Instrumental Variables Models

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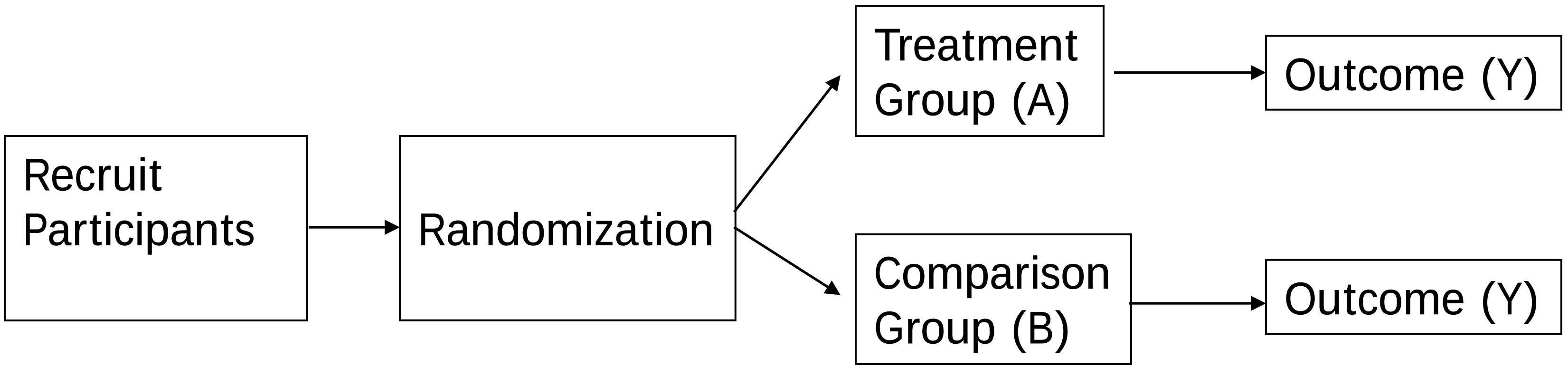
Outline

1. Causation Review
2. The IV approach
3. Examples
4. Testing the Instruments
5. Limitations

Causation

- Randomized trial provides the structure for understanding causation
  - Does daily dark chocolate affect health?
  - Does PT treatment following hip fracture reduce the risk of death?

RCT Review


Recruit Participants
Randomization
Treatment Group (A)
Comparison Group (B)
Outcome (Y)
Outcome (Y)

Randomization

- In OLS ($y_i = \alpha + \beta x_i + \varepsilon_i$)
  - The x's explain the variation in y
  - ε = the random error
  - Randomization assumes a high probability that the two groups are similar

However

- Randomized trials may be
  - Unethical
  - Infeasible
  - Impractical
  - Not scientifically justified

Observational Studies

- Natural Experiment
- Administrative Data
- Many observable characteristics (e.g. age, gender, smoking status) can be included in the model, BUT…….

Observational Studies

- Non-randomized groups differ in both observed AND unobserved characteristics

Unobserved characteristics….

- Covariates or confounders that may skew the data
- Can lead to violations of the assumptions of OLS
- Can lead to bias in the results
- Faulty inference of causality

The IV approach

- When randomization does not produce even distribution of characteristics

Mortality after AMI = *fn* (cardiac cath.) + other var.

- Does more intensive treatment of AMI in the elderly reduce mortality (McClellan; McNeil; Newhouse. JAMA. 9/21/94)
  - Elderly patients
  - Medicare claims data
  - Survival 4 years after AMI

Even distribution of observed?

	No Cath	Cath w/in 90 d.
Female	53.5%	39.7%
Age in years	77.4	71.6
Black	6.0%	4.3%
Cancer	2.2%	0.8%
Pulm. disease (uncompl.)	11.1%	9.3%
Dementia	1.2%	0.1%
Diabetes	18.3%	17.1%
Renal dis. (uncompl.)	2.3%	0.7%
CV disease	5.4%	2.8%

Even distribution of observed?

	No Cath	Cath w/in 90 days
Admit to cath/revasc hospital	40.9%	62.9%
One day mortality	10.3%	.9%
7-day Mortality	22.0%	3.3%
30-day mortality	26.6%	7.4%
1-year mortality	47.1%	16.6%
2-year mortality	55.3%	21.3%
4-year mortality	66.7%	29.9%
No. of observations	158,261	46,760

Mortality differences (adjusted)*

Mortality	Unadjusted Differences	Adj. for demographic characteristics	Adj. for demographic and co-morbidity differences
One day	-9.4 (0.2)	-6.7 (0.2)	-6.8(0.2)
7-day	-18.7 (0.2)	-13.7 (0.2)	-13.5(0.2)
30-day	-19.2 (0.3)	-18.7 (0.3)	-17.9 (0.3)
1-year	-30.5 (0.3)	-26.0 (0.3)	-24.1 (0.3)
2-year	-34.0 (0.3)	-28.7 (0.3)	-26.6 (0.3)
4-year	-36.8 (0.3)	-30.4 (0.3)	-28.1 (0.3)

*ANOVA

The IV approach

- When randomization does not produce even distribution of characteristics
- When unmeasured/unobserved characteristics potentially skew results

Unmeasured/unobserved characteristics….

- Are there differential/varying reasons why some patients receive care
  - Do sicker patients get treatment ?
  - Does distance from a hospital determine treatment?
  - Do certain physicians prefer specialty treatments?

Unobserved characteristics…..

- Are there differential determinants of *return for f/u care*
  - Economic/financial issues
  - Distance and transportation
  - Other insurance?

Choosing the IV

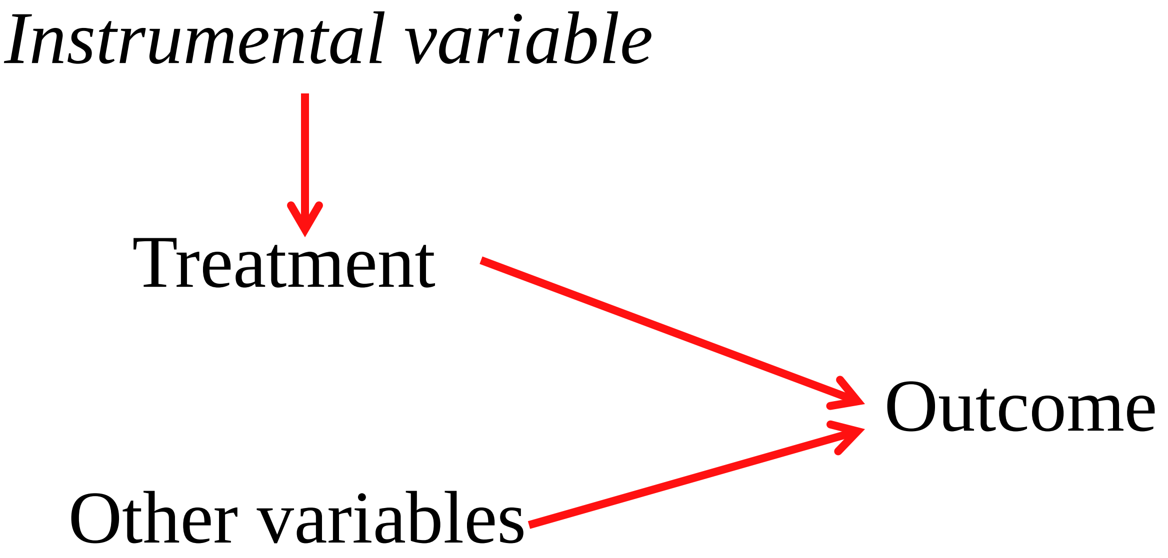
- Face validity
- Exogenous
- Strong predictor
- Just identified

Face validity

- Irrefutable relationship to treatment

Exogenous

- No direct or indirect effect on outcome



Strong Predictor

- Cause substantial variation in the variable of interest

Just identified

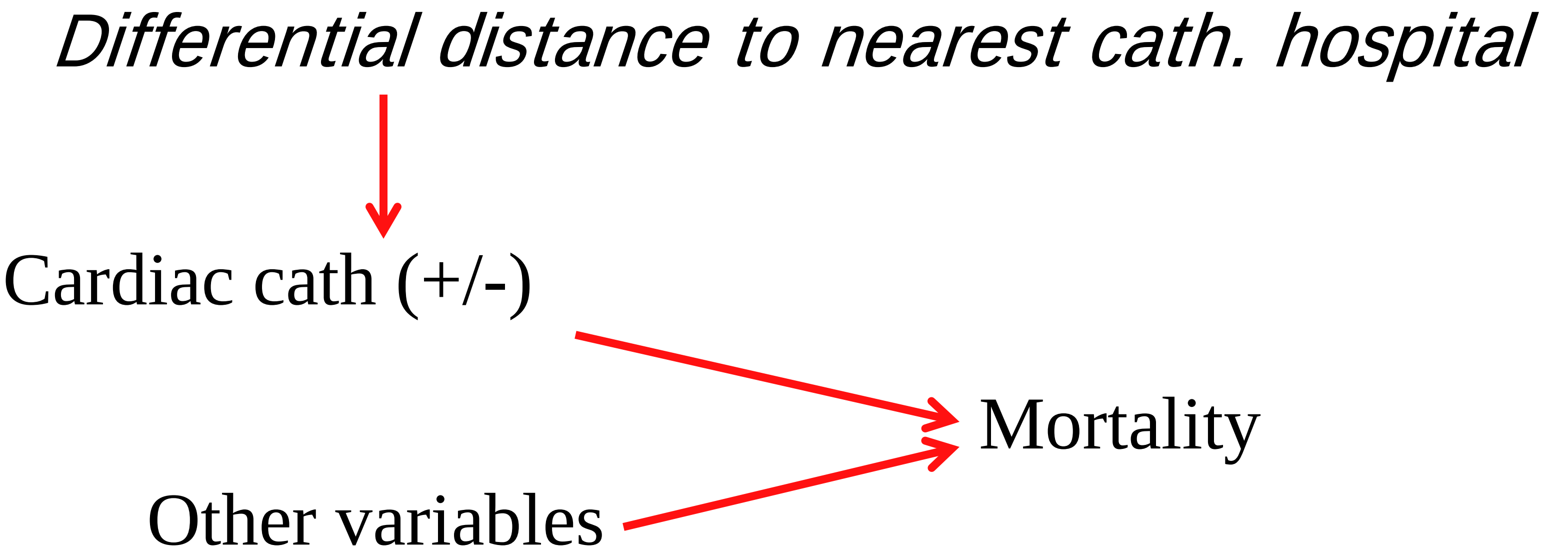
- Number of IVs $\leq$ number of exogenous variables

Example

- Mortality = *fn*(cath)
- What's missing?

Mortality after AMI = *fn* (cardiac cath.) + other var.

- No direct or indirect effect on outcome



Face validity

- Differential distance between nearest hospital and nearest catheterization facility/hospital
  - Pts w/AMI will go to nearest hospital
  - Distance from nearest hospital to nearest cath hospital will be independently predictive of catheterization for similar patients.

Strong predictor

	DD ≤ 2.5 miles	DD > 2.5 miles
Female	51.3%	49.5%
Age	76.1	76.1
Admit to cath hospital	45.4%	5.0%
90 day cath	26.2%	19.5%
1-day mortality	7.5%	8.88%
7-day mortality	16.80%	18.59%
30-day mortality	24.86%	26.35%
1-year mortality	39.79%	40.54%
2-year mortality	47.20%	47.89%
4-year mortality	58.06%	58.52%
No. of observations	102,516	102,505

Results w/DD IV

- That variation in IV causes variation in the treatment variable (cath) is satisfied
  - 26.2-19.5 = 6.75% point greater chance of getting cath within 90 days following AMI when differential distance is <=2.5 miles

Multiple regression results

- Patient characteristics
- Three IVs
  - High volume hospital (1,0),
  - Rural residence (1,0)
  - DD IV

Multiple regression w/IV results

	Rec'd cath	Admit hi-volume	Rural residence
1-day mortality	-5.0(1.1)*	-.88 (0.24)	0.57 (0.19)
7-day mortality	-8.0(1.8)	-1.23 (0.33)	0.49(0.26)
30-day mortality	-6.8(2.6)	-1.45(0.38)	0.50 (0.30)
1-year mortality	-4.8(3.2)	-1.07(0.88)	-0.15 (0.33)
2-year mortality	-5.4(3.3)	-.88 (0.43)	-0.02 (0.33)
4-year mortality	-5.1(3.2)	-.75 (0.42)	0.14 (0.32)

* In percentage points, standard errors in parens.

Summary of results

- Unadjusted – 37 % points effect on four year mortality
- Adjusted w/out IV – 28 % points effect
- Adjusted w/DD IV – 6.9 % points effect
- Adjusted with DD, high volume hospital and rural IVs – approx 5 percentage pts.

Interpretation

- Beneficial effects on mortality
  - (5.0 percentage points)
- At day one…
  - before the procedure could have any beneficial effect.
- Interpretation…is likely due to something other than cath

Examples

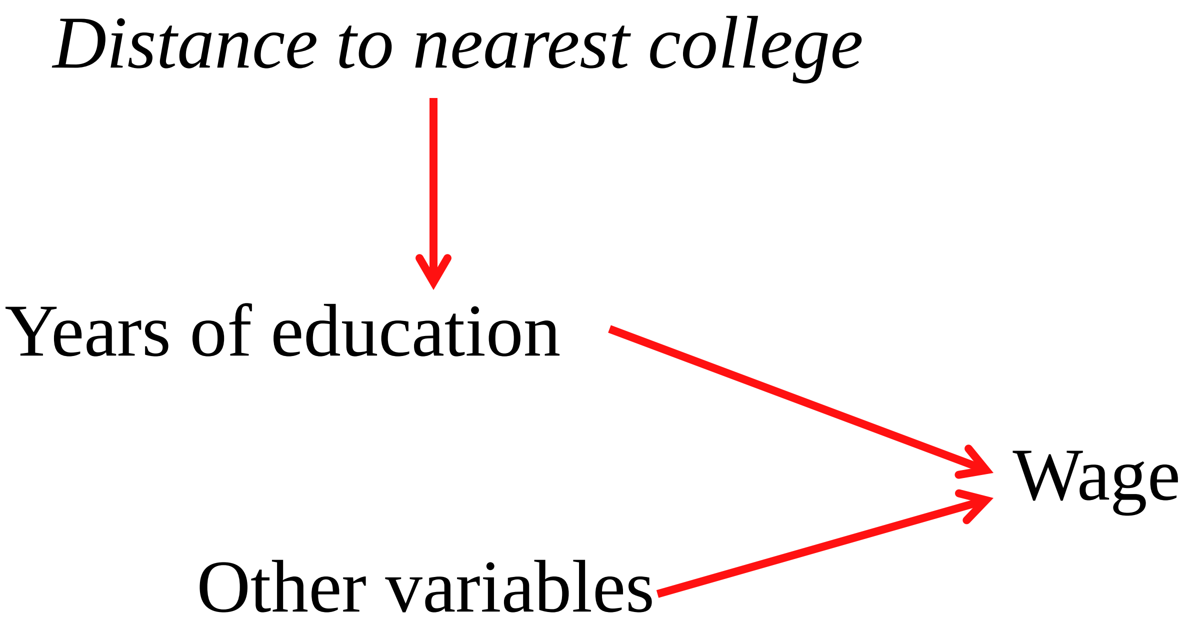
- Wage = *fn* (years of education) + ?
- School performance = *fn* (class size) + ?

IV Example

- Wage = *fn* (years of education) + ?
- What instrument ?
  - Years of education, but not ability nor wage

Wage = fn(years of education) + ability

- No direct or indirect effect on outcome

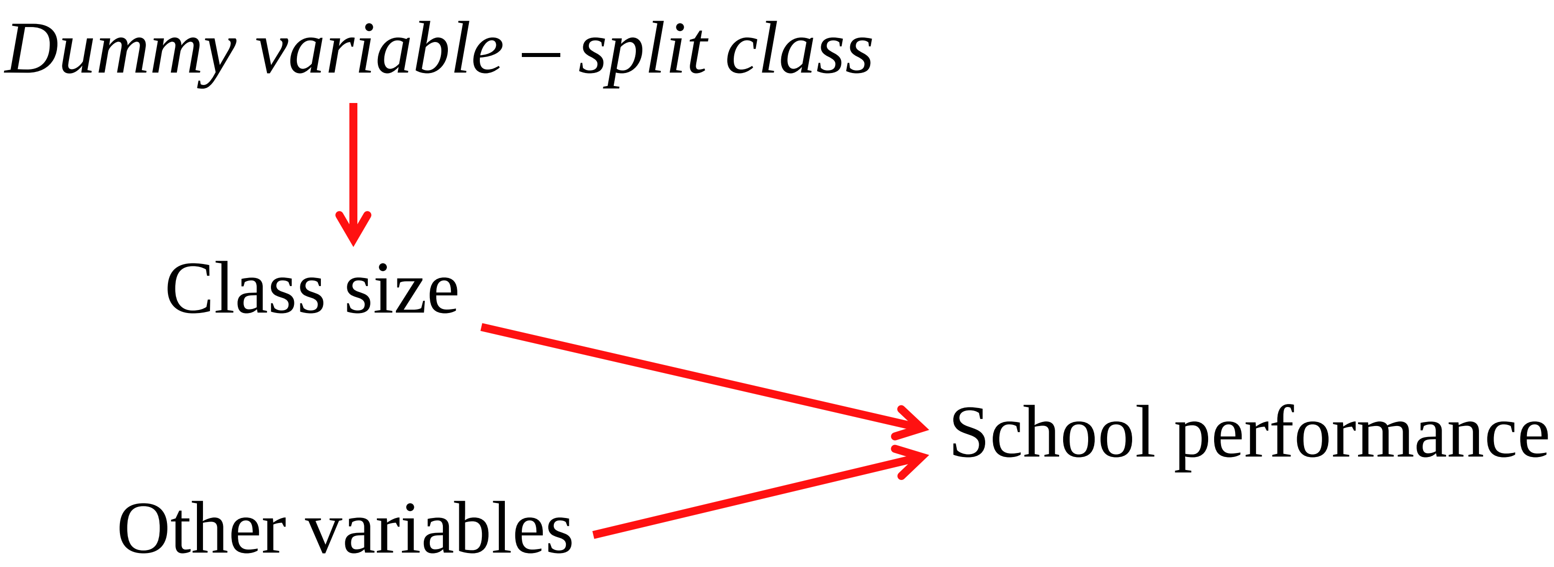


Example

- School performance = *fn* (class size)
- What's missing?

School performance = fn(class size)

- No direct or indirect effect on outcome



Inference

- RCT provides the average effect for the population eligible for the study

Inference

- Wide angle view of the effects of treatment
  - More general population than RCT
  - External validity
- Marginal effect on a selection of the population:
  - Problematic for clinicians
  - Policy implications – incremental effects

Testing the instruments

- Face validity
- Exogenous
- Strong predictor
- Just identified

Testing – Face Validity

- Tells a good story
- Does the instrument have the expected sign and is significant
- Compare to alternative instruments (if available)

Testing

- Defend assumption that instrument is NOT an explanatory variable
- Explain why instrument is not correlated with omitted explanatory variable

Testing - Exogenous

- Test if errors are correlated with regressors
  - Hausman test
- Test if instrument is uncorrelated with the error
  - Sargan test

Testing – Strong Predictor

- Test if the correlation between the instrument and the troublesome variable is strong enough
  - F statistic, regressing troublesome variable on all instruments – to test the null that the slopes of all instruments equal zero (F>10.)
- Staiger Stock test

Testing – Just identified

Conclusion

- Instrumental variables mimic randomization
- But good instruments are hard to find.
- An estimate of the marginal effect/influence on outcome
- CASE (copy and steal everything)
- But make sure the IV works for the study

VA IVs

- Distance to nearest VA/treatment (Slade , McCarthy; Pracht, Bass; Kim, Eisenberg)
- Distance to nearest VHA hospital minus distance to nearest non-VHA hospital (Helmer, Sambamoorthi)
- Racial mix by enrollees/utilizers (Simeonova)
- Visit intensity for all enrollees of a class (Kim, Eisenberg) (local practice)

References

1.McClellan M, McNeil BJ, Newhouse JP. Does more intensive treatment of acute myocardial infarction in the elderly reduce mortality? Analysis using instrumental variables. JAMA 1994;272:859-66.
2.Newhouse JP, McClellan M. Econometrics in outcomes research: the use of instrumental variables. Annu Rev Public Health 1998;19:17-34.
3.Rassen JA, Brookhart MA, Glynn RJ, Mittleman MA, Schneeweiss S. Instrumental variables I: instrumental variables exploit natural variation in nonexperimental data to estimate causal relationships. J Clin Epidemiol 2009;62:1226-32.
4.Rassen JA, Brookhart MA, Glynn RJ, Mittleman MA, Schneeweiss S. Instrumental variables II: instrumental variable application-in 25 variations, the physician prescribing preference generally was strong and reduced covariate imbalance. J Clin Epidemiol 2009;62:1233-4
5.Humphreys K, Phibbs CS, Moos RH. Addressing self-selection effects in evaluations of mutual help groups and professional mental health services: an introduction to two-stage sample selection models. Evaluation and Program Planning 1996;19:301-8.

References

6.Kennedy P. A Guide to Econometrics. Sixth ed. Malden, MA: Blackwell Publishing; 2008.
7. Kim HM, Eisenberg D, Ganoczy D, et al. Examining the Relationship between Clinical Monitoring and Suicide Risk among Patients with Depression: Matched Case–Control Study and Instrumental Variable Approaches. Health Services Research. 2010;45(5p1):1205-1226.
8. Pracht EE, Bass E. Exploring the Link between Ambulatory Care and Avoidable Hospitalizations at the Veteran Health Administration. Journal for Healthcare Quality. 2011;33(2):47-56.
9. Simeonova E. Race, Quality of Care and Patient Outcomes: What Can We Learn from the Department of Veterans Affairs? Atlantic Economic Journal. 2009;37(3):279-298.
10. Slade EP, McCarthy JF, Valenstein M, Visnic S, Dixon LB. Cost Savings from Assertive Community Treatment Services in an Era of Declining Psychiatric Inpatient Use. Health Services Research. 2012.

Other IV methods

- Randomization
- 2SLS

- Watch for HERC Technical Report, Wagner, Cowgill, 2012.