FLS 6441 - Methods III: Explanation and Causation

Week 6 - Instrumental Variables

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Section 1

Instrumental Variables

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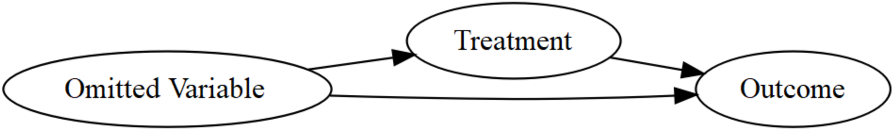
  - I.e. Independent of potential outcomes
  - Even if other variables linked to potential outcomes **also** affect treatment

Instrumental Variables



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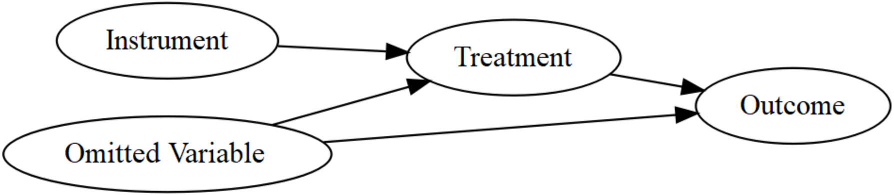

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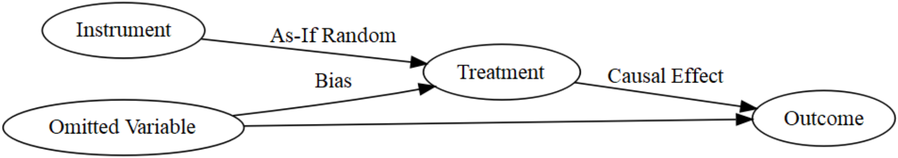

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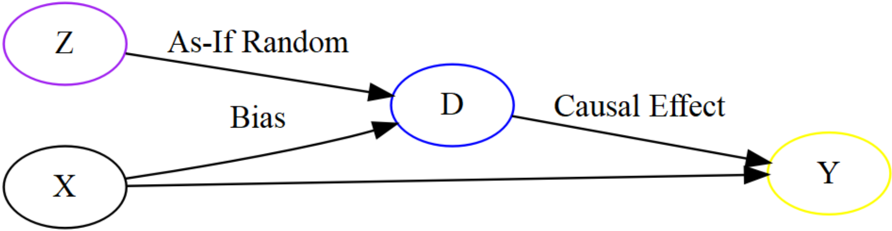

Instrumental Variables

- Example Instruments:
  - Rainfall for conflict
  - Gender of first two children for effect of having a third child
  - Distance from the coast for exposure to slave trade

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- Theory and qualitative evidence needed

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  4. **2-Stage Least Squares:** Two linear regressions: correct coefficient, wrong p-value: $D_i \sim Z_i$, then $Y_i \sim \hat{D}_i$
  5. **Reduced-Form Regression:** Estimate of the Instrument on the Outcome, *ignoring treatment*: $Y_i \sim Z_i$

Example

- **Our research question:** How does economic growth affect conflict?

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  $0.07 = 0.12 - 0.1 * 0.5$

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- **Second-Stage Regression:** $Conflict_i = \alpha + \beta_2 \hat{Growth}_i + \epsilon_i$

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- **First-Stage Regression:**
  $Conflict_i = 0.02 + 0.1 * Rainfall_i + \epsilon_i$
- **Fitted values from First-Stage Regression:**
  $\hat{Conflict}_i = 0.07, 0.02, 0.06, 0.12, 0.03...$
- **Second-Stage Regression:**
  $Conflict_i = 1.2 - 0.04 * \hat{Growth}_i + \epsilon_i$

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The Average Treatment Effect among the subset of units who are treated because of the instrument:
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- Remember, these 'Local' units might be very rare and unusual so our estimate might be very difficult to generalize

Section 2

Instrumenting for Institutions

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- What is the inferential problem here?
- Can we run a field experiment?
- Can we find a natural experiment?

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  1. **First Stage:**

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Instrumenting for Institutions

- They need an Instrumental Variable that:
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  2. **Exclusion Restriction:** *Only* affects growth through institutions
- They make the *argument* that Settler (soldier) mortality rates are an appropriate instrument for institutions

Instrumenting for Institutions

- **Population:**

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- **Population:** Ex-colonies

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- Supporting Evidence:

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- Supporting Evidence:
- "Mortality rates faced by the settlers more than 100 years ago explains over 25 percent of the variation in current institutions."

Instrumenting for Institutions

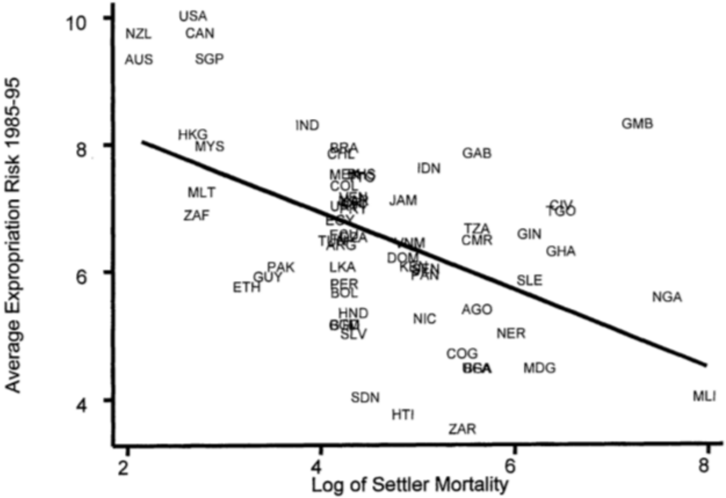

Figure 3. First-Stage Relationship Between Settler Mortality and Expropriation Risk

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- Supporting Evidence:
  - Mortality rates for locals are low and don't affect human capital or growth directly, due to local immunity
  - Control for other possible correlated variables - geography, climate, etc.

Instrumenting for Institutions

- Methodology:
  - $Institutions_i = \alpha + \beta_0 Settler\_Mortality_i + \epsilon_i$
  - $Growth_i = \alpha + \beta_1 \hat{Institutions_i} + \epsilon_i$

Instrumenting for Institutions

	Base sample (1)	Base sample (2)	Base sample without Neo-Europes (3)	Base sample without Neo-Europes (4)	Base sample without Africa (5)	Base sample without Africa (6)	Base sample with continent dummies (7)	Base sample with continent dummies (8)	Base sample, dependen variable i log outpu per worke (9)
Panel A: Two-Stage Least Squares									
Average protection against expropriation risk 1985–1995	0.94	1.00	1.28	1.21	0.58	0.58	0.98	1.10	0.98
	(0.16)	(0.22)	(0.36)	(0.35)	(0.10)	(0.12)	(0.30)	(0.46)	(0.17)
Latitude		−0.65		0.94		0.04		−1.20	
		(1.34)		(1.46)		(0.84)		(1.8)	
Asia dummy							−0.92	−1.10	
							(0.40)	(0.52)	
Africa dummy							−0.46	−0.44	
							(0.36)	(0.42)	
"Other" continent dummy							−0.94	−0.99	
							(0.85)	(1.0)	
Panel B: First Stage for Average Protection Against Expropriation Risk in 1985–1995									
Log European settler mortality	−0.61	−0.51	−0.39	−0.39	−1.20	−1.10	−0.43	−0.34	−0.63
	(0.13)	(0.14)	(0.13)	(0.14)	(0.22)	(0.24)	(0.17)	(0.18)	(0.13)
Latitude		2.00		−0.11		0.99		2.00	
		(1.34)		(1.50)		(1.43)		(1.40)	
Asia dummy							0.33	0.47	
							(0.49)	(0.50)	
Africa dummy							−0.27	−0.26	
							(0.41)	(0.41)	
"Other" continent dummy							1.24	1.1	
							(0.84)	(0.84)	
R^2	0.27	0.30	0.13	0.13	0.47	0.47	0.30	0.33	[illegible]

Instrumenting for Institutions

- **Results:** Improving Nigeria's institutions to Chile's level would raise GDP 7-fold

Section 3

Non-Compliance in Experiments

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Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly
  - Eg. We offer free health insurance to families at random, but some reject the offer
  - Who rejects treatment?
  - Those that decline treatment are *different* to those that accept (eg. richer)
- We cannot just compare units that *actually* received treatment to those that did not

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly
  - Eg. We offer free health insurance to families at random, but some reject the offer
  - Who rejects treatment?
  - Those that decline treatment are *different* to those that accept (eg. richer)
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- Omitted variable bias has returned!

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- We can divide our units into four types depending on how they accept or reject treatment assignment:

Treatment Status:

If Assigned to Control	**If Assigned to Treatment**	**Unit Type**
0	1	Complier
0	0	Never-taker
1	1	Always-taker
1	0	Defier

- Assignment to Treatment is now a separate step prior to treatment - so we can consider it like an instrument, Z_i

Non-Compliance in Experiments

$D_i(Z_i = 0)$ Treatment Status If Assigned to Control	$D_i(Z_i = 1)$ Treatment Status If Assigned to Treatment	Type?
0	1	
0	0	
0	1	
1	0	
1	1	
0	0	
0	1	
1	0	

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- We also need to **assume** Defiers don't exist

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Non-Compliance in Experiments

- The **'Strong First-Stage'** assumption here requires that treatment assignment affects treatment for at least some people
- The **'Exclusion Restriction'** assumption requires that outcomes depend on treatment and not treatment assignment
  - So being labelled 'treatment group' (without treatment) doesn't affect your outcome