

# Ec533: Labour Economics for Research Students

## Instrumental variables estimates of the returns to schooling

Jörn-Steffen Pischke

LSE

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# Two solutions to the ability bias problem

Remember that we would like to run the *long regression*

$$y_i = \alpha + \rho S_i + \gamma A_i + e_i.$$

- The **regression solution** was to look for variables which can act as proxies for ability  $A_i$ . The key to regression is that we need something that captures *all* the variation in  $A_i$ , otherwise we are left with OVB.
- The **IV solution** is to isolate variation in  $S_i$  which is unrelated to  $A_i$ . The variable which does the “isolating” is the instrumental variable. The good thing is that we just need *some* of the variation in  $A_i$ ; so the requirements on the instrument seem weaker than those on the regression control  $A_i$ . But IV comes with other possible complications.

# Conditions for a valid instrument

Call the instrumental variable  $Z_i$ . A valid instrument needs to satisfy three conditions:

- 1  $Z_i$  is as good as randomly assigned.
- 2  $Z_i$  satisfies the exclusion restriction, i.e. it does not appear as a separate regressor in the long regression we like to run.
- 3  $Z_i$  affects the endogenous regressor  $S_i$ .

Of these only condition 3. can be tested. This is the strength of the first stage. Conditions 1. and 2. have to be argued based on knowledge from outside the data we have.

# Three causal effects

There are three causal effects we can think about:

- 1 The causal effect of  $Z_i$  on  $S_i$ .
- 2 The causal effect of  $Z_i$  on  $y_i$ .
- 3 The causal effect of  $S_i$  on  $y_i$ .

The last one is the one we are ultimately interested in, the return to schooling  $\rho$ .

# Some instrumental variables language

The instrumental variables language comes from old style simultaneous equations models but we can think of it as related to the three causal effects.

- Structural equation: The regression of earnings on schooling is called the structural equation

$$y_i = \alpha + \rho S_i + \eta_i,$$

where  $\eta_i = \gamma A_i + e_i$ , i.e. it is a structural error term, not a regression residual. This involves causal effect number 3.

- First stage: The regression of schooling on the instrument is called the first stage (causal effect number 1)

$$S_i = \pi_{10} + \pi_{11} Z_i + \zeta_{1i}$$

- Reduced form: The regression of earnings on the instrument is called the reduced form (causal effect number 2)

$$y_i = \pi_{20} + \pi_{21} Z_i + \zeta_{2i}.$$

# You get what you pay for

- Conditions 1 and 3 on the instrument are enough to get causal effects 1 and 2. I.e. these conditions are sufficient for the first stage and reduced forms to have a causal interpretation. Often, the reduced form coefficient may be interesting in its own right. For example, the instrument might be a policy variable in which case it is the policy effect.
- To get causal effect 3, i.e. the structural parameter  $\rho$ , we also need condition 2, the exclusion restriction. This condition is often the most difficult requirement on an instrument. It is distinct from random assignment, so having experimental variation does not guarantee a valid IV interpretation of the estimates.

## Linking the three equations

The coefficients in the three equations are linked. Substitute the first stage into the structural equation:

$$\begin{aligned}y_i &= \alpha + \rho S_i + \eta_i \\&= \alpha + \rho [\pi_{10} + \pi_{11} Z_i + \xi_{1i}] + \eta_i \\&= (\alpha + \rho \pi_{10}) + \rho \pi_{11} Z_i + (\xi_{1i} + \eta_i) \\&= \pi_{20} + \pi_{21} Z_i + \xi_{2i}.\end{aligned}$$

Hence, the reduced form coefficients are:

$$\begin{aligned}\pi_{20} &= \alpha + \rho \pi_{10} \\ \pi_{21} &= \rho \pi_{11}\end{aligned}$$

It is straightforward to see that

$$\rho = \frac{\pi_{21}}{\pi_{11}},$$

i.e. the IV estimate is equal to the ratio of the reduced form coefficient on the instrument to the first stage coefficient. This is called *indirect least squares*.

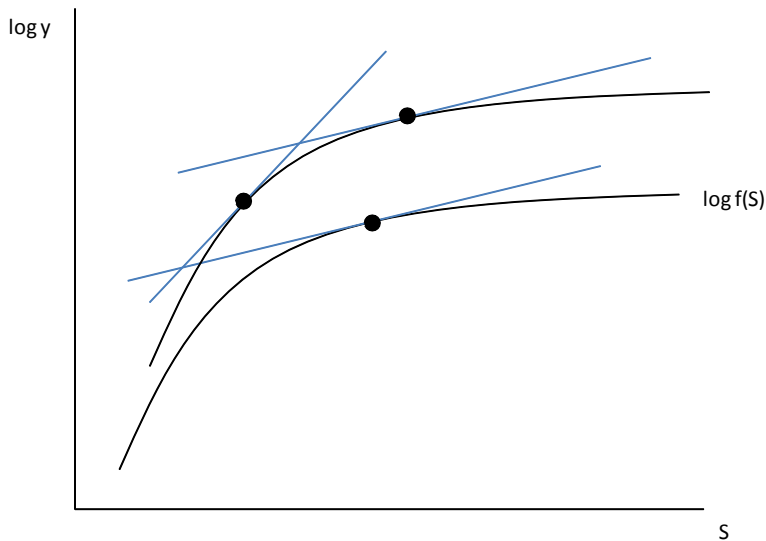
## Just identified vs. over-identified models

- Indirect least squares only works when there is one endogenous regressor and one instrument. Such a model is *just identified* (there is only one single solution to get  $\rho$  from the first stage and reduced form coefficients).
- If there are multiple instruments for a single endogenous regressor the model is *over-identified*.

$$\begin{aligned}S_i &= \pi_{10} + \pi_{11}Z_{1i} + \pi_{12}Z_{2i} + \zeta_{1i} \\y_i &= \pi_{20} + \pi_{21}Z_{1i} + \pi_{22}Z_{2i} + \zeta_{2i}.\end{aligned}$$

There is no unique way to get  $\rho$  from  $\pi_{11}$ ,  $\pi_{12}$ ,  $\pi_{21}$ , and  $\pi_{22}$ . Two stage least squares (2SLS) is a particular average (it is the optimally weighted GMM estimator for the homoskedastic model).

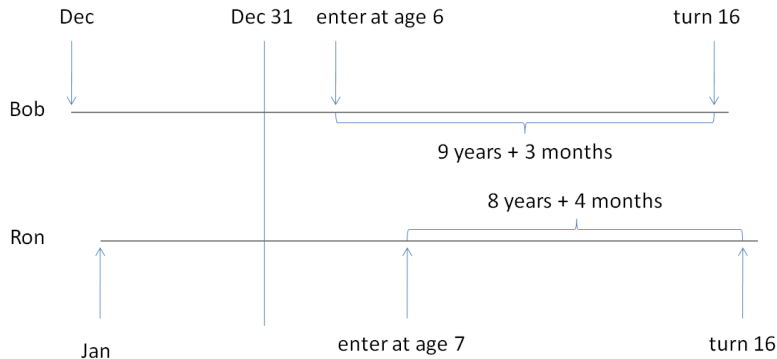
# So what's a good instrument?



# Angrist and Krueger (1991): US compulsory schooling and school entry rules

- US compulsory schooling laws are in terms of age, not number of years of schooling completed. If compulsory schooling age is 16, you can drop out on your 16th birthday (even if in the middle of the school year).
- School entry is once a year, and cutoffs are based on birthdays.
- The combination of these two generates variation in schooling for those who drop out as soon as they can. This variation depends on birthday within the year.

# How compulsory schooling laws and school entry rules interact



# Is this a good instrument?

Variation indeed comes from the cost/compulsion side of the schooling problem. Let's check the three conditions

- 1 Random assignment: Are birthdays random with respect to the counterfactual earnings for different schooling levels?
  - Probably not a lot of systematic selection of birthdays.
- 2 Do birthdays satisfies the exclusion restriction, or could birthdays be correlated with earnings for other reasons than their effect on schooling?
  - There are small differences in average SES by birthday throughout the year.
- 3 Do birthdays indeed affects schooling?
  - Check the first stage.

# Angrist and Krueger data

- Data are from the 1980 US Census.
- 329,509 men born 1930 to 1939 (i.e. in their 40s when observed).
- For these men we have year of birth, quarter of birth, years of schooling, and earnings in 1979.

# First stage regressions of schooling on quarter of birth

Regressor	Dependent variable: schooling			
	(1)	(2)	(3)	(4)
quarter 2		0.057 (0.017)		0.057 (0.016)
quarter 3		0.117 (0.016)		0.113 (0.016)
quarter 4	0.092 (0.013)	0.151 (0.016)	0.091 (0.013)	0.148 (0.016)
9 year of birth dummies			✓	✓

# Reduced form regressions of log wages on quarter of birth

Regressor	Dependent variable: log wages			
	(1)	(2)	(3)	(4)
quarter 2		0.0045 (0.0034)		0.0046 (0.0034)
quarter 3		0.0149 (0.0033)		0.0150 (0.0033)
quarter 4	0.0068 (0.0027)	0.0135 (0.0034)	0.0068 (0.0027)	0.0135 (0.0034)
9 year of birth dummies			✓	✓

# IV regressions of log wages on schooling

Coefficient on schooling from an OLS regression: 0.071 (0.0004)

Dependent variable: log wages

Regressor	(1)	(2)	(3)	(4)
schooling	0.074 (0.028)	0.103 (0.020)	0.075 (0.028)	0.105 (0.020)
Instruments	Quarter 4	4 quarter dummies	Quarter 4	4 quarter dummies
9 year of birth dummies			✓	✓

# IV with a dummy instrument: the Wald Estimator

A way to look at IV with a binary instrument, like the dummy for quarter 4, is the following. With  $Q4_i$  a dummy instrument it turns out that

$$\begin{aligned}\beta_{IV} &= \frac{\text{cov}(\ln y_i, Q4_i)}{\text{cov}(S_i, Q4_i)} \\ &= \frac{E[\ln y_i | Q4_i = 1] - E[\ln y_i | Q4_i = 0]}{E[S_i | Q4_i = 1] - E[S_i | Q4_i = 0]}.\end{aligned}$$

This is called the *Wald* estimator (due to Abraham Wald, 1944).

# Constructing the Wald Estimator

The first stage and reduced form are

$$\begin{aligned}S_i &= \pi_{11} + \pi_{14}Q4_i + \xi_{1i}, \\ \ln y_i &= \pi_{21} + \pi_{24}Q4_i + \xi_{2i}.\end{aligned}$$

Taking expectations conditionally on  $Q4_i$  yields

$$\begin{aligned}E[\ln y_i | Q4_i = 1] &= \pi_{21} + \pi_{24} \\ E[\ln y_i | Q4_i = 0] &= \pi_{21}\end{aligned}$$

Hence, the reduced form coefficients on  $Q4_i$  are the differences in group means with the instrument switched on and off:

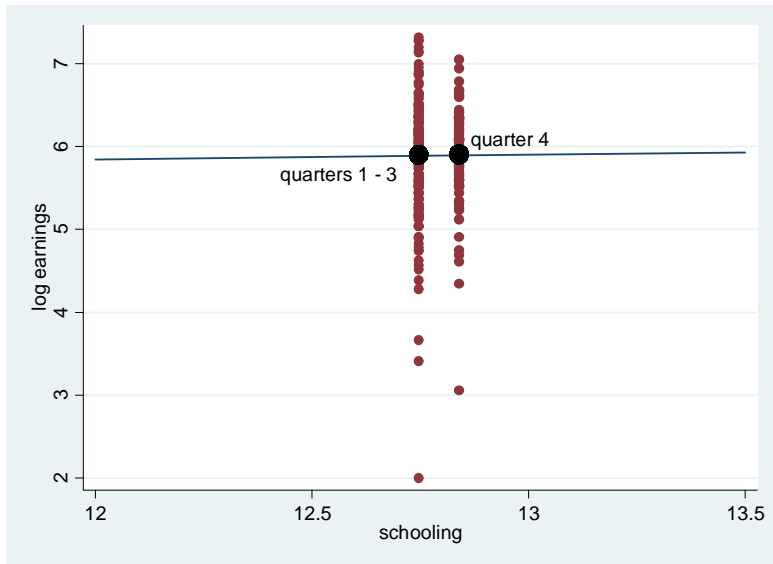
$$\begin{aligned}\pi_{24} &= E[\ln y_i | Q4_i = 1] - E[\ln y_i | Q4_i = 0] \\ \pi_{14} &= E[S_i | Q4_i = 1] - E[S_i | Q4_i = 0]\end{aligned}$$

The IV estimate is the ratio of the two.

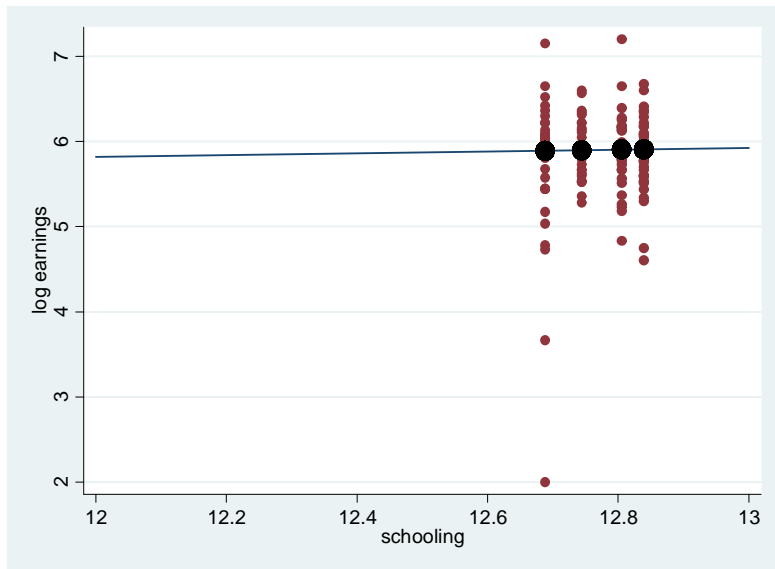
# The Wald estimate of the return to schooling

	born quarter 1, 2, 3	born quarter 4	Difference
log earnings	5.8983	5.9051	0.0068 (0.0027)
schooling	12.747	12.839	0.092 (0.013)
Wald estimate			0.074 (0.028)

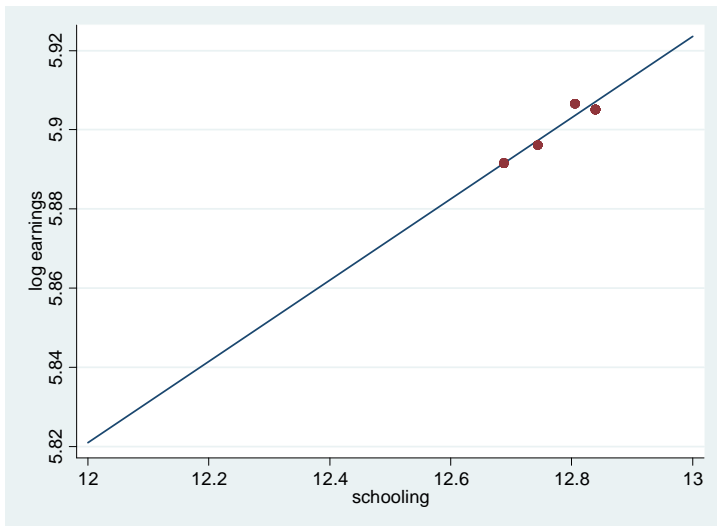
# A plot of the Wald estimate of the return to schooling



# We can do this with all four quarter dummies



Now the regression line doesn't fit the four means exactly anymore



# Grouping is IV

The analogy between IV and the Wald estimator can be extended to IV with multiple dummy instruments. Suppose we have a variable  $Q_i$ , for quarter, which takes on four values 1 to 4. Then, using the structural equation

$$\ln y_i = \alpha + \beta S_i + \eta_i.$$

we get

$$E[\ln y_i | Q_i] = \alpha + \beta E[S_i | Q_i].$$

The sample analog of  $E[\ln y_i | Q_i = j]$  is  $\overline{\ln y}_j$ , and similarly with  $E[S_i | Q_i]$ . Hence, the IV estimate of log earnings on schooling, instrumenting with a set of mutually exclusive and exhaustive dummy variables is the same as the regression using the group means

$$\overline{\ln y}_j = \alpha + \beta \overline{S}_j + \overline{\eta}_j$$

weighted by the size of the cells.

# So does it work in practice?

Here is 2SLS

```
. ivregress 2sls lnw (s = q2 q3 q4)
```

Instrumental variables (2SLS) regression

```
Number of obs = 329509  
Wald chi2(1) = 27.68  
Prob > chi2 = 0.0000  
R-squared = 0.0937  
Root MSE = .64622
```

lnw	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
s	.1025976	.0195006	5.26	0.000	.064377	.1408182
cons	4.589782	.2490241	18.43	0.000	4.101703	5.07786

Instrumented: s

Instruments: q2 q3 q4

# And here is grouped data

```
. generate n = 1
. collapse (mean) lnw s (sum) n, by(qob)
. regress lnw s [aweight=n]
(sum of wgt is 3.2951e+05)
```

Source	SS	df	MS	Number of obs =	4
Model	.000140329	1	.000140329	F( 1, 2) =	19.45
Residual	.00001443	2	7.2152e-06	Prob > F =	0.0478
Total	.000154759	3	.000051586	R-squared =	0.9068
				Adj R-squared =	0.8601
				Root MSE =	.00269

lnw	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
s	.1025991	.0232646	4.41	0.048	.0024997	.2026984
_cons	4.589763	.2970895	15.45	0.004	3.31149	5.868036

# A quick derivation

Consider a regression model in matrix notation:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

We have matrix of  $q$  exhaustive dummy variable instruments  $\mathbf{Z}$ . Note that

$$\mathbf{Z} = \begin{bmatrix} \boldsymbol{\iota}_1 & 0 & \cdots & 0 \\ 0 & \boldsymbol{\iota}_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \boldsymbol{\iota}_q \end{bmatrix}$$

where  $\boldsymbol{\iota}_j$  is a column vector of  $n_j$  ones.

# A quick derivation

The 2SLS estimator is

$$\beta_{2SLS} = \left[ \mathbf{X}'\mathbf{Z} (\mathbf{Z}'\mathbf{Z})^{-1} \mathbf{Z}'\mathbf{X} \right]^{-1} \mathbf{X}'\mathbf{Z} (\mathbf{Z}'\mathbf{Z})^{-1} \mathbf{Z}'\mathbf{y}.$$

Given the definition of  $\mathbf{Z}$ :

$$\mathbf{Z}'\mathbf{X} = \begin{bmatrix} \bar{x}_1 n_1 \\ \bar{x}_2 n_2 \\ \vdots \\ \bar{x}_q n_q \end{bmatrix}, \mathbf{Z}'\mathbf{y} = \begin{bmatrix} \bar{y}_1 n_1 \\ \bar{y}_2 n_2 \\ \vdots \\ \bar{y}_q n_q \end{bmatrix}, (\mathbf{Z}'\mathbf{Z})^{-1} = \begin{bmatrix} \frac{1}{n_1} & 0 & \cdots & 0 \\ 0 & \frac{1}{n_2} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{n_q} \end{bmatrix}$$

and hence

$$\beta_{2SLS} = \frac{\sum_{j=1}^q \bar{y}_j \bar{x}_j n_j}{\sum_{j=1}^q \bar{x}_j^2 n_j}$$

# Aside on grouped data

Discrete regressor: grouping is OLS

Consider a generic regression model

$$y_i = \alpha + \beta x_i + e_i$$

where  $x_i$  is a discrete regressor, taking on  $J$  different values. The regression

$$\bar{y}_j = \alpha + \beta x_j + \bar{e}_j$$

weighted by the cell size is identical to OLS on the micro data (see MHE, section 3.1.2).

# Aside on grouped data

Continuous regressor, discrete instrument: grouping is IV

If, on the other hand,  $x_i$  is continuous, and we have a discrete instrument,  $z_i$ , which takes on  $J$  different values, the IV estimation of the micro data model with  $J - 1$  dummy instruments is the same as

$$\bar{y}_j = \alpha + \beta \bar{x}_j + \bar{e}_j$$

weighted by the cell size.

Why are the two cases different?

- Discrete regressor: the regressor defines the groups. The grouped data regression is OLS because all the variation in  $x_i$  is only at the group level. By aggregating  $y_i$  we are not changing anything about  $x_i$ .
- Continuous regressor, discrete instrument: now the instrument defines the groups. The grouped data regression is IV because we are changing the variation in  $x_i$  by aggregating.

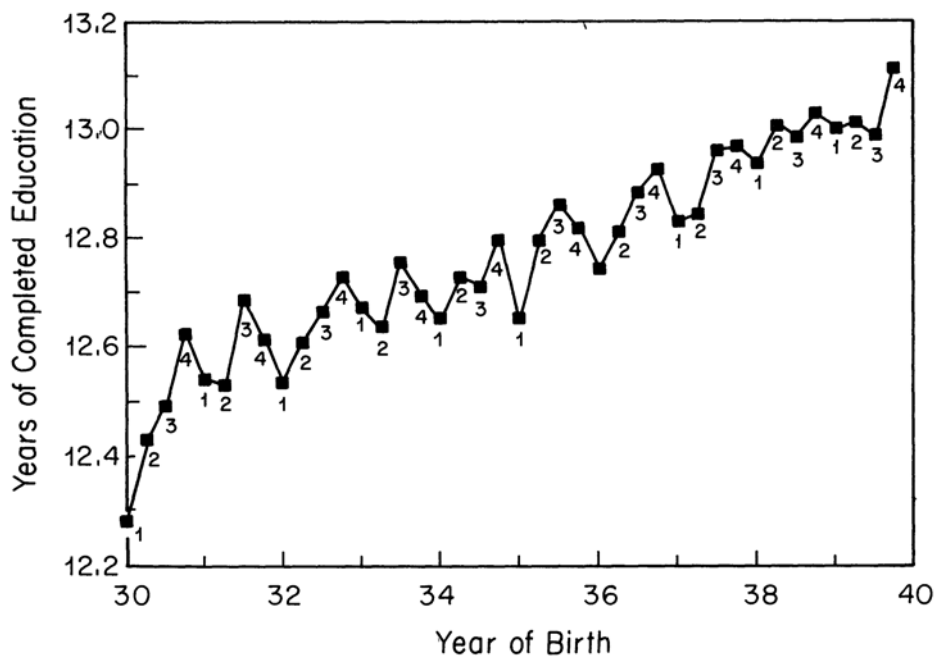


FIGURE I  
 Years of Education and Season of Birth  
 1980 Census  
 Note. Quarter of birth is listed below each observation.

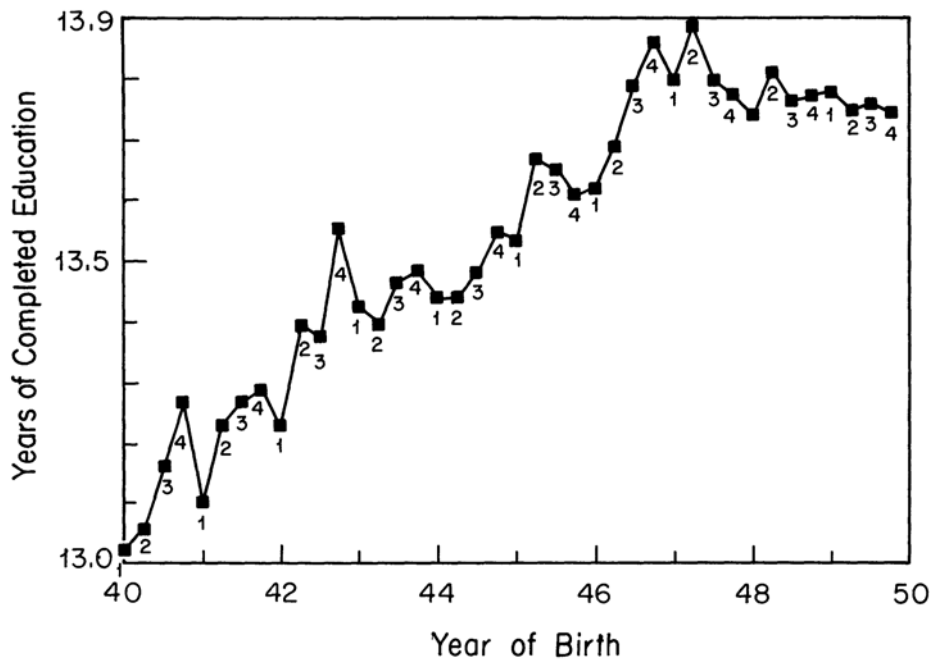


FIGURE II  
 Years of Education and Season of Birth  
 1980 Census  
 Note. Quarter of birth is listed below each observation.

TABLE I  
THE EFFECT OF QUARTER OF BIRTH ON VARIOUS EDUCATIONAL  
OUTCOME VARIABLES

Outcome variable	Birth cohort	Mean	Quarter-of-birth effect <sup>a</sup>			F-test <sup>b</sup> [P-value]
			I	II	III	
Total years of education	1930–1939	12.79	-0.124 (0.017)	-0.086 (0.017)	-0.015 (0.016)	24.9 [0.0001]
	1940–1949	13.56	-0.085 (0.012)	-0.035 (0.012)	-0.017 (0.011)	18.6 [0.0001]
High school graduate	1930–1939	0.77	-0.019 (0.002)	-0.020 (0.002)	-0.004 (0.002)	46.4 [0.0001]
	1940–1949	0.86	-0.015 (0.001)	-0.012 (0.001)	-0.002 (0.001)	54.4 [0.0001]
Years of educ. for high school graduates	1930–1939	13.99	-0.004 (0.014)	0.051 (0.014)	0.012 (0.014)	5.9 [0.0006]
	1940–1949	14.28	0.005 (0.011)	0.043 (0.011)	-0.003 (0.010)	7.8 [0.0017]
College graduate	1930–1939	0.24	-0.005 (0.002)	0.003 (0.002)	0.002 (0.002)	5.0 [0.0021]
	1940–1949	0.30	-0.003 (0.002)	0.004 (0.002)	0.000 (0.002)	5.0 [0.0018]
Completed master's degree	1930–1939	0.09	-0.001 (0.001)	0.002 (0.001)	-0.001 (0.001)	1.7 [0.1599]
	1940–1949	0.11	0.000 (0.001)	0.004 (0.001)	0.001 (0.001)	3.9 [0.0091]
Completed doctoral degree	1930–1939	0.03	0.002 (0.001)	0.003 (0.001)	0.000 (0.001)	2.9 [0.0332]
	1940–1949	0.04	-0.002 (0.001)	0.001 (0.001)	-0.001 (0.001)	4.3 [0.0050]

a. Standard errors are in parentheses. An  $MA(+2, -2)$  trend term was subtracted from each dependent variable. The data set contains men from the 1980 Census, 5 percent Public Use Sample. Sample size is 312,718 for 1930–1939 cohort and is 457,181 for 1940–1949 cohort.

b. F-statistic is for a test of the hypothesis that the quarter-of-birth dummies jointly have no effect.

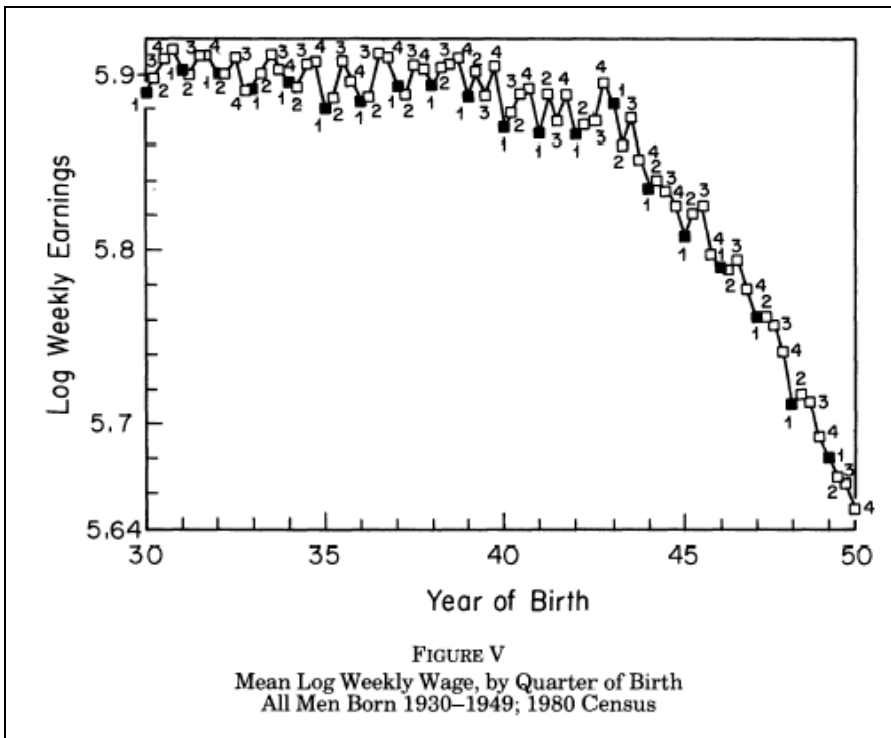
**TABLE II**  
**PERCENTAGE OF AGE GROUP ENROLLED IN SCHOOL BY BIRTHDAY AND LEGAL DROPOUT AGE<sup>a</sup>**

Date of birth	Type of state law <sup>b</sup>		Column (1) - (2)
	School-leaving age: 16 (1)	School-leaving age: 17 or 18 (2)	
Percent enrolled April 1, 1960			
1. Jan 1–Mar 31, 1944 (age 16)	87.6 (0.6)	91.0 (0.9)	-3.4 (1.1)
2. Apr 1–Dec 31, 1944 (age 15)	92.1 (0.3)	91.6 (0.5)	0.5 (0.6)
3. Within-state diff. (row 1 - row 2)	-4.5 (0.7)	-0.6 (1.0)	-4.0 (1.2)
Percent enrolled April 1, 1970			
4. Jan 1–Mar 31, 1954 (age 16)	94.2 (0.3)	95.8 (0.5)	-1.6 (0.6)
5. Apr 1–Dec 31, 1954 (age 15)	96.1 (0.1)	95.7 (0.3)	0.4 (0.3)
6. Within-state diff. (row 1 - row 2)	-1.9 (0.3)	0.1 (0.6)	-2.0 (0.6)
Percent enrolled April 1, 1980			
7. Jan 1–Mar 31, 1964 (age 16)	95.0 (0.1)	96.2 (0.2)	-1.2 (0.2)
8. Apr 1–Dec 31, 1964 (age 15)	97.0 (0.1)	97.7 (0.1)	-0.7 (0.1)
9. Within-state diff. (row 1 - row 2)	-2.0 (0.1)	-1.5 (0.2)	0.5 (0.3)

a. Standard errors are in parentheses.

b. Data set used to compute rows 1–3 is the 1960 Census, 1 percent Public Use Sample; data set used to compute rows 4–6 is 1970 Census, 1 percent State Public Use Sample (15 percent form); data set used to compute rows 7–9 is the 1980 Census, 5 percent Public Use Sample. Each sample contains both boys and girls. Sample sizes are 4,153 for row 1; 12,512 for row 2; 7,758 for row 4; 24,636 for row 5; 42,740 for row 7; and 131,020 for row 8.

Angrist and Krueger 1991: Figure 5



	(1) Born in 1st quarter of year	(2) Born in 2nd, 3rd, or 4th quarter of year	(3) Difference (std. error) (1) – (2)
ln (wkly. wage)	5.1484	5.1574	–0.00898 (0.00301)
Education	11.3996	11.5252	–0.1256 (0.0155)
Wald est. of return to education			0.0715 (0.0219)
OLS return to education <sup>b</sup>			0.0801 (0.0004)
<b>Panel B: Wald Estimates for 1980 Census—Men Born 1930–1939</b>			
	(1) Born in 1st quarter of year	(2) Born in 2nd, 3rd, or 4th quarter of year	(3) Difference (std. error) (1) – (2)
ln (wkly. wage)	5.8916	5.9027	–0.01110 (0.00274)
Education	12.6881	12.7969	–0.1088 (0.0132)
Wald est. of return to education			0.1020 (0.0239)
OLS return to education			0.0709 (0.0003)

a. The sample size is 247,199 in Panel A, and 327,509 in Panel B. Each sample consists of males born in the United States who had positive earnings in the year preceding the survey. The 1980 Census sample is drawn from the 5 percent sample, and the 1970 Census sample is from the State, County, and Neighborhoods 1 percent samples.

b. The OLS return to education was estimated from a bivariate regression of log weekly earnings on years of education.

Angrist and Krueger 1991: Table 4

**TABLE IV**  
OLS AND TSLS ESTIMATES OF THE RETURN TO EDUCATION FOR MEN BORN 1920–1929: 1970 CENSUS<sup>a</sup>

Independent variable	(1) OLS	(2) TSLS	(3) OLS	(4) TSLS	(5) OLS	(6) TSLS	(7) OLS	(8) TSLS
Years of education	0.0802 (0.0004)	0.0769 (0.0150)	0.0802 (0.0004)	0.1310 (0.0334)	0.0701 (0.0004)	0.0669 (0.0151)	0.0701 (0.0004)	0.1007 (0.0334)
Race (1 = black)	—	—	—	—	0.2980 (0.0043)	-0.3055 (0.0353)	-0.2980 (0.0043)	-0.2271 (0.0776)
SMSA (1 = center city)	—	—	—	—	0.1343 (0.0026)	0.1362 (0.0092)	0.1343 (0.0026)	0.1163 (0.0198)
Married (1 = married)	—	—	—	—	0.2928 (0.0037)	0.2941 (0.0072)	0.2928 (0.0037)	0.2804 (0.0141)
9 Year-of-birth dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8 Region-of-residence dummies	No	No	No	No	Yes	Yes	Yes	Yes
Age	—	—	0.1446 (0.0676)	0.1409 (0.0704)	—	—	0.1162 (0.0652)	0.1170 (0.0662)
Age-squared	—	—	-0.0015 (0.0007)	-0.0014 (0.0008)	—	—	-0.0013 (0.0007)	-0.0012 (0.0007)
$\chi^2$ [dof]	—	36.0 [29]	—	25.6 [27]	—	34.2 [29]	—	28.8 [27]

a. Standard errors are in parentheses. Sample size is 247,199. Instruments are a full set of quarter-of-birth times year-of-birth interactions. The sample consists of males born in the United States. The sample is drawn from the State, County, and Neighborhoods 1 percent samples of the 1970 Census (15 percent form). The dependent variable is the log of weekly earnings. Age and age-squared are measured in quarters of years. Each equation also includes an intercept.

Angrist and Krueger 1991: Table 5

**TABLE V**  
OLS AND TSLS ESTIMATES OF THE RETURN TO EDUCATION FOR MEN BORN 1930–1939: 1980 CENSUS<sup>a</sup>

Independent variable	(1) OLS	(2) TSLS	(3) OLS	(4) TSLS	(5) OLS	(6) TSLS	(7) OLS	(8) TSLS
Years of education	0.0711 (0.0003)	0.0891 (0.0161)	0.0711 (0.0003)	0.0760 (0.0290)	0.0632 (0.0003)	0.0806 (0.0164)	0.0632 (0.0003)	0.0600 (0.0299)
Race (1 = black)	—	—	—	—	-0.2575 (0.0040)	-0.2302 (0.0261)	-0.2575 (0.0040)	-0.2626 (0.0458)
SMSA (1 = center city)	—	—	—	—	0.1763 (0.0029)	0.1581 (0.0174)	0.1763 (0.0029)	0.1797 (0.0305)
Married (1 = married)	—	—	—	—	0.2479 (0.0032)	0.2440 (0.0049)	0.2479 (0.0032)	0.2486 (0.0073)
9 Year-of-birth dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8 Region-of-residence dummies	No	No	No	No	Yes	Yes	Yes	Yes
Age	—	—	-0.0772 (0.0621)	-0.0801 (0.0645)	—	—	-0.0760 (0.0604)	-0.0741 (0.0626)
Age-squared	—	—	0.0008 (0.0007)	0.0008 (0.0007)	—	—	0.0008 (0.0007)	0.0007 (0.0007)
$\chi^2$ [dof]	—	25.4 [29]	—	23.1 [27]	—	22.5 [29]	—	19.6 [27]

a. Standard errors are in parentheses. Sample size is 329,509. Instruments are a full set of quarter-of-birth times year-of-birth interactions. The sample consists of males born in the United States. The sample is drawn from the 5 percent sample of the 1980 Census. The dependent variable is the log of weekly earnings. Age and age-squared are measured in quarters of years. Each equation also includes an intercept.

Angrist and Krueger 1991: Table 6

**TABLE VI**  
OLS AND TSLS ESTIMATES OF THE RETURN TO EDUCATION FOR MEN BORN 1940–1949: 1980 CENSUS<sup>a</sup>

Independent variable	(1) OLS	(2) TSLS	(3) OLS	(4) TSLS	(5) OLS	(6) TSLS	(7) OLS	(8) TSLS
Years of education	0.0573 (0.0003)	0.0553 (0.0138)	0.0573 (0.0003)	0.0948 (0.0223)	0.0520 (0.0003)	0.0393 (0.0145)	0.0521 (0.0003)	0.0779 (0.0239)
Race (1 = black)	—	—	—	—	-0.2107 (0.0032)	-0.2266 (0.0183)	-0.2108 (0.0032)	-0.1786 (0.0296)
SMSA (1 = center city)	—	—	—	—	0.1418 (0.0023)	0.1535 (0.0135)	0.1419 (0.0023)	0.1182 (0.0220)
Married (1 = married)	—	—	—	—	0.2445 (0.0022)	0.2442 (0.0022)	0.2444 (0.0022)	0.2450 (0.0023)
9 Year-of-birth dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8 Region-of-residence dummies	No	No	No	No	Yes	Yes	Yes	Yes
Age	—	—	0.1800 (0.0389)	0.1325 (0.0486)	—	—	0.1518 (0.0379)	0.1215 (0.0474)
Age-squared	—	—	0.0023 (0.0006)	0.0016 (0.0007)	—	—	0.0019 (0.0005)	0.0015 (0.0007)
$\chi^2$ [dof]	—	101.6 [29]	—	49.1 [27]	—	93.6 [29]	—	50.6 [27]

a. Standard errors are in parentheses. Sample size is 486,926. Instruments are a full set of quarter-of-birth times year-of-birth interactions. Sample consists of males born in the United States. The sample is drawn from the 5 percent samples of the 1980 Census. The dependent variable is the log of weekly earnings. Age and age-squared are measured in quarters of years. Each equation also includes an intercept.

Angrist and Krueger 1991: Table 7

**TABLE VII**  
OLS AND TSLS ESTIMATES OF THE RETURN TO EDUCATION FOR MEN BORN 1930–1939: 1980 CENSUS<sup>a</sup>

Independent variable	(1) OLS	(2) TSLS	(3) OLS	(4) TSLS	(5) OLS	(6) TSLS	(7) OLS	(8) TSLS
Years of education	0.0673 (0.0003)	0.0928 (0.0093)	0.0673 (0.0003)	0.0907 (0.0107)	0.0628 (0.0003)	0.0831 (0.0095)	0.0628 (0.0003)	0.0811 (0.0109)
Race (1 = black)	—	—	—	—	-0.2547 (0.0043)	-0.2333 (0.0109)	-0.2547 (0.0043)	-0.2354 (0.0122)
SMSA (1 = center city)	—	—	—	—	0.1705 (0.0029)	0.1511 (0.0095)	0.1705 (0.0029)	0.1531 (0.0107)
Married (1 = married)	—	—	—	—	0.2487 (0.0032)	0.2435 (0.0040)	0.2487 (0.0032)	0.2441 (0.0042)
9 Year-of-birth dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8 Region-of-residence dummies	No	No	No	No	Yes	Yes	Yes	Yes
50 State-of-birth dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	—	—	-0.0757 (0.0617)	-0.0880 (0.0624)	—	—	-0.0778 (0.0603)	-0.0876 (0.0609)
Age-squared	—	—	0.0008 (0.0007)	0.0009 (0.0007)	—	—	0.0008 (0.0007)	0.0009 (0.0007)
$\chi^2$ [dof]	—	163 [179]	—	161 [177]	—	164 [179]	—	162 [177]

a. Standard errors are in parentheses. Excluded instruments are 30 quarter-of-birth times year-of-birth dummies and 150 quarter-of-birth times state-of-birth interactions. Age and age-squared are measured in quarters of years. Each equation also includes an intercept term. The sample is the same as in Table VI. Sample size is 329,509.