FLS 6441 - Methods III: Explanation and Causation

Week 6 - Instrumental Variables

Jonathan Phillips

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Section 1

Instrumental Variables

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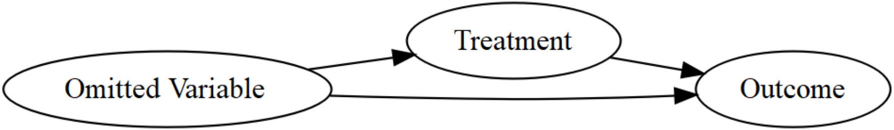
  - Eg. Some people *self-select* into treatment
- Natural experiments focus on a specific **component** of treatment assignment that is 'as-if' random
- An 'instrument' is a variable which assigns treatment in an 'as-if' random way
  - I.e. Independent of potential outcomes
  - Even if other variables **also** affect treatment

Instrumental Variables



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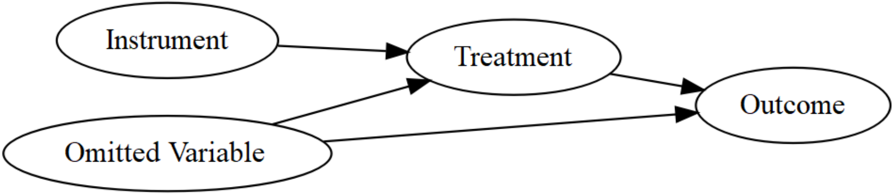

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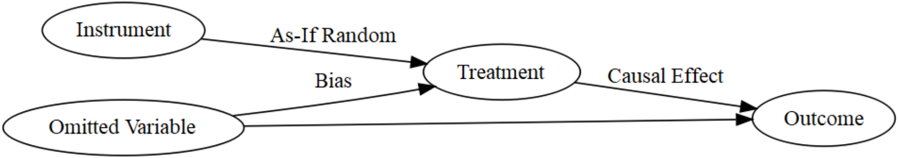

Instrumental Variables

- Example Instruments:
  - Rainfall for conflict
  - Sex-composition for effect of third child
  - Distance from the coast for exposure to slave trade

Instrumental Variables Assumption

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- Theory and qualitative evidence needed

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- 2. **All-in-one Package**
- Use an all-in-one package, eg. *ivreg* in the *AER* package
- Specify the formula: $Y\ D|Instrument$

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  4. **2-Stage Least Squares:** Two linear regressions: correct coefficient, wrong p-value: $D \sim IV, Y \sim \hat{D}$

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

LATE

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Local Average Treatment Effect (LATE)

The Average Treatment Effect among the subset of units who are treated because of the instrument
$(D_i|Z_i = 0) = 0$ and $(D_i|Z_i = 1) = 1$

- Remember, those 'Local' units are not representative so we can't generalize

Section 2

Non-Compliance in Experiments

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- 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

- With an instrument and treatment we can divide our units into four types:

Treatment Status if Instrument=0	**Treatment Status if Instrument=1**	**Unit Type**
0	1	Complier
0	0	Never-taker
1	1	Always-taker
1	0	Defier

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$D_i(Z_i = 0)$	$D_i(Z_i = 1)$	Type?
0	1	
0	0	
0	1	
1	0	
1	1	
0	0	
0	1	
1	0	

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The Average Treatment Effect among compliers

- LATE just means we don't learn anything about Never-takers and Always-takers from our Instrumental Variable

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- Because the instrument doesn’t do anything to affect treatment for these units

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- Because the instrument doesn't do anything to affect treatment for these units
- Never-takers and Always-takers are balanced across treatment assignment and do not affect the difference-in-means
- We also need to **assume** Defiers don't exist

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance
- **1. Intention-to-Treat Analysis**

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- The Effect of Treatment Assignment (the Instrument) on the Outcome

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- $Y_i \ \alpha + \beta Z_i + \epsilon_i$

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- **1. Intention-to-Treat Analysis**
- The Effect of Treatment Assignment (the Instrument) on the Outcome
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- A BIASED estimate (<LATE estimate)

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- For the FULL sample

- **2. LATE Instrumental Variables Analysis**

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- An UNBIASED estimate
- Only for COMPLIERS

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- The **'Strong First-Stage'** assumption here requires that treatment assignment affects treatment for at least some people

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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 potential outcomes depend on treatment and not treatment assignment
  - Eg. An always-taker has the same outcome if they are assigned to treatment or control (because they are always actually treated)

Section 3

Instrumenting for Institutions

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- Acemoglu & Robinson (2001)
    - **Theory:** Non-electoral **institutions** (property rights, rule of law, checks and balances) cause accountability and growth

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- Acemoglu & Robinson (2001)
  - **Theory:** Non-electoral **institutions** (property rights, rule of law, checks and balances) cause accountability and growth
- 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:

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    1. **First Stage:**

Instrumenting for Institutions

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

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- They need an Instrumental Variable that:
  1. **First Stage:** Predicts Institutions
  2. **Exclusion Restriction:**

Instrumenting for Institutions

- They need an Instrumental Variable that:
  1. **First Stage:** Predicts Institutions
  2. **Exclusion Restriction:** Only affects growth through institutions
- They *argue* that Settler (soldier) mortality rates are an appropriate instrument

Population:

Population: Ex-colonies

Population: Ex-colonies

Sample:

Population: Ex-colonies

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Treatment:

Population: Ex-colonies

Sample: Ex-colonies

Treatment: 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)

Population: Ex-colonies

Sample: Ex-colonies

Treatment: 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)

Control:

Population: Ex-colonies

Sample: Ex-colonies

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Instrument:

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Treatment Assignment Mechniams:

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Treatment Assignment Mechniams: Messy! But high settler mortality rates led to extractive institutions

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Outcome:

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Sample: Ex-colonies

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Control: ’Extractive’ institutions

Instrument: Settler (soldier) mortality rates

Treatment Assignment Mechniams: Messy! But high settler mortality rates led to extractive institutions

Outcome: Growth rates in 1995

Instrumenting for Institutions

First Stage Supporting Evidence:

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Exclusion Restriction Supporting Evidence:

Disease environment doesn't affect human capital/growth directly because locals have adapted

Instrumenting for Institutions

Exclusion Restriction Supporting Evidence:

Disease environment doesn’t affect human capital/growth directly because locals have adapted

Control for possible correlates - 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

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