

Test4_YM

May 13, 2018

```
In [2]: import pandas as pd
import numpy as np
import statsmodels.api as sm
from patsy import dmatrices, dmatrix
```

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0.0.1 Question (a)

Use OLS to estimate the parameters of the model

$$\log w = \beta_1 + \beta_2 \text{educ} + \beta_3 \text{exper} + \beta_4 \text{exper}^2 + \beta_5 \text{smsa} + \beta_6 \text{south} + \epsilon$$

Give an interpretation to the estimated 2 coefficient.

```
In [2]: df = pd.read_excel("Test4_data.xls")
df.head()
```

```
Out[2]:
```

	logw	educ	age	exper	smsa	south	nearc	daded	momed
0	6.306275	7	29	16	1	0	0	9.94	10.25
1	6.175867	12	27	9	1	0	0	8.00	8.00
2	6.580639	12	34	16	1	0	0	14.00	12.00
3	5.521461	11	27	10	1	0	1	11.00	12.00
4	6.591674	12	34	16	1	0	1	8.00	7.00

```
In [3]: y, X = dmatrices("logw ~ educ + exper + np.square(exper) + smsa + south", df)
```

The OLS estimation result is given as follows:

```
In [4]: mod = sm.OLS(y, X).fit()
print (mod.summary())
```

OLS Regression Results			
=====			
Dep. Variable:	logw	R-squared:	0.263
Model:	OLS	Adj. R-squared:	0.262
Method:	Least Squares	F-statistic:	214.6
Date:	Sun, 13 May 2018	Prob (F-statistic):	3.70e-196
Time:	21:48:56	Log-Likelihood:	-1365.6

```

No. Observations:      3010    AIC:                2743.
Df Residuals:          3004    BIC:                2779.
Df Model:               5
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	4.6110	0.068	67.914	0.000	4.478	4.744
educ	0.0816	0.003	23.315	0.000	0.075	0.088
exper	0.0838	0.007	12.377	0.000	0.071	0.097
np.square(exper)	-0.0022	0.000	-6.800	0.000	-0.003	-0.002
smsa	0.1508	0.016	9.523	0.000	0.120	0.182
south	-0.1752	0.015	-11.959	0.000	-0.204	-0.146
Omnibus:	52.759	Durbin-Watson:	1.853			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	62.537			
Skew:	-0.261	Prob(JB):	2.63e-14			
Kurtosis:	3.476	Cond. No.	1.26e+03			

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.26e+03. This might indicate that there are strong multicollinearity or other numerical problems.

0.02 Answer (a)

Other things being equal, taking one year education, the expected log of wage (logw) would increase by 0.086. Or put it another way, because

$$\log\left(\frac{w_2}{w_1}\right) = 0.0816 \Rightarrow \frac{w_2}{w_1} = e^{0.0816} = 1.085 \Rightarrow w_2 = (1 + 8.5\%)w_1 \Rightarrow$$

one additional year of education is associated with 8.5% increase on expected wage level.

0.03 Question (b)

OLS may be inconsistent in this case as **educ** and **exper** may be endogenous. Give a reason why this may be the case. Also indicate whether the estimate in part (a) is still useful.

0.04 Answer (b)

educ and exper might be endogenous due to **omitted variables**. For example, individual's characteristics are likely to influence individual's educ and exper. Individual with higher intellectual ability and motivation would likely to obtain higher education, i.e., more number of years of schooling (educ). Also, people with hard-working ethics tend to have more working experience. All these characteristics are likely to positively

influence wage level but not included in the model. Therefore, **educ** and **exper** are endogenous, resulting estimate in part(a) being inconsistent.

0.0.5 Question (c)

Give a motivation why **age** and **age2** can be used as instruments for **exper** and **exper2**.

0.0.6 Answer(c)

Older people tend to have longer working experience, nevertheless, the wage is unlikely to be influenced by age itself. Therefore, **age** and **age²** is likely to be correlated with **exper** and **exper²** but uncorrelated with error term (ϵ), which suffice them to be instruments for **exper** and **exper2**.

0.0.7 Question (d)

Run the first-stage regression for **educ** for the two-stage least squares estimation of the parameters in the model above when **age**, **age2**, **nearc**, **dadeduc**, and **momeduc** are used as additional instruments. What do you conclude about the suitability of these instruments for schooling?

```
In [5]: y2, X2 = dmatrices("educ ~ age + np.square(age) + nearc + dadeduc + momeduc", df)
```

```
In [6]: first_stage_mod = sm.OLS(y2, X2).fit()
        print (first_stage_mod.summary())
```

OLS Regression Results						
=====						
Dep. Variable:	educ	R-squared:	0.233			
Model:	OLS	Adj. R-squared:	0.232			
Method:	Least Squares	F-statistic:	182.5			
Date:	Sun, 13 May 2018	Prob (F-statistic):	4.51e-170			
Time:	21:48:56	Log-Likelihood:	-6835.1			
No. Observations:	3010	AIC:	1.368e+04			
Df Residuals:	3004	BIC:	1.372e+04			
Df Model:	5					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	-5.9233	4.011	-1.477	0.140	-13.787	1.940
age	0.9926	0.281	3.531	0.000	0.441	1.544
np.square(age)	-0.0171	0.005	-3.500	0.000	-0.027	-0.008
nearc	0.5288	0.093	5.704	0.000	0.347	0.711
daded	0.2020	0.016	12.898	0.000	0.171	0.233
momed	0.2484	0.017	14.580	0.000	0.215	0.282
=====						
Omnibus:	21.480	Durbin-Watson:	1.778			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	29.916			
Skew:	-0.070	Prob(JB):	3.19e-07			

Kurtosis: 3.468 Cond. No. 7.72e+04
=====

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 7.72e+04. This might indicate that there are strong multicollinearity or other numerical problems.

The above result suggests:

There are enough instruments.

The p-values suggest instruments are correlated with educ.

Therefore, these instruments are suitable for schooling. However, the validity of these instruments require following Sargon test.

0.0.8 Question (e)

Estimate the parameters of the model for log wage using two-stage least squares where you correct for the endogeneity of education and experience. Compare your result to the estimate in part (a).

As suggested by Question (b) and Question (c). *age*, *age2*, *nearc*, *dadeduc*, and *momeduc* can be used as instruments for *educ*, and *age* and *age*² would be instruments for *expr* and *expr*² respectively.

```
In [7]: y3, X3 = dmatrices("exper ~ age ", df )
        expr_stage1_mod = sm.OLS(y3, X3).fit()
        print (expr_stage1_mod.summary())
```

OLS Regression Results						
=====						
Dep. Variable:	exper		R-squared:	0.582		
Model:	OLS		Adj. R-squared:	0.582		
Method:	Least Squares		F-statistic:	4193.		
Date:	Sun, 13 May 2018		Prob (F-statistic):	0.00		
Time:	21:48:57		Log-Likelihood:	-7234.2		
No. Observations:	3010		AIC:	1.447e+04		
Df Residuals:	3008		BIC:	1.448e+04		
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	-19.4732	0.440	-44.236	0.000	-20.336	-18.610
age	1.0075	0.016	64.754	0.000	0.977	1.038
=====						
Omnibus:	33.319	Durbin-Watson:	1.593			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	35.593			
Skew:	0.227	Prob(JB):	1.87e-08			
Kurtosis:	3.279	Cond. No.	256.			

=====

Warnings:

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

```
In [8]: y4, X4 = dmatrices("np.square(exper) ~ np.square(age)", df )
        expr2_stage1_mod = sm.OLS(y4, X4).fit()
        print (expr2_stage1_mod.summary())
```

```

                        OLS Regression Results
=====
Dep. Variable:          np.square(exper)      R-squared:                0.553
Model:                  OLS                  Adj. R-squared:           0.553
Method:                 Least Squares        F-statistic:             3723.
Date:                  Sun, 13 May 2018      Prob (F-statistic):       0.00
Time:                  21:48:57              Log-Likelihood:          -16417.
No. Observations:      3010                  AIC:                     3.284e+04
Df Residuals:          3008                  BIC:                     3.285e+04
Df Model:               1
Covariance Type:       nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept             -183.1527      4.683     -39.110      0.000     -192.335     -173.970
np.square(age)         0.3482      0.006     61.017      0.000       0.337       0.359
=====
Omnibus:               741.263      Durbin-Watson:           1.629
Prob(Omnibus):         0.000      Jarque-Bera (JB):        2955.288
Skew:                  1.158      Prob(JB):                 0.00
Kurtosis:              7.267      Cond. No.                 3.73e+03
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.73e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Calculated the predicted values for *educ*, *exper*, *exper*²

```
In [9]: educ_explained = first_stage_mod.predict(X2)
```

```
In [10]: exper_explained = expr_stage1_mod.predict(X3)
```

```
In [11]: exper2_explained = expr2_stage1_mod.predict(X4)
```

Next, use the predicted values as variables the second stage OLS

```
In [12]: df_2sls = df[["logw", "smsa", "south"] ].copy()
df_2sls["educ_explained"] = educ_explained
df_2sls["exper_explained"] = exper_explained
df_2sls["exper2_explained"] = exper2_explained
```

```
In [13]: df_2sls.head()
```

```
Out[13]:
```

	logw	smsa	south	educ_explained	exper_explained	exper2_explained
0	6.306275	1	0	13.054551	9.743111	109.662945
1	6.175867	1	0	12.031066	7.728195	70.667282
2	6.580639	1	0	13.893543	14.780402	219.338246
3	5.521461	1	0	14.159474	7.728195	70.667282
4	6.591674	1	0	11.968116	14.780402	219.338246

```
In [14]: y, X_stage2 = dmatrices("logw ~ educ_explained + exper_explained+ exper2_explained+ smsa + south", df_2sls)
```

```
In [16]: stage2_mod = sm.OLS(y, X_stage2).fit()
print (stage2_mod.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  logw      R-squared:                0.219
Model:                            OLS      Adj. R-squared:            0.218
Method:                           Least Squares      F-statistic:            168.6
Date:                            Sun, 13 May 2018      Prob (F-statistic):       2.00e-158
Time:                            21:49:08      Log-Likelihood:           -1452.9
No. Observations:                 3010      AIC:                     2918.
Df Residuals:                     3004      BIC:                     2954.
Df Model:                          5
Covariance Type:                  nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	4.8025	0.197	24.322	0.000	4.415	5.190
educ_explained	0.0543	0.006	9.243	0.000	0.043	0.066
exper_explained	0.1246	0.047	2.648	0.008	0.032	0.217
exper2_explained	-0.0042	0.002	-1.797	0.072	-0.009	0.000
smsa	0.1646	0.016	10.064	0.000	0.133	0.197
south	-0.1862	0.015	-12.211	0.000	-0.216	-0.156

```

=====
Omnibus:                        58.465      Durbin-Watson:              1.836
Prob(Omnibus):                   0.000      Jarque-Bera (JB):           70.093
Skew:                           -0.276      Prob(JB):                   6.02e-16
Kurtosis:                       3.504      Cond. No.                   3.26e+03
=====

```

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 3.26e+03. This might indicate that there are

strong multicollinearity or other numerical problems.

below is the estimate from (a), in comparison, the impact of education on wage becomes less but the effect of experience grows. The non-linear term exper^2 remains negative but almost doubles the effect.

```
In [17]: print (mod.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  logw      R-squared:                  0.263
Model:                          OLS      Adj. R-squared:              0.262
Method:                        Least Squares      F-statistic:              214.6
Date:                          Sun, 13 May 2018      Prob (F-statistic):        3.70e-196
Time:                          21:49:09      Log-Likelihood:            -1365.6
No. Observations:              3010      AIC:                      2743.
Df Residuals:                  3004      BIC:                      2779.
Df Model:                      5
Covariance Type:               nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	4.6110	0.068	67.914	0.000	4.478	4.744
educ	0.0816	0.003	23.315	0.000	0.075	0.088
exper	0.0838	0.007	12.377	0.000	0.071	0.097
np.square(exper)	-0.0022	0.000	-6.800	0.000	-0.003	-0.002
smsa	0.1508	0.016	9.523	0.000	0.120	0.182
south	-0.1752	0.015	-11.959	0.000	-0.204	-0.146

```

=====
Omnibus:                      52.759      Durbin-Watson:              1.853
Prob(Omnibus):                0.000      Jarque-Bera (JB):           62.537
Skew:                        -0.261      Prob(JB):                   2.63e-14
Kurtosis:                     3.476      Cond. No.                   1.26e+03
=====

```

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.26e+03. This might indicate that there are strong multicollinearity or other numerical problems.

0.0.9 Question (f)

Perform the Sargan test for validity of the instruments. What is your conclusion?

1 . Calculate the residuals using formula $e_{\{2SLS\}} = y - Xb_{\{2SLS\}}$

```
In [18]: e_2sls = df.logw.values - stage2_mod.predict(X)
```

2 . Regress e_{2SLS} on Z , where Z is (constant, age, age2, nearc, dadeduc, momeduc, smsa, south)

```
In [19]: z = dmatrix("age + np.square(age) + nearc + daded + momed + smsa + south",
                    data= df ,return_type= "dataframe")
```

```
In [20]: z_mod = sm.OLS(e_2sls, z).fit()
        print (z_mod.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                  0.022
Model:                        OLS      Adj. R-squared:             0.020
Method:                    Least Squares      F-statistic:            9.757
Date:                Sun, 13 May 2018      Prob (F-statistic):        4.53e-12
Time:                        21:49:10      Log-Likelihood:           -1404.7
No. Observations:          3010      AIC:                      2825.
Df Residuals:              3002      BIC:                      2873.
Df Model:                   7
Covariance Type:            nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.2780	0.660	1.935	0.053	-0.017	2.573
age	-0.1058	0.046	-2.285	0.022	-0.197	-0.015
np.square(age)	0.0018	0.001	2.292	0.022	0.000	0.003
nearc	0.0242	0.016	1.469	0.142	-0.008	0.056
daded	0.0058	0.003	2.230	0.026	0.001	0.011
momed	0.0146	0.003	5.158	0.000	0.009	0.020
smsa	-0.0122	0.017	-0.726	0.468	-0.045	0.021
south	0.0158	0.015	1.044	0.296	-0.014	0.045

```

=====
Omnibus:                    53.838      Durbin-Watson:              1.843
Prob(Omnibus):              0.000      Jarque-Bera (JB):           63.790
Skew:                      -0.265      Prob(JB):                   1.41e-14
Kurtosis:                   3.478      Cond. No.                   7.72e+04
=====

```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.72e+04. This might indicate that there are strong multicollinearity or other numerical problems.

3 . calculate nR^2 , and $nR^2 \sim \chi^2(m - k)$, where $m = 8, k = 6$

```
In [21]: n = 3010
        R_2 = 0.022
        n * R_2
```


Out [21] : 66.22

since the critical value for $\chi^2(2)$ at 5% confidence level is 5.99 and $66.22 > 5.99$, therefore, we reject the null hypothesis and correlation Z and /epsilon is 0.

Conclusion: the instrument variables are actually not valid, further refinements are required.