

# Introduction to Stata – Lecture 4: Instrumental variables

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Key references: Cameron and Trivedi (2009) chapter 6, Angrist and Pischke (2009) chapter 4, Wooldridge (2009) chapter 15, Greene (2008) chapter 13.

## 1 Introduction

For OLS to give consistent estimators the error term must be unrelated to the regressors – that is  $E(u|\mathbf{x}) = 0$ . This is often not an assumption that can be made. One common approach is to use an instrumental variable (IV) estimator. The instrumental variable,  $z$ , needs to be correlated with the endogenous variable  $x$ , and uncorrelated with the error term so  $E(u|z) = 0$ . Finding a valid and strong instrument is often very hard – see Angrist and Pischke (2009) for a full discussion.

This lecture focuses on the implementation of IV estimation in Stata and the related tests available. I use the dataset from Angrist and Krueger’s (1991) article examining the economic return to schooling using quarter of birth and its interaction with compulsory school attendance laws as an instrument. The paper is available at <http://www.jstor.org/stable/2937954> and the dataset is available on my website.

The problem with estimating the economic returns to education is that of omitted variable bias. We can estimate the following equation:

$$lwage_i = \alpha + \beta schooling_i + \gamma X_i + \varepsilon_i \quad (1)$$

However, there is a key unmeasured determinant of wages – ability. This means that ability is subsumed into the error term  $\varepsilon_i$ . Since ability is also likely linked to schooling, this means that  $E(\varepsilon|schooling) \neq 0$ . So an OLS estimate of  $\beta$  is inconsistent.

The key to Angrist and Krueger’s approach is to recognise that there is a relationship between quarter of birth and the amount of schooling an individual receives:

“...most states require students to enter school in the calendar year in which they turn 6. School start age is therefore a function of date of birth. Specifically, those born late in the year are young for their grade. In states with a December 31 birthday cutoff, children born in the fourth quarter enter school shortly before they turn 6, while those born in the first quarter enter school at around  $6\frac{1}{2}$ . Furthermore, because compulsory schooling laws typically require students to remain in school only until their 16th birthday, these groups of students will be in different grades, or through a given grade to a different degree, when they reach the legal dropout age. The combination of school start-age policies and compulsory schooling laws creates a natural experiment in which children are compelled to attend school for different lengths of time, depending on their birthdays.”

Angrist and Pischke (2009) p.117

This means that quarter of birth can be used as an instrumental variable for schooling – it is correlated with schooling but there is no reason to believe that it also affects wages.

## 2 Data

We can load `angristkrueger.dta` into Stata and look at the data. `summarize` shows:

```
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
age	247199	44.72566	2.898535	40	50
ageq	247199	45.10029	2.877965	40.25	50
educ	247199	11.49334	3.360663	0	18
lwage	247199	5.155175	.6512804	-.0198026	8.947976
married	247199	.8928151	.3093488	0	1
census	247199	70	0	70	70
qob	247199	2.488068	1.112981	1	4
race	247199	.0820675	.2744681	0	1
smsa	247199	.3020036	.4591278	0	1
yob	247199	1924.528	2.861746	1920	1929
region	247199	3.433169	2.611136	0	8

So we have a large dataset of 247,199 observations with no missing observations. The minimum and maximum values look reasonable – the dataset is already cleaned. We need to create a variable for age squared – here using the `ageq` variable which has quarter years of age included.

```
. generate ageq2=ageq^2
```

## 3 Implementing instrumental variables estimation

We start by estimating the impact of years of education on log wages using OLS to give a baseline.

```
. xi: regress lwage educ race married smsa i.yob i.region ageq ageq2, vce(robust)
```

*output omitted*

So we are also controlling for race, marital status, size of town lived in, age and including a set of dummies for year of birth and region. The output suggests that an additional year of education is associated with a 7.0% increase in wages.

To get a better estimate using quarter of birth as an instrument for education, we use the `ivregress` command. The syntax is as follows:

```
ivregress estimator depvar [varlist1] (varlist2=varlistiv) [if] [in] [weight] [, options]
```

Here *estimator* is one of `2sls`, `gmm` or `liml`. These are different methods of estimating the model – you must include one. *varlist1* contains the exogenous regressors, *varlist2* the endogenous regressors and *varlistiv* the instruments.

So, to estimate the effect of education on wages, using a set of quarter of birth dummies as instruments, we type:

```
. xi: ivregress 2sls lwage race married smsa ageq ageq2 i.region i.yob (educ=i.qob),  
vce(robust)  
i.region      _Iregion_0-8      (naturally coded; _Iregion_0 omitted)  
i.yob         _Iyob_1920-1929  (naturally coded; _Iyob_1920 omitted)  
i.qob         _Iqob_1-4        (naturally coded; _Iqob_1 omitted)
```

Instrumental variables (2SLS) regression

Number of obs = 247199  
Wald chi2(23) =29586.85

Prob > chi2 = 0.0000  
R-squared = 0.2242  
Root MSE = .57364

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
educ	.0849189	.0653187	1.30	0.194	-.0431034	.2129411
race	-.2636648	.151434	-1.74	0.082	-.5604699	.0331403
married	.2867815	.0268903	10.66	0.000	.2340775	.3394855
smsa	-.1256149	.0385288	-3.26	0.001	-.2011301	-.0500998
ageq	.1166074	.0654006	1.78	0.075	-.0115755	.2447902
ageq2	-.0012151	.0007409	-1.64	0.101	-.0026672	.0002371
_Iregion_1	.030666	.0484413	0.63	0.527	-.0642772	.1256093
_Iregion_2	-.1833031	.108244	-1.69	0.090	-.3954574	.0288513
_Iregion_3	-.0063643	.030069	-0.21	0.832	-.0652984	.0525699
_Iregion_4	-.1245374	.0121238	-10.27	0.000	-.1482996	-.1007752
_Iregion_5	-.0266789	.0274541	-0.97	0.331	-.0804879	.0271301
_Iregion_6	-.0874231	.0723285	-1.21	0.227	-.2291844	.0543382
_Iregion_7	-.1328462	.0384853	-3.45	0.001	-.2082759	-.0574164
_Iregion_8	-.1345381	.0745719	-1.80	0.071	-.2806962	.0116201
_Iyob_1921	-.0009953	.0122851	-0.08	0.935	-.0250737	.0230831
_Iyob_1922	-.0037629	.0279409	-0.13	0.893	-.058526	.0510003
_Iyob_1923	-.0003771	.0393341	-0.01	0.992	-.0774706	.0767164
_Iyob_1924	.0040516	.0524957	0.08	0.938	-.0988382	.1069414
_Iyob_1925	.0186145	.0678595	0.27	0.784	-.1143877	.1516167
_Iyob_1926	.0255744	.0786054	0.33	0.745	-.1284894	.1796382
_Iyob_1927	.0366671	.0956002	0.38	0.701	-.1507059	.2240401
_Iyob_1928	.0461339	.1062542	0.43	0.664	-.1621204	.2543883
_Iyob_1929	.0421031	.113661	0.37	0.711	-.1806683	.2648746
_cons	1.233629	1.930212	0.64	0.523	-2.549517	5.016774

Instrumented: educ  
Instruments: race married smsa ageq ageq2 \_Iregion\_1 \_Iregion\_2 \_Iregion\_3  
\_Iregion\_4 \_Iregion\_5 \_Iregion\_6 \_Iregion\_7 \_Iregion\_8  
\_Iyob\_1921 \_Iyob\_1922 \_Iyob\_1923 \_Iyob\_1924 \_Iyob\_1925  
\_Iyob\_1926 \_Iyob\_1927 \_Iyob\_1928 \_Iyob\_1929 \_Iqob\_2 \_Iqob\_3  
\_Iqob\_4

Instrumenting for education here has led to a coefficient of 0.085 on education, but this is insignificantly different from zero (though note that with unrobust standard errors the coefficient retains its significance).

Angrist and Krueger actually use the interactions of the quarter of birth dummies with year of birth dummies, so have a larger set of instruments. A useful option for `ivregress` is `first` which reports the first stage regression as well as the full output. This is shown below:

```
. xi: ivregress 2sls lwage race married smsa ageq ageq2 i.region i.yob (educ=i.yob*i.qob),
vce(robust) first
i.region      _Iregion_0-8      (naturally coded; _Iregion_0 omitted)
i.yob         _Iyob_1920-1929   (naturally coded; _Iyob_1920 omitted)
i.qob         _Iqob_1-4         (naturally coded; _Iqob_1 omitted)
i.yob*i.qob   _IyobXqob_#_#     (coded as above)
note: _IyobXqob_1929_4 dropped due to collinearity
```

First-stage regressions

Number of obs = 247199  
 F( 50, 247148) = 318.76  
 Prob > F = 0.0000  
 R-squared = 0.0699  
 Adj R-squared = 0.0697  
 Root MSE = 3.2414

educ	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
race	-2.317499	.0263069	-88.09	0.000	-2.36906	-2.265938
married	.40606	.0225021	18.05	0.000	.3619564	.4501636
smsa	-.5882687	.0144997	-40.57	0.000	-.6166877	-.5598497
ageq	.442292	.5560267	0.80	0.426	-.6475056	1.53209
ageq2	-.0056273	.0061598	-0.91	0.361	-.0177004	.0064458
_Iregion_1	-.7393628	.0219049	-33.75	0.000	-.7822959	-.6964297
_Iregion_2	-1.652889	.0355642	-46.48	0.000	-1.722594	-1.583185
_Iregion_3	-.455914	.0223444	-20.40	0.000	-.4997083	-.4121196
_Iregion_4	-.155019	.0370815	-4.18	0.000	-.2276977	-.0823403
_Iregion_5	-.4105518	.0323985	-12.67	0.000	-.4740521	-.3470515
_Iregion_6	-1.104921	.0258032	-42.82	0.000	-1.155495	-1.054348
_Iregion_7	-.5818435	.0288952	-20.14	0.000	-.6384772	-.5252097
_Iregion_8	-1.139735	.0309536	-36.82	0.000	-1.200404	-1.079067
_Iyob_1921	.1376454	.0630084	2.18	0.029	.0141505	.2611402
_Iyob_1922	.0031841	.0922253	0.03	0.972	-.177575	.1839433
_Iyob_1923	.0358809	.1167224	0.31	0.759	-.1928919	.2646537
_Iyob_1924	.0087671	.1319694	0.07	0.947	-.2498895	.2674237
_Iyob_1925	-.0293336	.1361694	-0.22	0.829	-.2962222	.2375549
_Iyob_1926	-.0539437	.1294869	-0.42	0.677	-.3077346	.1998472
_Iyob_1927	-.1149449	.1115026	-1.03	0.303	-.3334871	.1035973
_Iyob_1928	-.0977601	.0852882	-1.15	0.252	-.2649227	.0694025
_Iyob_1929	(dropped)					
_Iqob_2	.0904968	.0546323	1.66	0.098	-.016581	.1975746
_Iqob_3	.2115748	.0544615	3.88	0.000	.1048317	.3183179
_Iqob_4	.2005132	.0419578	4.78	0.000	.118277	.2827494
_IyobXqo~1_2	-.1003874	.0814898	-1.23	0.218	-.2601052	.0593304
_IyobXqo~1_3	-.2249199	.0801459	-2.81	0.005	-.3820038	-.0678361
_IyobXqo~1_4	-.1309525	.0782446	-1.67	0.094	-.2843099	.0224049
_IyobXqo~2_2	-.0854015	.0820744	-1.04	0.298	-.2462652	.0754623
_IyobXqo~2_3	-.0504703	.0798497	-0.63	0.527	-.2069737	.1060331
_IyobXqo~2_4	-.1099786	.0765667	-1.44	0.151	-.2600474	.0400901
_IyobXqo~3_2	-.0911235	.080527	-1.13	0.258	-.2489544	.0667073
_IyobXqo~3_3	-.1085343	.0794706	-1.37	0.172	-.2642946	.047226
_IyobXqo~3_4	-.1499147	.0726453	-2.06	0.039	-.2922975	-.0075319
_IyobXqo~4_2	-.0964844	.0798402	-1.21	0.227	-.2529692	.0600003
_IyobXqo~4_3	-.1395907	.0790225	-1.77	0.077	-.2944728	.0152914
_IyobXqo~4_4	-.100248	.0713929	-1.40	0.160	-.2401763	.0396803
_IyobXqo~5_2	-.121421	.0802058	-1.51	0.130	-.2786222	.0357803
_IyobXqo~5_3	-.1286412	.0800122	-1.61	0.108	-.2854629	.0281806
_IyobXqo~5_4	-.1701297	.0722058	-2.36	0.018	-.3116511	-.0286083
_IyobXqo~6_2	-.1053616	.0809432	-1.30	0.193	-.2640082	.053285
_IyobXqo~6_3	-.0492929	.0815955	-0.60	0.546	-.2092179	.1106321
_IyobXqo~6_4	-.0674566	.073929	-0.91	0.362	-.2123555	.0774423
_IyobXqo~7_2	-.0674867	.0800262	-0.84	0.399	-.2243359	.0893624

_IyobXqo~7_3		-.1247802	.0823747	-1.51	0.130	-.2862324	.0366721
_IyobXqo~7_4		-.0731652	.0747712	-0.98	0.328	-.2197147	.0733843
_IyobXqo~8_2		-.0369743	.0810478	-0.46	0.648	-.1958259	.1218773
_IyobXqo~8_3		-.1049247	.0851365	-1.23	0.218	-.27179	.0619405
_IyobXqo~8_4		-.0316991	.0792725	-0.40	0.689	-.1870712	.123673
_IyobXqo~9_2		-.0442215	.0738958	-0.60	0.550	-.1890554	.1006124
_IyobXqo~9_3		-.1141512	.0723279	-1.58	0.115	-.2559121	.0276097
_cons		3.673014	12.42174	0.30	0.767	-20.67326	28.01929

Instrumental variables (2SLS) regression

Number of obs = 247199  
Wald chi2(23) = 28822.61  
Prob > chi2 = 0.0000  
R-squared = 0.2065  
Root MSE = .58017

lwage	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
educ	.1007152	.0335512	3.00	0.003	.0349561	.1664742
race	-.2270555	.0779375	-2.91	0.004	-.3798102	-.0743008
married	.2803622	.0143412	19.55	0.000	.2522539	.3084705
smsa	-.1163201	.0199067	-5.84	0.000	-.1553365	-.0773037
ageq	.1170352	.0661708	1.77	0.077	-.0126573	.2467276
ageq2	-.0011772	.0007366	-1.60	0.110	-.0026209	.0002664
_Iregion_1	.0423372	.0251233	1.69	0.092	-.0069035	.0915779
_Iregion_2	-.1571906	.0558419	-2.81	0.005	-.2666387	-.0477424
_Iregion_3	.0008335	.0158882	0.05	0.958	-.0303069	.0319738
_Iregion_4	-.1220909	.0085285	-14.32	0.000	-.1388065	-.1053752
_Iregion_5	-.0201888	.0149419	-1.35	0.177	-.0494742	.0090967
_Iregion_6	-.069971	.0373572	-1.87	0.061	-.1431898	.0032478
_Iregion_7	-.1236594	.0204492	-6.05	0.000	-.1637391	-.0835796
_Iregion_8	-.1165475	.0386157	-3.02	0.003	-.1922328	-.0408622
_Iyob_1921	.0010063	.010104	0.10	0.921	-.0187972	.0208099
_Iyob_1922	.0020042	.0190431	0.11	0.916	-.0353196	.039328
_Iyob_1923	.0079007	.0261617	0.30	0.763	-.0433753	.0591767
_Iyob_1924	.0154163	.0335622	0.46	0.646	-.0503645	.081197
_Iyob_1925	.0336961	.0416298	0.81	0.418	-.0478969	.115289
_Iyob_1926	.043175	.0475898	0.91	0.364	-.0500992	.1364492
_Iyob_1927	.0584277	.0562273	1.04	0.299	-.0517758	.1686313
_Iyob_1928	.0703787	.0622065	1.13	0.258	-.0515438	.1923013
_Iyob_1929	.0679547	.0670612	1.01	0.311	-.0634828	.1993922
_cons	.9314844	1.624969	0.57	0.566	-2.253397	4.116366

Instrumented: educ

Instruments: race married smsa ageq ageq2 \_Iregion\_1 \_Iregion\_2 \_Iregion\_3  
\_Iregion\_4 \_Iregion\_5 \_Iregion\_6 \_Iregion\_7 \_Iregion\_8  
\_Iyob\_1921 \_Iyob\_1922 \_Iyob\_1923 \_Iyob\_1924 \_Iyob\_1925  
\_Iyob\_1926 \_Iyob\_1927 \_Iyob\_1928 \_Iyob\_1929 \_Iqob\_2 \_Iqob\_3  
\_Iqob\_4 \_IyobXqob\_1921\_2 \_IyobXqob\_1921\_3 \_IyobXqob\_1921\_4  
\_IyobXqob\_1922\_2 \_IyobXqob\_1922\_3 \_IyobXqob\_1922\_4  
\_IyobXqob\_1923\_2 \_IyobXqob\_1923\_3 \_IyobXqob\_1923\_4  
\_IyobXqob\_1924\_2 \_IyobXqob\_1924\_3 \_IyobXqob\_1924\_4  
\_IyobXqob\_1925\_2 \_IyobXqob\_1925\_3 \_IyobXqob\_1925\_4

```

_IyobXqob_1926_2 _IyobXqob_1926_3 _IyobXqob_1926_4
_IyobXqob_1927_2 _IyobXqob_1927_3 _IyobXqob_1927_4
_IyobXqob_1928_2 _IyobXqob_1928_3 _IyobXqob_1928_4
_IyobXqob_1929_2 _IyobXqob_1929_3

```

Looking at the first stage we see that few of the instruments have coefficients significantly different from zero – we might be concerned that the instrument is weak. We will see how to test for this later. The coefficient on education is 0.10 and is significantly different from zero.

We can estimate this model using the `gmm` and `liml` options:

```

. xi: ivregress liml lwage race married smsa ageq ageq2 i.region i.yob (educ=i.yob*i.qob),
vce(robust)

```

*(output omitted)*

```

. xi: ivregress gmm lwage race married smsa ageq ageq2 i.region i.yob (educ=i.yob*i.qob),
vce(robust)

```

*(output omitted)*

Storing the estimates, we can then create a table to compare them:

```

. esttab ols twosls liml gmm, b se keep(educ ageq ageq2 race married smsa) mtitles

```

	(1)	(2)	(3)	(4)
	ols	twosls	liml	gmm
educ	0.0701*** (0.000388)	0.101** (0.0336)	0.282 (0.358)	0.100** (0.0335)
race	-0.298*** (0.00470)	-0.227** (0.0779)	0.193 (0.829)	-0.228** (0.0779)
married	0.293*** (0.00440)	0.280*** (0.0143)	0.207 (0.145)	0.280*** (0.0143)
smsa	-0.134*** (0.00259)	-0.116*** (0.0199)	-0.00960 (0.211)	-0.117*** (0.0199)
ageq	0.116 (0.0651)	0.117 (0.0662)	0.122 (0.103)	0.119 (0.0663)
ageq2	-0.00125 (0.000722)	-0.00118 (0.000737)	-0.000743 (0.00141)	-0.00120 (0.000738)
N	247199	247199	247199	247199

Standard errors in parentheses

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001

We see that the LIML coefficients are less precisely estimated than the other approaches. Instrumenting appears to increase the effect of schooling on wages.

## 4 Postestimation tests

Stata has a series of commands that can be used after `ivregress` to test various hypotheses. We first rerun the 2SLS regression.

```
. xi: ivregress 2sls lwage race married smsa ageq ageq2 i.region i.yob (educ=i.yob*i.qob),  
vce(robust)
```

*(output omitted)*

We can test for the endogeneity of education. The IV approach assumes that education is endogenous – if it is in fact exogenous then OLS would be more efficient. The command `estat endogenous` performs a test for this:

```
. estat endogenous
```

```
Tests of endogeneity  
Ho: variables are exogenous
```

```
Robust score chi2(1)          = .857777 (p = 0.3544)  
Robust regression F(1,247174) = .857705 (p = 0.3544)
```

This implements the Durbin-Wu-Hausman test (see p.183 of Cameron and Trivedi (2009) for details). The null hypothesis is that education is exogenous. Here we see that the hypothesis is not rejected so in fact we cannot reject exogeneity of education in this model.

A second test is a test of overidentifying restrictions. This is possible when there are more instruments than endogenous variables. The test assumes that one instrument is valid and then tests for the validity of all other instruments (ie. whether the instruments are uncorrelated with the error term in the second stage).

```
. estat overid
```

```
Test of overidentifying restrictions:
```

```
Score chi2(28)          = 29.0241 (p = 0.4113)
```

We do not reject the overidentifying restrictions. One note of caution here is that the test assumes that at least one instrument is valid. All of our instruments here are drawn from the same concept of quarter of birth affecting the amount of schooling – so, we would expect either all instruments, or no instruments, to be valid.

We can also test the strength of the instruments using `estat firststage`:

```
. estat firststage
```

```
note: _Iyob_1929 dropped because of collinearity
```

*(first stage regression output omitted)*

```
( 1)  _Iqob_2 = 0  
( 2)  _Iqob_3 = 0  
( 3)  _Iqob_4 = 0  
( 4)  _IyobXqob_1921_2 = 0  
( 5)  _IyobXqob_1921_3 = 0  
( 6)  _IyobXqob_1921_4 = 0  
( 7)  _IyobXqob_1922_2 = 0  
( 8)  _IyobXqob_1922_3 = 0  
( 9)  _IyobXqob_1922_4 = 0  
(10)  _IyobXqob_1923_2 = 0  
(11)  _IyobXqob_1923_3 = 0  
(12)  _IyobXqob_1923_4 = 0  
(13)  _IyobXqob_1924_2 = 0  
(14)  _IyobXqob_1924_3 = 0  
(15)  _IyobXqob_1924_4 = 0  
(16)  _IyobXqob_1925_2 = 0
```

```

(17) _IyobXqob_1925_3 = 0
(18) _IyobXqob_1925_4 = 0
(19) _IyobXqob_1926_2 = 0
(20) _IyobXqob_1926_3 = 0
(21) _IyobXqob_1926_4 = 0
(22) _IyobXqob_1927_2 = 0
(23) _IyobXqob_1927_3 = 0
(24) _IyobXqob_1927_4 = 0
(25) _IyobXqob_1928_2 = 0
(26) _IyobXqob_1928_3 = 0
(27) _IyobXqob_1928_4 = 0
(28) _IyobXqob_1929_2 = 0
(29) _IyobXqob_1929_3 = 0

```

```

F( 29,247148) = 3.02
Prob > F = 0.0000

```

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	Robust F(29,247148)	Prob > F
educ	0.0699	0.0697	0.0001	3.01972	0.0000

This tests the joint significance of all of the instruments. We see that they are jointly significantly different from zero, with a p-value of 0.0000. Their partial R squared is just 0.0001. This casts concern over the strength of the instruments. Generally an F statistic over 10 is required to suggest instruments are sufficiently strong. If the instruments are weak, we may find that 2SLS gives standard errors which are too small. LIML is thought to be a better approach if instruments are weak. See Murray (2006) for a good discussion on approaches to take to avoid problems with weak instruments.

## 5 An alternative command

Instead of using `ivregress` we can use the user written command `ivreg2`. This automatically calculates many additional statistics. I show it here with the `first` option to give all first stage statistics. Note that to get robust standard errors here the option is `robust` and not `vce(robust)`. Otherwise the syntax is similar to that for `ivregress`.

```

. xi: ivreg2 lwage race married smsa ageq ageq2 i.region i.yob (educ=i.yob*i.qob),
robust first

```

*(first stage regression output omitted)*

Partial R-squared of excluded instruments: 0.0001

Test of excluded instruments:

```

F( 28,247148) = 1.03
Prob > F = 0.4217

```

Summary results for first-stage regressions

Variable	Shea Partial R2	Partial R2	F( 28,247148)	P-value
educ	0.0001	0.0001	1.03	0.4217

NB: first-stage F-stat heteroskedasticity-robust

Underidentification tests

Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)

Ha: matrix has rank=K1 (identified)

Kleibergen-Paap rk LM statistic Chi-sq(28)=28.83 P-val=0.4211

Kleibergen-Paap rk Wald statistic Chi-sq(28)=28.84 P-val=0.4206

Weak identification test

Ho: equation is weakly identified

Kleibergen-Paap Wald rk F statistic 1.03

See main output for Cragg-Donald weak id test critical values

Weak-instrument-robust inference

Tests of joint significance of endogenous regressors B1 in main equation

Ho: B1=0 and overidentifying restrictions are valid

Anderson-Rubin Wald test F(28,247148)=1.21 P-val=0.2051

Anderson-Rubin Wald test Chi-sq(28)=33.88 P-val=0.2048

Stock-Wright LM S statistic Chi-sq(28)=33.94 P-val=0.2028

NB: Underidentification, weak identification and weak-identification-robust test statistics heteroskedasticity-robust

Number of observations N = 247199
Number of regressors K = 24
Number of instruments L = 51
Number of excluded instruments L1 = 28

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity

Number of obs = 247199
F( 23,247175) = 1253.02
Prob > F = 0.0000
Centered R2 = 0.2064
Uncentered R2 = 0.9875
Root MSE = .5802
Total (centered) SS = 104853.0198
Total (uncentered) SS = 6674371.774
Residual SS = 83215.58688

Table with 7 columns: lwage, Coef., Robust Std. Err., z, P>|z|, [95% Conf. Interval]. Rows include variables like educ, race, married, smsa, ageq, ageq2, and \_Iregion\_1 through \_Iregion\_4.

_Iregion_5		-.020162	.0149428	-1.35	0.177	-.0494494	.0091253
_Iregion_6		-.0698987	.0373596	-1.87	0.061	-.1431221	.0033248
_Iregion_7		-.1236214	.0204505	-6.04	0.000	-.1637036	-.0835392
_Iregion_8		-.1164728	.0386181	-3.02	0.003	-.1921629	-.0407827
_Iyob_1921		.0009451	.0101047	0.09	0.925	-.0188597	.0207499
_Iyob_1922		.0019085	.0190443	0.10	0.920	-.0354176	.0392346
_Iyob_1923		.007784	.0261633	0.30	0.766	-.0434951	.0590632
_Iyob_1924		.0152995	.0335643	0.46	0.649	-.0504853	.0810843
_Iyob_1925		.0336004	.0416324	0.81	0.420	-.0479976	.1151984
_Iyob_1926		.0431142	.0475927	0.91	0.365	-.0501658	.1363942
_Iyob_1927		.0584271	.0562308	1.04	0.299	-.0517833	.1686376
_Iyob_1928		.0704497	.0622104	1.13	0.257	-.0514805	.1923798
_Iyob_1929		.0681133	.0670654	1.02	0.310	-.0633324	.199559
_cons		.9112057	1.625074	0.56	0.575	-2.273881	4.096292

-----  
Underidentification test (Kleibergen-Paap rk LM statistic): 28.832  
Chi-sq(28) P-val = 0.4211  
-----

Weak identification test (Kleibergen-Paap rk Wald F statistic): 1.030  
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 21.42  
10% maximal IV relative bias 11.34  
20% maximal IV relative bias 6.13  
30% maximal IV relative bias 4.32  
10% maximal IV size 81.40  
15% maximal IV size 42.37  
20% maximal IV size 29.12  
25% maximal IV size 22.43

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

-----  
Hansen J statistic (overidentification test of all instruments): 29.020  
Chi-sq(27) P-val = 0.3599  
-----

Instrumented: educ  
Included instruments: race married smsa ageq ageq2 \_Iregion\_1 \_Iregion\_2  
\_Iregion\_3 \_Iregion\_4 \_Iregion\_5 \_Iregion\_6 \_Iregion\_7  
\_Iregion\_8 \_Iyob\_1921 \_Iyob\_1922 \_Iyob\_1923 \_Iyob\_1924  
\_Iyob\_1925 \_Iyob\_1926 \_Iyob\_1927 \_Iyob\_1928 \_Iyob\_1929  
Excluded instruments: \_Iqob\_2 \_Iqob\_3 \_IyobXqob\_1921\_2 \_IyobXqob\_1921\_3  
\_IyobXqob\_1921\_4 \_IyobXqob\_1922\_2 \_IyobXqob\_1922\_3  
\_IyobXqob\_1922\_4 \_IyobXqob\_1923\_2 \_IyobXqob\_1923\_3  
\_IyobXqob\_1923\_4 \_IyobXqob\_1924\_2 \_IyobXqob\_1924\_3  
\_IyobXqob\_1924\_4 \_IyobXqob\_1925\_2 \_IyobXqob\_1925\_3  
\_IyobXqob\_1925\_4 \_IyobXqob\_1926\_2 \_IyobXqob\_1926\_3  
\_IyobXqob\_1926\_4 \_IyobXqob\_1927\_2 \_IyobXqob\_1927\_3  
\_IyobXqob\_1927\_4 \_IyobXqob\_1928\_2 \_IyobXqob\_1928\_3  
\_IyobXqob\_1928\_4 \_IyobXqob\_1929\_2 \_IyobXqob\_1929\_3  
Duplicates: \_Iyob\_1921 \_Iyob\_1922 \_Iyob\_1923 \_Iyob\_1924 \_Iyob\_1925  
\_Iyob\_1926 \_Iyob\_1927 \_Iyob\_1928 \_Iyob\_1929  
Dropped collinear: \_Iqob\_4 \_IyobXqob\_1929\_4  
-----

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