Unit 3 Wooldridge exercise C152

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Econometrics II, Bachelor degree in Economics

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- **C2** The data in FERTIL2 include, for women in Botswana during 1988, information on number of children, years of education, age, and religious and economic status variables.
 - (i) Estimate the model

children =
$$\beta_0 + \beta_1 educ + \beta_2 age + \beta_3 age^2 + u$$

by OLS and interpret the estimates. In particular, holding *age* fixed, what is the estimated effect of another year of education on fertility? If 100 women receive another year of education, how many fewer children are they expected to have?

- (ii) The variable *frsthalf* is a dummy variable equal to one if the woman was born during the first six months of the year. Assuming that *frsthalf* is uncorrelated with the error term from part (i), show that *frsthalf* is a reasonable IV candidate for *educ*. (*Hint*: You need to do a regression.)
- (iii) Estimate the model from part (i) by using *frsthalf* as an IV for *educ*. Compare the estimated effect of education with the OLS estimate from part (i).
- (iv) Add the binary variables *electric*, tv, and *bicycle* to the model and assume these are exogenous.Estimate the equation by OLS and 2SLS and compare the estimated coefficients on *educ*. Interpret the coefficient on tv and explain why television ownership has a negative effect on fertility.

```
[17]: # TOOLS
import numpy as np
import pandas as pd
from statsmodels.formula.api import ols
from scipy.stats import t
```

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      [1719 rows x 27 columns]
     i)
[19]: # Initial model
```

OLS Regression Results

modelA = ols("children ~ educ + age + agesq", data = dataExcel).fit()

print(modelA.summary())

Dep. Variable: children R-squared: 0.402 Model: OLS Adj. R-squared: 0.401

Method:	Least Squares	F-statistic:	383.7
Date:	Fri, 13 Nov 2020	Prob (F-statistic):	1.24e-190
Time:	20:29:04	Log-Likelihood:	-3306.5
No. Observations:	1719	AIC:	6621.
Df Residuals:	1715	BIC:	6643.
Df Model:	3		
Covariance Type:	nonrohust		

educ -0.1217 0.010 -12.729 0.000 -0.140 -0.10 age 0.4985 0.044 11.420 0.000 0.413 0.58 agesq -0.0052 0.001 -8.005 0.000 -0.006 -0.00 0.000 0.413 0.58 0.000 0.000 0.413 0.58 0.000 0.000 0.413 0.58 0.000 0.000 0.413 0.58 0.000 0.000 0.413 0.58 0.000 0.000 0.413 0.58 0.58 0.000 0.000 0.413 0.58 0.58 0.000 0.000 0.413 0.58 0.000 0.000 0.413 0.58 0.58 0.000 0.000 0.413 0.58 0.000 0.000 0.000 0.413 0.58 0.000 0.0		coef	std err	t	P> t	[0.025	0.975]
Omnibus: 29.415 Durbin-Watson: 1.80 Prob(Omnibus): 0.000 Jarque-Bera (JB): 55.75	educ age	-0.1217 0.4985	0.010 0.044	-12.729 11.420	0.000	-0.140 0.413	-4.758 -0.103 0.584 -0.004
· ·	Omnibus: Prob(Omnibu Skew:	=======	29 (======================================		1.807 55.751 7.83e-13 2.17e+04

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.17e+04. This might indicate that there are strong multicollinearity or other numerical problems.

The OLS model would be:

```
children = -6.1621 - 0.1217 * educ + 0.4985 * age - 0.0052 * agesq
```

An additional year of education, keeping age fixed, would result in an expected reduction of 0.1217 in the number of children. In other words, if 100 women decide to receive another year of education then it would result in an overall expected reduction of approximately 12 children.

ii)

```
[20]: # Instrumental test model
modelB = ols("educ ~ frsthalf", data = dataExcel).fit()
print(modelB.summary())
```

OLS Regression Results

Dep. Variable:	educ	R-squared:	0.018
Model:	OLS	Adj. R-squared:	0.017
Method:	Least Squares	F-statistic:	30.88
Date:	Fri, 13 Nov 2020	Prob (F-statistic):	3.17e-08
Time:	20:29:04	Log-Likelihood:	-4904.9
No. Observations:	1719	AIC:	9814.
Df Residuals:	1717	BIC:	9825.

Df Model: 1
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	5.8110	0.154	37.793	0.000	5.509	6.113
frsthalf	-1.1358	0.204	-5.557	0.000	-1.537	-0.735
========	=======					========
Omnibus:		60	.191 Durk	oin-Watson:		1.257
Prob(Omnibus):	0	.000 Jaro	que-Bera (JB):	58.300
Skew:		0	.409 Prob	(JB):		2.19e-13
Kurtosis:		2	.621 Cond	d. No.		2.80
========		========				========

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The t statistic of the **frsthalf** coefficient regressor of the OLS model of **educ** on **frsthalf** is -5.557 which means that them both have a statistically significant negative correlation. In fact, **frsthalf** explains arround a 2% of the variation in the sample.

iii)

```
[21]: # Initial model using
dataExcel['educIv'] = modelB.fittedvalues

modelC = ols("children ~ educIv + age + agesq", data = dataExcel).fit()
print(modelC.summary())
```

OLS Regression Results

===========			
Dep. Variable:	children	R-squared:	0.348
Model:	OLS	Adj. R-squared:	0.347
Method:	Least Squares	F-statistic:	305.1
Date:	Fri, 13 Nov 2020	Prob (F-statistic):	1.08e-158
Time:	20:29:05	Log-Likelihood:	-3380.2
No. Observations:	1719	AIC:	6768.
Df Residuals:	1715	BIC:	6790.
Df Model:	3		

Covariance Type: nonrobust

=========				=======	========	=======
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-6.0302	0.834	-7.233	0.000	-7.665	-4.395
educIv	-0.2046	0.074	-2.759	0.006	-0.350	-0.059
age	0.5064	0.046	11.116	0.000	0.417	0.596
agesq	-0.0051	0.001	-7.616	0.000	-0.006	-0.004

Omnibus:	29.722	Durbin-Watson:	1.697
Prob(Omnibus):	0.000	Jarque-Bera (JB):	43.523
Skew:	0.180	Prob(JB):	3.54e-10
Kurtosis:	3.692	Cond. No.	2.42e+04

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.42e+04. This might indicate that there are strong multicollinearity or other numerical problems.

The OLS model would be:

```
children = -6.0302 - 0.2046 * educ + 0.5064 * age - 0.0051 * agesq
```

An additional year of education, keeping age fixed, would result in an expected reduction of 0.2046 in the number of children. In other words, if 100 women decide to receive another year of education then it would result in an overall expected reduction of approximately 20 children. As wee see now the expected reduction has become bigger, what might mean the OLS estimate of the initial model is too small.

It is important to note that as expected there is also a bigger standard error for **educ** and where if we perform this t test:

```
h0: b1 = -0.1217
h1: b1 != -0.1217
t test = \mid (- 0.2046 - 0.1217) / 0.074 \mid = 4.4094
```

```
[22]: p_value = (1 - t.cdf(x=4.4094, df=1715)) * 2 p_value
```

[22]: 1.1009215059365474e-05

As we see the null hypothesis cannot be rejected and therefore the 99% confidence interval contains the original OLS estimate.

iv)

```
[23]: modelD = ols("children ~ educ + age + agesq + electric + tv + bicycle", data = u → dataExcel).fit()

print(modelD.summary())

modelE= ols("educ ~ electric + tv + bicycle", data = dataExcel).fit()

print(modelE.summary())

dataExcel['instEduc'] = modelE.fittedvalues

modelF = ols("children ~ instEduc + age + agesq", data = dataExcel).fit()

print(modelF.summary())
```

OLS Regression Results

Dep. Variable: children R-squared: 0.419

Model:	OLS	Adj. R-squared:	0.417
Method:	Least Squares	F-statistic:	205.5
Date:	Fri, 13 Nov 2020	Prob (F-statistic):	1.51e-197
Time:	20:29:06	Log-Likelihood:	-3281.6
No. Observations:	1719	AIC:	6577.
Df Residuals:	1712	BIC:	6615.
Df Model.	6		

Df Model: 6
Covariance Type: nonrobust

=========			========		=======	=======
	coef	std err	t	P> t	[0.025	0.975]
Intercept educ	-6.6770 -0.0882	0.713 0.011	-9.371 -7.796	0.000	-8.074 -0.110	-5.280 -0.066
age	0.5158	0.043	11.914	0.000	0.431	0.601
agesq	-0.0053	0.001	-8.367	0.000	-0.007	-0.004
electric	-0.4323	0.136	-3.170	0.002	-0.700	-0.165
tv	-0.4672	0.160	-2.929	0.003	-0.780	-0.154
bicycle	0.3647	0.086	4.226	0.000	0.195	0.534
						4 050
Omnibus:		30.	035 Durbir	n-Watson:		1.858
Prob(Omnibus	3):	0.	000 Jarque	e-Bera (JB):		57.532
Skew:		0.	021 Prob(JB):		3.21e-13
Kurtosis:		3.	895 Cond.	No.		2.19e+04
=========			========		========	=======

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.19e+04. This might indicate that there are strong multicollinearity or other numerical problems.

OLS Regression Results

ULS Regression Results						
=======================================	======		======			
Dep. Variable:		educ	R-squa	ared:		0.283
Model:		OLS	Adj. H	R-squared:		0.282
Method:	I	Least Squares	F-stat	tistic:		225.9
Date:	Fri	, 13 Nov 2020	Prob	(F-statistic):		1.65e-123
Time:		20:29:06	Log-Li	ikelihood:		-4634.0
No. Observations:		1719	AIC:			9276.
Df Residuals:		1715	BIC:			9298.
Df Model:		3				
Covariance Type:		nonrobust				
=======================================						
С	oef	std err	t	P> t	[0.025	0.975]

=======================================	========		==========
Omnibus:	84.577	Durbin-Watson:	1.608
<pre>Prob(Omnibus):</pre>	0.000	Jarque-Bera (JB):	43.857
Skew:	0.213	Prob(JB):	3.00e-10
Kurtosis:	2.344	Cond. No.	4.98

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

OLS Regression Results							
Dep. Variable:	child:	 ren	R-sai	 uared:		0.391	
Model:			-	R-squared:		0.390	
Method:	Least Squa:		-	atistic:		366.7	
Date:	Fri, 13 Nov 2			(F-statistic):		5.50e-184	
Time:	20:29			Likelihood:		-3321.8	
No. Observations:			AIC:	ariiorriioou.		6652.	
Df Residuals:			BIC:			6673.	
Df Model:	-	3	DIO.			0010.	
	nonrob	•					
=======================================		=====	-====				
coe	f std err		t	P> t	[0.025	0.975]	
Intercept -6.704	5 0.719	 -9.	.320	0.000	-8.116	-5.294	
instEduc -0.204	2 0.018	-11.	.348	0.000	-0.240	-0.169	
age 0.543	0.044	12.	.313	0.000	0.457	0.630	
agesq -0.005	0.001	-8.	.607	0.000	-0.007	-0.004	
Omnibus:	 32.(===== 686	Durb	======== in-Watson:	======	1.814	
Prob(Omnibus):				ue-Bera (JB):		56.247	
Skew:			Prob			6.11e-13	
Kurtosis:		844	Cond			2.16e+04	

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.16e+04. This might indicate that there are strong multicollinearity or other numerical problems.

The OLS model would be:

children = -6.6770 - 0.0882 * educ + 0.5158 * age - 0.0053 * agesq - 0.4323 * electric - 0.467* $\mathbf{tv} + 0.3647$ * $\mathbf{bicycle}$

The Auxiliar instrumental model would be:

instEduc = 4.0563 + 2.9248 * electric + 4.1408 * tv + 0.2631 * bicycle

The 2SLS model would be:

children = - 6.7045 - 0.2042 * instEduc + 0.5438 * age - 0.0056 * agesq

The coefficients **electric**, **tv** and **bicycle** seem to be correlated with **educ**, specially **electric** and **tv** that have a significance level of 99% and between them all explain arround 28% of the variation in the sample of instEduc. So they can be considered as rational instrumental variables.

Using the 2SLS model, tv has an effect on **educ** and consequently **educ** has an effect on the fertility variable **children**

tv seems to be related with **educ**, in other words, having a tv seems to be related on average with 4 additional years of education and this is intuitive since the poor people, the ones who do not have a tv, will probably not have the same resources to study as the richer ones.

Since having a **tv** is related on average with more education an a higher **educ** seems to be related with smaller amount of **children**, then we could consider the statement that having a tv is on average related with less children. This observation is reflected in the normal OLS model and in the 2SLS model.