

Econometrics Qualifying Exam

May 2022

Instructions

This is a two-hour exam, but you have three hours to complete it. Answer all questions. You may answer out of order if you clearly label which question you are answering. For question 3, the associated Stata output is appended at the end of the exam. For all questions, rigorously show/justify all work (rule of thumb is to make sure enough is shown so that we can see how you got your answer). There are 100 points possible. Good luck!

1. Raising Tuition

How do increases in tuition affect undergraduate university enrollment? To answer this question, you have collected data on the total undergraduate enrollment of $i = 1, \dots, n$ four-year universities across $t = 1, \dots, T$ years, denoted by y_{it} , which you regress on the average cost of attending university i in year t , denoted by x_{it} . The cost variable includes costs of tuition, housing, and food, but does *not* include financial aid. Specifically, you estimate

$$y_{it} = \beta_0 + \beta_1 x_{it} + e_{it}$$

where $e_{it} = y_{it} - \mathbf{E}[y_{it} | x_{i1}, \dots, x_{iT}]$.

- [a] Under what set of circumstances does an omitted variable bias arise?
- [b] Identify two sources of omitted variable bias in the model above, *other* than the omission of financial aid. Many answers may be correct. Your answers will be evaluated based on your explanations.

For the rest of the question, suppose that you introduce control variables to address concerns about omitted variable bias.

- [c] Suppose you observe a variable z_{it} measuring the percentage of undergraduate students receiving financial aid, and the mean across i and t , given by \bar{z} , is 40%. You add the term $\beta_2(z_{it} - \bar{z})x_{it}$ to the regression. Carefully interpret β_1 and β_2 in this regression. What do you expect of the sign on β_2 ?
- [d] Public universities like ours charge two tuition rates. The in-state tuition rate is substantially lower than the out-of-state tuition rate. The out-of-state market is more competitive. The largest universities in the country are public universities. Give a reason why including an additive dummy/indicator/binary variable – i.e., $+\beta_3 D_{it}$ – for the type of university (public or private) would *not* be adequate to capture this distinction.

2. Nonlinearity

Consider two iid sequences of mean-zero random variables (x_i) and (y_i) such that

$$\mathbf{E}[y_i|x_i] = \beta_1 x_i - \exp(\beta_2) x_i^2$$

for $i = 1, \dots, n$.

- [a] Why might you estimate $-\exp(\beta_2)x_i^2$ instead of simply $\beta_3 x_i^2$ with $\beta_3 = -\exp(\beta_2)$?
- [b] Show that the ordinary least squares estimator of the vector $\beta = (\beta_1, -\exp(\beta_2))$ is consistent. If you do not remember all of the formulas you need for a proof, then explain in words for partial credit.
- [c] Can you estimate β_2 consistently using the consistent estimator in part [c]? Explain.
- [d] Suppose you are only interested in estimating β_1 , so you estimate a model with only $\beta_1 x_i$ and you omit $-\exp(\beta_2)x_i^2$. Is it possible for the ordinary least squares estimator to be consistent? Either show that consistency is impossible regardless of the properties of (x_i) and (y_i) or else provide a counterexample in which OLS is consistent.

3. Treatment Effect of Job Training Program

The following questions pertain to the Stata output generated from a subset of the observational data in Dehejia and Wahba (1999) on a job training program in the United States in the late 1970s. The outcome is *unem78*, a binary indicator if the man was unemployed in 1978 – after the training program took place in 1977. The key explanatory variable is *train*, indicating whether the man participated in the job training program.

- [a] Consider the regression of *unem78* on *train*, *age*, *educ*, *black*, *hisp*, and *married*. What is the estimated effect of participating in the job training on the unemployment probability? Participation in the job training program is voluntary (not randomly assigned). Explain why this will cause endogeneity in this setting. What direction is the OLS estimate biased?
- [b] Consider the proxy variables *re75* and *unem75*. State the two conditions needed for a proxy variable to be a valid proxy. Do you believe these two variables could be valid proxies? Explain. What is the estimated effect of participating in the job training on the unemployment probability when using these proxy variables?
- [c] Now consider the maximum likelihood estimate of the probit model including *unem78* on *train*, *age*, *educ*, *black*, *hisp*, *married*, *re75*, and *unem75* as covariates. What is the estimated average treatment effect of participating in the job training? Compare the ATE estimates and standard errors to what you find in part [b].
- [d] For the estimated model in part [c], what are the average treatment effects for individuals who are unemployed in 1975 vs the average treatment effects for individuals who are employed in 1975? Are they very similar? Very different? Explain by writing out the formula for the two average treatment effects.
- [e] Now consider the probit model that also includes interactive effects between *train* and *unem75*. What are the average treatment effects for individuals who are unemployed in 1975 vs the average treatment effects for individuals who are employed in 1975? Compare to what you found in part [d] and explain.

References

Dehejia, R.H. and Wahba, S.. “Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs.” *Journal of the American Statistical Association* 94, 1053-1062.

```

name: <unnamed>
log: C:\Users\alyss\Dropbox\Teaching\Qualifying Exams\Spring2022\jtrain.log
log type: text
opened on: 19 May 2022, 10:59:42

```

```
. describe
```

Contains data from JTRAIN3.dta

```
obs:      806
vars:      10      19 May 2022 10:43
```

variable name	storage type	display format	value label
train	byte	%9.0g	=1 if in job training
age	byte	%9.0g	in years, 1977
educ	byte	%9.0g	years of schooling
black	byte	%9.0g	=1 if black
hisp	byte	%9.0g	=1 if Hispanic
married	byte	%9.0g	=1 if married
re75	float	%9.0g	'75 earnings, \$1000s '82
unem75	byte	%9.0g	=1 if unem. all of '75
re78	float	%9.0g	'78 earnings, \$1000s '82
unem78	byte	%9.0g	=1 if unem. all of '78

Sorted by:

Note: Dataset has changed since last saved.

```
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
train	806	.2233251	.4167331	0	1
age	806	32.48511	11.22372	17	55
educ	806	10.86725	3.0012	0	17
black	806	.4627792	.4989223	0	1
hisp	806	.0545906	.2273204	0	1
married	806	.6488834	.4776157	0	1
re75	806	3.088299	3.492438	0	9.93987
unem75	806	.4466501	.4974543	0	1
re78	806	7.988779	10.30933	0	121.174
unem78	806	.3238213	.4682233	0	1

```
.  
. // Part (a)  
. reg unem78 train age educ black hisp married, vce(robust)
```

Linear regression Number of obs = 806

F(6, 799) = 27.26
 Prob > F = 0.0000
 R-squared = 0.1552
 Root MSE = .43198

unem78	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
train	.0613226	.0452368	1.36	0.176	-.0274744	.1501196
age	.017233	.0015084	11.42	0.000	.0142721	.020194
educ	.0160402	.0061042	2.63	0.009	.0040581	.0280223
black	-.0867674	.0349235	-2.48	0.013	-.1553201	-.0182148
hisp	-.1729479	.057347	-3.02	0.003	-.2855164	-.0603794
married	-.0805822	.0375103	-2.15	0.032	-.1542125	-.0069518
_cons	-.3221199	.1029239	-3.13	0.002	-.524153	-.1200868

```

.
. // Part (b)
. ivregress 2sls unem78 (train = re75 unem75) age educ black hisp married, vce(robust)
> t)

```

Instrumental variables (2SLS) regression

 Number of obs = 806
 Wald chi2(6) = 177.47
 Prob > chi2 = 0.0000
 R-squared = .
 Root MSE = .59373

unem78	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
train	1.304458	.1744243	7.48	0.000	.9625926	1.646323
age	.0234272	.0020744	11.29	0.000	.0193615	.0274929
educ	.0217214	.0076952	2.82	0.005	.0066392	.0368037
black	-.3556239	.0601565	-5.91	0.000	-.4735285	-.2377193
hisp	-.3684556	.0955703	-3.86	0.000	-.5557699	-.1811413
married	.3637192	.0884255	4.11	0.000	.1904084	.53703
_cons	-1.015907	.1557649	-6.52	0.000	-1.321201	-.7106138

Instrumented: train
 Instruments: age educ black hisp married re75 unem75

```

.
. regress unem78 train age educ black hisp married re75 unem75, vce(robust)

```

Linear regression

 Number of obs = 806
 F(8, 797) = 48.36
 Prob > F = 0.0000

R-squared = 0.2768
 Root MSE = .40017

unem78	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
train	-.1274731	.0493552	-2.58	0.010	-.2243547	-.0305915
age	.0102473	.0016449	6.23	0.000	.0070184	.0134761
educ	.0039438	.005904	0.67	0.504	-.0076454	.0155329
black	-.0447396	.0328418	-1.36	0.173	-.1092062	.019727
hisp	-.1305906	.0551496	-2.37	0.018	-.2388462	-.0223349
married	-.0593282	.0375249	-1.58	0.114	-.1329876	.0143311
re75	-.0253681	.0064781	-3.92	0.000	-.0380843	-.012652
unem75	.2171584	.0517864	4.19	0.000	.1155046	.3188122
_cons	.0242295	.1064316	0.23	0.820	-.1846899	.2331489

```
.
. // Part (c)
. probit unem78 i.train age educ i.black i.hisp i.married re75 i.unem75
```

```
Iteration 0: log likelihood = -507.55141
Iteration 1: log likelihood = -388.11949
Iteration 2: log likelihood = -386.6129
Iteration 3: log likelihood = -386.6086
Iteration 4: log likelihood = -386.6086
```

Probit regression

Number of obs = 806
 LR chi2(8) = 241.89
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.2383

Log likelihood = -386.6086

unem78	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1.train	-.3650487	.1662081	-2.20	0.028	-.6908105	-.0392869
age	.0353563	.0057181	6.18	0.000	.0241491	.0465634
educ	.0130961	.0192422	0.68	0.496	-.024618	.0508102
1.black	-.1403094	.1324467	-1.06	0.289	-.3999002	.1192815
1.hisp	-.6457841	.2735679	-2.36	0.018	-1.181967	-.1096008
1.married	-.2622174	.1370278	-1.91	0.056	-.530787	.0063521
re75	-.1040066	.0277702	-3.75	0.000	-.1584352	-.0495781
1.unem75	.5547259	.1748952	3.17	0.002	.2119377	.8975141
_cons	-1.455061	.3934711	-3.70	0.000	-2.226251	-.6838721

```
.
. margins, dydx(*)
```

Average marginal effects Number of obs = 806
Model VCE : OIM

```
Expression : Pr(unem78), predict()
dy/dx w.r.t. : 1.train age educ 1.black 1.hisp 1.married re75 1.unem75
```

	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.train	-.0961086	.0423562	-2.27	0.023	-.1791252	-.0130919
age	.0095304	.0014285	6.67	0.000	.0067307	.0123301
educ	.0035301	.0051787	0.68	0.495	-.00662	.0136802
1.black	-.0381743	.0362787	-1.05	0.293	-.1092792	.0329306
1.hisp	-.1536766	.054956	-2.80	0.005	-.2613884	-.0459649
1.married	-.0700292	.036039	-1.94	0.052	-.1406643	.000606
re75	-.0280354	.0073375	-3.82	0.000	-.0424166	-.0136542
1.unem75	.16539	.0558689	2.96	0.003	.055889	.2748909

Note: dy/dx for factor levels is the discrete change from the base level.

```
. margins, dydx(*) atmeans
```

```
Conditional marginal effects      Number of obs      =      806
Model VCE      : OIM
```

```
Expression : Pr(unem78), predict()
dy/dx w.r.t.: 1.train age educ 1.black 1.hisp 1.married re75 1.unem75
```

```
at      : 0.train      = .7766749 (mean)
         1.train      = .2233251 (mean)
         age          = 32.48511 (mean)
         educ         = 10.86725 (mean)
         0.black      = .5372208 (mean)
         1.black      = .4627792 (mean)
         0.hisp       = .9454094 (mean)
         1.hisp       = .0545906 (mean)
         0.married    = .3511166 (mean)
         1.married    = .6488834 (mean)
         re75         = 3.088299 (mean)
         0.unem75     = .5533499 (mean)
         1.unem75     = .4466501 (mean)
```

	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
1.train	-.1144115	.0483507	-2.37	0.018	-.2091771	-.0196458
age	.0118555	.0019086	6.21	0.000	.0081147	.0155963
educ	.0043913	.0064526	0.68	0.496	-.0082555	.0170381
1.black	-.0468777	.044066	-1.06	0.287	-.1332454	.03949

1.hisp	-.1746436	.0551029	-3.17	0.002	-.2826433	-.0666439
1.married	-.0897246	.0475727	-1.89	0.059	-.1829654	.0035163
re75	-.034875	.0092079	-3.79	0.000	-.0529221	-.0168278
1.unem75	.1875445	.0593636	3.16	0.002	.0711194	.3038949

```
. margins, atmeans
```

	Margin	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]
_cons	.2777679	.0181565	15.30	0.000	.2421819 .313354

Average marginal effects Number of obs = 806
Model VCE : OIM

		Delta-method				
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
0.train	(base outcome)					
1.train						
	_at					
	1	-.0905206	.0387715	-2.33	0.020	-.1665115 -.0145298
	2	-.1176718	.0529663	-2.22	0.026	-.2214837 -.0138598

Note: dy/dx for factor levels is the discrete change from the base level.

```
.
. // Part (e)
. probit unem78 i.train#i.unem75 age educ i.black i.hisp i.married re75 i.unem75
```

```
Iteration 0: log likelihood = -507.55141
Iteration 1: log likelihood = -380.98751
Iteration 2: log likelihood = -379.42299
Iteration 3: log likelihood = -379.41727
Iteration 4: log likelihood = -379.41727
```

Probit regression	Number of obs	=	806
	LR chi2(9)	=	256.27
	Prob > chi2	=	0.0000
Log likelihood = -379.41727	Pseudo R2	=	0.2525

unem78	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
train#unem75					
1 0	.253371	.2259572	1.12	0.262	-.189497 .6962389
1 1	-.7657804	.1987921	-3.85	0.000	-1.155406 -.376155
age	.0336294	.0058061	5.79	0.000	.0222497 .0450091
educ	.0071471	.0195483	0.37	0.715	-.0311668 .0454611
1.black	-.1156055	.1337079	-0.86	0.387	-.3776682 .1464572
1.hisp	-.6497728	.2746377	-2.37	0.018	-1.188053 -.1114928
1.married	-.3171294	.1390778	-2.28	0.023	-.5897169 -.0445419
re75	-.0704559	.0291213	-2.42	0.016	-.1275325 -.0133792
1.unem75	.9686407	.2078686	4.66	0.000	.5612258 1.376056
_cons	-1.592083	.4000805	-3.98	0.000	-2.376226 -.8079397

```
.
. margins, dydx(train) at(unem75 = (0 1))
```

Average marginal effects	Number of obs	=	806
Model VCE : OIM			

Expression : Pr(unem78), predict()
dy/dx w.r.t. : 1.train

1._at : unem75 = 0

2._at : unem75 = 1

		Delta-method		z	P> z	[95% Conf. Interval]					
	dy/dx	Std. Err.									
0.train	(base outcome)										
1.train											
_at											
1	.0696381	.0644983	1.08	0.280	-.0567762	.1960524					
2	-.2557733	.0655207	-3.90	0.000	-.3841915	-.1273552					

Note: dy/dx for factor levels is the discrete change from the base level.

.
. log close
name: <unnamed>
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closed on: 19 May 2022, 10:59:44