Weak instruments

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Weak instruments

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Bound, Jaeger, and Baker (1995) pointed out that the quarter of birth instruments explain only a tiny proportion of the variation in schooling. This leads to two distinct problems:

- The 2SLS estimator with weak instruments is biased in small samples.
- Any inconsisency from a small violation of the exclusion restriction gets magnified by weak instruments.

Start with the 2SLS small sample bias. To get an intuition for this situation, look at the simplest formulation of the IV problem:

$$y_i = \beta x_i + \eta_i$$
 (structural equation)
 $x_i = \pi_1 z_i + \xi_i$ (first stage)

The small sample behavior with one instrument

• If an instrument is basically irrelevant then $\pi_1 \approx 0$. Recall

$$\beta_{IV} = \frac{cov\left(y_i, z_i\right)}{cov\left(x_i, z_i\right)}$$

but

$$cov\left(x_{i}, z_{i}
ight) = cov\left(\pi_{1}z_{i} + \xi_{i}, z_{i}
ight) = \pi_{1}\sigma_{Z}^{2}$$

So if $\pi_1 = 0$,

$$cov(x_i, z_i) = 0$$

and the IV estimator doesn't exist.

 Even when π₁ is truly zero, in any finite sample the sample analogue to cov (x_i, z_i) will not be exactly zero. But this is of little comfort as the sampling variation in cov (x_i, z_i) is not helpful to estimate β.

The 2SLS bias with many instruments

With multiple instruments the first stage is:

$$x=Z\pi+\xi.$$

OLS estimates are biased because η_i is correlated with ξ_i . The instruments Z_i are uncorrelated with ξ_i by construction and uncorrelated with η_i by assumption. The 2SLS estimator is

$$\widehat{\beta}_{2SLS} = \left(x' P_Z x\right)^{-1} x' P_Z y = \beta + \left(x' P_Z x\right)^{-1} x' P_Z \eta$$

where $P_Z = Z(Z'Z)^{-1}Z'$ is the projection matrix that produces fitted values from a regression of x on Z. Substitute the first stage for x in $x'P_Z\eta$ to get

$$\widehat{\beta}_{2SLS} - \beta = (x'P_Z x)^{-1} (\pi' Z' + \xi') P_Z \eta$$

= $(x'P_Z x)^{-1} \pi' Z' \eta + (x'P_Z x)^{-1} \xi' P_Z \eta$

Group asymptotics

The expectation of this expression is hard to evaluate because the expectation operator does not pass through the inverse $(x'P_Zx)^{-1}$, a nonlinear function.

- Trick: group asymptotics. Still use an asymptotic argument but let the number of instruments grow at the same rate as the sample size. This "keeps the instruments weak."
- Group asymptotics gives us something like an expectation, it essentially says that we can take these expectations through non-linear functions anyway:

$$E[\widehat{\beta}_{2SLS} - \beta] \approx \left(E[x'P_Z x]\right)^{-1} E[\pi' Z'\eta] + \left(E[x'P_Z x]\right)^{-1} E[\xi' P_Z \eta].$$

This approximation is much better than the usual first-order asymptotic approximation invoked in large-sample theory, so it gives us a good measure of the finite-sample behavior of the 2SLS estimator. Remember the instruments Z_i are uncorrelated with ξ_i and η_i . Therefore $E[\pi' Z' \eta] = 0$, and we have

$$E[\widehat{\beta}_{2SLS} - \beta] \approx (E[x'P_Z x])^{-1} E[\pi' Z'\eta] + (E[x'P_Z x])^{-1} E[\xi'P_Z \eta]$$

= $(E[x'P_Z x])^{-1} E[\xi'P_Z \eta].$

Substitute in the first stage again.

$$E[\widehat{\beta}_{2SLS} - \beta] \approx \left(E[(\pi'Z' + \xi') P_Z (Z\pi + \xi)] \right)^{-1} E[\xi' P_Z \eta].$$

Note that $E[\pi' Z'\xi] = 0$, so we get no cross-terms:

$$E[\widehat{\beta}_{2SLS} - \beta] \approx \left[E\left(\pi' Z' Z \pi\right) + E(\xi' P_Z \xi) \right]^{-1} E\left(\xi' P_Z \eta\right).$$

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The 2SLS bias with many instruments

Matrix algebra trick: $\xi' P_Z \xi$ is a scalar, therefore equal to its trace; the trace is a linear operator which passes through expectations and is invariant to cyclic permutations; finally, the trace of P_Z , an idempotent matrix, is equal to it's rank, Q. Using these facts

$$E(\xi' P_Z \xi) = E[tr(\xi' P_Z \xi)]$$

= $E[tr(P_Z \xi \xi')]$
= $tr(P_Z E[\xi \xi'])$
= $tr(P_Z \sigma_{\xi}^2 I)$
= $\sigma_{\xi}^2 tr(P_Z)$
= $\sigma_{\xi}^2 Q,$

where we have assumed that ξ_i is homoskedastic. Similarly, applying the trace trick to $\xi' P_Z \eta$ shows that this term is equal to $\sigma_{\eta\xi}Q$.

The 2SLS bias with many instruments

Now we have

$$\begin{split} E[\widehat{\beta}_{2SLS} - \beta] &\approx \sigma_{\eta\xi} Q \left[E\left(\pi' Z' Z \pi\right) + \sigma_{\xi}^2 Q \right]^{-1} \\ &= \frac{\sigma_{\eta\xi}}{\sigma_{\xi}^2} \left[\frac{E\left(\pi' Z' Z \pi\right) / Q}{\sigma_{\xi}^2} + 1 \right]^{-1} \end{split}$$

Note that

$$F = \frac{E\left(\pi' Z' Z \pi\right) / Q}{\sigma_{\xi}^2}$$

is the population F-statistic for the joint significance of all regressors in the first stage regression and hence

$$E[\hat{\beta}_{2SLS} - \beta] \approx \frac{\sigma_{\eta\xi}}{\sigma_{\xi}^2} \frac{1}{F+1}.$$

.

Suppose the first stage coefficients π are truely zero. Then F = 0. Furthermore

$$\sigma_x^2 = \sigma_{\xi}^2.$$

Hence

$$\mathsf{E}[\widehat{\beta}_{2SLS} - \beta] \approx \frac{\sigma_{\eta\xi}}{\sigma_x^2}$$

but this is just the bias in the OLS estimator, since

$$\beta_{OLS} = \frac{cov(y_i, x_i)}{var(x_i)} = \frac{cov(\beta x_i + \eta_i, x_i)}{var(x_i)}$$
$$= \beta + \frac{cov(\eta_i, x_i)}{var(x_i)} = \frac{\sigma_{\eta\xi}}{\sigma_x^2}$$

since $cov(\eta_i, x_i) = \sigma_{\eta\xi}$ if $\pi = 0$.

Where does this come from?

- If π is truly zero, then any variation in x̂_i in the sample just comes from ζ_i. So, the variation in x̂_i is no different from the variation in x_i, and hence OLS and 2SLS have to estimate the same quantity on average.
- If π is not truly zero but F is small, then 2SLS will be biased towards OLS.

The weak instrument bias tends to get worse as we add more (weak) instruments. To see this consider

$$F = \frac{E\left(\pi' Z' Z \pi\right) / Q}{\sigma_{\xi}^2}$$

Suppose you have some existing instruments, and you add new ones with no additional exploratory power. I.e. the π coefficients on the additional instruments will be zero.

- $\pi' Z' Z \pi$ will remain the same as before adding more instruments.
- Since the first stage regression is unchanged by the additional instruments, $\sigma_{\tilde{c}}^2$ will also remain the same.
- Q will go up.

As a result, F will go down, and the 2SLS bias will get worse.

With weak instruments

- 2SLS is biased towards OLS.
- The bias will tend to be worse when there are many overidentifying restrictions (many instruments compared to endogenous regressors).
- Just identified IV is approximately unbiased (or less biased) even with weak instruments (although it is not possible to see this from the bias formula).
- Estimated standard errors of 2SLS and IV estimators may be too small.

- There are alternative estimators, which have better small sample properties than 2SLS with weak instruments. One such estimator is *LIML* (limited information maximum likelihood).
- LIML is a linear combination of the OLS and 2SLS estimate (with the weights depending on the data), and the weights happen to be such that they (approximately) eliminate the 2SLS bias.

Simulate data from the following model

$$egin{array}{rcl} y_i &=& eta x_i + eta_i \ x_i &=& \sum_{j=1}^Q \pi_j z_{ij} + eta_i \end{array}$$

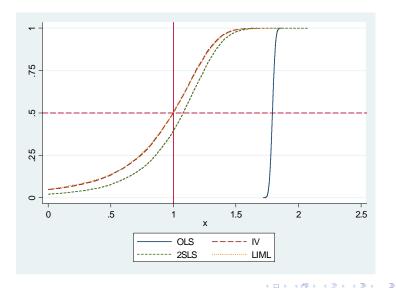
with eta=1, $\pi_1=$ 0.1, $\pi_j=$ 0 for j= 2, ..., Q,

$$\left(\begin{array}{c} \eta_i \\ \xi_i \end{array} \right) \bigg| \, Z \sim \mathit{N} \left(\left(\begin{array}{c} 0 \\ 0 \end{array} \right), \left(\begin{array}{c} 1 & 0.8 \\ 0.8 & 1 \end{array} \right) \right),$$

where the z_{ij} are independent, normally distributed random variables with mean zero and unit variance. The sample size is 1000.

Monte Carlo Results

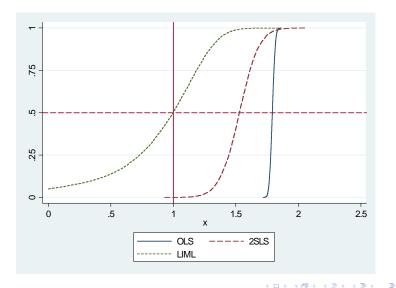
2SLS, LIML: 2 instruments, IV: one instrument



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Monte Carlo Results

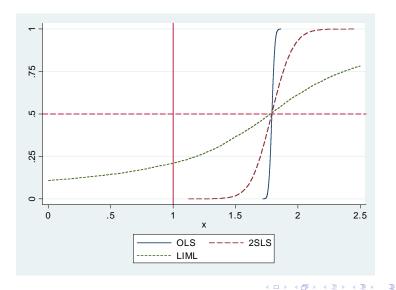
20 instruments



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Monte Carlo Results

20 garbage instruments



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What should you do in practice?

- Report the first stage and think about whether it makes sense. Are the magnitude and sign as you would expect?
- Report the *F*-statistic on the excluded instruments. The bigger this is, the better. *F*s above 10 to 20 are considered relatively safe, lower *F*s put you in the danger zone.
- Pick your best single instrument and report just-identified estimates using this one only. Just-identified IV is approximately median-unbiased.
- Check over-identified 2SLS estimates with LIML. If the LIML estimates are very different, or standard errors are much bigger, worry.
- Look at the coefficients, *t*-statistics, and *F*-statistics for excluded instruments in the reduced-form regression of dependent variables on instruments. The reduced-form estimates are just OLS, so don't have the same bias problem. If the relationship you expect is not in the reduced form, it's probably not there.

 TABLE 4.6.2

 Alternative IV estimates of the economic returns to schooling

| | | | | | • | |
|---|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 2SLS | .105 | .435 | .089 | .076 | .093 | .091 |
| LIML | (.020) .106 (.020) | (.450) .539 (.627) | (.016) .093 (.018) | (.029) .081 (.041) | (.009) .106 (.012) | (.011) .110 (.015) |
| F-statistic (excluded instruments) | 32.27 | .42 | 4.91 | 1.61 | 2.58 | 1.97 |
| <i>Controls</i> Year of birth State of birth | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark |
| Age, age squared | | \checkmark | | \checkmark | V | \checkmark |
| <i>Excluded instruments</i> Quarter-of-birth dummies | \checkmark | \checkmark | | | | |
| Quarter of birth*year of birth Quarter of birth*state of birth | | | \checkmark | \checkmark | \checkmark | \checkmark |
| Number of excluded instruments | 3 | 2 | 30 | 28 | 180 | 178 |

New developments James Stock/Isaiah Andrews NBER minicourse

- Previous results depend heavily on homoskedasticity
- Use Montiel-Olea-Pflueger (2013) F-statistic
 - Screening on F-statistic not necessarily recommended
- For weak instruments, use weak instrument robust inference
- LIML or other alternative estimators aren't necessarily better than 2SLS
- Different IV estimators can have different LATEs

http://www.nber.org/econometrics_minicourse_2018/

New developments

Alwyn Young "Consistency Without Inference: Instrumental Variables in Practical Application." June 2018

Abstract: I use Monte Carlo simulations, the jackknife and bootstrap to study a sample of 1359 IV regressions in 31 papers published in the journals of the AEA. Monte Carlo simulations based upon published regressions show that non-iid error processes adversely affect the size and power of IV estimates, while increasing the bias of IV relative to OLS, producing a very low ratio of power to size and mean squared error that is almost always larger than biased OLS. Weak instrument pre-tests based upon F-statistics are found to be largely uninformative of both size and bias. In published papers, statistically significant IV results generally depend upon only one or two observations or clusters, excluded instruments often appear to be irrelevant, there is little statistical evidence that OLS is actually substantively biased, and IV confidence intervals almost always include OLS point estimates.

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- In general, we do not believe that any of the assumptions we are making in statistics are literally true. But we typically proceed if we think our assumptions are "pretty good."
- Is "pretty good" enough for the exclusion restriction? Suppose we have a candidate instrument Z_i for a regressor D_i . Write

$$y_i = \alpha + \rho D_i + \gamma Z_i + e_i$$

$$D_i = \pi_0 + \pi_1 Z_i + \xi_i.$$

The exclusion restriction amounts to the assumption $\gamma = 0$.

Weak instruments and the exclusion restriction

What happens if $\gamma = \gamma_0 \neq 0$?

$$\rho_{IV} = \frac{\cos\left(\alpha + \rho D_i + \gamma_0 Z_i + e_i, Z_i\right)}{\cos\left(D_i, Z_i\right)}$$
$$= \frac{\rho \cos\left(D_i, Z_i\right) + \gamma_0 \sin\left(Z_i\right)}{\cos\left(D_i, Z_i\right)}$$
$$= \rho + \gamma_0 \frac{\sin\left(Z_i\right)}{\cos\left(D_i, Z_i\right)} = \rho + \frac{\gamma_0}{\pi_1}$$

- The IV estimate of ho is biased, the bias is γ_0/π_1 .
- The bias is larger in absolute value the closer π₁ is to zero. I.e. the bias is worse with weak instruments.
- With π_1 very close to zero, a very small violation of the exclusion restriction can lead to a large (asymptotic) bias.

Can violation of the exclusion restriction explain AK91?

- School starting age (SSA) is a candidate violation of the exclusion restriction. Individuals born in quarter 4 start school younger.
- The best paper on school starting age is Black, Devereux, and Salvanes, "Too Young to Leave the Nest?" *REStat* 2011 for Norway. They find an effect on log earnings of -0.1 at age 25, -0.01 (not significant) at age 30, 0.0 at age 35, suggesting SSA works through lost labor market experience. (AK91 sample is in their 40s.)
- To play with the numbers:
 - $\pi_1 = 0.09$, this is the difference in schooling between quarter 4 and other quarters
 - Those born in quarter 4 start school about 6 months younger, or -0.5 of a year.
 - γ_0 is the effect of school starting age on earnings. Using the age 30 γ_0 of -0.01

$$\frac{\gamma_0}{\pi_1} = \frac{-0.01 * -0.5}{0.09} = 0.055$$

Violations of random assignment

Suppose control X_i is necessary for random assignment of instrument Z_i .

$$y_i = \alpha + \rho D_i + \gamma X_i + e_i$$

$$D_i = \pi_0 + \pi_1 Z_i + \pi_2 X_i + \xi_i$$

What happens if $\gamma \neq 0$ but we omit X_i ?

$$\rho_{IV} = \frac{\cot (\alpha + \rho D_i + \gamma X_i + e_i, Z_i)}{\cot (D_i, Z_i)}$$
$$= \frac{\rho \cot (D_i, Z_i) + \gamma \cot (X_i, Z_i)}{\cot (D_i, Z_i)}$$
$$= \rho + \gamma \frac{\cot (X_i, Z_i)}{\cot (D_i, Z_i)}$$

This looks like and is an omitted variables bias formula. The standard OLS coefficient $cov(X_i, D_i) / var(D_i)$ is being replaced by it's IV analogue: for the auxiliary regression run X_i on D_i and instrument by $Z_{i \circ n \circ n}$

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Can violation of random assignment explain AK91?

• Magnitude: The bias is equal to

$$\gamma \frac{\text{cov}(X_i, Z_i)}{\text{cov}(D_i, Z_i)} = \gamma \frac{E[SES_i | Q4_i = 1] - E[SES_i | Q4_i = 0]}{E[S_i | Q4_i = 1] - E[S_i | Q4_i = 0]}$$

- γ is the effect of SES_i on child's earnings. Intergenerational correlations are about 0.4.
- The top is the difference in SES_i; BJB report family income between first and other quarter births differs by about 2%, so this is 0.02.
- The bottom is 1st stage with one instrument, 0.09.

$$\gamma \frac{E\left[SES_i | Q1_i = 1\right] - E\left[SES_i | Q1_i = 0\right]}{E\left[S_i | Q4_i = 1\right] - E\left[S_i | Q4_i = 0\right]} = 0.4 \frac{0.02}{0.09} = 0.088$$

- Pattern: Buckles and Hungerman (2008): Data on mother's education and month of birth.
 - Patterns don't line up: kid's schooling peaks in quarter 4 (Oct Dec), mother's schooling peaks in May.

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