS) called the [Merged Outgoing Rotation Group](#) (MORG). This data is compiled by the National Bureau of Economic Research (NBER) and has been used in many famous studies of the US economy. The CPS has a rather unique rotating panel design: “The monthly CPS is a rotating panel design; households are interviewed for four consecutive months, are not in the sample for the next eight months, and then are interviewed for four more consecutive months.” (source: [IPUMS](#)). The NBER’s MORG keeps only the outgoing rotation group’s observations.

The MORG .dta files can be found at: <https://data.nber.org/morg/annual/>.

## Preamble

<IPython.core.display.HTML object>

Create a do-file for this problem set and include a preamble that sets the directory and opens the data **directly from the NBER website**. Of course, this requires a good internet connection. For example,

```
clear
//or, to remove all stored values (including macros, matrices, scalars, etc.)
*clear all

* Replace $rootdir with the relevant path to on your local harddrive.
cd "$rootdir/problem-sets/ps-4"

cap log close
log using problem-set-4-log.txt, replace
```

```
use "https://data.nber.org/morg/annual/morg19.dta", clear
```

You can, of course, download the data and open it locally on your computer.

## Questions

1. Create a new variable `exper` equal to age minus (years of education + 6). This is referred to as potential years of experience. Check how each variable defines missing values before proceeding. You will need to create a years of education variable for this. Here is the suggested code:

```
tab grade92, m
gen eduyrs = .
  replace eduyrs = .3 if grade92==31
  replace eduyrs = 3.2 if grade92==32
  replace eduyrs = 7.2 if grade92==33
  replace eduyrs = 7.2 if grade92==34
  replace eduyrs = 9   if grade92==35
  replace eduyrs = 10  if grade92==36
  replace eduyrs = 11  if grade92==37
  replace eduyrs = 12  if grade92==38
  replace eduyrs = 12  if grade92==39
  replace eduyrs = 13  if grade92==40
  replace eduyrs = 14  if grade92==41
  replace eduyrs = 14  if grade92==42
  replace eduyrs = 16  if grade92==43
  replace eduyrs = 18  if grade92==44
  replace eduyrs = 18  if grade92==45
  replace eduyrs = 18  if grade92==46
  lab var eduyrs "completed education"
tab grade92, sum(eduyrs)
```

Highest grade completed	Freq.	Percent	Cum.
31	814	0.28	0.28
32	1,495	0.51	0.79
33	3,071	1.05	1.85

34		4,123	1.41	3.26
35		5,244	1.80	5.06
36		7,824	2.69	7.75
37		9,271	3.18	10.93
38		4,226	1.45	12.38
39		82,795	28.41	40.79
40		50,112	17.20	57.99
41		12,392	4.25	62.24
42		16,161	5.55	67.79
43		59,438	20.40	88.19
44		25,374	8.71	96.89
45		3,785	1.30	98.19
46		5,265	1.81	100.00

-----+-----

Total		291,390	100.00
-------	--	---------	--------

(291,390 missing values generated)

(814 real changes made)

(1,495 real changes made)

(3,071 real changes made)

(4,123 real changes made)

(5,244 real changes made)

(7,824 real changes made)

(9,271 real changes made)

(4,226 real changes made)

(82,795 real changes made)

(50,112 real changes made)

(12,392 real changes made)

(16,161 real changes made)

(59,438 real changes made)

(25,374 real changes made)

(3,785 real changes made)

(5,265 real changes made)

Highest		Summary of completed education		
grade		Mean	Std. dev.	Freq.
completed				
31		.30000001	0	814
32		3.2	0	1,495
33		7.19999998	0	3,071
34		7.19999998	0	4,123
35		9	0	5,244
36		10	0	7,824

37		11	0	9,271
38		12	0	4,226
39		12	0	82,795
40		13	0	50,112
41		14	0	12,392
42		14	0	16,161
43		16	0	59,438
44		18	0	25,374
45		18	0	3,785
46		18	0	5,265
-----+				
Total		13.556855	2.7030576	291,390

```
tab age, m
gen exper = age-(eduyrs+6)
```

Age		Freq.	Percent	Cum.
-----+				
16		4,661	1.60	1.60
17		4,630	1.59	3.19
18		4,417	1.52	4.70
19		4,039	1.39	6.09
20		3,915	1.34	7.43
21		3,996	1.37	8.81
22		3,918	1.34	10.15
23		3,950	1.36	11.51
24		4,194	1.44	12.94
25		4,185	1.44	14.38
26		4,325	1.48	15.87
27		4,476	1.54	17.40
28		4,600	1.58	18.98
29		4,633	1.59	20.57
30		4,829	1.66	22.23
31		4,735	1.62	23.85
32		4,601	1.58	25.43
33		4,748	1.63	27.06
34		4,646	1.59	28.66
35		4,730	1.62	30.28
36		4,742	1.63	31.91
37		4,848	1.66	33.57
38		4,550	1.56	35.13

39	4,735	1.62	36.76
40	4,667	1.60	38.36
41	4,503	1.55	39.90
42	4,390	1.51	41.41
43	4,309	1.48	42.89
44	4,193	1.44	44.33
45	4,253	1.46	45.79
46	4,266	1.46	47.25
47	4,447	1.53	48.78
48	4,563	1.57	50.34
49	4,698	1.61	51.96
50	4,646	1.59	53.55
51	4,477	1.54	55.09
52	4,555	1.56	56.65
53	4,523	1.55	58.20
54	4,736	1.63	59.83
55	5,010	1.72	61.55
56	5,035	1.73	63.27
57	4,976	1.71	64.98
58	5,030	1.73	66.71
59	5,066	1.74	68.45
60	5,124	1.76	70.20
61	5,067	1.74	71.94
62	5,035	1.73	73.67
63	4,927	1.69	75.36
64	4,892	1.68	77.04
65	4,554	1.56	78.60
66	4,526	1.55	80.16
67	4,344	1.49	81.65
68	4,328	1.49	83.13
69	4,100	1.41	84.54
70	4,058	1.39	85.93
71	4,008	1.38	87.31
72	3,897	1.34	88.65
73	3,147	1.08	89.73
74	2,815	0.97	90.69
75	2,809	0.96	91.66
76	2,623	0.90	92.56
77	2,373	0.81	93.37
78	2,201	0.76	94.13
79	1,977	0.68	94.80
80	7,799	2.68	97.48
85	7,340	2.52	100.00

```
-----+-----
Total |    291,390    100.00
```

2. Keep only those between the ages of 18 and 54. Check the distribution of ‘exper’ and replace any negative values to 0.

```
keep if inrange(age,18,54)
sum exper, det
replace exper=0 if exper<0
```

(126,352 observations deleted)

```

                                exper
-----
Percentiles      Smallest
1%                0          -6
5%                1          -5
10%              2          -4      Obs          165,038
25%              7          -4      Sum of wgt.    165,038

50%              16
                                Largest      Mean          16.50623
                                47.7          Std. dev.      10.57401
75%              25          47.7
90%              31          47.7      Variance          111.8097
95%              34          47.7      Skewness           .1296908
99%              36          47.7      Kurtosis           1.887811
(1,078 real changes made)
```

3. Create a categorical variable that takes on 4 values: 1 “less than High School”; 2 “High School Diploma”; 3 “some Higher Education”; 4 “Bachelors”; 5 “Postgraduate”. This variable should be based on the the grade921 variable. You can find the value labels for this variable in this document: <<https://data.nber.org/morg/docs/cpsx.pdf>>. I suggest using therecodecommand, which allows you to create value labels while assigning values. Check the distributio ofexper’ by education category.

```
recode grade92 (31/38 = 1 "<HS") (39 = 2 "HS") (40/42 = 3 "HS+") (43 = 4 "BA") (44/46 = 5 "P
tab grade92 educat, m

tab educat, sum(exper)
```

(165,038 differences between grade92 and educat)

Highest grade completed	RECODE of grade92 (Highest grade completed)					Total
	<HS	HS	HS+	BA	PG	
31	398	0	0	0	0	398
32	578	0	0	0	0	578
33	1,515	0	0	0	0	1,515
34	1,571	0	0	0	0	1,571
35	1,971	0	0	0	0	1,971
36	2,198	0	0	0	0	2,198
37	4,373	0	0	0	0	4,373
38	2,440	0	0	0	0	2,440
39	0	45,013	0	0	0	45,013
40	0	0	30,934	0	0	30,934
41	0	0	7,154	0	0	7,154
42	0	0	9,708	0	0	9,708
43	0	0	0	37,557	0	37,557
44	0	0	0	0	14,804	14,804
45	0	0	0	0	2,021	2,021
46	0	0	0	0	2,803	2,803
Total	15,044	45,013	47,796	37,557	19,628	165,038

RECODE of grade92 (Highest grade completed)	Summary of exper		
	Mean	Std. dev.	Freq.
<HS	19.29665	12.82301	15,044
HS	17.726435	11.044222	45,013
HS+	15.643589	10.806949	47,796
BA	15.376841	9.3440749	37,557
PG	15.900092	8.1569821	19,628
Total	16.514468	10.560511	165,038

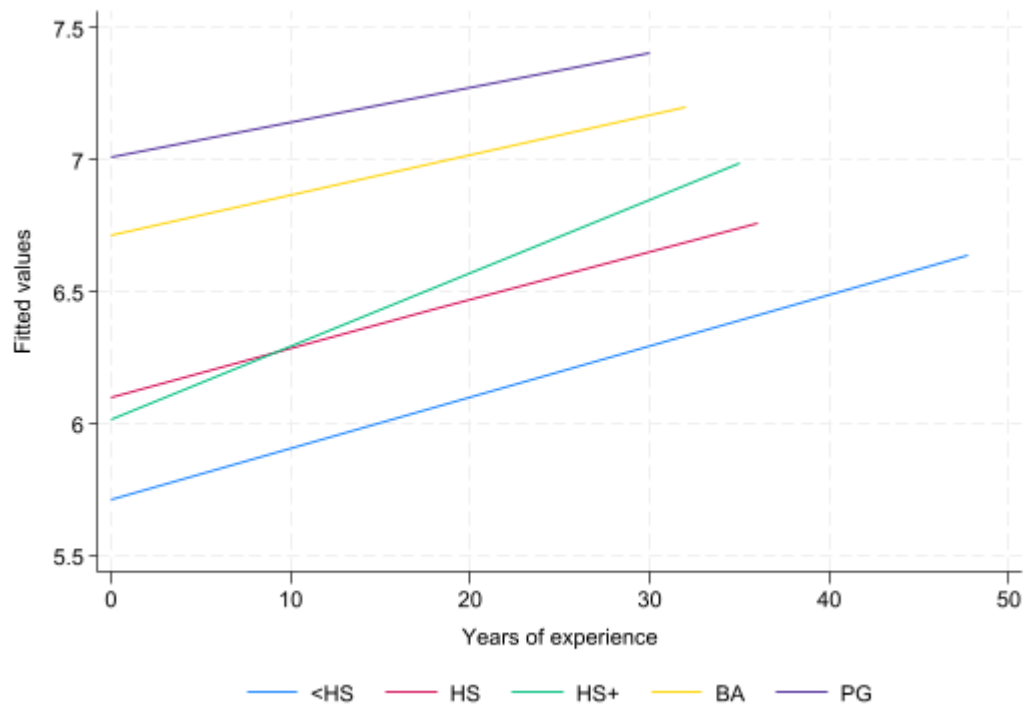
4. Create the variable `lnwage` equal to the (natural) log of weekly earnings. Create a figure that shows the predicted *linear* fit of `lnwage` against `exper`, by `educat`. Try to place all 5 fitted lines in the same graph.

```

gen lnwage = ln(earnwke)
twoway (lfit lnwage exper if educat==1) (lfit lnwage exper if educat==2) (lfit lnwage exper

```

(49,686 missing values generated)



5. Estimate a linear regression model that allows the slope coefficient on **exper** and constant term to vary by education category (**educat**). Let the base (excluded) education category be 2 “High School diploma”.

$$\ln(Wage_i) = \alpha + \sum_{j \neq 2} \psi_j \mathbf{1}\{Educate_i = j\} + \beta Exper_i + \sum_{j \neq 2} \gamma_j Exper_i \times \mathbf{1}\{Educate_i = j\} + v_i$$

```

reg lnwage ib2.educat##c.exper

```

Source		SS	df	MS	Number of obs	=	115,352
-----+-----					F(9, 115342)	=	4039.95
Model		17435.5509	9	1937.28343	Prob > F	=	0.0000



Residual		55310.0589	115,342	.479530951	R-squared	=	0.2397
-----+-----							
Total		72745.6098	115,351	.63064568	Adj R-squared	=	0.2396
					Root MSE	=	.69248

lnwage		Coefficient	Std. err.	t	P> t	[95% conf. interval]	
-----+-----							
educat							
<HS		-.3882762	.0178644	-21.73	0.000	-.4232902	-.3532622
HS+		-.0839435	.0104229	-8.05	0.000	-.1043722	-.0635149
BA		.6145964	.0109763	55.99	0.000	.5930831	.6361097
PG		.9055692	.0141961	63.79	0.000	.877745	.9333933
exper		.0182621	.0003709	49.24	0.000	.0175351	.0189891
educat#							
c.exper							
<HS		.001037	.0007627	1.36	0.174	-.000458	.0025319
HS+		.0095156	.0005186	18.35	0.000	.0084991	.0105321
BA		-.0032067	.0005743	-5.58	0.000	-.0043324	-.0020811
PG		-.0051215	.0007698	-6.65	0.000	-.0066302	-.0036128
_cons		6.101809	.0077485	787.48	0.000	6.086622	6.116996
-----+-----							

6. Show that after 13 years of experience, those with some Higher Education (but no Bachelors), out earn those with just a high school diploma. You can assume that there is a 2 year difference between the experience (education).

```
dis _b[exper]*14
dis (_b[exper] + _b[3.educat#exper])*12 + _b[3.educat]

dis _b[exper]*15
dis (_b[exper] + _b[3.educat#exper])*13 + _b[3.educat]
```

```
.25566943
.24938901
.27393153
.27716672
```

7. Use the post-estimation `test` command to test the null hypothesis:  $H_0 : 15\beta = 13(\beta + \gamma_3) + \psi_3$ .

```
test exper*15 = (exper+3.educat#exper)*13+3.educat
```

```
( 1) - 3.educat + 2*exper - 13*3.educat#c.exper = 0
```

```
F( 1,115342) = 0.32
Prob > F = 0.5734
```

8. Estimate a transformed version of the above model allowing you to test the above hypothesis using the coefficient from a single regressor. That is, the resulting test should be a simple t-test of  $H_0 : \phi = 0$ , where  $\phi$  is the coefficient on the interaction of **exper** and a dummy variable for **educat=3**. This will be easier to do if you estimate the model using only the relevant sample: those with High School diplomas and some Higher Education. I suggest avoiding the use of factor notation to create the dummy variables and interaction terms for this exercise. For example, the following should replicate the relevant coefficients from Q5.

```
gen hasHE = educat==3 if inlist(educat,2,3)
gen hasHEexp = hasHE*exper

reg lnwage exper hasHE hasHEexp
```

(72,229 missing values generated)

(72,229 missing values generated)

Source		SS	df	MS	Number of obs	=	62,811
-----+-----					F(3, 62807)	=	2860.46
Model		4000.16053	3	1333.38684	Prob > F	=	0.0000
Residual		29277.0845	62,807	.466143655	R-squared	=	0.1202
-----+-----					Adj R-squared	=	0.1202
Total		33277.2451	62,810	.529808073	Root MSE	=	.68275

lnwage		Coefficient	Std. err.	t	P> t	[95% conf. interval]	
-----+-----							
exper		.0182621	.0003657	49.94	0.000	.0175453	.0189789
hasHE		-.0839435	.0102764	-8.17	0.000	-.1040852	-.0638019
hasHEexp		.0095156	.0005113	18.61	0.000	.0085134	.0105178
_cons		6.101809	.0076396	798.71	0.000	6.086835	6.116782
-----+-----							

```
gen experR = exper+hasHEexp*2/13
gen hasHER = hasHE-hasHEexp/13
reg lnwage experR hasHER hasHEexp
```

(72,229 missing values generated)

(72,229 missing values generated)

Source		SS	df	MS	Number of obs	=	62,811
-----+							
Model		4000.16052	3	1333.38684	F(3, 62807)	=	2860.46
Residual		29277.0845	62,807	.466143655	Prob > F	=	0.0000
-----+							
Total		33277.2451	62,810	.529808073	R-squared	=	0.1202
					Adj R-squared	=	0.1202
					Root MSE	=	.68275

lnwage		Coefficient	Std. err.	t	P> t	[95% conf. interval]	
-----+							
experR		.0182621	.0003657	49.94	0.000	.0175453	.0189789
hasHER		-.0839435	.0102764	-8.17	0.000	-.1040852	-.0638019
hasHEexp		.0002489	.0004358	0.57	0.568	-.0006053	.001103
_cons		6.101809	.0076396	798.71	0.000	6.086835	6.116782

9. Verify that the F-statistic from Q7 is the square of the above T-statistic.

```
dis (_b[hasHEexp]/_se[hasHEexp])^2
```

10. Use the restricted OLS approach to replicate the F-statistic and p-value from Q7.

```
reg lnwage exper hasHE hasHEexp
scalar RSSu = e(rss)
scalar DOFu = e(df_r)
reg lnwage experR hasHER
scalar RSSr = e(rss)
scalar DOFr = e(df_r)

scalar Fstat = ((RSSr-RSSu)/(DOFr-DOFu))/(RSSu/DOFu)
scalar pval = Ftail(1,DOFu,Fstat)

scalar list Fstat pval
```

.32610143

Source	SS	df	MS	Number of obs	=	62,811
Model	4000.16053	3	1333.38684	F(3, 62807)	=	2860.46
Residual	29277.0845	62,807	.466143655	Prob > F	=	0.0000
				R-squared	=	0.1202
				Adj R-squared	=	0.1202
Total	33277.2451	62,810	.529808073	Root MSE	=	.68275

lnwage	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
exper	.0182621	.0003657	49.94	0.000	.0175453	.0189789
hasHE	-.0839435	.0102764	-8.17	0.000	-.1040852	-.0638019
hasHEexp	.0095156	.0005113	18.61	0.000	.0085134	.0105178
_cons	6.101809	.0076396	798.71	0.000	6.086835	6.116782

Source	SS	df	MS	Number of obs	=	62,811
Model	4000.00851	2	2000.00425	F(2, 62808)	=	4290.58
Residual	29277.2366	62,808	.466138654	Prob > F	=	0.0000
				R-squared	=	0.1202
				Adj R-squared	=	0.1202
Total	33277.2451	62,810	.529808073	Root MSE	=	.68274

lnwage	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
experR	.0182233	.0003593	50.71	0.000	.017519	.0189277
hasHER	-.0882792	.0069253	-12.75	0.000	-.1018527	-.0747056
_cons	6.104077	.0065255	935.42	0.000	6.091287	6.116867

Fstat = .32612066

pval = .5679544

**11.** Use the restricted OLS approach to test the following hypothesis corresponding to the model in Q5:

$$H_0 : \gamma_j = 0 \quad \text{for } j = 1, 3, 4, 5$$

Compute the F-statistic and p-value. Verify your result using the post-estimation `test` command.

```

reg lnwage ib2.educat##c.exper
scalar RSSu = e(rss)
scalar DOFu = e(df_r)
reg lnwage ib2.educat exper
scalar RSSr = e(rss)
scalar DOFr = e(df_r)

scalar Fstat = ((RSSr-RSSu)/(DOFr-DOFu))/(RSSu/DOFu)
scalar pval = Ftail(DOFr-DOFu,DOFu,Fstat)

scalar list Fstat pval

** verify
reg lnwage ib2.educat##c.exper
test 1.educat#exper 3.educat#exper 4.educat#exper 5.educat#exper

```

Source		SS	df	MS	Number of obs	=	115,352
-----+					F(9, 115342)	=	4039.95
Model		17435.5509	9	1937.28343	Prob > F	=	0.0000
Residual		55310.0589	115,342	.479530951	R-squared	=	0.2397
-----+					Adj R-squared	=	0.2396
Total		72745.6098	115,351	.63064568	Root MSE	=	.69248

-----						
lnwage		Coefficient	Std. err.	t	P> t	[95% conf. interval]
-----						
educat						
<HS		-.3882762	.0178644	-21.73	0.000	-.4232902    -.3532622
HS+		-.0839435	.0104229	-8.05	0.000	-.1043722    -.0635149
BA		.6145964	.0109763	55.99	0.000	.5930831    .6361097
PG		.9055692	.0141961	63.79	0.000	.877745    .9333933
exper		.0182621	.0003709	49.24	0.000	.0175351    .0189891
educat#						
c.exper						
<HS		.001037	.0007627	1.36	0.174	-.000458    .0025319
HS+		.0095156	.0005186	18.35	0.000	.0084991    .0105321
BA		-.0032067	.0005743	-5.58	0.000	-.0043324    -.0020811
PG		-.0051215	.0007698	-6.65	0.000	-.0066302    -.0036128

_cons		6.101809	.0077485	787.48	0.000	6.086622	6.116996
-------	--	----------	----------	--------	-------	----------	----------

Source		SS	df	MS	Number of obs	=	115,352
					F(5, 115346)	=	7085.67
Model		17093.4651	5	3418.69301	Prob > F	=	0.0000
Residual		55652.1448	115,346	.482480058	R-squared	=	0.2350
					Adj R-squared	=	0.2349
Total		72745.6098	115,351	.63064568	Root MSE	=	.69461

lnwage		Coefficient	Std. err.	t	P> t	[95% conf. interval]
educat						
<HS		-.3724213	.0090073	-41.35	0.000	-.3900754 -.3547671
HS+		.0726614	.0055618	13.06	0.000	.0617604 .0835624
BA		.5714202	.0057563	99.27	0.000	.5601379 .5827025
PG		.8295498	.0068114	121.79	0.000	.8161996 .8428999
exper		.0201711	.0002025	99.60	0.000	.0197742 .0205681
_cons		6.067685	.0054116	1121.24	0.000	6.057079 6.078292

Fstat = 178.34399

pval = 1.32e-152

Source		SS	df	MS	Number of obs	=	115,352
					F(9, 115342)	=	4039.95
Model		17435.5509	9	1937.28343	Prob > F	=	0.0000
Residual		55310.0589	115,342	.479530951	R-squared	=	0.2397
					Adj R-squared	=	0.2396
Total		72745.6098	115,351	.63064568	Root MSE	=	.69248

lnwage		Coefficient	Std. err.	t	P> t	[95% conf. interval]
educat						
<HS		-.3882762	.0178644	-21.73	0.000	-.4232902 -.3532622
HS+		-.0839435	.0104229	-8.05	0.000	-.1043722 -.0635149
BA		.6145964	.0109763	55.99	0.000	.5930831 .6361097
PG		.9055692	.0141961	63.79	0.000	.877745 .9333933
exper		.0182621	.0003709	49.24	0.000	.0175351 .0189891

educat#						
c.exper						
<HS	.001037	.0007627	1.36	0.174	-.000458	.0025319
HS+	.0095156	.0005186	18.35	0.000	.0084991	.0105321
BA	-.0032067	.0005743	-5.58	0.000	-.0043324	-.0020811
PG	-.0051215	.0007698	-6.65	0.000	-.0066302	-.0036128
_cons	6.101809	.0077485	787.48	0.000	6.086622	6.116996

---

```

( 1) 1.educat#c.exper = 0
( 2) 3.educat#c.exper = 0
( 3) 4.educat#c.exper = 0
( 4) 5.educat#c.exper = 0

F( 4,115342) = 178.34
Prob > F = 0.0000

```

**12.** Compute the relevant Chi-squared distributed test statistic and corresponding p-value for the above test, assuming  $n$  is large (enough).

```

scalar Cstat = Fstat*(DOFr-DOFu)
scalar pval = chi2tail(DOFr-DOFu,Cstat)
scalar list Cstat pval

```

```

Cstat = 713.37597
pval = 4.42e-153

```

**13.** Using the data from Problem Set 2, estimate the simple linear regression model using OLS,

$$\ln(Wage_i) = \beta_0 + \beta_1 Educ_i + \beta_2 Female_i + \varepsilon_i$$

```

use "$rootdir/problem-sets/ps-2/problem-set-2-data.dta", clear
reg lwage educ female
est sto ols
estadd scalar sigma = e(rmse)

```

(PSID wage data 1976-82 from Baltagi and Khanti-Akom (1990))

Source	SS	df	MS	Number of obs	=	4,165
				F(2, 4162)	=	732.99
Model	231.021419	2	115.51071	Prob > F	=	0.0000
Residual	655.883483	4,162	.157588535	R-squared	=	0.2605
				Adj R-squared	=	0.2601
Total	886.904902	4,164	.212993492	Root MSE	=	.39697

lwage	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
educ	.0651382	.0022066	29.52	0.000	.0608121	.0694642
female	-.4737645	.0194589	-24.35	0.000	-.5119143	-.4356147
_cons	5.89297	.0290891	202.58	0.000	5.83594	5.95

added scalar:

e(sigma) = .39697422

14. Estimate the Mincer equation using Maximum Likelihood. Take a look at <https://www.stata.com/manuals13/rmlexp.pdf>, the documentation for the `mlexp` command. It has a discussion on estimating the CLRM using ML.<sup>1</sup>

```
mlexp (ln(normalden(lwage, {xb: educ female _cons}, exp({theta}))))
ereturn list
nlcom (sigma: exp(_b[/theta]))
estadd scalar sigma = r(b)[1,1]
eststo ml
```

```
Initial:      Log likelihood = -97095.356
Alternative:  Log likelihood = -35297.969
Rescale:      Log likelihood = -12999.606
Rescale eq:   Log likelihood = -7350.6222
Iteration 0:  Log likelihood = -7350.6222 (not concave)
Iteration 1:  Log likelihood = -3936.054
Iteration 2:  Log likelihood = -2187.1092 (backed up)
Iteration 3:  Log likelihood = -2073.0429
Iteration 4:  Log likelihood = -2060.4271
Iteration 5:  Log likelihood = -2060.4019
Iteration 6:  Log likelihood = -2060.4019
```

<sup>1</sup>You can also look at the following resource for a more flexible approach to ML estimation in Stata: <https://www.stata.com/features/overview/maximum-likelihood-estimation/>



Maximum likelihood estimation

Log likelihood = -2060.4019

Number of obs = 4,165

		Coefficient	Std. err.	z	P> z	[95% conf. interval]	
xb							
	educ	.0651382	.0022058	29.53	0.000	.060815	.0694614
	female	-.4737645	.0194519	-24.36	0.000	-.5118895	-.4356396
	_cons	5.89297	.0290786	202.66	0.000	5.835977	5.949963
	/theta	-.9242442	.0109566	-84.35	0.000	-.9457188	-.9027696

scalars:

```
e(rank) = 4
e(N) = 4165
e(ic) = 6
e(k) = 4
e(k_eq) = 2
e(converged) = 1
e(rc) = 0
e(ll) = -2060.40189888505
e(k_aux) = 1
e(df_m) = 4
e(k_eq_model) = 0
```

macros:

```
e(cmdline) : "mlexp (ln(normalden(lwage, {xb: educ female _cons..}"
e(cmd) : "mlexp"
e(predict) : "mlexp_p"
e(estat_cmd) : "mlexp_estat"
e(marginsnotok) : "SCores"
e(marginsok) : "default xb"
e(marginsprop) : "nochainrule"
e(lexp) : "ln(normalden(lwage,{xb:},exp({theta:})))"
e(params) : "xb:educ xb:female xb:_cons theta:_cons"
e(opt) : "moptimize"
e(vce) : "oim"
e(ml_method) : "lf0"
e(technique) : "nr"
```

```

e(properties) : "b V"

matrices:
      e(b) : 1 x 4
      e(V) : 4 x 4
      e(init) : 1 x 4
      e(ilog) : 1 x 20
      e(gradient) : 1 x 4

functions:
      e(sample)

      sigma: exp(_b[/theta])

```

	Coefficient	Std. err.	z	P> z	[95% conf. interval]
sigma	.3968312	.0043479	91.27	0.000	.3883094 .405353

```

added scalar:
      e(sigma) = .39683123

```

**15.** Estimate the Mincer equation using Method of Moments. You can use the `gmm` command in Stata. Hint: the regressors will be their own instruments and use the `onestep` option.<sup>2</sup>

```

gmm (lwage - {xb: educ female _cons}), instruments(educ female) onestep
eststo mm

esttab ols ml mm, se drop(theta:_cons) scalar(N sigma) mtitle(OLS ML MM)

```

Step 1

```

Iteration 0:  GMM criterion Q(b) = 44.629069
Iteration 1:  GMM criterion Q(b) = 2.101e-24
Iteration 2:  GMM criterion Q(b) = 1.368e-31

```

note: model is exactly identified.

<sup>2</sup>Here is a resource on GMM in Stata: <https://www.stata.com/features/overview/generalized-method-of-moments/>

# GMM estimation

Number of parameters = 3

Number of moments = 3

Initial weight matrix: Unadjusted

Number of obs = 4,165

		Robust				
	Coefficient	std. err.	z	P> z	[95% conf. interval]	
educ	.0651382	.0023187	28.09	0.000	.0605935	.0696828
female	-.4737645	.0177811	-26.64	0.000	-.5086148	-.4389143
_cons	5.89297	.0300924	195.83	0.000	5.83399	5.95195

Instruments for equation 1: educ female \_cons

	(1) OLS	(2) ML	(3) MM
main			
educ	0.0651*** (0.00221)	0.0651*** (0.00221)	0.0651*** (0.00232)
female	-0.474*** (0.0195)	-0.474*** (0.0195)	-0.474*** (0.0178)
_cons	5.893*** (0.0291)	5.893*** (0.0291)	5.893*** (0.0301)
N	4165	4165	4165
sigma	0.397	0.397	

Standard errors in parentheses

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001

## Postamble

log close