

FLS 6441 - Methods III: Explanation and Causation

Week 6 - Instrumental Variables

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Section 1

Instrumental Variables

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- What can we do when the treatment assignment mechanism is not 'as-if' random?

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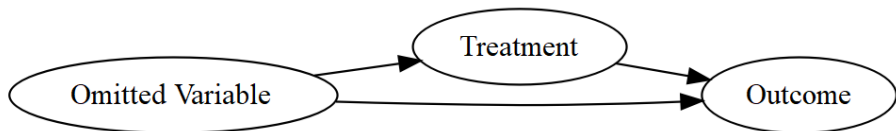
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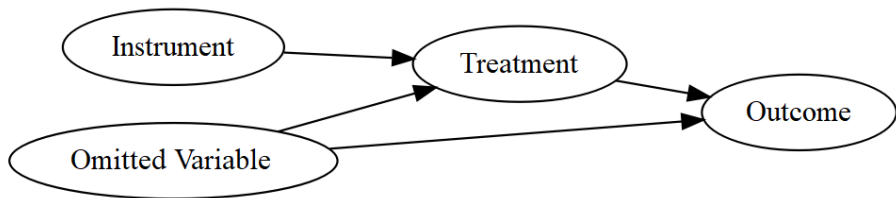
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 - ▶ I.e. Independent of potential outcomes
 - ▶ Even if other variables linked to potential outcomes **also** affect treatment

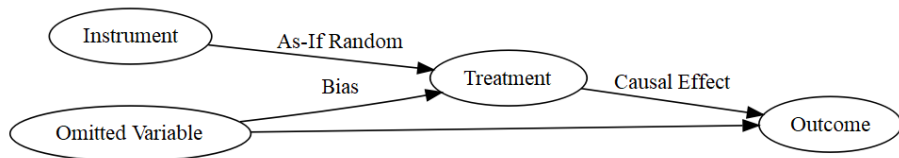
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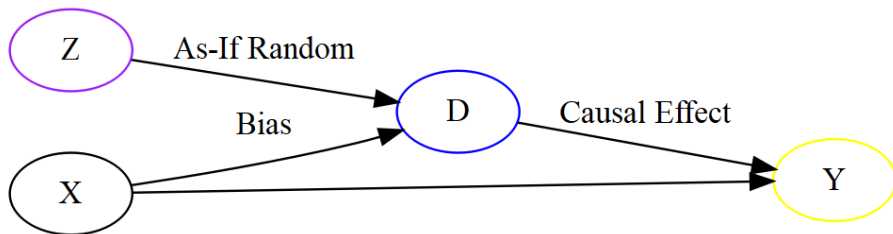
Instrumental Variables



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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

Instrumental Variables Assumption

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- ▶ **We cannot test or prove this assumption!**
- ▶ Theory and qualitative evidence needed

Instrumental Variables Methodologies

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4. **2-Stage Least Squares:** Two linear regressions: correct coefficient, wrong p-value: $D_i \sim Z_i$, then $Y_i \sim \hat{D}_i$

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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

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 $Growth_i = 0.12 - 0.1 * Rainfall_i + \epsilon_i$
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 $\hat{Growth}_i = 0.12 - 0.1 * 0.5 + \epsilon_i$

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

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 $Conflict_i = 0.02 + 0.1 * Rainfall_i + \epsilon_i$
- ▶ **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:

$$(D_i|Z_i = 0) = 0 \text{ and } (D_i|Z_i = 1) = 1$$

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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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 - ▶ **Theory:** Non-electoral **institutions** (property rights, rule of law, checks and balances) cause economic growth

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

Instrumenting for Institutions

- They need an Instrumental Variable that:

Instrumenting for Institutions

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Instrumenting for Institutions

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Instrumenting for Institutions

- ▶ They need an Instrumental Variable that:
 1. **First Stage:** Predicts Institutions
 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:

Instrumenting for Institutions

- **Population:** Ex-colonies

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- ▶ **Instrument:** Settler (soldier) mortality rates

Instrumenting for Institutions

► First Stage:

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- **First Stage:** Settler mortality rates predict institutions

Instrumenting for Institutions

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- ▶ Supporting Evidence:

Instrumenting for Institutions

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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

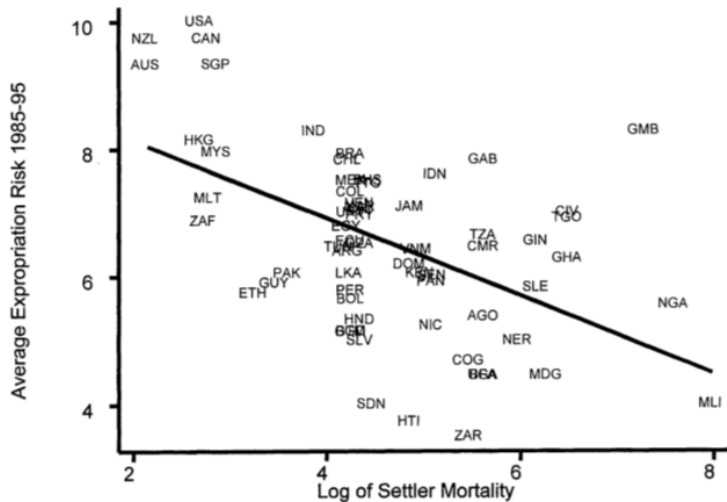


FIGURE 3. FIRST-STAGE RELATIONSHIP BETWEEN SETTLER MORTALITY AND EXPROPRIATION RISK

Instrumenting for Institutions

► **Exclusion Restriction:**

Instrumenting for Institutions

- **Exclusion Restriction:** Settler mortality rates ONLY affect growth through institutions

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 - ▶ 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, dependent variable log output per worker (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	26/338

Instrumenting for Institutions

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

Section 3

Non-Compliance in Experiments

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly

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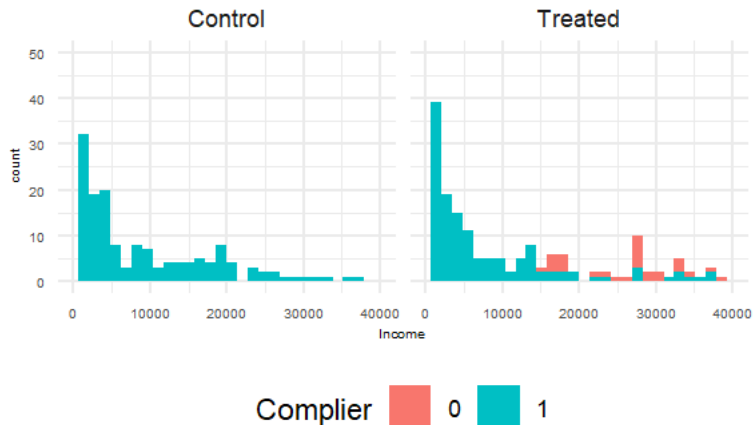
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- We can divide our units into four types depending on how they accept or reject treatment assignment:

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

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

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- ▶ 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