

(R)

Statistics/Data Analysis

User: Jiahao Ye
Project: LAB2

```

name: <unnamed>
log: D:\Econ4G03LAB2\output.smcl
log type: smcl
opened on: 1 Oct 2020, 12:35:05

```

```

1 . set more off

2 .

3 . use ${DtaDir}\LFS-71M0001-E-2020-January_F1, clear

4 .

5 .
end of do-file

6 . do "C:\Users\LOCAL_~3\Temp\STD000000000.tmp"

7 . /*Generate a table for sex*/
8 . tab SEX, m

```

Sex of respondent	Freq.	Percent	Cum.
Male	48,398	48.80	48.80
Female	50,777	51.20	100.00
Total	99,175	100.00	

```
9 . tab SEX, m nolabel
```

Sex of respondent	Freq.	Percent	Cum.
1	48,398	48.80	48.80
2	50,777	51.20	100.00
Total	99,175	100.00	

```
10 . label list SEX
SEX:
```

```

1 Male
2 Female

```

```

11 .
12 .
13 . gen byte female=. /* "Byte" stands for a float variable */
    (99175 missing values generated)

14 . replace female=0 if SEX==1
    (48398 real changes made)

15 . replace female=1 if SEX==2
    (50777 real changes made)

16 .
17 . tab female SEX, missing /*Replacing variable for sex,and generate a table.*/

```

female	Sex of respondent		Total
	Male	Female	
0	48,398	0	48,398
1	0	50,777	50,777
Total	48,398	50,777	99,175

```

18 .
19 . /*Question ii):*/
20 . /*Generate indicator variables for four regions: east, qc, on, west */
21 . tab PROV, nolabel

```

Province	Freq.	Percent	Cum.
10	3,722	3.75	3.75
11	2,609	2.63	6.38
12	5,191	5.23	11.62
13	5,058	5.10	16.72
24	17,883	18.03	34.75
35	28,353	28.59	63.34
46	7,800	7.86	71.20
47	7,071	7.13	78.33
48	9,561	9.64	87.97
59	11,927	12.03	100.00
Total	99,175	100.00	

```

22 . label list PROV
    PROV:

```

```

    10 Newfoundland and Labrador
    11 Prince Edward Island
    12 Nova Scotia
    13 New Brunswick
    24 Quebec
    35 Ontario
    46 Manitoba
    47 Saskatchewan
    48 Alberta
    59 British Columbia

```

```

23 .
24 . /*Here, I change the province(east west QC ON) into a categorical variable */
25 . label list PROV
    PROV:

```

```

    10 Newfoundland and Labrador
    11 Prince Edward Island
    12 Nova Scotia
    13 New Brunswick
    24 Quebec
    35 Ontario
    46 Manitoba
    47 Saskatchewan
    48 Alberta
    59 British Columbia

```

```

26 . gen east=1 if PROV <=14
    (82595 missing values generated)

```

```

27 . replace east=0 if PROV >14
    (82595 real changes made)

```

```

28 . tab east

```

east	Freq.	Percent	Cum.
0	82,595	83.28	83.28
1	16,580	16.72	100.00
Total	99,175	100.00	

```

29 .
30 . gen west=1 if PROV >=46
    (62816 missing values generated)

```

```

31 . replace west=0 if PROV <46
    (62816 real changes made)

```

```

32 . tab west

```

west	Freq.	Percent	Cum.
0	62,816	63.34	63.34
1	36,359	36.66	100.00
Total	99,175	100.00	

```

33 .
34 . gen on=1 if PROV == 35
    (70822 missing values generated)

```

```

35 . replace on=0 if PROV != 35
    (70822 real changes made)

```

```

36 . tab on

```

on	Freq.	Percent	Cum.
0	70,822	71.41	71.41
1	28,353	28.59	100.00
Total	99,175	100.00	

```

37 .
38 . gen qc=1 if PROV == 24
    (81292 missing values generated)

```

```

39 . replace qc=0 if PROV != 24
    (81292 real changes made)

```

```

40 . tab qc

```

qc	Freq.	Percent	Cum.
0	81,292	81.97	81.97
1	17,883	18.03	100.00
Total	99,175	100.00	

```

41 .
42 . /*Question iii):create a new age variable*/
43 .
44 . tab AGE_12

```

Five-year age group of respondent	Freq.	Percent	Cum.
15 to 19 years	6,608	6.66	6.66
20 to 24 years	6,309	6.36	13.02
25 to 29 years	6,980	7.04	20.06
30 to 34 years	7,594	7.66	27.72
35 to 39 years	7,912	7.98	35.70
40 to 44 years	7,630	7.69	43.39
45 to 49 years	7,545	7.61	51.00
50 to 54 years	7,986	8.05	59.05
55 to 59 years	9,215	9.29	68.34
60 to 64 years	8,616	8.69	77.03
65 to 69 years	7,674	7.74	84.77
70 and over	15,106	15.23	100.00
Total	99,175	100.00	

```

45 . label list AGE_12
    AGE_12:
        1 15 to 19 years
        2 20 to 24 years
        3 25 to 29 years
        4 30 to 34 years
        5 35 to 39 years
        6 40 to 44 years
        7 45 to 49 years
        8 50 to 54 years
        9 55 to 59 years
        10 60 to 64 years
        11 65 to 69 years
        12 70 and over

46 .
47 . gen age=17 if AGE_12==1
    (92567 missing values generated)

48 . replace age=22 if AGE_12==2
    (6309 real changes made)

49 . replace age=27 if AGE_12==3
    (6980 real changes made)

50 . replace age=32 if AGE_12==4
    (7594 real changes made)

51 . replace age=37 if AGE_12==5
    (7912 real changes made)

52 . replace age=42 if AGE_12==6
    (7630 real changes made)

53 . replace age=47 if AGE_12==7
    (7545 real changes made)

54 . replace age=52 if AGE_12==8
    (7986 real changes made)

55 . replace age=57 if AGE_12==9
    (9215 real changes made)

56 . replace age=62 if AGE_12==10
    (8616 real changes made)

57 . replace age=67 if AGE_12==11
    (7674 real changes made)

58 . replace age=72 if AGE_12==12
    (15106 real changes made)

59 .
60 . tab age

```

age	Freq.	Percent	Cum.
17	6,608	6.66	6.66
22	6,309	6.36	13.02
27	6,980	7.04	20.06
32	7,594	7.66	27.72
37	7,912	7.98	35.70
42	7,630	7.69	43.39
47	7,545	7.61	51.00
52	7,986	8.05	59.05
57	9,215	9.29	68.34
62	8,616	8.69	77.03
67	7,674	7.74	84.77
72	15,106	15.23	100.00
Total	99,175	100.00	

```

61 .
62 . /*Question iv use LFSSTAT): Exam "HRLYEARN", create variances=0 if missing values
>
>
> */
63 . tab LFSSTAT

```

Labour force status	Freq.	Percent	Cum.
Employed, at work	53,557	54.00	54.00
Employed, absent from work	4,660	4.70	58.70
Unemployed	3,962	3.99	62.70
Not in labour force	36,996	37.30	100.00
Total	99,175	100.00	

```

64 . label list LFSSTAT
LFSSTAT:

```

```

1 Employed, at work
2 Employed, absent from work
3 Unemployed
4 Not in labour force

```

```

65 . gen status=0 if LFSSTAT==4 | LFSSTAT==2 /*missing value, either not in labor force or
(57519 missing values generated)

66 . replace status=1 if LFSSTAT==1 /*Non-missing value */
(53557 real changes made)

67 . replace status=. if LFSSTAT==3 /*unemployed*/
(0 real changes made)

```

```

68 .
69 . tab status

```

status	Freq.	Percent	Cum.
0	41,656	43.75	43.75
1	53,557	56.25	100.00
Total	95,213	100.00	

```

70 .
71 . /*In this LAB, we will be focusing on non-missing samples, which is status = 1. */
72 .
73 . /*Question 2): Run regression analysis*/
74 . /* i)reg HRLYEARN age female */
75 . regress HRLYEARN age female

```

Source	SS	df	MS	Number of obs =	49264
Model	569503.468	2	284751.734	F(2, 49261) =	1559.13
Residual	8996755.24	49261	182.634442	Prob > F =	0.0000
Total	9566258.71	49263	194.187498	R-squared =	0.0595
				Adj R-squared =	0.0595
				Root MSE =	13.514

HRLYEARN	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	.2045397	.00438	46.70	0.000	.1959549	.2131245
female	-3.690772	.1217903	-30.30	0.000	-3.929482	-3.452061
_cons	21.26753	.2017506	105.41	0.000	20.87209	21.66296

```

76 .
77 . /*Explanation: Regression line: HRLYEARN = 21.26753-3.690772*female+0.2045397*age
> Equation shows female has less HRLYEARN than male does(When female=1,negative slope, which de
> holding age constant).
> HRLYEARN increases, on average, by 0.2045397 for unit increase in age group (5-year increase
78 .
79 . /* ii)repeat above, but with robust (reweighted OLS, allowing heteroskedasticity) this time */
80 . regress HRLYEARN age female, robust

```

Linear regression

Number of obs = **49264**
F(2, 49261) = **1627.57**
Prob > F = **0.0000**
R-squared = **0.0595**
Root MSE = **13.514**

HRLYEARN	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.2045397	.0041641	49.12	0.000	.196378	.2127014
female	-3.690772	.1219684	-30.26	0.000	-3.929831	-3.451712
_cons	21.26753	.178266	119.30	0.000	20.91812	21.61693

```

81 .
82 . /*Robust OLS: Very similar to above, which means outliers do not have significant impact */
83 .
84 . /* iii)Regression Y=ln(HRLYEARN), X=Age,female */
85 . gen llearn = ln(HRLYEARN)
(49911 missing values generated)

```

```

86 . regress llearn age female

```

Source	SS	df	MS	Number of obs =		
Model	748.578845	2	374.289423	F(2, 49261) =	1848.26	
Residual	9975.82495	49261	.202509591	Prob > F =	0.0000	
Total	10724.4038	49263	.217696929	R-squared =	0.0698	
				Adj R-squared =	0.0698	
				Root MSE =	.45001	

llearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0075549	.0001458	51.80	0.000	.0072691	.0078408
female	-.1276835	.0040555	-31.48	0.000	-.1356323	-.1197346
_cons	2.968137	.0067181	441.81	0.000	2.954969	2.981304

```

87 .
88 . /*age coefficient=0.0075549, female coefficient=-0.12768
> An unit increase in age will have a 0.0075549 increase in ln(HRLYEARN).*/
89 .
90 . /* iv)Regression Y=HRLYEARN, X=ln(age) female */
91 . gen lnage = ln(age)

```

```

92 . regress HRLYEARN lnage female

```

Source	SS	df	MS	Number of obs =		
Model	782336.527	2	391168.264	F(2, 49261) =	2193.71	
Residual	8783922.18	49261	178.313923	Prob > F =	0.0000	
Total	9566258.71	49263	194.187498	R-squared =	0.0818	
				Adj R-squared =	0.0817	
				Root MSE =	13.353	

HRLYEARN	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnage	9.566883	.1634185	58.54	0.000	9.246581	9.887185
female	-3.694531	.1203398	-30.70	0.000	-3.930398	-3.458663
_cons	-5.282225	.6049176	-8.73	0.000	-6.467871	-4.096579

```

93 .
94 . /* v) Regression Y=ln(HRLYEARN), x=ln(age) female */
95 . regress lnearn lnage female

```

Source	SS	df	MS	Number of obs = 49264		
Model	1074.03141	2	537.015705	F(2, 49261) = 2741.23		
Residual	9650.37238	49261	.195902892	Prob > F = 0.0000		
				R-squared = 0.1001		
				Adj R-squared = 0.1001		
Total	10724.4038	49263	.217696929	Root MSE = .44261		

lnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnage	.3607236	.0054166	66.60	0.000	.350107	.3713403
female	-.1277958	.0039888	-32.04	0.000	-.1356138	-.1199778
_cons	1.960524	.0200504	97.78	0.000	1.921224	1.999823

```

96 .
97 . /*Explanation: While holding female constant, a unit increase in ln(age) will have
> a 0.3607236 increase in ln(HRLYEARN).
> The R^2 (Explanatory power) increased, as I applied logarithmic. Log function has a
> advantage of transferring skewed data into linear relationship, which will give us better
> result for linear regression analysis. */
98 .
99 . /* vi)Factor variables, Three types of variables: Categ. variables, indicator variables, cont
100 . regress lnearn c.age i.female c.age#i.female, robust

```

Linear regression

Number of obs = **49264**
F(3, 49260) = **1188.23**
Prob > F = **0.0000**
R-squared = **0.0710**
Root MSE = **.44973**

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0087097	.0002181	39.93	0.000	.0082821	.0091372
1.female	-.0317036	.0124616	-2.54	0.011	-.0561284	-.0072787
female#c.age 1	-.0023131	.0002979	-7.77	0.000	-.002897	-.0017293
_cons	2.920114	.0091378	319.56	0.000	2.902204	2.938024

```

101 .
102 . /*""#stands for interaction variables ""#""means a factorial of interaction.
> Here, we are trying to model it like: HRLYEARN=b0+b1*age+b2*female+b3*age*female(interaction
> Results here shows that, as age for women increases, HRLYEARN tends to decrease.
> But for men, it is less of an issue */
103 .
104 . /* vii) */
105 . regress lnearn c.age c.age#c.age female,robust

```

Linear regression

Number of obs = **49264**
F(3, 49260) = **5314.23**
Prob > F = **0.0000**
R-squared = **0.1789**
Root MSE = **.4228**

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0725511	.0007419	97.79	0.000	.0710969	.0740052
c.age#c.age	-.0007754	9.15e-06	-84.69	0.000	-.0007933	-.0007574
female	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
_cons	1.758419	.0137591	127.80	0.000	1.731451	1.785387

106 . margins, dydx(*)at(age=(25(5)60))

Average marginal effects
Model VCE : **Robust**

Number of obs = **49264**

Expression : **Linear prediction, predict()**
dy/dx w.r.t. : **age female**

1._at	: age	=	25
2._at	: age	=	30
3._at	: age	=	35
4._at	: age	=	40
5._at	: age	=	45
6._at	: age	=	50
7._at	: age	=	55
8._at	: age	=	60

		Delta-method dy/dx	Std. Err.	t	P> t	[95% Conf. Interval]	
age							
	_at						
	1	.0337827	.0003006	112.38	0.000	.0331935	.0343719
	2	.026029	.0002205	118.02	0.000	.0255968	.0264613
	3	.0182754	.0001539	118.76	0.000	.0179738	.018577
	4	.0105217	.0001244	84.57	0.000	.0102778	.0107656
	5	.002768	.0001551	17.85	0.000	.0024641	.0030719
	6	-.0049856	.0002222	-22.44	0.000	-.0054212	-.0045501
	7	-.0127393	.0003024	-42.12	0.000	-.0133321	-.0121466
	8	-.020493	.0003877	-52.86	0.000	-.0212529	-.0197331
female							
	_at						
	1	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
	2	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
	3	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
	4	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
	5	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
	6	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
	7	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449
	8	-.132411	.0038092	-34.76	0.000	-.139877	-.1249449


```
107 . marginsplot
```

```
Variables that uniquely identify margins: age _deriv
```

```
108 . /* c.age#c.age means age squared. Regression line:
```

```
> HRLYEARN = 0.0725511*age - 0.0007754*age^2 - 0.132411*female + 1.758419,
```

```
> take the partial derivative w.r.t age*/
```

```
109 .
```

```
110 . margins, at(age=(25(5)65)) /*This commands calculate the exact prediction value */
```

```
Predictive margins                                Number of obs   =      49264
Model VCE      : Robust
```

```
Expression    : Linear prediction, predict()
```

```
1._at         : age                =      25
```

```
2._at         : age                =      30
```

```
3._at         : age                =      35
```

```
4._at         : age                =      40
```

```
5._at         : age                =      45
```

```
6._at         : age                =      50
```

```
7._at         : age                =      55
```

```
8._at         : age                =      60
```

```
9._at         : age                =      65
```

	Delta-method				[95% Conf. Interval]	
	Margin	Std. Err.	t	P> t		
_at						
1	3.020418	.0024066	1255.06	0.000	3.015701	3.025135
2	3.169947	.00234	1354.69	0.000	3.165361	3.174533
3	3.280708	.0025835	1269.88	0.000	3.275644	3.285772
4	3.352701	.0027416	1222.92	0.000	3.347327	3.358074
5	3.385925	.0027177	1245.87	0.000	3.380598	3.391252
6	3.380381	.0026318	1284.44	0.000	3.375223	3.385539
7	3.336068	.0028349	1176.79	0.000	3.330512	3.341625
8	3.252988	.0037247	873.36	0.000	3.245687	3.260288
9	3.131139	.0053713	582.94	0.000	3.120611	3.141666

```
111 . marginsplot
```

```
Variables that uniquely identify margins: age
```

```
112 .
```

```
113 . /* viii) */
```

```
114 . margins, at(age=(25(5)65))by(female)
```

```
Predictive margins                                Number of obs   =      49264
Model VCE      : Robust
```

```
Expression    : Linear prediction, predict()
over          : female
```

```
1._at         : 0.female
                  age                =      25
                  1.female
                  age                =      25
```

```

2._at      : 0.female
              age          =          30
              1.female
              age          =          30

3._at      : 0.female
              age          =          35
              1.female
              age          =          35

4._at      : 0.female
              age          =          40
              1.female
              age          =          40

5._at      : 0.female
              age          =          45
              1.female
              age          =          45

6._at      : 0.female
              age          =          50
              1.female
              age          =          50

7._at      : 0.female
              age          =          55
              1.female
              age          =          55

8._at      : 0.female
              age          =          60
              1.female
              age          =          60

9._at      : 0.female
              age          =          65
              1.female
              age          =          65

```

	Delta-method					
	Margin	Std. Err.	t	P> t	[95% Conf. Interval]	
_at#female						
1 0	3.087591	.0031353	984.78	0.000	3.081446	3.093736
1 1	2.95518	.0030031	984.05	0.000	2.949294	2.961066
2 0	3.23712	.0030565	1059.11	0.000	3.231129	3.243111
2 1	3.104709	.0029781	1042.50	0.000	3.098872	3.110546
3 0	3.347881	.0032282	1037.07	0.000	3.341554	3.354208
3 1	3.21547	.0031913	1007.58	0.000	3.209215	3.221725
4 0	3.419874	.0033461	1022.06	0.000	3.413315	3.426432
4 1	3.287463	.0033303	987.13	0.000	3.280935	3.293999
5 0	3.453098	.0033244	1038.72	0.000	3.446582	3.459614
5 1	3.320687	.0033129	1002.36	0.000	3.314194	3.32718
6 0	3.447554	.0032603	1057.42	0.000	3.441164	3.453944
6 1	3.315143	.003237	1024.13	0.000	3.308798	3.321488
7 0	3.403242	.0034395	989.45	0.000	3.3965	3.409983
7 1	3.270831	.0033913	964.48	0.000	3.264184	3.277478
8 0	3.320161	.0042202	786.73	0.000	3.311889	3.328433
8 1	3.18775	.0041471	768.66	0.000	3.179621	3.195878
9 0	3.198312	.0057431	556.90	0.000	3.187055	3.209568
9 1	3.065901	.0056556	542.10	0.000	3.054816	3.076986

```
115 . marginsplot
```

Variables that uniquely identify margins: age female

```
116 . /*From the result, we can show that, for both men&women, the margin starts to decline
> at around age group 5~6.*/
```

```
117 .
```

```
118 . /*Then, run another regression, for DIFFERENT INTERCEPT & DIFFERENT SLOPE
> for men&women w.r.t how earnings change with age.
```

```
> Approach: 1)HRLYEARN = b1*age + b2*age*female +b3
```

```
> 2)HRLYEARN = b1*age + b2*age^2+ b3*age*female +b4
```

```
> refer to textbook page 259, fig8.8 */
```

```
119 .
```

```
120 . regress HRLYEARN c.age c.age#i.female, robust
```

Linear regression

Number of obs = **49264**
 F(2, 49261) = **1522.48**
 Prob > F = **0.0000**
 R-squared = **0.0612**
 Root MSE = **13.503**

HRLYEARN	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.2485544	.0045477	54.66	0.000	.2396409	.2574679
female#c.age 1	-.0881511	.0029879	-29.50	0.000	-.0940075	-.0822948
_cons	19.42031	.1659044	117.06	0.000	19.09513	19.74548

```
121 . margins, at (age=(25(5)65))by(female)
```

Predictive margins

Number of obs = **49264**

Model VCE : **Robust**

Expression : **Linear prediction, predict()**
 over : **female**

1._at	: 0.female		
	age	=	25
	1.female		
	age	=	25
2._at	: 0.female		
	age	=	30
	1.female		
	age	=	30
3._at	: 0.female		
	age	=	35
	1.female		
	age	=	35
4._at	: 0.female		
	age	=	40
	1.female		
	age	=	40
5._at	: 0.female		
	age	=	45
	1.female		
	age	=	45
6._at	: 0.female		
	age	=	50
	1.female		
	age	=	50

```

7._at      : 0.female
              age              =          55
              1.female
              age              =          55

8._at      : 0.female
              age              =          60
              1.female
              age              =          60

9._at      : 0.female
              age              =          65
              1.female
              age              =          65

```

	Delta-method					
	Margin	Std. Err.	t	P> t	[95% Conf. Interval]	
_at#female						
1 0	25.63417	.0868602	295.12	0.000	25.46392	25.80442
1 1	23.43039	.0856394	273.59	0.000	23.26254	23.59824
2 0	26.87694	.0815535	329.56	0.000	26.71709	27.03679
2 1	24.23241	.077802	311.46	0.000	24.07991	24.3849
3 0	28.11971	.0824095	341.22	0.000	27.95819	28.28124
3 1	25.03442	.0754403	331.84	0.000	24.88656	25.18229
4 0	29.36248	.0892509	328.99	0.000	29.18755	29.53742
4 1	25.83644	.0790466	326.85	0.000	25.68151	25.99137
5 0	30.60526	.1008673	303.42	0.000	30.40756	30.80296
5 1	26.63846	.0878892	303.09	0.000	26.46619	26.81072
6 0	31.84803	.1158307	274.95	0.000	31.621	32.07506
6 1	27.44047	.1005967	272.78	0.000	27.2433	27.63764
7 0	33.0908	.1330164	248.77	0.000	32.83009	33.35151
7 1	28.24249	.1159047	243.67	0.000	28.01531	28.46966
8 0	34.33357	.1516708	226.37	0.000	34.0363	34.63085
8 1	29.0445	.1329178	218.51	0.000	28.78398	29.30503
9 0	35.57634	.1713148	207.67	0.000	35.24057	35.91212
9 1	29.84652	.1510609	197.58	0.000	29.55044	30.1426

```
122 . marginsplot
```

Variables that uniquely identify margins: age female

```
123 .
```

```
124 . regress HRLYEARN c.age c.age#c.age c.age#i.female
note: age omitted because of collinearity
```

Source	SS	df	MS	Number of obs = 49264		
Model	1341264.67	3	447088.224	F(3, 49260) = 2677.64		
Residual	8224994.04	49260	166.971052	Prob > F = 0.0000		
				R-squared = 0.1402		
				Adj R-squared = 0.1402		
Total	9566258.71	49263	194.187498	Root MSE = 12.922		

HRLYEARN	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	1.903573	.0249796	76.20	0.000	1.854613	1.952533
age	0	(omitted)				
c.age#c.age	-.0197163	.000293	-67.30	0.000	-.0202905	-.019142
female#c.age						
1	-.09275	.002662	-34.84	0.000	-.0979675	-.0875326
_cons	-11.39969	.493259	-23.11	0.000	-12.36648	-10.43289

```
125 . margins, at(age=(25(5)65))by(female)
```

```
Predictive margins                                Number of obs   =    49264
Model VCE      : OLS
```

```
Expression    : Linear prediction, predict()
over          : female
```

```
1._at        : 0.female
               age          =    25
               1.female
               age          =    25

2._at        : 0.female
               age          =    30
               1.female
               age          =    30

3._at        : 0.female
               age          =    35
               1.female
               age          =    35

4._at        : 0.female
               age          =    40
               1.female
               age          =    40

5._at        : 0.female
               age          =    45
               1.female
               age          =    45

6._at        : 0.female
               age          =    50
               1.female
               age          =    50

7._at        : 0.female
               age          =    55
               1.female
               age          =    55

8._at        : 0.female
               age          =    60
               1.female
               age          =    60

9._at        : 0.female
               age          =    65
               1.female
               age          =    65
```

	Delta-method					
	Margin	Std. Err.	t	P> t	[95% Conf. Interval]	
_at#female						
1 0	23.86698	.1001691	238.27	0.000	23.67065 24.06331	
1 1	21.54823	.0998627	215.78	0.000	21.3525 21.74396	
2 0	27.96288	.0874138	319.89	0.000	27.79154 28.13421	
2 1	25.18037	.0861247	292.37	0.000	25.01157 25.34918	
3 0	31.07296	.0911292	340.98	0.000	30.89435 31.25157	
3 1	27.82671	.0890978	312.32	0.000	27.65208 28.00134	
4 0	33.19723	.0979049	339.08	0.000	33.00534 33.38913	
4 1	29.48723	.0955347	308.65	0.000	29.29998 29.67448	
5 0	34.33569	.101649	337.79	0.000	34.13646 34.53492	
5 1	30.16194	.0993063	303.73	0.000	29.9673 30.35658	
6 0	34.48833	.1033548	333.69	0.000	34.28576 34.69091	
6 1	29.85083	.1015344	294.00	0.000	29.65182 30.04984	
7 0	33.65517	.1098092	306.49	0.000	33.43994 33.8704	
7 1	28.55392	.1091926	261.50	0.000	28.3399 28.76793	

8 0	31.83619	.1310385	242.95	0.000	31.57935	32.09303
8 1	26.27119	.1320762	198.91	0.000	26.01232	26.53006
9 0	29.0314	.1732618	167.56	0.000	28.6918	29.37099
9 1	23.00264	.1757867	130.86	0.000	22.6581	23.34719

126 . marginsplot

Variables that uniquely identify margins: age female

```

127 .
128 . /*As we can see from plottin the graph, the wage gap enlarges b/w men&women,
> as age increases. From the above two regression analysis result, the coefficients
> in front of age##female are both negative, which indicates firmly, that there
> exists a gender inequality in terms of workplace earning.*/
129 .
130 .
131 . /*Q3: Run the following regression */
132 .
133 .
134 . regress lnearn age female east qc west, robust

```

```

Linear regression                                Number of obs =   49264
                                                F(   5, 49258) =   920.17
                                                Prob > F       =   0.0000
                                                R-squared      =   0.0864
                                                Root MSE      =   .44598

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0076787	.0001478	51.95	0.000	.007389	.0079684
female	-.1249803	.0040202	-31.09	0.000	-.1328599	-.1171006
east	-.173054	.0064204	-26.95	0.000	-.1856381	-.1604699
qc	-.0595095	.0058914	-10.10	0.000	-.0710567	-.0479624
west	-.0058784	.0050138	-1.17	0.241	-.0157055	.0039488
_cons	3.000941	.0072677	412.91	0.000	2.986696	3.015185

```

135 . /*i) ON is being omitted because of collinearity. If ON and QC both exist in the model,
> STATA will omit QC since ON & QC are highly corelated. */

```

```

136 .
137 . /*ii) Whats the difference b/w men and female, conditonal on other variables?*/
138 . regress lnearn age female, robust

```

```

Linear regression                                Number of obs =   49264
                                                F(   2, 49261) =  1820.69
                                                Prob > F       =   0.0000
                                                R-squared      =   0.0698
                                                Root MSE      =   .45001

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0075549	.000149	50.69	0.000	.0072628	.007847
female	-.1276835	.0040574	-31.47	0.000	-.1356361	-.1197308
_cons	2.968137	.0066289	447.76	0.000	2.955144	2.98113

```

139 .
140 . /*As can be see from the result, -.1290945 is the difference */
141 .
142 . /*iii)Repeat above, without conditional this time */
143 . regress lnearn age female east qc west, robust

```

Linear regression

```

Number of obs = 49264
F( 5, 49258) = 920.17
Prob > F      = 0.0000
R-squared     = 0.0864
Root MSE     = .44598

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0076787	.0001478	51.95	0.000	.007389	.0079684
female	-.1249803	.0040202	-31.09	0.000	-.1328599	-.1171006
east	-.173054	.0064204	-26.95	0.000	-.1856381	-.1604699
qc	-.0595095	.0058914	-10.10	0.000	-.0710567	-.0479624
west	-.0058784	.0050138	-1.17	0.241	-.0157055	.0039488
_cons	3.000941	.0072677	412.91	0.000	2.986696	3.015185

```

144 . /*Without conditioning, it will be -.12498 */
145 .
146 . /*iv)Compare east and west */
147 . regress lnearn west, robust

```

Linear regression

```

Number of obs = 49264
F( 1, 49262) = 141.69
Prob > F      = 0.0000
R-squared     = 0.0029
Root MSE     = .46591

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
west	.0517451	.0043471	11.90	0.000	.0432248	.0602654
_cons	3.197281	.0026444	1209.08	0.000	3.192098	3.202464

```

148 . regress lnearn east, robust

```

Linear regression

```

Number of obs = 49264
F( 1, 49262) = 672.24
Prob > F      = 0.0000
R-squared     = 0.0133
Root MSE     = .46346

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
east	-.1507873	.0058157	-25.93	0.000	-.1621862	-.1393885
_cons	3.239501	.0022675	1428.65	0.000	3.235057	3.243945

```

149 . /*As a ran the above two regressions, results show that "west" has a positive coeff
> while "east" has a negative coeff. Conditonal on other variables, in general, "west"
> has a higher HRLYEARN than "east" */

```

```

150 .
151 . /*v)Compare east and Ontario */
152 . regress lnearn on, robust

```

Linear regression

```

Number of obs = 49264
F( 1, 49262) = 150.42
Prob > F      = 0.0000
R-squared     = 0.0030
Root MSE     = .46588

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
on	.0568566	.0046358	12.26	0.000	.0477704	.0659428
_cons	3.200587	.0024873	1286.79	0.000	3.195712	3.205462

```

153 . regress lnearn east, robust

```

Linear regression

```

Number of obs = 49264
F( 1, 49262) = 672.24
Prob > F      = 0.0000
R-squared     = 0.0133
Root MSE     = .46346

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
east	-.1507873	.0058157	-25.93	0.000	-.1621862	-.1393885
_cons	3.239501	.0022675	1428.65	0.000	3.235057	3.243945

```

154 .
155 . /*vi)change qc to on instead */
156 . regress lnearn age female east on west, robust

```

Linear regression

```

Number of obs = 49264
F( 5, 49258) = 920.17
Prob > F      = 0.0000
R-squared     = 0.0864
Root MSE     = .44598

```

lnearn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
age	.0076787	.0001478	51.95	0.000	.007389	.0079684
female	-.1249803	.0040202	-31.09	0.000	-.1328599	-.1171006
east	-.1135445	.0068888	-16.48	0.000	-.1270467	-.1000423
on	.0595095	.0058914	10.10	0.000	.0479624	.0710567
west	.0536312	.0055987	9.58	0.000	.0426576	.0646048
_cons	2.941431	.007601	386.98	0.000	2.926533	2.956329

```

157 . /*The results show that, coeff on east is -.1135. If I put "on" instead of "qc",
> STATA will omit none of the result, which shows that Ontario earning is not highly
> correlated with other area's earning. */
158 .

```



```

159 . /*Section#2 Omitted variable bias */
160 . clear

161 . capture drop _all

162 . set obs 10000
    obs was 0, now 10000

163 . set seed 2000

164 . more

165 .
166 . gen schl = round(10 + 10*runiform(), 1) /*Generate a variable called schl */

167 . gen detrm = runiform()*10

168 .
169 . more

170 .
171 . tab schl

```

schl	Freq.	Percent	Cum.
10	514	5.14	5.14
11	1,006	10.06	15.20
12	953	9.53	24.73
13	1,043	10.43	35.16
14	1,054	10.54	45.70
15	954	9.54	55.24
16	948	9.48	64.72
17	1,055	10.55	75.27
18	1,008	10.08	85.35
19	984	9.84	95.19
20	481	4.81	100.00
Total	10,000	100.00	

```

172 . sum detrm, d

```

detrm				
	Percentiles	Smallest		
1%	.0973219	.0000191		
5%	.4872551	.000447		
10%	.9971442	.0009003	Obs	10000
25%	2.504195	.0010381	Sum of Wgt.	10000
50%	4.985089		Mean	5.015467
		Largest	Std. Dev.	2.89706
75%	7.551486	9.997013		
90%	9.00843	9.997205	Variance	8.392955
95%	9.538775	9.997805	Skewness	-.00307
99%	9.925169	9.999406	Kurtosis	1.802995

```

173 .
174 . gen wage = 5 + 0.1*schl + 0.2*detrm + invnorm(runiform())

175 . /*generate function called wage */

```

176 .
 177 . list in 1/10

	schl	detrm	wage
1.	11	1.031281	6.34586
2.	10	8.695457	9.396244
3.	11	4.699914	6.620628
4.	11	.3991777	4.479694
5.	10	6.511797	9.842613
6.	11	9.959957	8.58425
7.	15	4.428554	7.546886
8.	18	4.721651	8.374249
9.	12	6.707707	7.594052
10.	14	.4922629	6.409592

178 . sum wage, d

wage					
	Percentiles	Smallest			
1%	4.777252	3.202093			
5%	5.523408	3.318614			
10%	5.957373	3.411666	Obs	10000	
25%	6.69338	3.464624	Sum of Wgt.	10000	
50%	7.496738		Mean	7.513497	
		Largest	Std. Dev.	1.203672	
75%	8.331977	11.33636			
90%	9.055006	11.35213	Variance	1.448826	
95%	9.512343	11.36492	Skewness	.0322359	
99%	10.3262	11.86834	Kurtosis	2.898942	

179 .
 180 . corr wage schl detrm /*Check correlation*/
 (obs=10000)

	wage	schl	detrm
wage	1.0000		
schl	0.2501	1.0000	
detrm	0.4815	0.0091	1.0000

181 . regress wage schl detrm

Source	SS	df	MS	Number of obs = 10000		
Model	4233.34566	2	2116.67283	F(2, 9997) =	2063.73	
Residual	10253.4634	9997	1.02565403	Prob > F =	0.0000	
Total	14486.809	9999	1.44882579	R-squared =	0.2922	
				Adj R-squared =	0.2921	
				Root MSE =	1.0127	

wage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
schl	.1015889	.0034788	29.20	0.000	.0947697	.1084082
detrm	.1991217	.0034961	56.96	0.000	.1922687	.2059748
_cons	4.992702	.0557689	89.52	0.000	4.883384	5.102021

```
182 . /*Determination is not easy to observe, so we omit detrm */
183 . regress wage schl
```

Source	SS	df	MS	Number of obs =	10000
Model	906.195669	1	906.195669	F(1, 9998) =	667.14
Residual	13580.6134	9998	1.358333	Prob > F =	0.0000
				R-squared =	0.0626
				Adj R-squared =	0.0625
Total	14486.809	9999	1.44882579	Root MSE =	1.1655

wage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
schl	.1034018	.0040033	25.83	0.000	.0955545 .1112491
_cons	5.964228	.0611035	97.61	0.000	5.844453 6.084003

```
184 . /*Coeff on schooling becomes larger. And, as we see from the corr calculation above,
> corr(wage,detrm)=0.4815, corr(detrm,schl)=0.0091 (Which is closed to zero correlation),
> therefore there are no omitted variable bias, corr()!=0 not satisfied*/
185 .
186 . /* 5)Coded by me,
> create a new variable schl2, with variable 1,random number drawn from distribution
>
> variable wage2, with variable 1,schl2
>
>
187 . gen schl2 = round(10 + 10*runiform(), 1) + detrm
188 . list in 1/10
```

	schl	detrm	wage	schl2
1.	11	1.031281	6.34586	12.03128
2.	10	8.695457	9.396244	25.69546
3.	11	4.699914	6.620628	15.69991
4.	11	.3991777	4.479694	11.39918
5.	10	6.511797	9.842613	24.5118
6.	11	9.959957	8.58425	26.95996
7.	15	4.428554	7.546886	20.42855
8.	18	4.721651	8.374249	21.72165
9.	12	6.707707	7.594052	20.70771
10.	14	.4922629	6.409592	17.49226

```
189 .
190 .
191 . gen wage2 = schl2 + detrm + invnorm(runiform())
192 . sum wage2, d
```

wage2				
	Percentiles	Smallest		
1%	11.67679	8.849176		
5%	14.30382	8.862227		
10%	16.22426	9.409176	Obs	10000
25%	19.91388	9.4366	Sum of Wgt.	10000
50%	24.98862		Mean	25.02529
		Largest	Std. Dev.	6.596099
75%	30.03234	41.0708		
90%	33.9467	41.30936	Variance	43.50852
95%	35.76719	41.55243	Skewness	.016538
99%	38.51094	41.72418	Kurtosis	2.230368

```

193 .
194 . corr wage2 schl2 detrm /*Check correlation*/
      (obs=10000)

```

	wage2	schl2	detrm
wage2	1.0000		
schl2	0.9389	1.0000	
detrm	0.8833	0.7086	1.0000

```

195 . /*result shows that these three variables are highly correlated,
      > with corr(wage2,schl2)=0.938, corr(wage2,detrm)=0.8839, corr(schl2,detrm)=0.7070*/
196 .
197 . regress wage2 schl2 detrm

```

Source	SS	df	MS	Number of obs =	10000
Model	425044.404	2	212522.202	F(2, 9997) =	.
Residual	9997.31888	9997	1.0000319	Prob > F =	0.0000
				R-squared =	0.9770
				Adj R-squared =	0.9770
Total	435041.723	9999	43.5085232	Root MSE =	1

wage2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
schl2	1.003955	.0034316	292.56	0.000	.9972284	1.010682
detrm	.9969656	.0048923	203.78	0.000	.9873758	1.006555
_cons	-.061455	.055031	-1.12	0.264	-.1693269	.0464168

```

198 . /*Estimated regression line: wage2 = 0.9972522*schl + 1.00*detrm + 0.044 */
199 .
200 . regress wage2 schl2

```

Source	SS	df	MS	Number of obs =	10000
Model	383515.208	1	383515.208	F(1, 9998) =	74415.76
Residual	51526.5154	9998	5.15368228	Prob > F =	0.0000
				R-squared =	0.8816
				Adj R-squared =	0.8815
Total	435041.723	9999	43.5085232	Root MSE =	2.2702

wage2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
schl2	1.499488	.0054968	272.79	0.000	1.488714	1.510263
_cons	-4.975527	.1122953	-44.31	0.000	-5.195648	-4.755405

```

201 . /*wage2 = 1.49416*schl2 - 4.8838 */
202 .
203 . /*Omitted variable bias: check the following two conditions:
      > 1) A determinant of Y
      > 2) Correlated with another covariate , cov(X,Z)!=0
      > In this case, detrm is indeed an omitted variable, and a1 is a biased estimator
      > a1 --> true a1 + biase term */
204 .
205 .
206 . /* 6)Another coded by me:
      > create something so that: schl&detrm are correlated,
      > but NO CAUSAL RELATIONSHIP
      > */

```

```

207 . matrix C = (1,.25\ .25, 1) /*Backward slash to seperate rows, this is a 2x2 matrix*/
208 . drawnorm y1 y2, n($obs) corr(C)
209 . /*Here, create a matrix with corr(y1,y2) = 0.25 */
210 .
211 . gen schl3 = round(10 + y1*2,1)
212 . gen detrm3 = 20 + 5*y2
213 . drop y1 y2
214 .
215 . gen wage3 = schl3 + detrm3 + invnorm(runiform())
216 .
217 . regress wage3 schl3 detrm3

```

Source	SS	df	MS	Number of obs =	10000
Model	344537.985	2	172268.992	F(2, 9997) =	.
Residual	10026.8542	9997	1.00298631	Prob > F =	0.0000
Total	354564.839	9999	35.4600299	R-squared =	0.9717
				Adj R-squared =	0.9717
				Root MSE =	1.0015

wage3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
schl3	1.006409	.005091	197.68	0.000	.9964298 1.016389
detrm3	1.001966	.0020523	488.22	0.000	.9979434 1.005989
_cons	-.0890153	.0581162	-1.53	0.126	-.2029348 .0249043

```

218 . /* wage3 = 1.0061*schl3 + 1.001966*detrm3-0.0890153 */
219 . regress wage3 schl3

```

Source	SS	df	MS	Number of obs =	10000
Model	105465.377	1	105465.377	F(1, 9998) =	4233.02
Residual	249099.462	9998	24.9149292	Prob > F =	0.0000
Total	354564.839	9999	35.4600299	R-squared =	0.2975
				Adj R-squared =	0.2974
				Root MSE =	4.9915

wage3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
schl3	1.602663	.024633	65.06	0.000	1.554378 1.650949
_cons	13.90172	.251993	55.17	0.000	13.40776 14.39568

```

220 . /*wage3 = 1.602*schl3 + 13.918 */
221 .
222 . corr wage3 schl3 detrm3
      (obs=10000)

```

	wage3	schl3	detrm3
wage3	1.0000		
schl3	0.5454	1.0000	
detrm3	0.9280	0.2399	1.0000

```
223 . /*corr(wage3,schl3)=0.555, corr(wage3,detrm3)=0.9259, corr(schl3,detrm3)=0.2461.  
> In this case, determination has a higher correlation than schooling does */  
224 .  
end of do-file  
  
225 . log close  
      name: <unnamed>  
      log:  D:\Econ4G03LAB2\output.smcl  
      log type: smcl  
closed on:  1 Oct 2020, 12:36:48
```
