

FLS 6441 - Methods III: Explanation and Causation

Week 2 - A Framework for Explanation

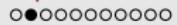
Jonathan Phillips

March 2020

Section 1

Explanation

Explanation



Causal Inference

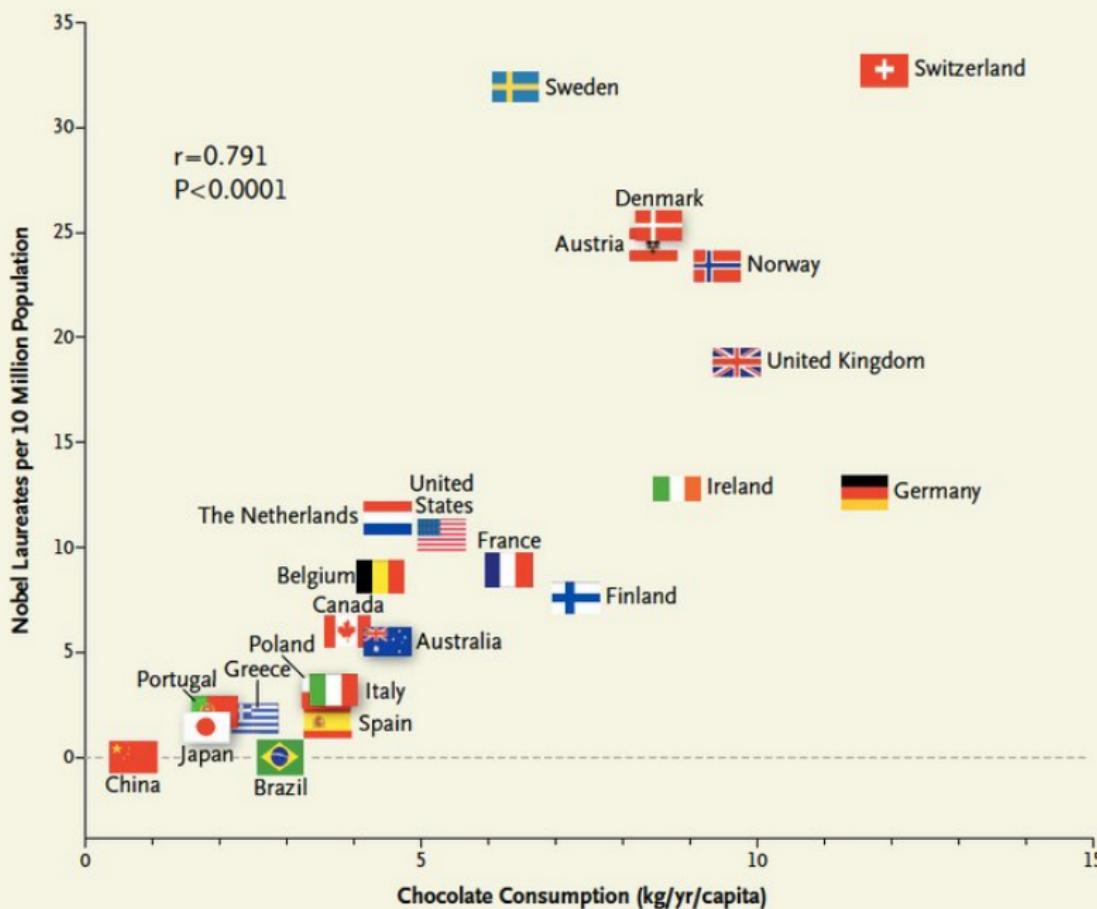


Why Observational Data is Biased



Rest of the Course





Explanation

- ## ► Why isn't correlation enough?

Explanation

- ▶ Why isn't correlation enough?
 - ▶ For **prediction**, correlation is fine: If we know a country has chocolate consumption of 10kg/yr/capita we can reasonably predict it will have about 25 Nobel Laureates

Explanation

► Why isn't correlation enough?

- For **prediction**, correlation is fine: If we know a country has chocolate consumption of 10kg/yr/capita we can reasonably predict it will have about 25 Nobel Laureates
- But for **intervention**, correlation does not help: forcing people to eat more chocolate does nothing on its own to produce more Nobel Laureates

Explanation

► Why isn't correlation enough?

- For **prediction**, correlation is fine: If we know a country has chocolate consumption of 10kg/yr/capita we can reasonably predict it will have about 25 Nobel Laureates
- But for **intervention**, correlation does not help: forcing people to eat more chocolate does nothing on its own to produce more Nobel Laureates
- For **explanation**, correlation also fails - it is no *explanation* to say that Switzerland has the most Nobel Laureates because it has the highest chocolate consumption

Explanation

- What does it mean to explain something?

Explanation

- ▶ What does it mean to explain something?
 - ▶ To give an account of what happens, *and why*
 - ▶ The 'chain of causation'

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Explanation

- ▶ What does it mean to explain something?
 - ▶ To give an account of what happens, *and why*
 - ▶ The 'chain of causation'
 - ▶ If D explains y , we are saying that the *absence* of D would have led to a different value of y
 - ▶ There exists a 'counterfactual' possibility that did not happen

Explanation

Deterministic Explanation

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- ▶ **Sufficient conditions:**

Every time D happens, Y happens

Explanation

Deterministic Explanation

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 - ▶ **Necessary conditions:** Y does not happen if D does not happen ('but for')

Probabilistic Explanation

- ▶ If D happens, the **probability** of Y increases
 - ▶ Treatment effects are a distribution, not a single value

Explanation

- ▶ Two perspectives on explanation:

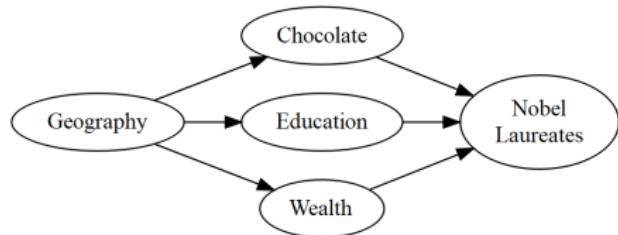
Explanation

- ▶ Two perspectives on explanation:

Causes of Effects	Effects of Causes
What caused Y?	Does D cause Y?
Why does Switzerland have so many Nobel laureates?	Does chocolate cause more Nobel laureates?
Backward-looking	Forward-looking

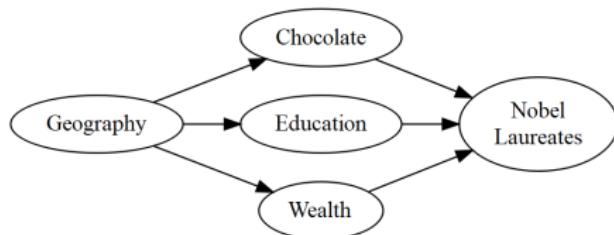
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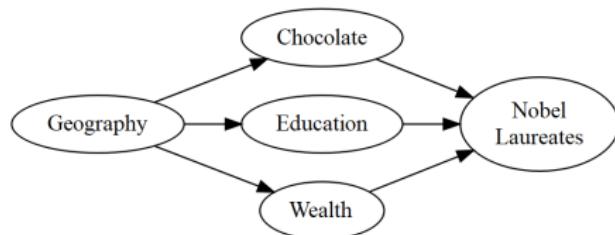
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- ▶ Identifying the source of **ALL** of the variation in Nobel Laureates

Explanation

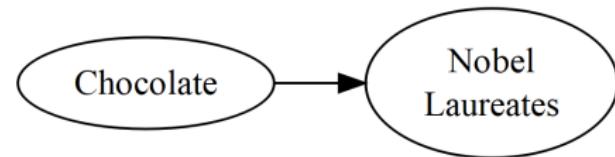
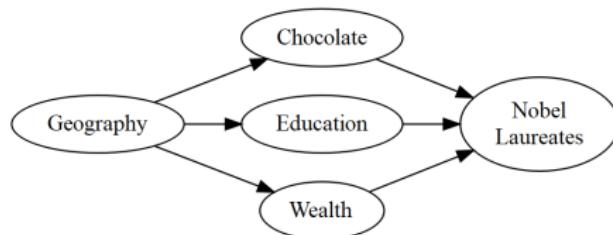
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- ▶ Identifying the source of **ALL** of the variation in Nobel Laureates
- ▶ An infinite task!

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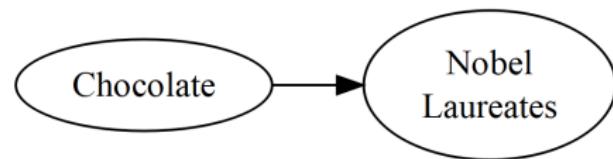
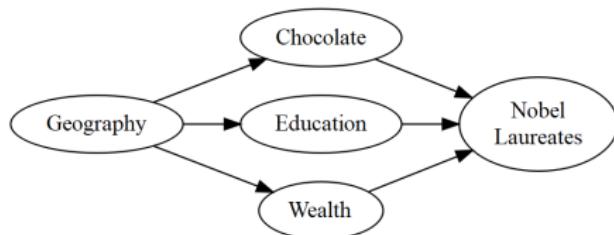
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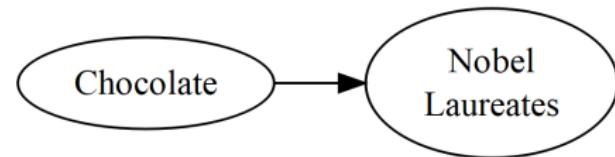
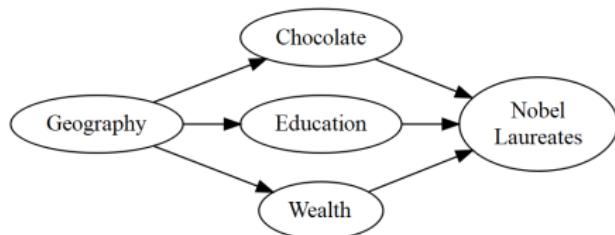


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- ▶ Identifying how much **ONE** variable causes variation in Nobel Laureates

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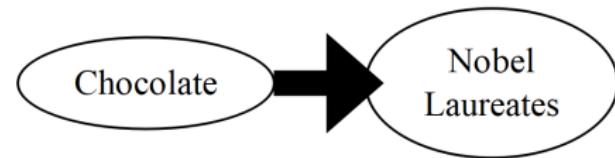
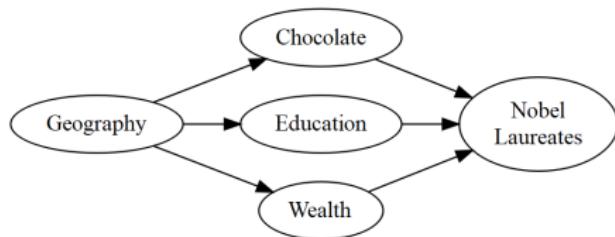
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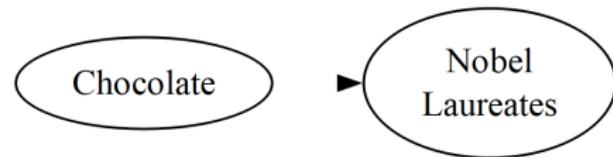
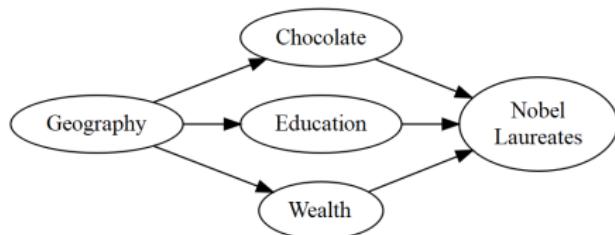
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- ▶ A focus on a single explanatory variable D requires a clear definition of '**Treatment**'
- ▶ AND to clearly define a '**Control**'
 - ▶ What is the opposite of investing \$1bn in education?
 - ▶ No investment, or investing it elsewhere?
- ▶ Define treatment:

$$D_i = \begin{cases} 1, & \text{if treated} \\ 0, & \text{if not treated} \end{cases}$$

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- ▶ So we usually want to study a **single outcome**

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 - ▶ But our analysis needs to take account of the 'clustered' treatment
- ▶ Units are **time-specific**: the same person 10 minutes later is a different unit

Section 2

Causal Inference

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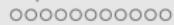
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Causal Inference



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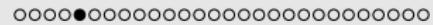
Rest of the Course



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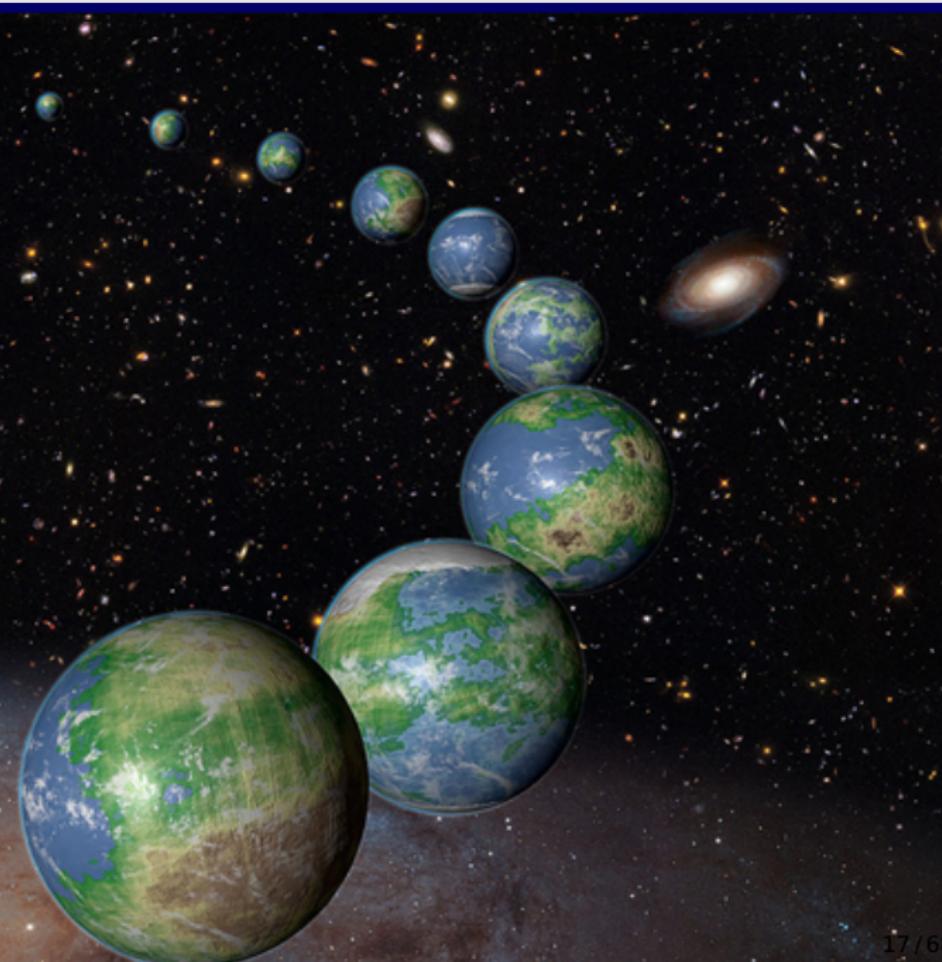
Causal Inference



Why Observational Data is Biased



Rest of the Course



Causal Inference

Potential Outcomes are just another Variable for each Unit

	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
	Y_1	Y_0	$Y_1 - Y_0$
Brasil	4	1	3
Argentina	7	4	3
Bolivia	2	4	-2
Colombia	7	7	0
Peru	5	4	1

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$$ATE = E(\alpha_i) = E(Y_1 - Y_0) = E(Y_1) - E(Y_0) = \frac{\sum_i (Y_{1i} - Y_{0i})}{N}$$

Causal Inference

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Average Treatment Effect on the Treated

$$\text{ATT} = E(\alpha_i | D = 1) = E(Y_1 - Y_0 | D = 1) = \frac{\sum_i (Y_{1i} - Y_{0i} | D=1)}{N_{Treated}} (1)$$

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Average Treatment Effect on the Untreated (Control)

$$ATU = E(\alpha_i | D = 0) = E(Y_1 - Y_0 | D = 0) = \frac{\sum_i (Y_{1i} - Y_{0i} | D=0)}{N_{Control}}$$

(2)

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- The three effect estimates are usually different

Causal Inference

Potential Outcomes Example

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
	D_i	Y_1	Y_0	$Y_1 - Y_0$
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ATT	1	3	2.5	0.5

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ATU	0	6.3	5	1.3

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$$Y_i^{obs} = \begin{cases} Y_{1i} & \text{if } D_i = 1 \\ Y_{0i} & \text{if } D_i = 0 \end{cases}$$

$$Y_i^{obs} = D_i \cdot Y_{1i} + (1 - D_i) \cdot Y_{0i}$$

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Peru	0	?	4	?

Causal Inference

Potential Outcomes Example

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	Observed GDP Growth
	D_i	Y_1	Y_0	Y^{obs}
Brasil	1	4	?	4
Argentina	0	?	4	4
Bolivia	1	2	?	2
Colombia	0	?	7	7
Peru	0	?	4	4

Causal Inference

What we see in our Data:

	Democracy?	Observed GDP Growth
	D_i	Y^{obs}
Brasil	1	4
Argentina	0	4
Bolivia	1	2
Colombia	0	7
Peru	0	4

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Average Treatment Effect		5	4	1

Causal Inference

- ▶ Actually, nothing stops us calculating the **Average Treatment Effect**
- ▶ The question is, is the ATE accurate?

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	4	?	?
Argentina	0	?	4	?
Bolivia	1	2	?	?
Colombia	0	?	7	?
Peru	0	?	4	?
Average Treatment Effect		3	5	-2

Causal Inference

- ▶ **So what went wrong?**

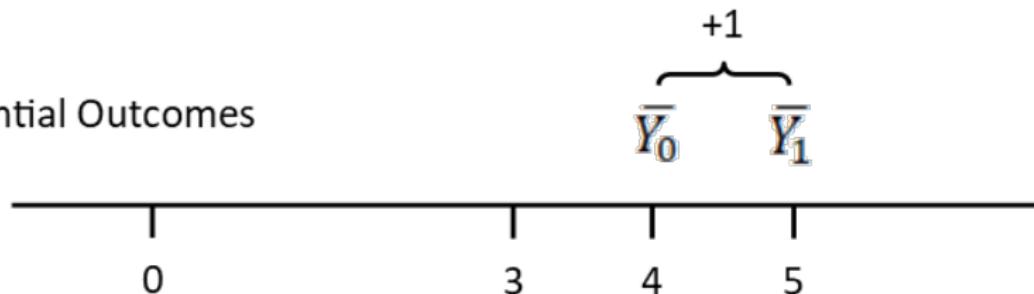
Causal Inference

- ▶ **So what went wrong?**
- ▶ The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units

Causal Inference

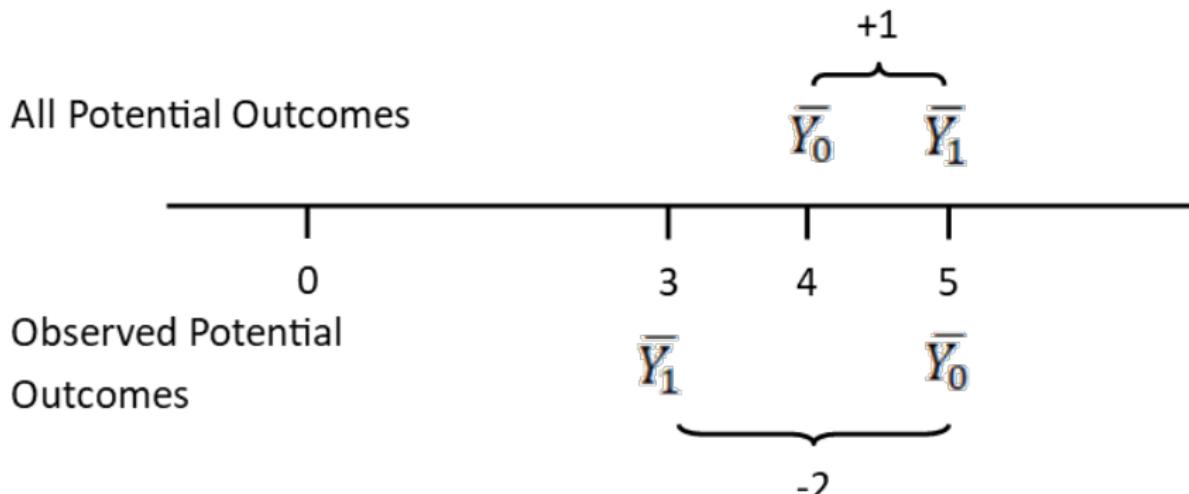
- ▶ **So what went wrong?**
- ▶ The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units

All Potential Outcomes



Causal Inference

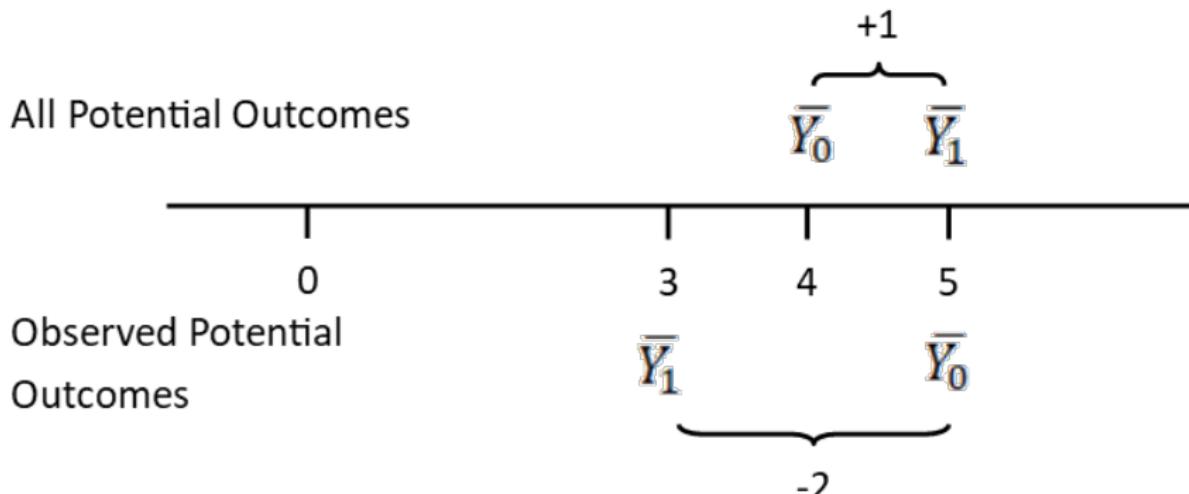
- ▶ **So what went wrong?**
- ▶ The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units



- ▶ $E(Y_1)$ values are **biased lower** in the observed data

Causal Inference

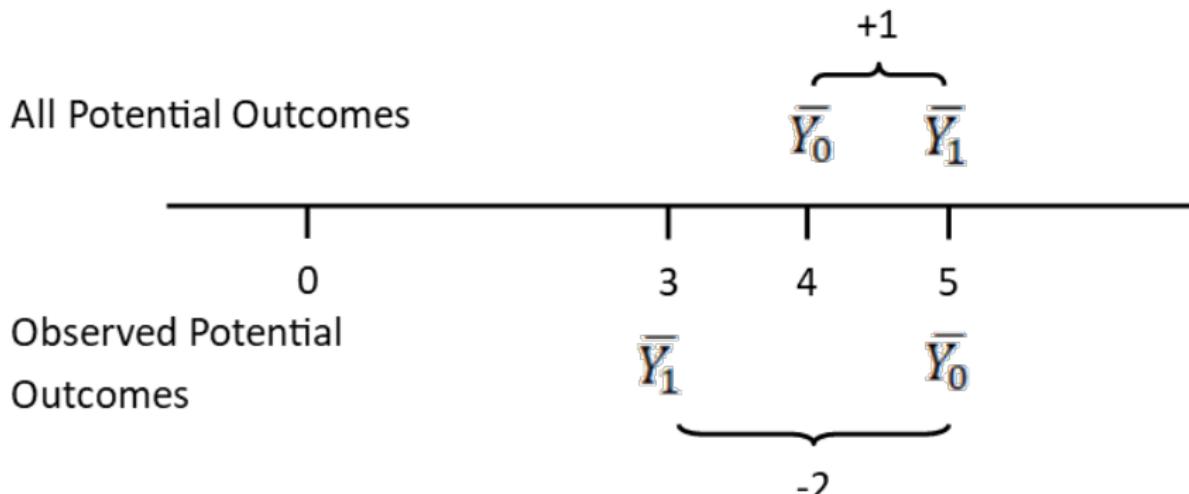
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Causal Inference

- **So what went wrong?**
- The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units



- $E(Y_1)$ values are **biased lower** in the observed data
- $E(Y_0)$ values are **biased higher** in the observed data
- So $E(Y_1) - E(Y_0)$ is **biased**

Causal Inference

- ▶ The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**

Causal Inference

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- ▶ Comparing treated i and control j units

Causal Inference

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- ▶ If potential outcomes are biased in our observed data:

Causal Inference

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 - ▶ Our **counterfactual case** j does not represent what would have happened to i in the absence of treatment

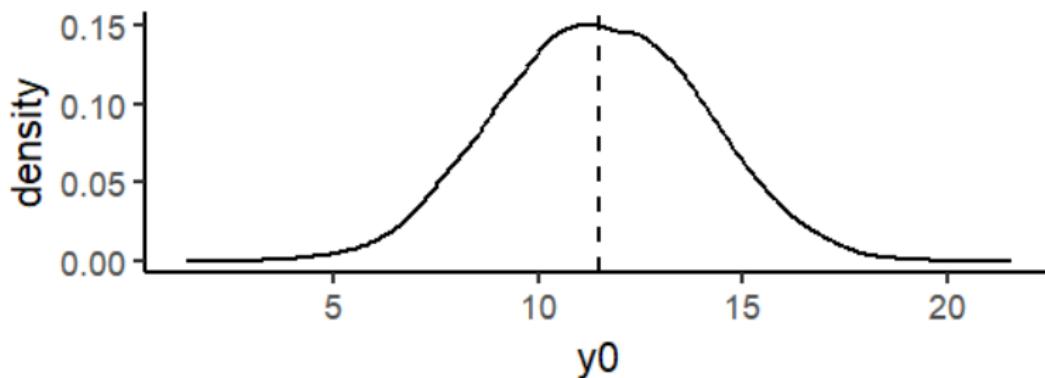
Causal Inference

- ▶ The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**
- ▶ Comparing treated i and control j units
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 - ▶ Counterfactuals are not **plausible**

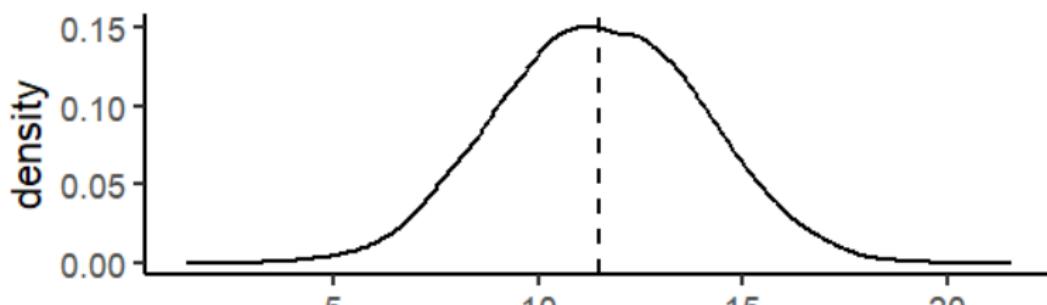
Causal Inference

- ▶ The Fundamental Problem of Causal Inference means we can only discover causal relationships by comparing **across units**
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- ▶ If potential outcomes are biased in our observed data:
 - ▶ Our **counterfactual case** j does not represent what would have happened to i in the absence of treatment
 - ▶ Counterfactuals are not **plausible**
 - ▶ Causal effects are **biased**

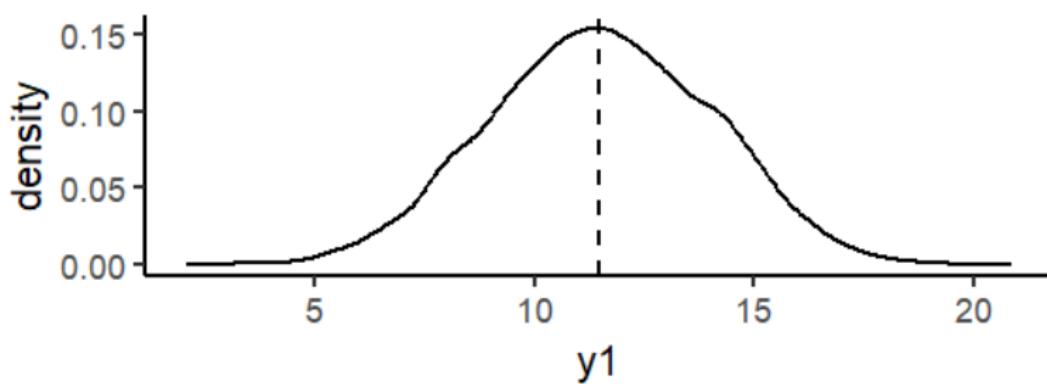
Causal Inference



Causal Inference

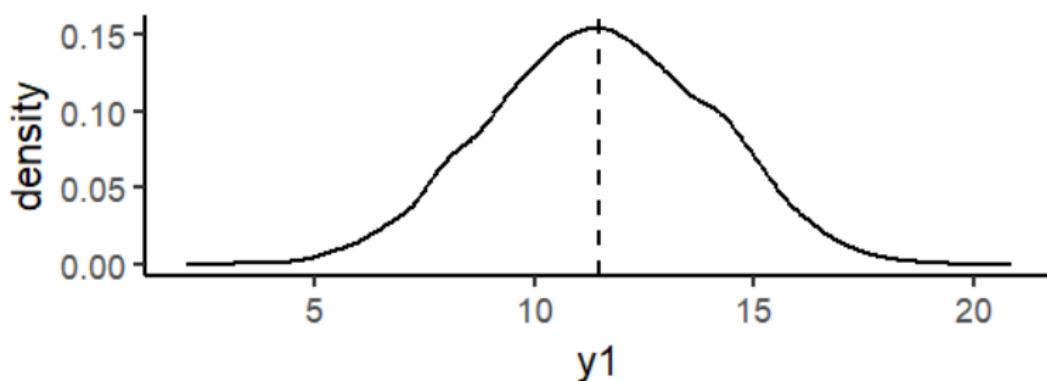
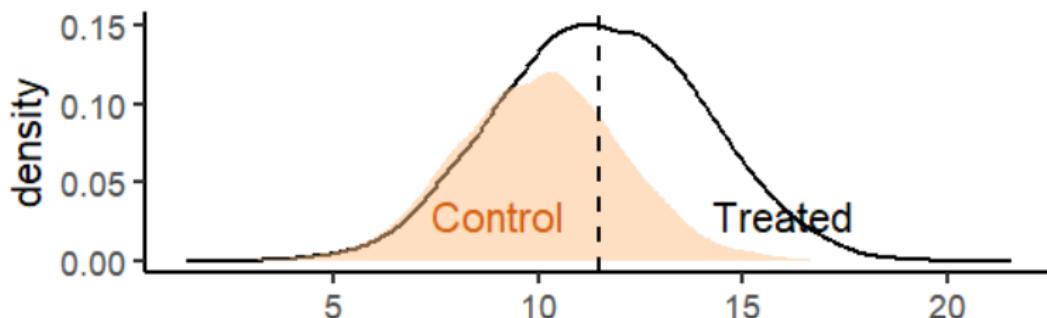


y_0

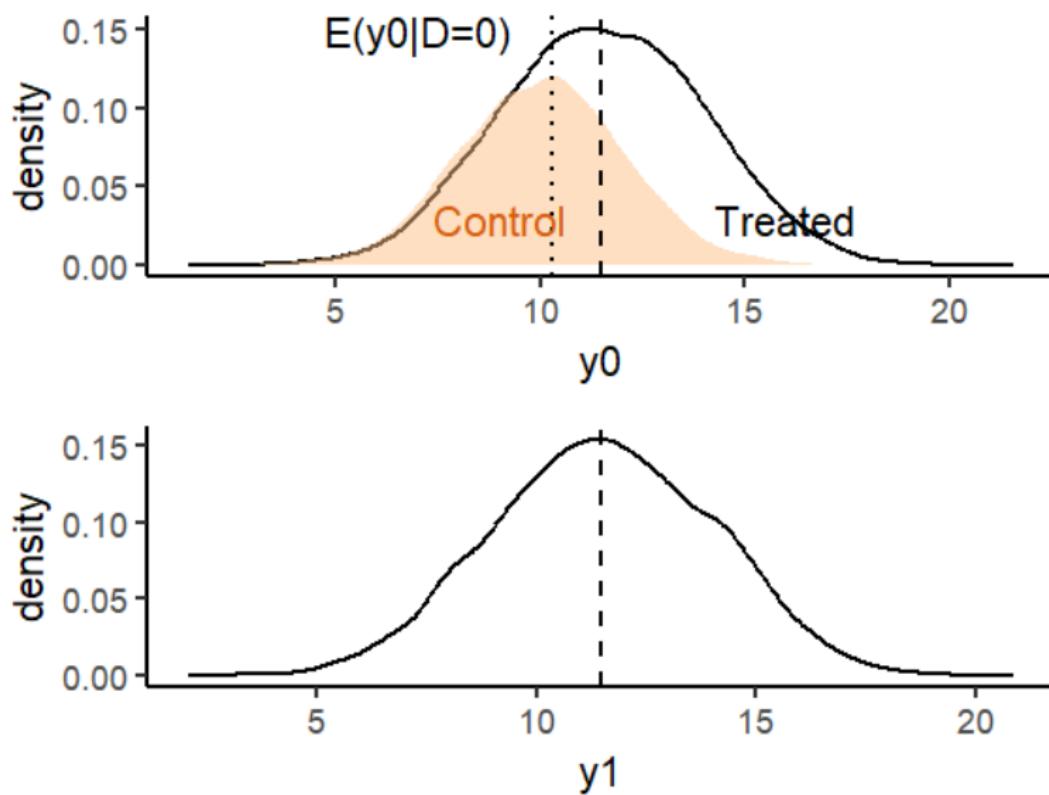


y_1

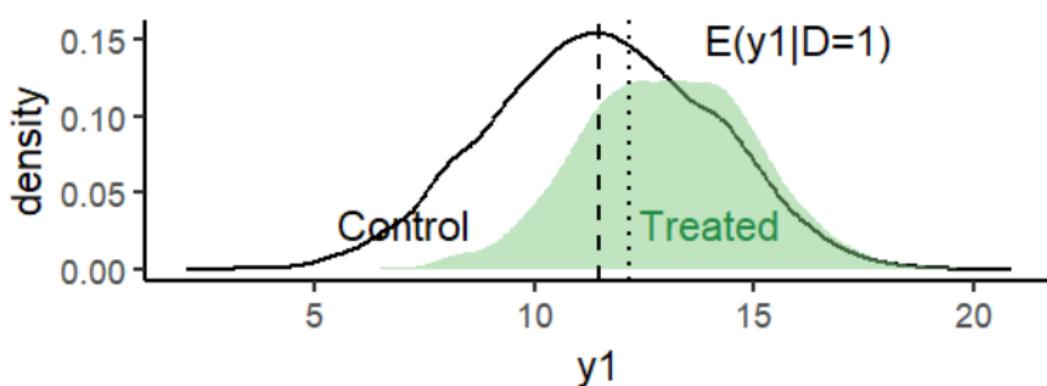
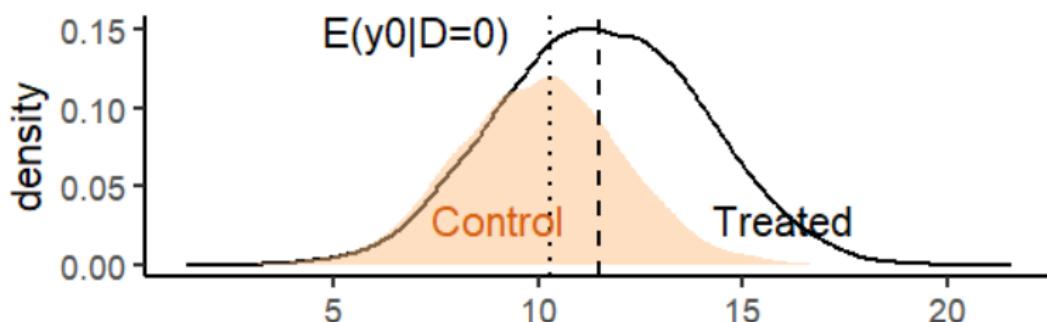
Causal Inference



Causal Inference



Causal Inference



Causal Inference

- ▶ Lots of averages:

		Hypothetical outcome	
		Y_0	Y_1
Actual Treatment	$D = 0$	$E(Y_{0i} D = 0)$	$E(Y_{1i} D = 0)$
	$D = 1$	$E(Y_{0i} D = 1)$	$E(Y_{1i} D = 1)$

Causal Inference

- ▶ Lots of averages:

		Hypothetical outcome	
		Y_0	Y_1
Actual Treatment	$D = 0$	$E(Y_{0i} D = 0)$	$E(Y_{1i} D = 0)$
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Causal Inference

- ▶ All our causal estimates are **averages**

Causal Inference

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 - ▶ We cannot distinguish the null hypothesis of no average effect from the sharp null hypothesis of no individual effects

Causal Inference

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 - ▶ We cannot distinguish the null hypothesis of no average effect from the sharp null hypothesis of no individual effects

	No Average Effect $E(Y_1 - Y_0) = 0$	"Sharp null": No individual effects $(Y_{1i} - Y_{0i} = 0)$
Brasil	2	0
Argentina	-1	0
Bolivia	1	0
Colombia	0	0
Peru	-2	0
Average	0	0

Section 3

Why Observational Data is Biased

Bias

- ▶ Why are potential outcomes biased in our data?

Bias

- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables

Bias

- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables
 2. Reverse Causation

Bias

- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables
 2. Reverse Causation
 3. Selection Bias

Bias

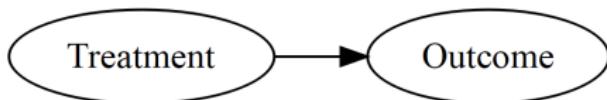
- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables
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- ▶ In all of these cases **the potential outcomes are distorted**

Bias

- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables
 2. Reverse Causation
 3. Selection Bias
- ▶ In all of these cases **the potential outcomes are distorted**
- ▶ So basic regression is **biased**

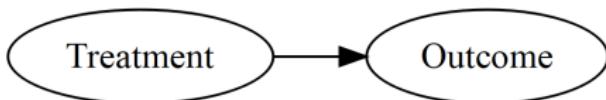
Omitted Variable Bias

A real causal relationship:

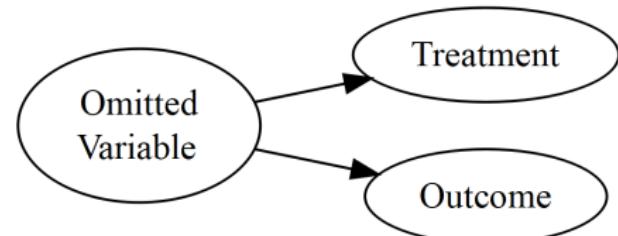


Omitted Variable Bias

A real causal relationship:

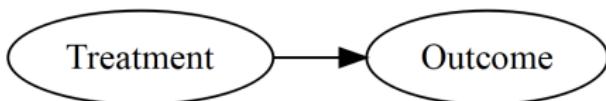


Being misled by omitted variable bias:

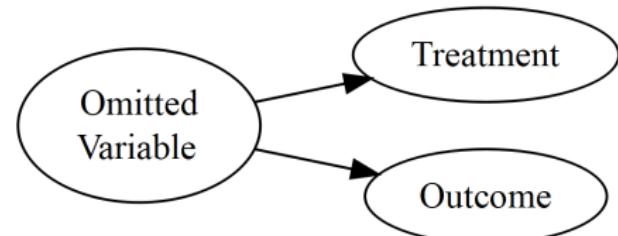


Omitted Variable Bias

A real causal relationship:



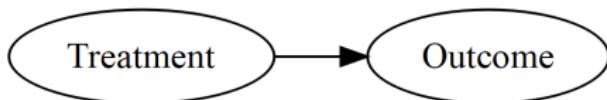
Being misled by omitted variable bias:



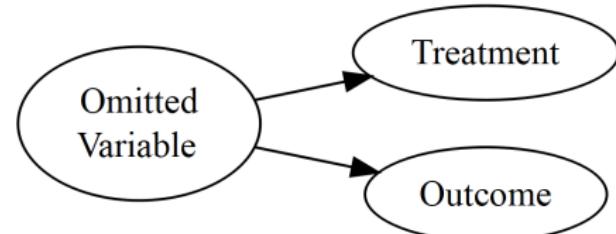
- ▶ A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**

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A real causal relationship:



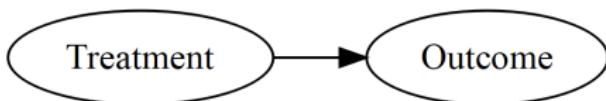
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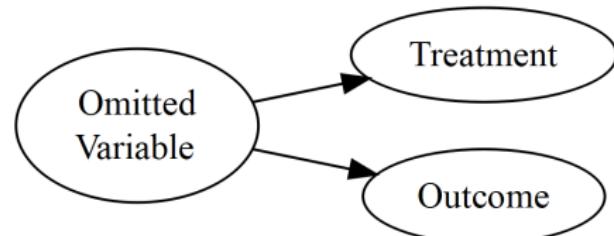
- ▶ A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
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Omitted Variable Bias

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Being misled by omitted variable bias:



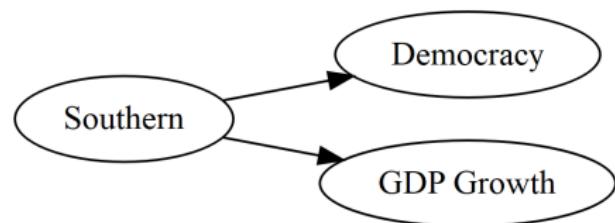
- ▶ A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- ▶ So treated units have non-representative Y_1
- ▶ And control units have non-representative Y_0

Omitted Variable Bias

A real causal relationship:

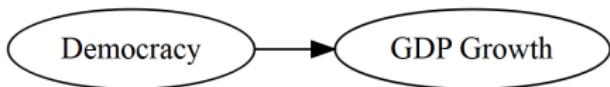


Being misled by omitted variable bias:

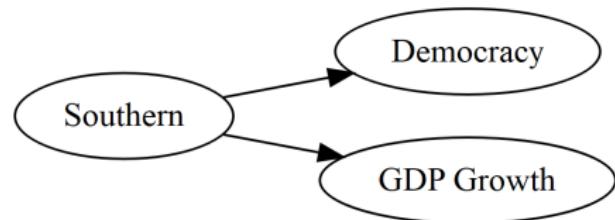


Omitted Variable Bias

A real causal relationship:

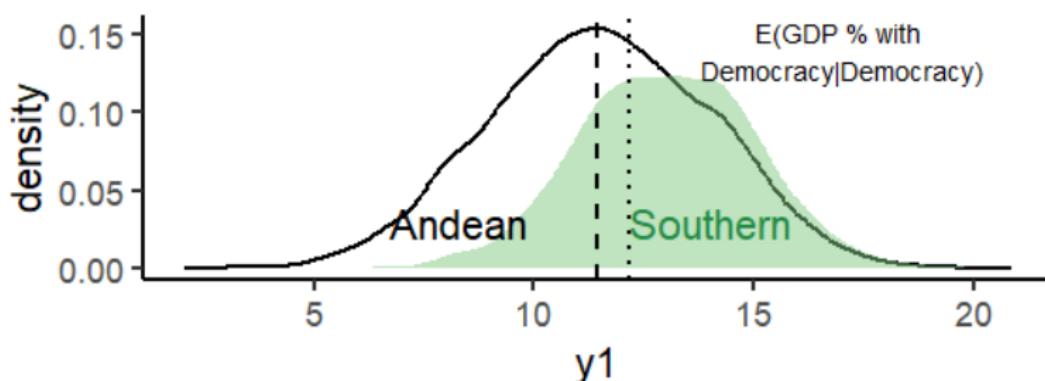
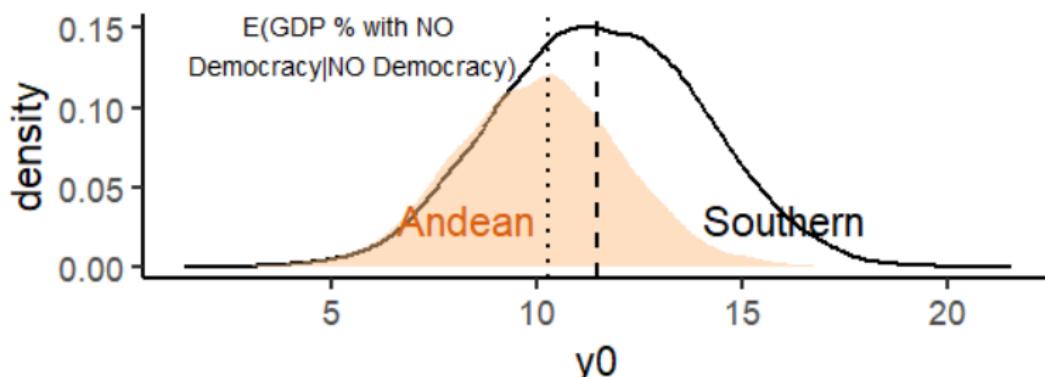


Being misled by omitted variable bias:



- Southern Cone countries faced conditions that encouraged both democracy and rapid GDP growth

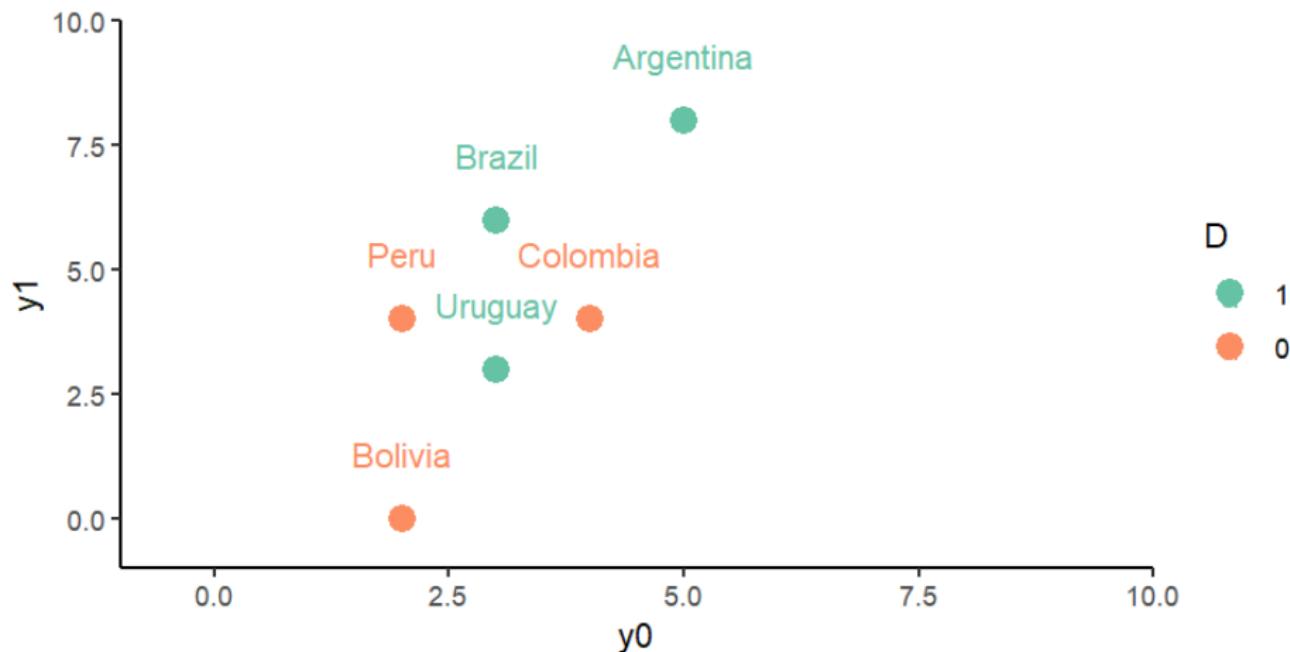
Omitted Variable Bias



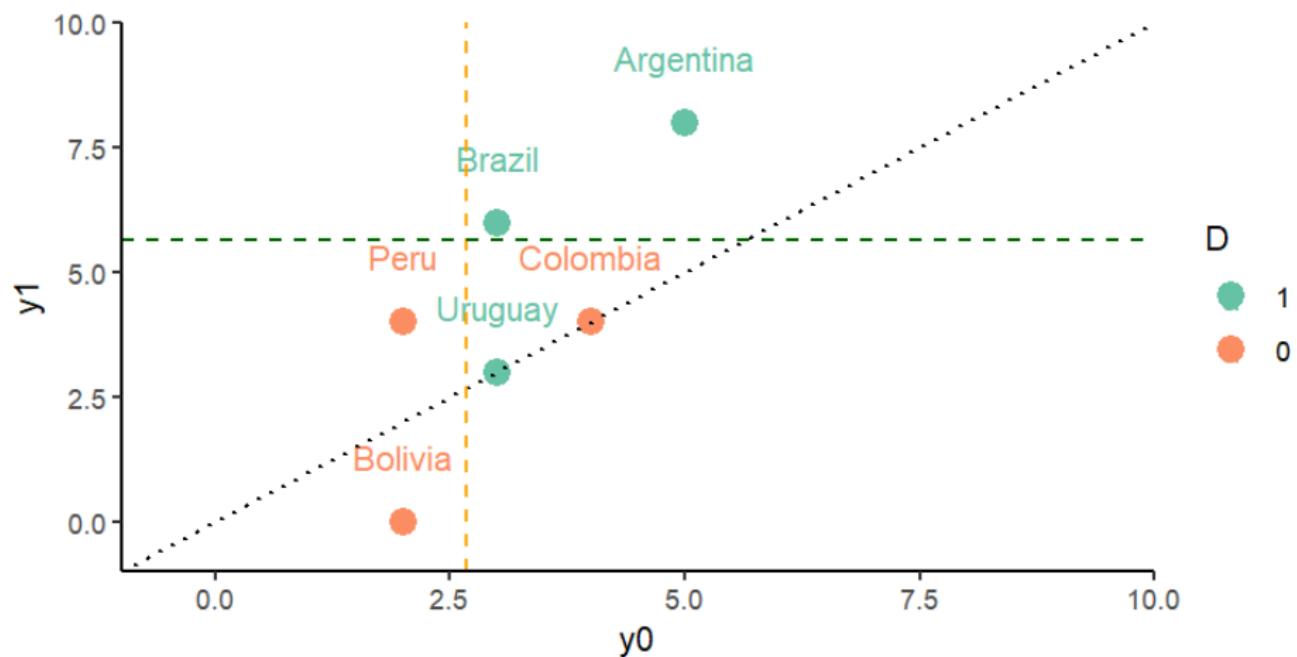
Omitted Variable Bias

	Andean?	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	Treatment Effect
	X_i	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	1	6	?	?
Argentina	1	1	8	?	?
Uruguay	1	1	3	?	?
Bolivia	0	0	?	2	?
Colombia	0	0	?	4	?
Peru	0	0	?	2	?
Average Treatment Effect			5.7	2.7	3

Omitted Variable Bias



Omitted Variable Bias



$$\blacktriangleright E(Y_1|D=1) - E(Y_0|D=0) = 5.7 - 2.7 = 3$$

Omitted Variable Bias

- ▶ Let's say that $Y_{1i} = Y_{0i} + \alpha$, where α is the real constant treatment effect

$$\hat{ATE} = E(Y_1|D=1) - E(Y_0|D=0)$$

Omitted Variable Bias

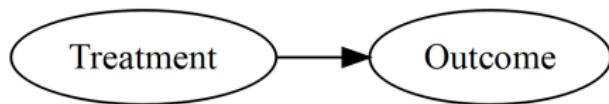
- Let's say that $Y_{1i} = Y_{0i} + \alpha$, where α is the real constant treatment effect

$$\hat{ATE} = E(Y_1|D=1) - E(Y_0|D=0)$$

$$\hat{ATE} = \underbrace{\alpha}_{\text{Real ATE}} + \underbrace{E(Y_0|D=1) - E(Y_0|D=0)}_{\text{Bias}}$$

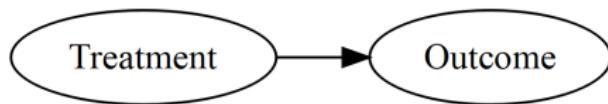
Reverse Causation

A real causal relationship:

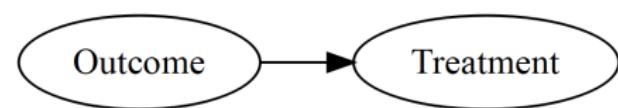


Reverse Causation

A real causal relationship:

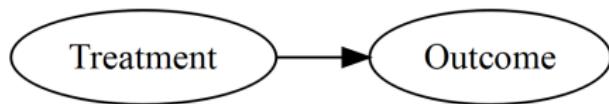


Being misled by reverse causation:

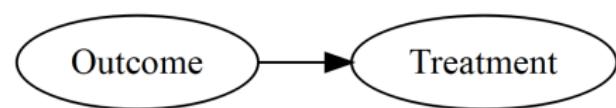


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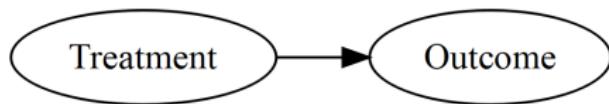
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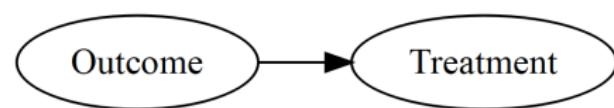
- ▶ D does not affect Y , but higher Y makes treatment (D) more likely

Reverse Causation

A real causal relationship:



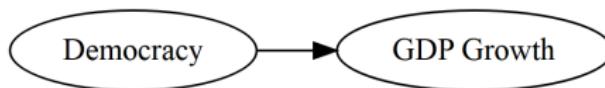
Being misled by reverse causation:



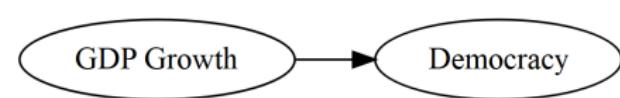
- ▶ D does not affect Y , but higher Y makes treatment (D) more likely
- ▶ So the two variables are **correlated**

Reverse Causation

A real causal relationship:



Being misled by reverse causation:

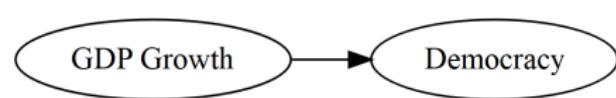


Reverse Causation

A real causal relationship:



Being misled by reverse causation:



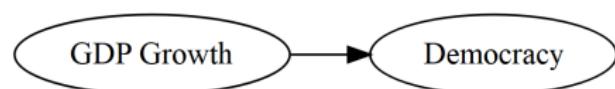
- ▶ GDP Growth encourages democratization

Reverse Causation

A real causal relationship:

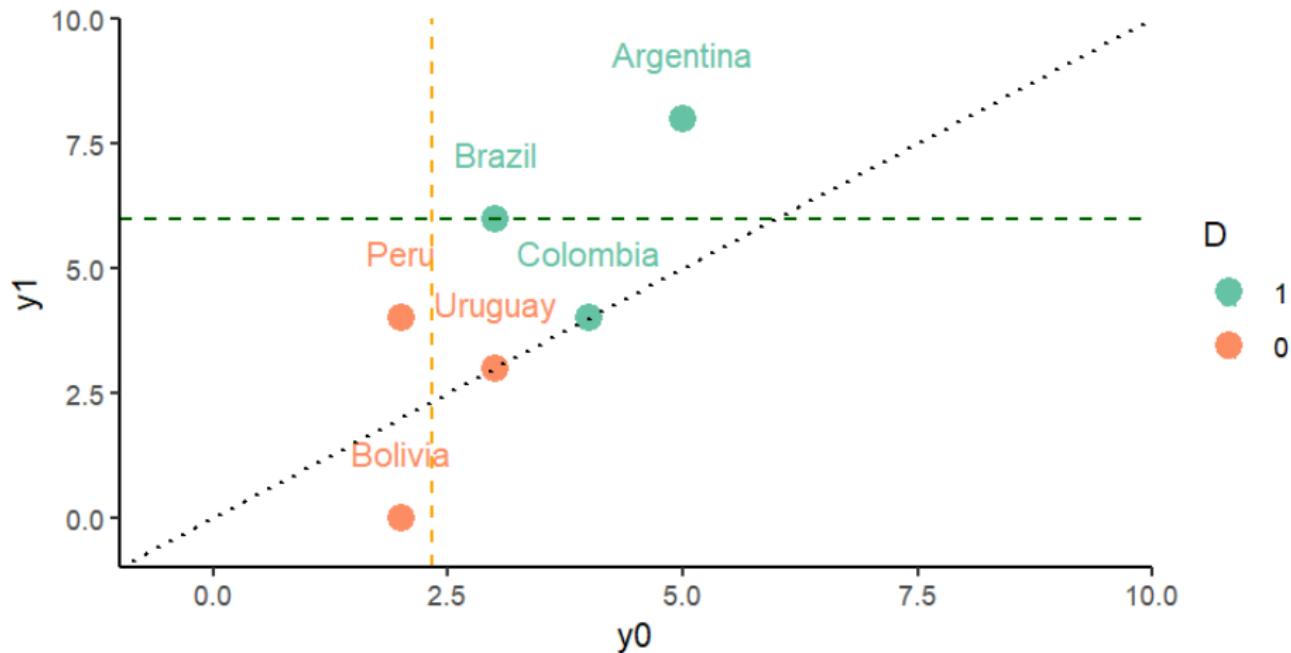


Being misled by reverse causation:



- ▶ GDP Growth encourages democratization
- ▶ So democracies are more likely to have experienced high growth rates

Reverse Causation



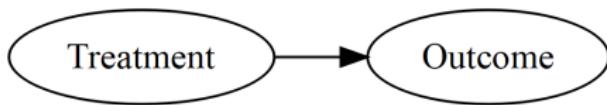
$$\blacktriangleright E(Y_1|D=1) - E(Y_1|D=0) = 6 - 2.3 = 3.7$$

Causal Inference

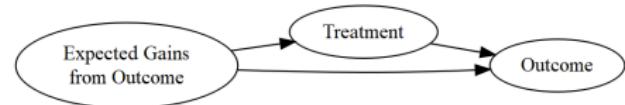
	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	Treatment Effect
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	6	?	?
Argentina	1	8	?	?
Uruguay	0	?	3	?
Bolivia	0	?	2	?
Colombia	1	4	?	?
Peru	0	?	2	?
Average Treatment Effect		6	2.3	3.7

Selection Bias

A real causal relationship:



Being misled by Selection Bias:

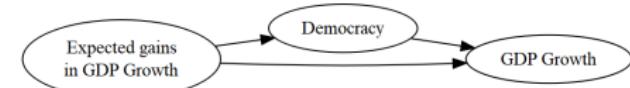


Selection Bias

A real causal relationship:

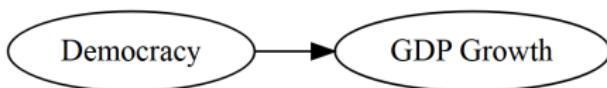


Being misled by Selection Bias:

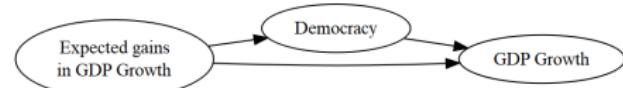


Selection Bias

A real causal relationship:



Being misled by Selection Bias:



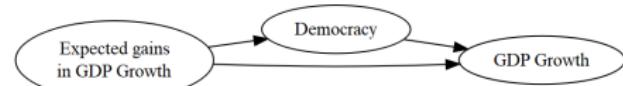
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**

Selection Bias

A real causal relationship:



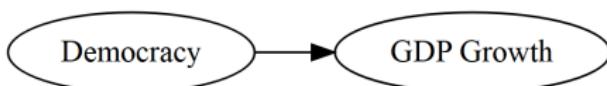
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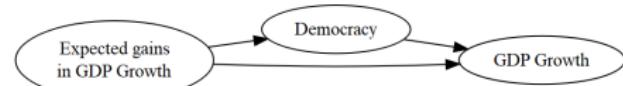
- ▶ The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- ▶ We don't see any of the low y_1 's of units which avoid treatment

Selection Bias

A real causal relationship:



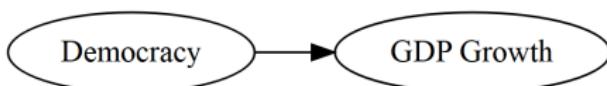
Being misled by Selection Bias:



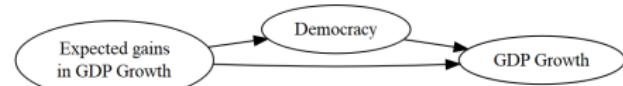
- ▶ The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- ▶ We don't see any of the low y_1 's of units which avoid treatment
 - ▶ Countries which can boost their GDP growth by becoming a democracy choose to democratize

Selection Bias

A real causal relationship:



Being misled by Selection Bias:

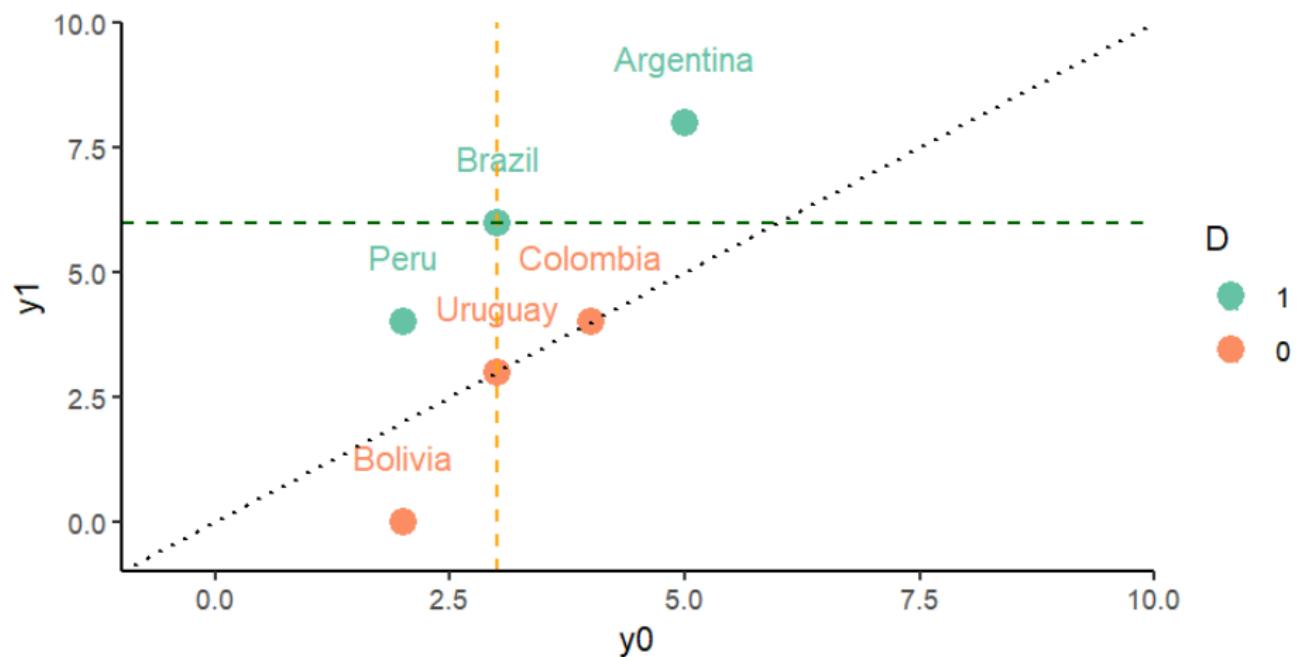


- ▶ The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- ▶ We don't see any of the low y_1 's of units which avoid treatment
 - ▶ Countries which can boost their GDP growth by becoming a democracy choose to democratize
 - ▶ Ex. Mexico? Myanmar?

Self-Selection Bias

	Democracy?	GDP Growth if Dem	GDP Growth if NOT Dem	Treatment Effect
	D_i	Y_1	Y_0	$Y_1 - Y_0$
Brasil	1	6	?	?
Argentina	1	8	?	?
Uruguay	0	?	3	?
Bolivia	0	?	2	?
Colombia	0	?	4	?
Peru	1	4	?	?
Average Treatment Effect		6	3	3

Self-Selection Bias



$$\blacktriangleright E(y_1|D=1) - E(y_0|D=0) = 6 - 3 = 3$$

Self-Selection Bias

- ▶ Allow treatment effects to vary across individuals, so
$$Y_{1i} = Y_{0i} + \alpha_i$$

Self-Selection Bias

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- $$Y_{1i} = Y_{0i} + \alpha_i$$

$$\underbrace{E(Y_i|D=1) - E(Y_i|D=0)}_{\text{Observed Effect}} = \underbrace{E(Y_{1i} - Y_{0i})}_{\text{Real ATE}}$$

$$+ \underbrace{\frac{1}{2} [E(Y_{1i}|D=1) - E(Y_{1i}|D=0)]}_{\text{Imbalance on } Y_1} + \underbrace{\frac{1}{2} [E(Y_{0i}|D=1) - E(Y_{0i}|D=0)]}_{\text{Imbalance on } Y_0}$$

(3)

NB: For equal-sized treatment and control groups

Self-Selection Bias

- Allow treatment effects to vary across individuals, so

$$Y_{1i} = Y_{0i} + \alpha_i$$

$$\underbrace{E(Y_i|D=1) - E(Y_i|D=0)}_{\text{Observed Effect}} = \underbrace{E(Y_{1i} - Y_{0i})}_{\text{Real ATE}}$$

$$+ \underbrace{\frac{1}{2} [E(Y_{1i}|D=1) - E(Y_{1i}|D=0)]}_{\text{Imbalance on } Y_1} + \underbrace{\frac{1}{2} [E(Y_{0i}|D=1) - E(Y_{0i}|D=0)]}_{\text{Imbalance on } Y_0}$$

(3)

NB: For equal-sized treatment and control groups

Self-Selection Bias

- ▶ Selection Bias occurs where our data sample does not tell the complete story:

Self-Selection Bias

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 - ▶ Only wealthy democracies 'select' into our sample
 3. **Survival Bias:** Some types of units drop out of our sample
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Problems with Observational Data

- ▶ Depending on the treatment assignment mechanism we get a range of Average Treatment Effects:

Comparing Average Treatment Effects

Treated Units	ATE
Real Effect for all units	1
Bolivia and Colombia treated	-1.25
Omitted Variable Bias (Southern Cone)	3
Reverse Causation	3.7
Self-selection (Biggest GDP gains)	3

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 - ▶ What would happen if the control units got treated?

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The set of factors that determine why some units have $D = 0$ and others have $D = 1$

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Summary

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 - Self-Selection?

DOES OIL HINDER DEMOCRACY?

By MICHAEL L. ROSS*

INTRODUCTION

POLITICAL scientists believe that oil has some very odd properties. Many studies show that when incomes rise, governments tend to become more democratic. Yet some scholars imply there is an exception to this rule: if rising incomes can be traced to a country's oil wealth, they suggest, this democratizing effect will shrink or disappear. Does oil really have antidemocratic properties? What about other minerals and other commodities? What might explain these effects?

The claim that oil and democracy do not mix is often used by area specialists to explain why the high-income states of the Arab Middle East have not become democratic. If oil is truly at fault, this insight could help explain—and perhaps, predict—the political problems of oil exporters around the world, such as Nigeria, Indonesia, Venezuela, and the oil-rich states of Central Asia. If other minerals have similar properties, this effect might help account for the absence or weakness of democracy in dozens of additional states in sub-Saharan Africa, Latin America, and Southeast Asia. Yet the "oil impedes democracy" claim has received little attention outside the circle of Mideast scholars; moreover, it has not been carefully tested with regression analysis, either within or beyond the Middle East.

I use pooled time-series cross-national data from 113 states between 1971 and 1997 to explore three aspects of the oil-impedes-democracy claim. The first is the claim's validity: is it true? Although the claim has been championed by Mideast specialists, it is difficult to test by examining only cases from the Middle East because the region provides scholars with

* Previous versions of this article were presented to seminars at Princeton University, Yale University, and the University of California, Los Angeles, and at the September 2000 annual meeting of the American Political Science Association in Washington, D.C. For their thoughtful comments on earlier drafts, I am grateful to Pradeep Chhibber, Indra de Soysa, Geoffrey Garrett, Phil Keefer, Steve Knack, Miriam Lowi, Ellen Lust-Okar, Lant Pritchett, Nicholas Sambanis, Jennifer Widner, Michael Woolcock, and three anonymous reviewers. I owe special thanks to Irfan Nooruddin for his research assistance and advice and to Colin Xu for his help with the Stata. I wrote this article while I was a visiting scholar at The World Bank in Washington, D.C. The views I express in this article, and all remaining errors, are mine alone.

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Summary

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- ▶ Can you create an artificial effect between D and Y even when there is no direct causal effect?
- ▶ Under what conditions can you recover the real treatment effect?

Section 4

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 - ▶ **Design-Based Solutions** to the Fundamental Problem of Causal Inference: Which treatment assignment mechanisms **avoid these biases** and provide plausible counterfactuals
 - ▶ How much can we learn with better research design?
 - ▶ **Model-Based Solutions:** Not so much.

Rest of the Course

		Independence of Treatment Assignment	Researcher Con- trols Treatment Assignment?
Controlled Experi- ments	Field Experiments	✓	✓
	Survey and Lab Experiments	✓	✓
Natural Ex- periments	Randomized Natural Experi- ments	✓	
	Instrumental Variables	✓	
	Discontinuities	✓	
Observational Studies	Difference-in-Differences		
	Controlling for Confounding		
	Matching		
	Comparative Cases and Process Tracing		