

Jugal Marfatia

Instrumental Variable (PS 3)

Question 1

```
In [1]: import pandas as pd

df = pd.read_excel('/Users/jugalmarfatia/Downloads/excelfiles/affairs.xls')

df = df.rename(columns=lambda x: x.strip())
df.head()
```

Out[1]:

	id	male	age	yrsmarr	kids	relig	educ	occup	ratemarr	naffairs	affair	vryhap	hapavg	avgmarr	unhap	vryrel	smerel
0	4	1	37.0	10.0	0	3	18	7	4	0	0	0	1	0	0	0	0
1	5	0	27.0	4.0	0	4	14	6	4	0	0	0	1	0	0	0	1
2	6	1	27.0	1.5	0	3	18	4	4	3	1	0	1	0	0	0	0
3	11	0	32.0	15.0	1	1	12	1	4	0	0	0	1	0	0	0	0
4	12	0	27.0	4.0	1	3	17	1	5	3	1	1	0	0	0	0	0

A. Regression

$$Kids_i = \alpha_0 + \alpha_1 Age_i + \alpha_2 Yrsmarr_i + e_i$$

```
In [2]: import statsmodels.formula.api as sm

ols = sm.ols(formula="kids ~ age + yrsmarr", data=df).fit()

print(ols.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          kids      R-squared:          0.330
Model:                  OLS      Adj. R-squared:       0.327
Method:                 Least Squares  F-statistic:       147.0
Date:                   Fri, 21 Sep 2018  Prob (F-statistic): 1.21e-52
Time:                   13:29:51   Log-Likelihood:    -254.32
No. Observations:       601      AIC:               514.6
Df Residuals:           598      BIC:               527.8
Df Model:                2
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.3990	0.063	6.364	0.000	0.276	0.522
age	-0.0029	0.003	-1.116	0.265	-0.008	0.002
yrsmarr	0.0502	0.004	11.626	0.000	0.042	0.059

```

=====
Omnibus:                 18.966   Durbin-Watson:          2.076
Prob(Omnibus):            0.000   Jarque-Bera (JB):        15.057
Skew:                     -0.300   Prob(JB):                 0.000538
Kurtosis:                  2.508   Cond. No.                  145.
=====

```

Warnings:

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

B. Regression

First run two regressions:

$$Kids_i = \alpha_0 + \alpha_1 Age_i + e_i$$

$$Age_i = \beta_0 + \beta_1 Yrsmarr_i + u_i$$

Predict \hat{e}_i and \hat{u}_i

Run regression:

$$\hat{e}_i = \theta_0 + \theta_1 \hat{u}_i + v_i$$

```
In [3]: ols_y = sm.ols(formula="kids ~ age ", data=df).fit()
ols_x1 = sm.ols(formula="age ~ yrsmarr", data=df).fit()

df['kids_error'] = df['kids'] - ols_y.predict()
df['age_error'] = df['age'] - ols_x1.predict()

ols = sm.ols(formula="kids_error ~ age_error", data=df).fit()

print(ols.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  kids_error    R-squared:                0.111
Model:                            OLS        Adj. R-squared:           0.110
Method:                    Least Squares    F-statistic:                75.14
Date:                Fri, 21 Sep 2018        Prob (F-statistic):        4.10e-17
Time:                13:29:52                Log-Likelihood:            -280.04
No. Observations:                601         AIC:                    564.1
Df Residuals:                    599         BIC:                    572.9
Df Model:                        1
Covariance Type:                nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.023e-16	0.016	6.5e-15	1.000	-0.031	0.031
age_error	-0.0234	0.003	-8.668	0.000	-0.029	-0.018

```

=====
Omnibus:                138.122    Durbin-Watson:           2.069
Prob(Omnibus):           0.000    Jarque-Bera (JB):        77.054
Skew:                    -0.740    Prob(JB):                1.85e-17
Kurtosis:                2.057    Cond. No.                5.84
=====

```

Warnings:

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

C. Regression

Run regressions:

$$Kids_i = \omega_0 + \omega_1 \hat{u}_i + v_i$$

```
In [4]: ols = sm.ols(formula="kids ~ age_error", data=df).fit()

print(ols.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          kids      R-squared:          0.001
Model:                  OLS      Adj. R-squared:       -0.000
Method:                 Least Squares    F-statistic:       0.8372
Date:                   Fri, 21 Sep 2018    Prob (F-statistic): 0.361
Time:                   13:29:52    Log-Likelihood:    -374.04
No. Observations:       601      AIC:              752.1
Df Residuals:           599      BIC:              760.9
Df Model:                1
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.7155	0.018	38.838	0.000	0.679	0.752
age_error	-0.0029	0.003	-0.915	0.361	-0.009	0.003

```

=====
Omnibus:                 261.852    Durbin-Watson:          2.049
Prob(Omnibus):            0.000    Jarque-Bera (JB):       120.379
Skew:                     -0.952    Prob(JB):               7.25e-27
Kurtosis:                 1.914    Cond. No.:               5.84
=====

```

Warnings:

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

Yes they are the same because:

$$u_i = Age_i - \beta_0 + \beta_1 Yrsmarr_i$$

Therefore:

$$Kids_i = \omega_0 + \omega_1 \hat{u}_i + v_i = \omega_0 + \omega_1 (Age_i - \beta_0 + \beta_1 Yrsmarr_i) + v_i$$

Implies: We get the same coefficient estimates.

Question 2

IV estimate using GMM

```
In [5]: from linearmodels.iv import IVGMM

mod = IVGMM.from_formula(formula="kids ~ 1 + [age ~ yrsmarr]", data=df).fit()

print(mod.summary)
```

IV-GMM Estimation Summary

```
=====
Dep. Variable:          kids      R-squared:          0.0789
Estimator:             IV-GMM    Adj. R-squared:     0.0774
No. Observations:      601       F-statistic:      225.97
Date:                  Fri, Sep 21 2018   P-value (F-stat)   0.0000
Time:                  13:29:52    Distribution:      chi2(1)
Cov. Estimator:        robust
```

Parameter Estimates

```
=====
      Parameter  Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
Intercept      -0.4481     0.0834   -5.3700    0.0000    -0.6117    -0.2846
age             0.0358     0.0024   15.032    0.0000     0.0311     0.0405
=====
```

```
Endogenous: age
Instruments: yrsmarr
GMM Covariance
Debiased: False
Robust (Heteroskedastic)
```

IV estimate using 2SLS

```
In [6]: ols = sm.ols(formula="age ~ yrsmarr", data=df).fit()
df['age_hat'] = ols.predict()

ols = sm.ols(formula="kids ~ age_hat", data=df).fit()

print(ols.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          kids      R-squared:          0.328
Model:                  OLS      Adj. R-squared:       0.327
Method:                 Least Squares  F-statistic:       292.6
Date:                  Fri, 21 Sep 2018  Prob (F-statistic): 1.04e-53
Time:                  13:29:52   Log-Likelihood:    -254.94
No. Observations:      601      AIC:              513.9
Df Residuals:          599      BIC:              522.7
Df Model:              1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.4481	0.070	-6.431	0.000	-0.585	-0.311
age_hat	0.0358	0.002	17.105	0.000	0.032	0.040

```

=====
Omnibus:              19.672   Durbin-Watson:       2.083
Prob(Omnibus):        0.000   Jarque-Bera (JB):    15.594
Skew:                 -0.306   Prob(JB):            0.000411
Kurtosis:             2.502   Cond. No.            154.
=====

```

Warnings:

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

IV using Coefficient ratio i.e.

$$\beta_{iv} = \frac{\beta_{yz}}{\beta_{xz}}$$


```
In [7]: ols = sm.ols(formula="age ~ yrsmarr", data=df).fit()  
ols1 = sm.ols(formula="kids ~ yrsmarr", data=df).fit()  
  
print("Beta_IV_beta_ratio: " + str(ols1.params[1]/ols.params[1]))
```

Beta_IV_beta_ratio: 0.035816413472169316

IV using sample covariance ratio i.e.

$$\beta_{iv} = \frac{scov(y,z)}{scov(x,z)}$$

```
In [8]: scov_zx = df[['age', 'yrsmarr']].cov()  
scov_zy = df[['kids', 'yrsmarr']].cov()  
  
print("Beta_IV_scov_ratio: " + str(scov_zy.loc['kids', 'yrsmarr']/scov_zx.loc['age', 'yrsmarr']))
```

Beta_IV_scov_ratio: 0.03581641347216924

The results from above four methods show that indeed we get the same IV estimates using the different techniques.