4.1) Proxy vs Indicator

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Proxy vs Indicator

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k + \gamma q + v$$

Proxy: $q = \theta_0 + \theta_1 z_1 + r_1$

$$Cov(z, r_1) = 0, \; Cov(x, r_1) = 0$$

Indicator: $q_1 = \delta_0 + \delta_1 q + a_1$

$$Cov(q, a_1) = 0, \; Cov(x, a_1) = 0$$

$$q = -\frac{\delta_0}{\delta_1} + \frac{q_1}{\delta_1} - \frac{a_1}{\delta_1}$$

$$Cov(q_1, a_1) \neq 0$$

Solutions Using Indicators of the Unobservables

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k + \gamma q + v$$

$$q = -\frac{\delta_0}{\delta_1} + \frac{q_1}{\delta_1} - \frac{a_1}{\delta_1}$$

$$q_2 = \rho_0 + \rho_1 q + a_2$$

$$\rho_1 \neq 0,\ Cov(a_1, a_2) = 0$$

$$y = -\frac{\gamma\delta_0}{\delta_1} + x\beta + \frac{\gamma}{\delta_1} q_1 + (v - \frac{\gamma}{\delta_1} a_1)$$

Blackburn and Neumark (1992)

```
import pandas as pd
from linearmodels import IVGMM
```

```
file="https://github.com/VitorKamada/ECO7110/raw/master/Data/nls80.dta"
df = pd.read_stata(file)
df.head()
```

	wage	hours	iq	kww	educ	exper	tenure	age	married
0	769	40	93	35	12	11	2	31	1
1	808	50	119	41	18	11	16	37	1
2	825	40	108	46	14	11	9	33	1
3	650	40	96	32	12	13	7	32	1
4	562	40	74	27	11	14	5	34	1

```
Xs = ['exper', 'tenure', 'married', 'south','urban','black']
print(df[['lwage','educ','iq','kww'] +
          Xs].describe(percentiles=[]))
```

	lwage	educ	iq
count	935.000000	935.000000	935.000000
mean	6.779002	13.468449	101.282353
std	0.421144	2.196654	15.052636
min	4.744932	9.000000	50.000000
50%	6.807935	12.000000	102.000000
max	8.032035	18.000000	145.000000

south	urban	black
935.000000	935.000000	935.000000
0.341176	0.717647	0.128342
0.474358	0.450385	0.334650
0.000000	0.000000	0.000000
0.000000	1.000000	0.000000
1.000000	1.000000	1.000000

Summary of Previous Approach

```
df['const'] = 1
Xs = ['const'] + Xs
```

```
OLS = IVGMM(df.lwage, df[Xs+['educ']],
            None, None).fit()
```

```
Proxy = IVGMM(df.lwage, df[Xs+['educ']+['iq']],
              None, None).fit()
```

```
IV_IQ = IVGMM(df.lwage, df[Xs],
     df.educ, df[['iq']]).fit()
```

```
IV_IQ_KWW = IVGMM(df.lwage, df[Xs],
   df.educ, df[['iq','kww']]).fit()
```

```
from linearmodels.iv.results import compare
print(compare({'OLS':OLS,'Proxy': Proxy,
   'IV_IQ': IV_IQ, 'IV_IQ_KWW': IV_IQ_KWW}))
```

	IV_IQ	IV_IQ_KWW	OLS	Proxy
	4.6730	4.7120	5.3955	5.1764
const	(21.300)	(23.778)	(47.899)	(42.909)
	0.0244	0.0239	0.0140	0.0141
exper	(5.7388)	(5.9135)	(4.3548)	(4.3896)
	0.0105	0.0104	0.0117	0.0114
tenure	(4.0037)	(4.0035)	(4.6472)	(4.5138)
	0.2055	0.2076	0.1994	0.1998
married	(4.9297)	(5.0389)	(5.0455)	(5.1352)
	-0.0820	-0.0827	-0.0909	-0.0802
south	(-2.9593)	(-2.9947)	(-3.3364)	(-2.9042)
	0.1712	0.1716	0.1839	0.1819
urban	(6.1361)	(6.1709)	(6.8125)	(6.8368)
	-0.1458	-0.1470	-0.1883	-0.1431
black	(-3.7309)	(-3.7860)	(-5.1537)	(-3.8203)
	0.1105	0.1080	0.0654	0.0544
educ	(8.3428)	(9.1599)	(10.253)	(7.5175)
				0.0036
iq				(3.7394)

KWW as an Instrument for IQ

```
KWWasIVforIQ = IVGMM(df.lwage, df[Xs+['educ']],
                     df.iq, df['kww']).fit()
print(KWWasIVforIQ)
```

	Parameter	Std. Err.	T-stat	P-value
const	4.5925	0.3501	13.117	0.0000
exper	0.0144	0.0034	4.2234	0.0000
tenure	0.0105	0.0028	3.7258	0.0002
married	0.2007	0.0404	4.9616	0.0000
south	-0.0516	0.0339	-1.5201	0.1285
urban	0.1767	0.0274	6.4470	0.0000
black	-0.0226	0.0798	-0.2826	0.7775
educ	0.0250	0.0187	1.3410	0.1799
iq	0.0130	0.0055	2.3835	0.0171

IQ as an Instrument for KWW

```
IQasIVforKWW = IVGMM(df.lwage, df[Xs+['educ']],
                     df.kww, df['iq']).fit()
print(IQasIVforKWW)
```

```
                          Parameter  Std. Err.     T-stat    P-value
--------------------------------------------------------------------
const                        5.1700     0.1357     38.095     0.0000
exper                        0.0029     0.0049     0.5892     0.5557
tenure                       0.0076     0.0031     2.4707     0.0135
married                      0.1382     0.0480     2.8792     0.0040
south                       -0.0952     0.0299    -3.1789     0.0015
urban                        0.1325     0.0315     4.2086     0.0000
black                       -0.0404     0.0606    -0.6662     0.5053
educ                         0.0175     0.0161     1.0893     0.2760
kww                          0.0309     0.0091     3.4107     0.0006
```