FLS 6441 - Methods III: Explanation and Causation

Week 6 - Instrumental Variables

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Section 1

Instrumental Variables

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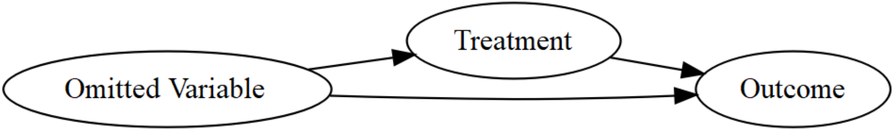
- An 'instrument' is a variable which assigns treatment in an 'as-if' random way
  - I.e. Independent of potential outcomes
  - Even if other variables **also** affect treatment

Instrumental Variables



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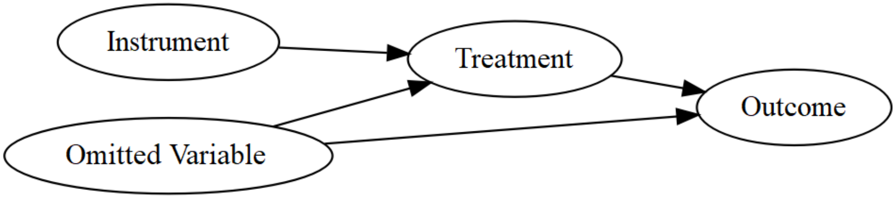

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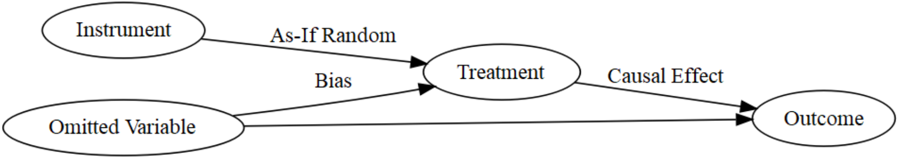

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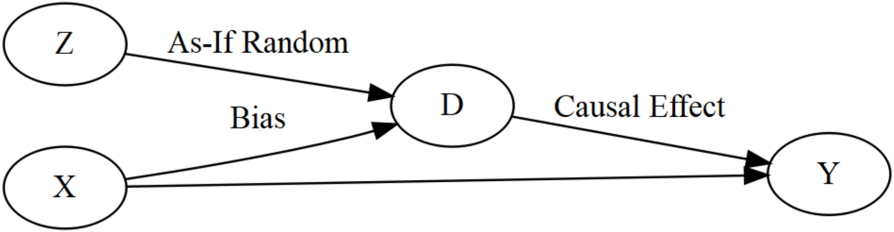

Instrumental Variables

- 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*: $Y_i \sim Z_i$

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- **First-Stage Regression:** $Conflict_i = 0.12 - 0.1 * Rainfall_i + \epsilon_i$
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- **Second-Stage Regression:** $Growth_i = \alpha + \beta_2 \hat{Conflict}_i + \epsilon_i$

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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:** $Growth_i = 1.2 - 0.04 * \hat{Conflict}_i + \epsilon_i$

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- Remember, these 'Local' units might be very rare and unusual so we can't generalize

Section 2

Instrumenting for Institutions

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- Can we run a field experiment?
- Can we find a natural experiment?

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- They *argue* that Settler (soldier) mortality rates are an appropriate instrument for institutions

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- **Population:** Ex-colonies

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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

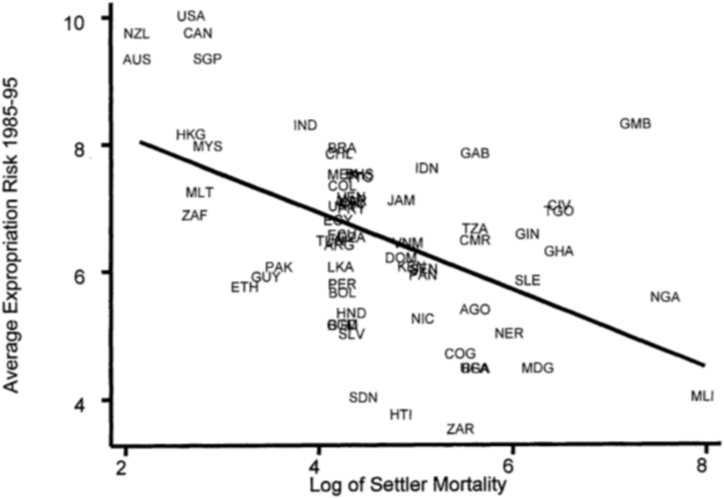

FIGURE 3. FIRST-STAGE RELATIONSHIP BETWEEN SETTLER MORTALITY AND EXPROPRIATION RISK

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

Instrumenting for Institutions

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

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, depender variable i log outpu per worke (9)
Panel A: Two-Stage Least Squares									
Average protection against expropriation risk 1985–1995	0.94 (0.16)	1.00 (0.22)	1.28 (0.36)	1.21 (0.35)	0.58 (0.10)	0.58 (0.12)	0.98 (0.30)	1.10 (0.46)	0.98 (0.17)
Latitude		−0.65 (1.34)		0.94 (1.46)		0.04 (0.84)		−1.20 (1.8)	
Asia dummy							−0.92 (0.40)	−1.10 (0.52)	
Africa dummy							−0.46 (0.36)	−0.44 (0.42)	
"Other" continent dummy							−0.94 (0.85)	−0.99 (1.0)	
Panel B: First Stage for Average Protection Against Expropriation Risk in 1985–1995									
Log European settler mortality	−0.61 (0.13)	−0.51 (0.14)	−0.39 (0.13)	−0.39 (0.14)	−1.20 (0.22)	−1.10 (0.24)	−0.43 (0.17)	−0.34 (0.18)	−0.63 (0.13)
Latitude		2.00 (1.34)		−0.11 (1.50)		0.99 (1.43)		2.00 (1.40)	
Asia dummy							0.33 (0.49)	0.47 (0.50)	
Africa dummy							−0.27 (0.41)	−0.26 (0.41)	
"Other" continent dummy							1.24 (0.84)	1.1 (0.84)	
R^2	0.27	0.30	0.13	0.13	0.47	0.47	0.30	0.33	0.28

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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- Those groups are no longer ’balanced’
- Omitted variable bias has returned!

Non-Compliance in Experiments

Income	Treatment Assignment	Treatment Status
Rich	1	0
Poor	0	0
Poor	0	0
Poor	1	1
Rich	1	0
Poor	0	0
Poor	1	1
Rich	0	0
Poor	0	0

Non-Compliance in Experiments

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

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

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$D_i(Z_i = 0)$ If Assigned to Control	$D_i(Z_i = 1)$ 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' doesn't affect your attitude to redistribution