FLS 6441 - Methods III: Explanation and Causation

Week 6 - Instrumental Variables

Jonathan Phillips

April 2020

Section 1

Instrumental Variables

Instrumental Variables

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

Instrumental Variables

- What can we do when the treatment assignment mechanism is not 'as-if' random?
  - Eg. An omitted variable affects both treatment and the outcome

Instrumental Variables

- What can we do when the treatment assignment mechanism is not 'as-if' random?
  - Eg. An omitted variable affects both treatment and the outcome
- Natural experiments focus on a specific **component** of treatment assignment that is 'as-if' random

Instrumental Variables

- What can we do when the treatment assignment mechanism is not 'as-if' random?
  - Eg. An omitted variable affects both treatment and the outcome
- 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

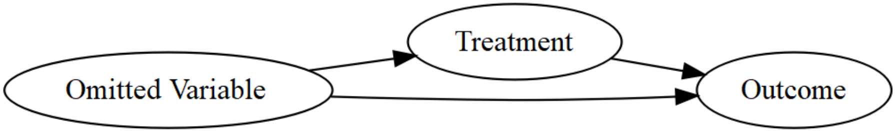
Instrumental Variables

- What can we do when the treatment assignment mechanism is not ’as-if’ random?
  - Eg. An omitted variable affects both treatment and the outcome
- 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

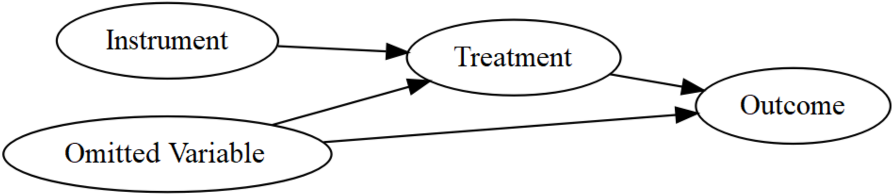
Instrumental Variables

- What can we do when the treatment assignment mechanism is not 'as-if' random?
  - Eg. An omitted variable affects both treatment and the outcome
- 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 linked to potential outcomes **also** affect treatment

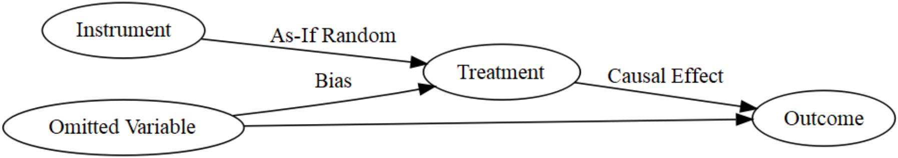
Instrumental Variables



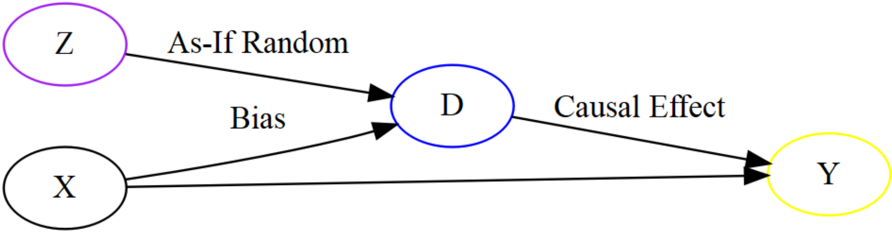
Instrumental Variables



Instrumental Variables



Instrumental Variables



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

- 1. **Strong 'First Stage':**

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:
- $D_i = \alpha + \beta Z_i + \epsilon_i$

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:
- $D_i = \alpha + \beta Z_i + \epsilon_i$
- The instrument should be a significant predictor of treatment

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:
- $D_i = \alpha + \beta Z_i + \epsilon_i$
- The instrument should be a significant predictor of treatment
- Rule-of-thumb: $F - statistic > 10$

- 2. **Exclusion Restriction**

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:
- $D_i = \alpha + \beta Z_i + \epsilon_i$
- The instrument should be a significant predictor of treatment
- Rule-of-thumb: $F - statistic > 10$

- 2. **Exclusion Restriction**
- The Instrument *ONLY* affects the outcome through its effect on treatment, and not directly

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:
- $D_i = \alpha + \beta Z_i + \epsilon_i$
- The instrument should be a significant predictor of treatment
- Rule-of-thumb: $F - statistic > 10$

- 2. **Exclusion Restriction**
- The Instrument *ONLY* affects the outcome through its effect on treatment, and not directly
- Formally, $cov(Z_i, \epsilon_i \text{ in } Y_i \sim D_i) = 0$

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:
- $D_i = \alpha + \beta Z_i + \epsilon_i$
- The instrument should be a significant predictor of treatment
- Rule-of-thumb: $F - statistic > 10$

- 2. **Exclusion Restriction**
- The Instrument *ONLY* affects the outcome through its effect on treatment, and not directly
- Formally, $cov(Z_i, \epsilon_i$ in $Y_i \sim D_i) = 0$
- **We cannot test or prove this assumption!**

Instrumental Variables Assumption

- 1. **Strong 'First Stage':**
- Instrument Predicts Treatment
- We can assess this with a simple regression:
- $D_i = \alpha + \beta Z_i + \epsilon_i$
- The instrument should be a significant predictor of treatment
- Rule-of-thumb: $F - statistic > 10$

- 2. **Exclusion Restriction**
- The Instrument *ONLY* affects the outcome through its effect on treatment, and not directly
- Formally, $cov(Z_i, \epsilon_i$ in $Y_i \sim D_i) = 0$
- **We cannot test or prove this assumption!**
- Theory and qualitative evidence needed

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument:
  $D_i = \alpha + \beta_1 Z_i + \epsilon_i$

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument: $D_i = \alpha + \beta_1 Z_i + \epsilon_i$
- Save the predicted values from this regression: $\hat{D}_i = \hat{\alpha} + \hat{\beta}_1 Z_i$

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument: $D_i = \alpha + \beta_1 Z_i + \epsilon_i$
- Save the predicted values from this regression: $\hat{D}_i = \hat{\alpha} + \hat{\beta}_1 Z_i$
- Estimate how the predicted values affect the outcome: $Y_i = \alpha + \beta_2 \hat{D}_i$

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument: $D_i = \alpha + \beta_1 Z_i + \epsilon_i$
- Save the predicted values from this regression: $\hat{D}_i = \hat{\alpha} + \hat{\beta}_1 Z_i$
- Estimate how the predicted values affect the outcome: $Y_i = \alpha + \beta_2 \hat{D}_i$
- Interpret the coefficient on $\hat{D}_i$

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument: $D_i = \alpha + \beta_1 Z_i + \epsilon_i$
- Save the predicted values from this regression: $\hat{D}_i = \hat{\alpha} + \hat{\beta}_1 Z_i$
- Estimate how the predicted values affect the outcome: $Y_i = \alpha + \beta_2 \hat{D}_i$
- Interpret the coefficient on $\hat{D}_i$
- But our Standard Errors won't be accurate

- 2. **All-in-one Package**

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument: $D_i = \alpha + \beta_1 Z_i + \epsilon_i$
- Save the predicted values from this regression: $\hat{D}_i = \hat{\alpha} + \hat{\beta}_1 Z_i$
- Estimate how the predicted values affect the outcome: $Y_i = \alpha + \beta_2 \hat{D}_i$
- Interpret the coefficient on $\hat{D}_i$
- But our Standard Errors won't be accurate

- 2. **All-in-one Package**
- Use an all-in-one package, eg. *ivreg* in the *AER* package

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument: $D_i = \alpha + \beta_1 Z_i + \epsilon_i$
- Save the predicted values from this regression: $\hat{D}_i = \hat{\alpha} + \hat{\beta}_1 Z_i$
- Estimate how the predicted values affect the outcome: $Y_i = \alpha + \beta_2 \hat{D}_i$
- Interpret the coefficient on $\hat{D}_i$
- But our Standard Errors won't be accurate

- 2. **All-in-one Package**
- Use an all-in-one package, eg. *ivreg* in the *AER* package
- Specify the formula: $Y_i \sim D_i | Z_i$

Instrumental Variables Methodologies

- 1. **2-Stage Least Squares (2SLS):**
- Isolate the variation in treatment caused by the instrument: $D_i = \alpha + \beta_1 Z_i + \epsilon_i$
- Save the predicted values from this regression: $\hat{D}_i = \hat{\alpha} + \hat{\beta}_1 Z_i$
- Estimate how the predicted values affect the outcome: $Y_i = \alpha + \beta_2 \hat{D}_i$
- Interpret the coefficient on $\hat{D}_i$
- But our Standard Errors won't be accurate

- 2. **All-in-one Package**
- Use an all-in-one package, eg. *ivreg* in the *AER* package
- Specify the formula: $Y_i \sim D_i | Z_i$
- Interpret the coefficient on D_i

Instrumental Variables

- Types of IV Regressions:

Instrumental Variables

- Types of IV Regressions:
    1. **Biased Regression:** The regression ignoring omitted variable bias: $Y_i \sim D_i$

Instrumental Variables

- Types of IV Regressions:
  1. **Biased Regression:** The regression ignoring omitted variable bias: $Y_i \sim D_i$
  2. **First-Stage Regression:** Checking the instrument is valid: $D_i \sim Z_i$

Instrumental Variables

- Types of IV Regressions:
  1. **Biased Regression:** The regression ignoring omitted variable bias: $Y_i \sim D_i$
  2. **First-Stage Regression:** Checking the instrument is valid: $D_i \sim Z_i$
  3. **IV Regression:** All-in-one estimate of the effect of treatment on the outcome: $Y_i \sim D_i | Z_i$

Instrumental Variables

- Types of IV Regressions:
  1. **Biased Regression:** The regression ignoring omitted variable bias: $Y_i \sim D_i$
  2. **First-Stage Regression:** Checking the instrument is valid: $D_i \sim Z_i$
  3. **IV Regression:** All-in-one estimate of the effect of treatment on the outcome: $Y_i \sim D_i | Z_i$
  4. **2-Stage Least Squares:** Two linear regressions: correct coefficient, wrong p-value: $D_i \sim Z_i$, then $Y_i \sim \hat{D}_i$

Instrumental Variables

- Types of IV Regressions:
  1. **Biased Regression:** The regression ignoring omitted variable bias: $Y_i \sim D_i$
  2. **First-Stage Regression:** Checking the instrument is valid: $D_i \sim Z_i$
  3. **IV Regression:** All-in-one estimate of the effect of treatment on the outcome: $Y_i \sim D_i | Z_i$
  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 conflict affect economic growth?

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
  1. **First Stage:** Low Rainfall -> + Conflict

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
  1. **First Stage:** Low Rainfall -> + Conflict ✓

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
  1. **First Stage:** Low Rainfall -> + Conflict ✓
  2. **Exclusion Restriction:** Low Rainfall *only* affects Economic Growth through Conflict

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
  1. **First Stage:** Low Rainfall -> + Conflict ✓
  2. **Exclusion Restriction:** Low Rainfall *only* affects Economic Growth through Conflict ✓?

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
  1. **First Stage:** Low Rainfall -> + Conflict ✓
  2. **Exclusion Restriction:** Low Rainfall *only* affects Economic Growth through Conflict ✓?
- **First Stage Regression:** $Conflict_i \sim \alpha + \beta_1 Rainfall_i + \epsilon_i$

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
- **First-Stage Regression:**
  $Conflict_i = 0.12 - 0.1 * Rainfall_i + \epsilon_i$

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
- **First-Stage Regression:**
  $Conflict_i = 0.12 - 0.1 * Rainfall_i + \epsilon_i$
- **Fitted values from First-Stage Regression:**
  $\hat{Conflict}_i = 0.12 - 0.1 * 0.5 + \epsilon_i$

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
- **First-Stage Regression:** $Conflict_i = 0.12 - 0.1 * Rainfall_i + \epsilon_i$
- **Fitted values from First-Stage Regression:** $0.07 = 0.12 - 0.1 * 0.5$

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
- **First-Stage Regression:** $Conflict_i = 0.12 - 0.1 * Rainfall_i + \epsilon_i$
- **Fitted values from First-Stage Regression:** $\hat{Conflict}_i = 0.07, 0.02, 0.06, 0.12, 0.03...$

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
- **First-Stage Regression:** $Conflict_i = 0.12 - 0.1 * Rainfall_i + \epsilon_i$
- **Fitted values from First-Stage Regression:** $\hat{Conflict}_i = 0.07, 0.02, 0.06, 0.12, 0.03...$
- **Second-Stage Regression:** $Growth_i = \alpha + \beta_2 \hat{Conflict}_i + \epsilon_i$

Example

- **Our research question:** How does conflict affect economic growth?
- **Our instrument for treatment:** Low Rainfall
- **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:** $Growth_i = 1.2 - 0.04 * \hat{Conflict}_i + \epsilon_i$

LATE

- IV Interpretation:

LATE

- IV Interpretation:
  - Your coefficient is a causal estimate ONLY for units that were actually treated **because of the instrument**

LATE

- IV Interpretation:
  - Your coefficient is a causal estimate ONLY for units that were actually treated **because of the instrument**
  - They don't tell us about the causal effect for other units that *never responded to the instrument*

LATE

- IV Interpretation:
  - Your coefficient is a causal estimate ONLY for units that were actually treated **because of the instrument**
  - They don't tell us about the causal effect for other units that *never responded to the instrument*
  - Eg. For places where conflict started because of ethnic tensions or an accident

LATE

- IV Interpretation:
  - Your coefficient is a causal estimate ONLY for units that were actually treated **because of the instrument**
  - They don't tell us about the causal effect for other units that *never responded to the instrument*
  - Eg. For places where conflict started because of ethnic tensions or an accident

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 $(D_i|Z_i = 1) = 1$

LATE

- IV Interpretation:
  - Your coefficient is a causal estimate ONLY for units that were actually treated **because of the instrument**
  - They don't tell us about the causal effect for other units that *never responded to the instrument*
  - Eg. For places where conflict started because of ethnic tensions or an accident

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

Section 2

Instrumenting for Institutions

Instrumenting for Institutions

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

Instrumenting for Institutions

- Acemoglu & Robinson (2001)
  - **Theory:** Non-electoral **institutions** (property rights, rule of law, checks and balances) cause economic growth
- What is the inferential problem here?

Instrumenting for Institutions

- Acemoglu & Robinson (2001)
  - **Theory:** Non-electoral **institutions** (property rights, rule of law, checks and balances) cause economic growth
- What is the inferential problem here?
- Can we run a field experiment?

Instrumenting for Institutions

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

Instrumenting for Institutions

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

Instrumenting for Institutions

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

Instrumenting for Institutions

- 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

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 for institutions

Instrumenting for Institutions

- **Population:**

Instrumenting for Institutions

- **Population:** Ex-colonies

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:**

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:**

Instrumenting for Institutions

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

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)
- **Control:**

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)
- **Control:** 'Extractive' institutions

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)
- **Control:** 'Extractive' institutions
- **Outcome:**

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)
- **Control:** 'Extractive' institutions
- **Outcome:** Growth rates in 1995

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)
- **Control:** 'Extractive' institutions
- **Outcome:** Growth rates in 1995
- **Treatment Assignment Mechniams:**

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** ’Settler’ Institutions in ex-colonies (measured by ’risk of expropriation’ index 1985-95)
- **Control:** ’Extractive’ institutions
- **Outcome:** Growth rates in 1995
- **Treatment Assignment Mechniams:** Messy! But high settler mortality rates led to extractive institutions

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)
- **Control:** 'Extractive' institutions
- **Outcome:** Growth rates in 1995
- **Treatment Assignment Mechniams:** Messy! But high settler mortality rates led to extractive institutions
- **Instrument:**

Instrumenting for Institutions

- **Population:** Ex-colonies
- **Sample:** Ex-colonies
- **Treatment:** 'Settler' Institutions in ex-colonies (measured by 'risk of expropriation' index 1985-95)
- **Control:** 'Extractive' institutions
- **Outcome:** Growth rates in 1995
- **Treatment Assignment Mechniams:** Messy! But high settler mortality rates led to extractive institutions
- **Instrument:** Settler (soldier) mortality rates

Instrumenting for Institutions

- **First Stage:**

Instrumenting for Institutions

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

Instrumenting for Institutions

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

Instrumenting for Institutions

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

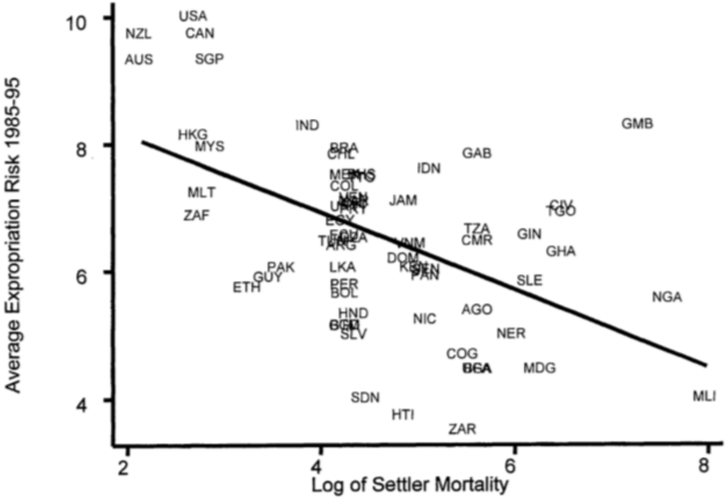


FIGURE 3. FIRST-STAGE RELATIONSHIP BETWEEN SETTLER MORTALITY AND EXPROPRIATION RISK

Instrumenting for Institutions

- **Exclusion Restriction:**

Instrumenting for Institutions

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

Instrumenting for Institutions

- **Exclusion Restriction:** Settler mortality rates ONLY affect growth through institutions
- Supporting Evidence:
  - Mortality rates for locals are low and don't affect human capital/growth directly, due to local immunity

Instrumenting for Institutions

- **Exclusion Restriction:** Settler mortality rates ONLY affect growth through institutions
- 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:
  - $Institutions_i = \alpha + \beta_0 Settler\_Mortality_i + \epsilon_i$
  - $Growth_i = \alpha + \beta_1 \hat{Institutions}_i + \epsilon_i$

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 (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

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly
  - Eg. We offer free health insurance to families at random, but some decline

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly
  - Eg. We offer free health insurance to families at random, but some decline
  - What is the Treatment Assignment Mechanism?

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly
  - Eg. We offer free health insurance to families at random, but some decline
  - What is the Treatment Assignment Mechanism?
  - Those that decline treatment are *different* to those that accept (eg. richer)

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly
  - Eg. We offer free health insurance to families at random, but some decline
  - What is the Treatment Assignment Mechanism?
  - 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 decline
  - What is the Treatment Assignment Mechanism?
  - 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
- Those groups are no longer ’balanced’

Non-Compliance in Experiments

- Sometimes field experiments don't work perfectly
  - Eg. We offer free health insurance to families at random, but some decline
  - What is the Treatment Assignment Mechanism?
  - 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
- 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

Non-Compliance in Experiments

$D_i(Z_i = 0)$ 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	

Non-Compliance in Experiments

- Simple difference-in-means estimates are biased

Non-Compliance in Experiments

- Simple difference-in-means estimates are biased
- But we can still use the randomized component of **treatment assignment as an instrumental variable**

Non-Compliance in Experiments

- Simple difference-in-means estimates are biased
- But we can still use the randomized component of **treatment assignment as an instrumental variable**

Local Average Treatment Effect (LATE)

The Average Treatment Effect among Compliers

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

Non-Compliance in Experiments

- Simple difference-in-means estimates are biased
- But we can still use the randomized component of **treatment assignment as an instrumental variable**

Local Average Treatment Effect (LATE)

The Average Treatment Effect among Compliers

- LATE just means we don't learn anything about Never-takers and Always-takers from our Instrumental Variable
  - Because the instrument doesn't do anything to affect treatment for these units

Non-Compliance in Experiments

- Simple difference-in-means estimates are biased
- But we can still use the randomized component of **treatment assignment as an instrumental variable**

Local Average Treatment Effect (LATE)

The Average Treatment Effect among Compliers

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

Non-Compliance in Experiments

- Simple difference-in-means estimates are biased
- But we can still use the randomized component of **treatment assignment as an instrumental variable**

Local Average Treatment Effect (LATE)

The Average Treatment Effect among Compliers

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

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance
- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance
- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome
- $Y_i \, \alpha + \beta Z_i + \epsilon_i$

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance
- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome
- $Y_i \; \alpha + \beta Z_i + \epsilon_i$
- A BIASED estimate (<LATE estimate)

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance

- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome
- $Y_i \; \alpha + \beta Z_i + \epsilon_i$
- A BIASED estimate (<LATE estimate)
- For the FULL sample

- **2. LATE Instrumental Variables Analysis**

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance

- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome
- $Y_i \; \alpha + \beta Z_i + \epsilon_i$
- A BIASED estimate (<LATE estimate)
- For the FULL sample

- **2. LATE Instrumental Variables Analysis**
- The Effect of Treatment on the Outcome

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance

- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome
- $Y_i \ \alpha + \beta Z_i + \epsilon_i$
- A BIASED estimate (<LATE estimate)
- For the FULL sample

- **2. LATE Instrumental Variables Analysis**
- The Effect of Treatment on the Outcome
- $Y_i \ \alpha + \beta D_i | Z_i + \epsilon_i$

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance

- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome
- $Y_i \; \alpha + \beta Z_i + \epsilon_i$
- A BIASED estimate (<LATE estimate)
- For the FULL sample

- **2. LATE Instrumental Variables Analysis**
- The Effect of Treatment on the Outcome
- $Y_i \; \alpha + \beta D_i | Z_i + \epsilon_i$
- An UNBIASED estimate

Non-Compliance in Experiments

- Two methodologies for Experiments with Non-Compliance

- **1. Intention-to-Treat Analysis**
- The Effect of Treatment **Assignment** (the Instrument) on the Outcome
- $Y_i \ \alpha + \beta Z_i + \epsilon_i$
- A BIASED estimate (<LATE estimate)
- For the FULL sample

- **2. LATE Instrumental Variables Analysis**
- The Effect of Treatment on the Outcome
- $Y_i \ \alpha + \beta D_i | Z_i + \epsilon_i$
- An UNBIASED estimate
- Only for COMPLIERS

Non-Compliance in Experiments

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

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