Instrumental Variable III

Ye Wang
University of North Carolina at Chapel Hill

Linear Methods in Causal Inference
POLI784

Review

- The previous lecture focuses on the economic tradition of using IVs.
- It is seen as an exogenous factor that may affect an agent's rational choice in the triangular system.
- Common approaches to use an IV include two-stage least squares, control function, and GMM.
- There exists a deep connection between an IV and non-compliance conceptually.
- Results from 2SLS can be identical to that from the Wald estimator under certain conditions.

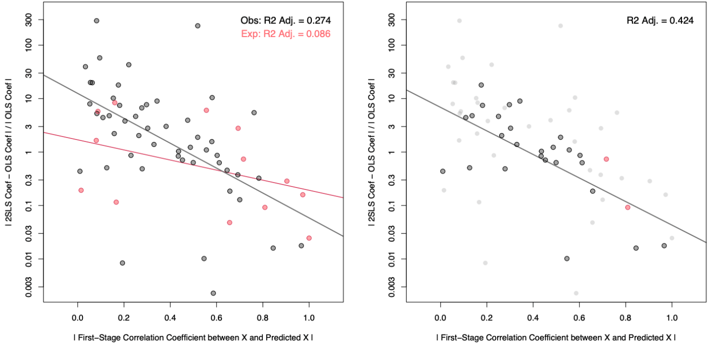
Testing assumptions in IV estimation

- We have seen that the LATE framework and the triangular system rely on similar assumptions:
  1. random assignment of the instrument.
  2. exclusion restriction.
  3. first stage.
  4. monotonicity.
- It is easier to ensure that all these assumptions are satisfied in experiments.
- In observational studies, these assumptions are less plausible.
- It explains why IV is becoming less popular in observational studies.
- Testing their validity is necessary.

Weak instruments

- Let's start from an assumption that seems easy to be satisfied: first stage.
- Remember that $\hat{\tau} = \frac{\hat{\xi}}{\hat{\delta}}$.
- If Z_i and D_i are only weakly correlated, $\hat{\delta}$ will be close to zero and the finite sample bias of $\hat{\tau}$ will be huge.
- The bias may even larger than that from OLS.
- Lal et al. (2023) show that this is a common problem in political science.
- The difference between 2SLS and OLS is larger when the IV is weaker.

Weak instruments



(a) Full Sample

(b) Subsample with Significant OLS Results

Weak instruments

- A well-known example is Angrist and Krueger (1991).
- They instrument students' schooling years with their season of birth.
- But the correlation between the two variables is very weak.
- Bound, Jaeger, and Baker (1995) show that replacing the actual season of birth with randomly assigned ones does not change the estimate.

Weak instruments

- The confidence intervals of $\hat{\tau}$ will not have the correct coverage when the IV is weak.
- A traditional rule of thumb for a strong IV is that $F = \frac{\hat{\delta}^2}{\widehat{V}(\hat{\delta})}$ is larger than 10 (Staiger and Stock 1997).
- If there are multiple instruments, we should test the joint null hypothesis that all these coefficients are zero.
- Yet Lee et al. (2022) show that this is not sufficient.
- If we impose no restrictions on the DGP, F must be larger than 104.7 to ensure the correct coverage.
- Or we use the critical value of 3.43.

Weak instruments

- Intuitively, the distribution of $\hat{\tau}$ deviates from normality significantly if $\hat{\delta}$ is not distinguishable from zero.
- The degree of deviation hinges on the value of F.
- There are several solutions to this problem.
- Anderson and Rubin (1949) propose to test the null hypothesis $\xi = \xi_0 = \delta\tau_0$ instead of $\tau = \tau_0$.
- We can see that $\hat{\xi} - \hat{\delta}\tau_0 \rightarrow \mathcal{N}(0, \Sigma)$ under the null, where

$$\Sigma = Var[\hat{\xi}] - 2\tau_0 Cov[\hat{\delta}, \hat{\xi}] + \tau_0^2 Var[\hat{\delta}].$$

- Such a test is valid even when $\hat{\delta}$ is zero.

Weak instruments

- The Anderson-Rubin (AR) test avoids the issue of taking the ratio but the result is hard to interpret.
- Lee et al. (2022) note the following relationship

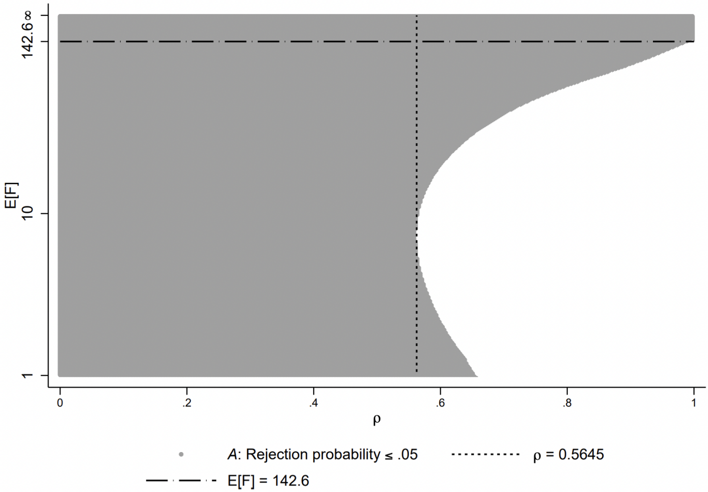
$$t^2 = \frac{t_{AR}^2}{1 - 2\rho \frac{t_{AR}}{F} + \frac{t_{AR}^2}{F^2}},$$

  where ρ is the correlation between ν_i and ε_i.
- The relative performance of the t-test to the AR test is decided by the value of F.
- They hence suggest that we should combine the tests from the first stage and the second stage.
- For each value of F, they provide the corresponding critical value in the second stage.
- Or, we can impose more restrictions on the DGP, such as ρ.

Weak instruments

- Lee et al. (2022) show the rejection rate under different combinations of the parameters:

Figure 3: Values for ρ and $E[F]$ for which $|t| > 1.96$ is valid



Weak instruments: application

```
## The 2SLS estimate is 2.989306

## The first-stage F-statistic value is: 179.525

## The p-value from the Anderson-Rubin test is: 7.549517e-1
```

Test exclusion restriction

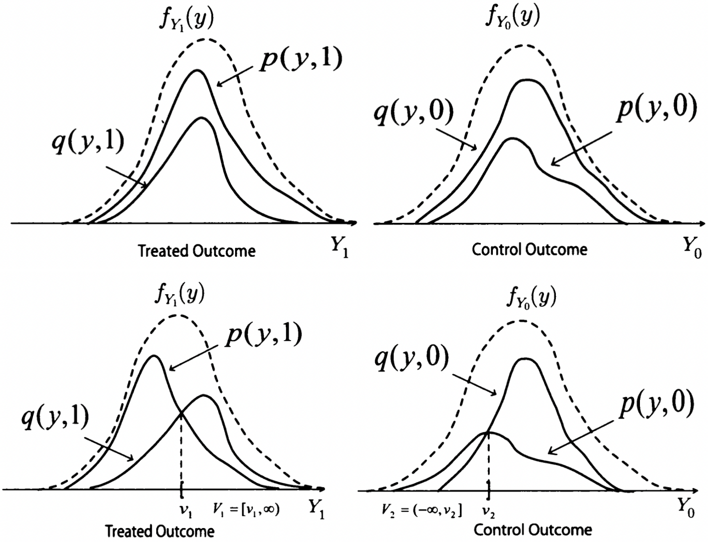
- Kitagawa (2015) and Huber and Mellace (2015) suggest that we may test exclusion restriction and monotonicity altogether.
- These two assumptions imply that

$$P(y, D = 1|Z = 1) > P(y, D = 1|Z = 0)$$
$$P(y, D = 0|Z = 1) < P(y, D = 0|Z = 0)$$

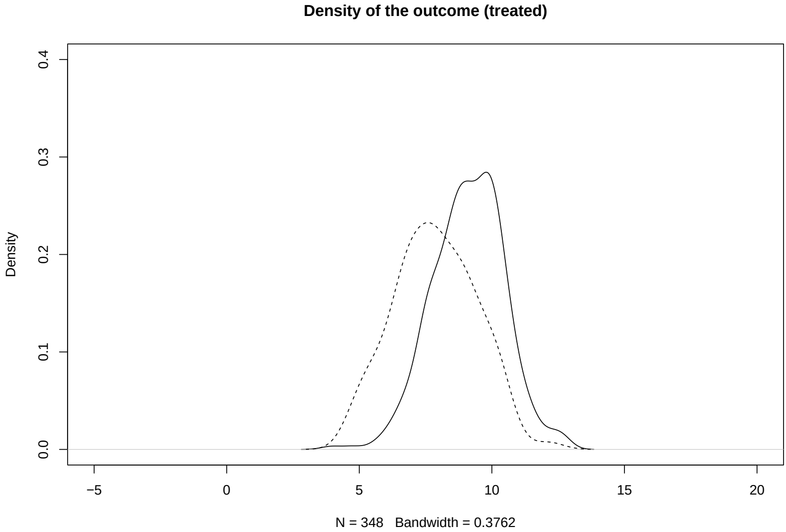
  for all y.
- We can test these two inequalities with data.
- To obtain critical values, we need to construct a variance-weighted Kolmogorov-Smirnov test statistic and apply bootstrap to it.
- But visualization alone can be helpful.

Test exclusion restriction

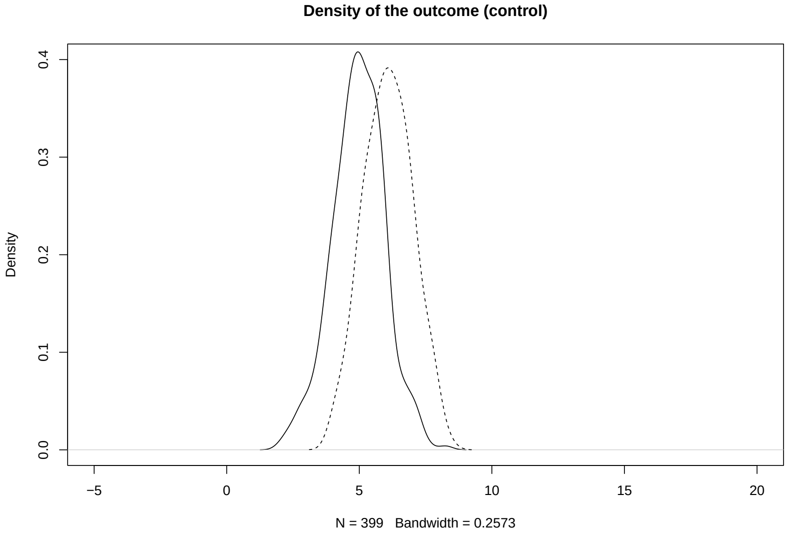
- We want to see the plots on the top rather than the ones on the bottom:



Test exclusion restriction: application



Test exclusion restriction: application



Exclusion restriction in practice

- It is common that exclusion restriction is violated in observational studies.
- Two popular instrumental variables in practice are rainfall and distance to the location where an event happened.
- Sarsons (2015) demonstrates that in Indian areas with dams, rainfall still affects conflicts even though it is not correlated with income.
- Zhao (2023) shows that using distance to any German city as the instrument can replicate the results in Becker and Woessmann (2009).
- The problem is that excluding all the other channels is more difficult than we thought.
- Glaeser et al. (2004) suggest that settlers' mortality may also influence the level of human capital in former colonies.

Nonparametric estimation with IVs

- Generalizing the LATE framework to scenarios with continuous treatments or instruments is challenging.
- Consider the most general triangular system:

$$
\begin{aligned}
Y_i &= m(D_i, \varepsilon_i), \\
D_i &= g(Z_i, \nu_i), \\
Z_i &\perp \nu_i, \varepsilon_i \not\perp \nu_i.
\end{aligned}
$$

- In practice, we need to assume either the separability between the unobservables and observable variables (Newey and Powell 2003) or the unidimensionality of ν_i (Imbens and Newey 2009).
- The basic idea is to generalize the control function method.
- If we allow for treatment effect heterogeneity but estimate the LATE with 2SLS, the result will be a convex combination of individualistic treatment effects (Angrist and Imbens 1995)
- We have an expert next door (Kédagni and Mourifié 2020).

Generalizing the LATE

- It is reasonable to assume that the principal strata are determined by observable attributes of units.
- Abadie (2003) proposes a statistic (Abadie's κ):

$$\kappa_i = 1 - \frac{D_i(1-Z_i)}{P(Z_i = 0|\mathbf{X}_i)} - \frac{(1-D_i)Z_i}{P(Z_i = 1|\mathbf{X}_i)}.$$

- He shows that for any function $g(Y_i, D_i, \mathbf{X}_i)$,

$$\begin{aligned} &E[g(Y_i, D_i, \mathbf{X}_i)|D_i(1) > D_i(0)] \\ =&\frac{1}{P(D_i(1) > D_i(0))} E[\kappa_i g(Y_i, D_i, \mathbf{X}_i)]. \end{aligned}$$

- It means that we can estimate the average of any statistic over compliers by calculating its average weighted by κ_i.

Compliance score

- Under the same assumption, we can explicitly model the relationship between principal strata and covariates.
- We define $q_{ic} = q_c(\mathbf{X}_i)$ as the compliance score (Aronow and Carnegie 2013).
- We need to impose assumptions on the form of $q_c(\mathbf{X}_i)$.
- To estimate the ATE, we weight each observation with $\frac{1}{q_{ic}}$ and apply the Wald estimator.
- The intuition resembles the IPW estimator.

Compliance score

- Let's assume that

$$\begin{aligned} q_a(\mathbf{X}_i) + q_c(\mathbf{X}_i) &= h(\mathbf{X}_i \beta_{a,c}), \\ \frac{q_a(\mathbf{X}_i)}{q_a(\mathbf{X}_i) + q_c(\mathbf{X}_i)} &= h(\mathbf{X}_i \beta_{a|(a,c)}), \end{aligned}$$

- We observe (D_i, Z_i) in the data with the likelihood

$$\prod_{i=1}^{N} (h(\mathbf{X}_i\beta_{a,c})(1 - h(\mathbf{X}_i\beta_{a|(a,c)}))Z_i + h(\mathbf{X}_i\beta_{a,c})h(\mathbf{X}_i\beta_{a|(a,c)}))^{D_i} *$$
$$(1 - h(\mathbf{X}_i\beta_{a,c})(1 - h(\mathbf{X}_i\beta_{a|(a,c)}))Z_i - h(\mathbf{X}_i\beta_{a,c})h(\mathbf{X}_i\beta_{a|(a,c)}))^{(1-D_i)}$$

- We estimate $\beta_{a,c}$ and $\beta_{a|(a,c)}$ via MLE and obtain the compliance score.

References I

Abadie, Alberto. 2003. "Semiparametric Instrumental Variable Estimation of Treatment Response Models." *Journal of Econometrics* 113 (2): 231–63.

Anderson, Theodore W, and Herman Rubin. 1949. "Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations." *The Annals of Mathematical Statistics* 20 (1): 46–63.

Angrist, Joshua D, and Guido W Imbens. 1995. "Two-Stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity." *Journal of the American Statistical Association* 90 (430): 431–42.

Angrist, Joshua D, and Alan B Krueger. 1991. "Does Compulsory School Attendance Affect Schooling and Earnings?" *The Quarterly Journal of Economics* 106 (4): 979–1014.

Aronow, Peter M, and Allison Carnegie. 2013. "Beyond LATE: Estimation of the Average Treatment Effect with an Instrumental Variable." *Political Analysis*, 492–506.

References II

Becker, Sascha O, and Ludger Woessmann. 2009. "Was Weber Wrong? A Human Capital Theory of Protestant Economic History." *The Quarterly Journal of Economics* 124 (2): 531–96.

Bound, John, David A Jaeger, and Regina M Baker. 1995. "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable Is Weak." *Journal of the American Statistical Association* 90 (430): 443–50.

Glaeser, Edward L, Rafael La Porta, Florencio Lopez-de-Silanes, and Andrei Shleifer. 2004. "Do Institutions Cause Growth?" *Journal of Economic Growth* 9: 271–303.

Huber, Martin, and Giovanni Mellace. 2015. "Testing Instrument Validity for LATE Identification Based on Inequality Moment Constraints." *Review of Economics and Statistics* 97 (2): 398–411.

References III

Imbens, Guido W, and Whitney K Newey. 2009. "Identification and Estimation of Triangular Simultaneous Equations Models Without Additivity." *Econometrica* 77 (5): 1481–1512.

Kédagni, Désiré, and Ismael Mourifié. 2020. "Generalized Instrumental Inequalities: Testing the Instrumental Variable Independence Assumption." *Biometrika* 107 (3): 661–75.

Kitagawa, Toru. 2015. "A Test for Instrument Validity." *Econometrica* 83 (5): 2043–63.

Lal, Apoorva, Mac Lockhart, Yiqing Xu, and Ziwen Zu. 2023. "How Much Should We Trust Instrumental Variable Estimates in Political Science? Practical Advice Based on over 60 Replicated Studies." *arXiv Preprint arXiv:2303.11399*.

Lee, David S, Justin McCrary, Marcelo J Moreira, and Jack Porter. 2022. "Valid t-Ratio Inference for IV." *American Economic Review* 112 (10): 3260–90.

References IV

Newey, Whitney K, and James L Powell. 2003. "Instrumental Variable Estimation of Nonparametric Models." *Econometrica* 71 (5): 1565–78.

Sarsons, Heather. 2015. "Rainfall and Conflict: A Cautionary Tale." *Journal of Development Economics* 115: 62–72.

Staiger, Douglas, and James H Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica: Journal of the Econometric Society*, 557–86.

Zhao, Qiyi C. 2023. "Rethinking'distance from': Lessons from Wittenberg and Mainz." *Available at SSRN 4495711*.