

Problem Set 3

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DIS 206

Problem 1

b)

. reg y x1						
Source	SS	df	MS	Number of obs	=	1,000
Model	44095.0772	1	44095.0772	F(1, 998)	=	374.88
Residual	117389.163	998	117.624412	Prob > F	=	0.0000
Total	161484.24	999	161.645886	R-squared	=	0.2731
				Adj R-squared	=	0.2723
				Root MSE	=	10.845
y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-6.471674	.3342491	-19.36	0.000	-7.127586	-5.815762
_cons	-8.291288	.3431456	-24.16	0.000	-8.964658	-7.617919

. reg y x2						
Source	SS	df	MS	Number of obs	=	1,000
Model	128608.217	1	128608.217	F(1, 998)	=	3904.09
Residual	32876.0232	998	32.9419071	Prob > F	=	0.0000
Total	161484.24	999	161.645886	R-squared	=	0.7964
				Adj R-squared	=	0.7962
				Root MSE	=	5.7395
y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-4.653856	.0744823	-62.48	0.000	-4.800016	-4.507696
_cons	-.3337941	.223727	-1.49	0.136	-.7728235	.1052352

Both the coefficients differ substantially from their specified coefficients in the population model due to omitted variable bias. Omitting x2 in the first regression leads the x1 coefficient to be more negative than its population value. Omitting x1 in the second regression leads the x2 coefficient to be less negative than its population value.

c)

. reg y x1 x2						
Source	SS	df	MS	Number of obs	=	1,000
Model	136523.194	2	68261.5969	F(2, 997)	=	2726.52
Residual	24961.0463	997	25.0361548	Prob > F	=	0.0000
				R-squared	=	0.8454
				Adj R-squared	=	0.8451
Total	161484.24	999	161.645886	Root MSE	=	5.0036

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	4.143288	.2330259	17.78	0.000	3.686011	4.600566
x2	-5.961827	.0981208	-60.76	0.000	-6.154374	-5.76928
_cons	1.825082	.2297475	7.94	0.000	1.374238	2.275926

This regression results in coefficients much closer to the true population values. Compared to b), x1 now has the appropriate positive sign, and x2 is more negative. The coefficient estimate in c) for x1 is closer to the true value and has a lower standard error than that in b). The coefficient estimate in c) for x2 is closer to the true value and has a higher standard error than that in b). R^2 is higher in c) compared to both regressions in b). The regression on just x2 in b) has a much higher R^2 than the regression on just x1 in b). Adjusted R^2 values follow the behavior of the R^2 values.

d)

. reg y x1 x2 x3						
Source	SS	df	MS	Number of obs	=	1,000
Model	136529.767	3	45509.9224	F(3, 996)	=	1816.42
Residual	24954.4729	996	25.0546917	Prob > F	=	0.0000
				R-squared	=	0.8455
				Adj R-squared	=	0.8450
Total	161484.24	999	161.645886	Root MSE	=	5.0055

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	4.300229	.3849936	11.17	0.000	3.544737	5.055721
x2	-6.121832	.3274377	-18.70	0.000	-6.764379	-5.479285
x3	-.1614444	.315189	-0.51	0.609	-.7799552	.4570664
_cons	1.983575	.3854454	5.15	0.000	1.227197	2.739953

The x1 and x2 coefficients are slightly larger in magnitude, and have higher standard errors relative to those in c). As x3 is an imperfect linear combination of x1 and x2, we get exaggerated slope coefficients and larger standard errors. The R^2 value is very slightly higher as x3 improves prediction by chance, while the R^2 adjusted value is slightly lower due to the penalty for an additional covariate.

e)

```
. di x1_coef_avg  
3.9970031  
  
. di x2_coef_avg  
-6.0014029  
  
. di x1_cor_avg  
-.52371615  
  
. di x2_cor_avg  
-.86075681
```

The average of 1000 repetitions leads to coefficient means and correlations that are very close to the true specified values. See .do file code for details.

Problem 2

a)

```
. reg course_eval beauty, r
```

Linear regression		Number of obs	=	463
		F(1, 461)	=	16.94
		Prob > F	=	0.0000
		R-squared	=	0.0357
		Root MSE	=	.54545

course_eval	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
beauty	.1330014	.0323189	4.12	0.000	.0694908	.1965121
_cons	3.998272	.0253493	157.73	0.000	3.948458	4.048087

The estimated slope of .1330014 is statistically significant at the 1% level.

b)

```
. reg course_eval beauty intro onecredit female minority nnenglish, r
```

Linear regression		Number of obs	=	463
		F(6, 456)	=	17.03
		Prob > F	=	0.0000
		R-squared	=	0.1546
		Root MSE	=	.51351

course_eval	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
beauty	.16561	.0315686	5.25	0.000	.1035721	.2276478
intro	.011325	.0561741	0.20	0.840	-.0990673	.1217173
onecredit	.6345271	.1080864	5.87	0.000	.4221178	.8469364
female	-.1734774	.0494898	-3.51	0.001	-.2707337	-.0762212
minority	-.1666154	.0674115	-2.47	0.014	-.2990912	-.0341397
nnenglish	-.2441613	.0936345	-2.61	0.009	-.42817	-.0601526
_cons	4.068289	.0370092	109.93	0.000	3.995559	4.141019

The coefficient of beauty is .16561, so an increase by beauty of 1 raises course evaluation score by .16561 on average. The regression from a) suffers from OVB, the included control variables in b) theoretically influence course evaluations, and should be accounted for. Beauty is downwards biased in a). R^2 improves significantly as the additional controls improve the regression fit. The confidence intervals from a) and b) overlap so we cannot reject the null hypothesis that the effect of beauty is the same. The additional variables 'female', 'minority', 'nnenglish' have statistically significant negative effects on

course evaluation score. The variable 'onecredit' has a statistically significant positive effect, and 'intro' appears to have no effect.

c)

```
. reg course_o beauty_o, r
```

Linear regression		Number of obs	=	463
		F(1, 461)	=	27.82
		Prob > F	=	0.0000
		R-squared	=	0.0599
		Root MSE	=	.51071

course_o	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
beauty_o	.16561	.0313969	5.27	0.000	.1039112	.2273087
_cons	7.17e-09	.0237348	0.00	1.000	-.0466419	.0466419

Frisch-Waugh results in the exact same coefficient estimate for beauty.

d)

Professor Smith score = $4.068289 + .16561 * (0) + .011325 * (0) + .6345271 * (0) + -.1734774 * (0) + -.1666154 * (1) + -.2441613 * (0) = 3.9016736$

Problem 3

a)

The further the nearest four-year college, the fewer years of education completed. So negative sign for 'dist' coefficient. This is because a longer commute may be too expensive or time consuming to justify continued education.

b)

Linear regression				Number of obs	=	3,796
				F(1, 3794)	=	29.83
				Prob > F	=	0.0000
				R-squared	=	0.0074
				Root MSE	=	1.8074
yrsted	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
dist	-.0733727	.0134334	-5.46	0.000	-.0997101	-.0470353
_cons	13.95586	.0378112	369.09	0.000	13.88172	14.02999

The estimated slope of -.0733727 is statistically significant at the 1% level. The distance to college does **not** explain a large fraction of the variance in educational attainment across individuals. The R^2 value of 0.0074 is small, indicating the linear relationship is a poor predictor.

c)

Linear regression

Number of obs = 3,796

F(11, 3784) = 183.54

Prob > F = 0.0000

R-squared = 0.2829

Root MSE = 1.5383

yrsted	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
dist	-.0308039	.0116178	-2.65	0.008	-.0535816	-.0080262
bytest	.0924474	.0030009	30.81	0.000	.0865638	.0983309
female	.1433777	.0502841	2.85	0.004	.0447912	.2419642
black	.3538083	.0674994	5.24	0.000	.2214695	.4861471
hispanic	.4023514	.0737302	5.46	0.000	.2577966	.5469063
incomehi	.3665952	.0622404	5.89	0.000	.2445672	.4886233
ownhome	.1456416	.0648174	2.25	0.025	.0185612	.2727221
dadcoll	.5699153	.0762509	7.47	0.000	.4204185	.7194121
momcoll	.3791836	.0835917	4.54	0.000	.2152945	.5430728
cue80	.024418	.0092692	2.63	0.008	.0062449	.0425911
stwmfg80	-.0502044	.0195902	-2.56	0.010	-.0886128	-.011796
_cons	8.861373	.2410771	36.76	0.000	8.38872	9.334027

The estimated effect of dist is now -.0308039. It is much lower in magnitude compared to the slope in b). This suggests negative OVB exists in b). We still need relevant controls to claim OVB, and such controls are appropriately included in c).

d)

'dadcoll' indicates if the father is a college graduate. The coefficient effect tells us that individuals whose dads are college graduates attain an additional .5699153 years of education on average.

e)

'ue80' and 'stwmfg80' proxy labor opportunities for low education individuals. The more local labor opportunities, the less individuals would be inclined to get more education. 'ue80' has a coefficient of .02441, which makes sense. Higher unemployment leads to fewer labor opportunities, so it may be better to stay in school. 'stwmfg80' has a coefficient of -.0502044, which seems to suggest higher wages for low-skilled workers encourages attending more schools. This is unexpected.

f)

Bob education = $8.861373 + -.0308039 (2) + .0924474 (58) + .1433777 (0) + .3538083 (1) + .4023514 (0) + .3665952 (1) + .1456416 (1) + .5699153 (0) + .3791836$

$$(1) + .024418 (7.5) + -.0502044 (9.75) = \mathbf{15.1005852}$$

Problem 4

a)

Using white men alone controls for race, which likely has a significant effect on log hourly wages.

b)

The coefficient on 9 of -0.277 is the mean difference in log hourly wages between those who have completed 9 years of education and those who have completed 12 years of education.

c)

The 14th year of college can correspond to the completion of a 2-year degree, so it has its own diploma effect. The 15th year has no diploma effect.

d)

Following college graduation, a senior would get the average diploma effect of a Bachelor's degree 0.245 (which is relative to high school). Completing the 16th year of education would give an effect of 0.178 (which is relative to 12 years). So the average difference following graduation is 0.423

e)

If your goal is to earn a higher wage, a professional degree is better than a doctoral degree. The marginal effect over a bachelor's is 0.286 for a professional degree, which is higher than 0.067 for a doctoral degree.

f)

Perform an F-test

H_0 : Diploma dummies have coefficients of 0

H_1 : Some diploma dummies do not have coefficient 0

$q = 8$: There are 8 diploma effect variables.

$k = 26$: There are dummies for 0-18 years of education excluding 12. And the 8 diploma dummies

n = 8957: observations

$$F = [(0.154 - 0.147) / 8] / [(1 - 0.154)/(8957 - 26 - 1)] = 9.23611111111$$

The p-value is 0.0 using the $F_{8,8930}$ distribution. Therefore, we reject the null at the 5% level. Diploma effects exist.

```

* 1a
set obs 1000
set seed 0
generate u = rnormal(0,5)
gen x1 = rnormal()
gen x2 = exp(x1)
gen y = 2 + 4 * x1 - 6 * x2 + u
* 1b
reg y x1
reg y x2
* 1c
reg y x1 x2
* 1d
gen v = rnormal(0, 0.5)
gen x3 = 1 + x1 - x2 + v
reg y x1 x2 x3
* 1e
gen x1_coef_avg = 0
gen x2_coef_avg = 0
gen x1_cor_avg = 0
gen x2_cor_avg = 0
forvalues i = 1/1000 {
    quietly {
        replace u = rnormal(0,5)
        replace x1 = rnormal()
        replace x2 = exp(x1)
        replace y = 2 + 4 * x1 - 6 * x2 + u
        reg y x1 x2
        replace x1_coef_avg = x1_coef_avg + _b[x1]
        replace x2_coef_avg = x2_coef_avg + _b[x2]
        cor y x1
        replace x1_cor_avg = x1_cor_avg + r(rho)
        cor y x2
        replace x2_cor_avg = x2_cor_avg + r(rho)
    }
}
replace x1_coef_avg = x1_coef_avg / 1000
replace x2_coef_avg = x2_coef_avg / 1000
replace x1_cor_avg = x1_cor_avg / 1000
replace x2_cor_avg = x2_cor_avg / 1000
* 2a
use "TeachingRatings.dta", clear
reg course_eval beauty, r
* 2b
reg course_eval beauty intro onecredit female minority nnenglish, r
* 2c
reg course_eval intro onecredit female minority nnenglish, r
predict fit_c, xb
gen course_o = course_eval - fit_c
reg beauty intro onecredit female minority nnenglish, r
predict fit_b, xb
gen beauty_o = beauty - fit_b
reg course_o beauty_o, r

```

* 3b

reg yrsed dist, r

* 3c

reg yrsed dist bytest female black hispanic incomehi ownhome dadcoll momcoll cue80 stwmfg80, r