FLS 6441 - Methods III: Explanation and Causation

Week 2 - A Framework for Explanation

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March 2019

Section 1

Explanation

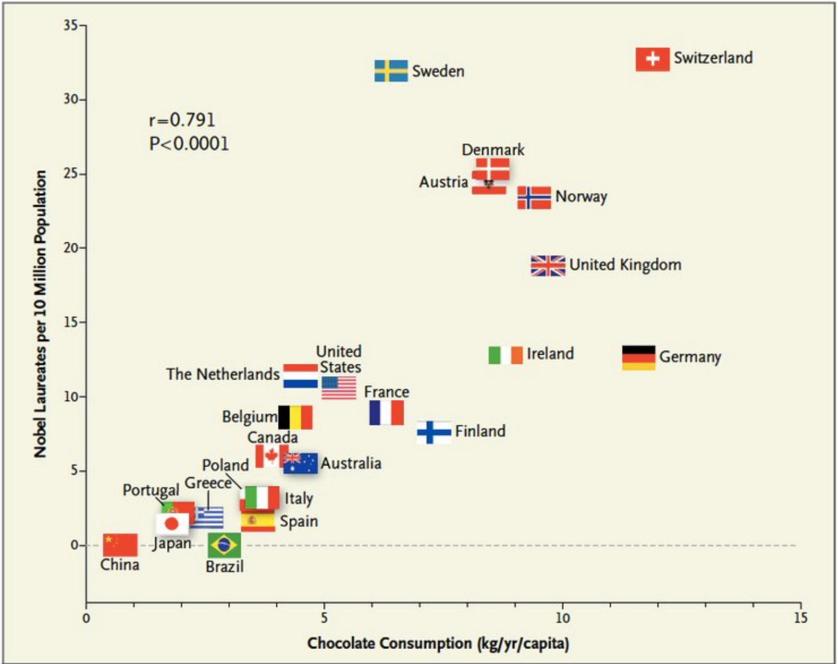

Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

Explanation

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    - 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

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- 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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Probabilistic Explanation

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- Treatment effects are a distribution, not a single value

Explanation

- Two perspectives on explanation:

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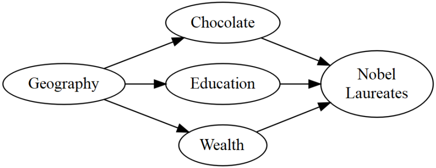
Causes of Effects	**Effects of Causes**
What caused Y?	Does D cause Y?
Why does Switzerland have so many Nobel laureates?	Does chocolate cause more Nobel laureates?
Backward-looking	Forward-looking

Explanation

- Two perspectives on explanation:



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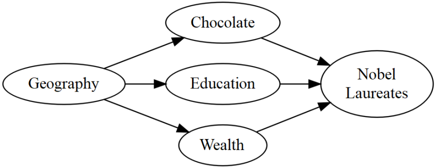

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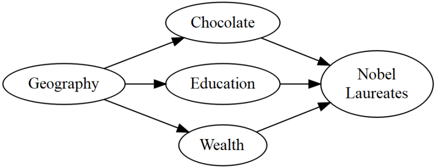

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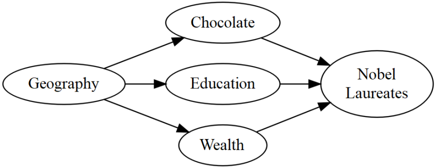

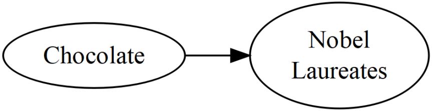

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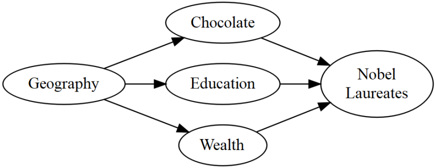

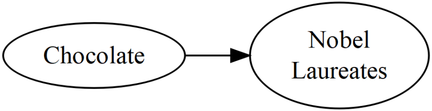

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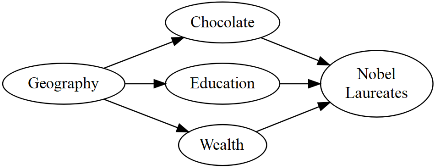

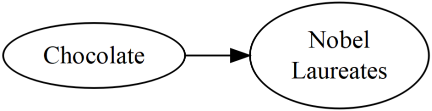

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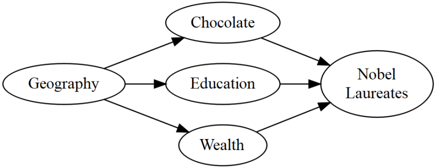

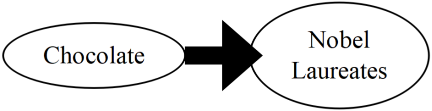

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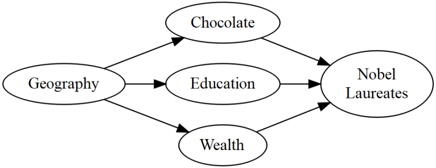

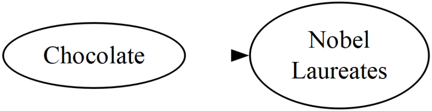

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- A focus on a single explanatory variable D requires a clear definition of **’Treatment’**
- AND to clearly define a **’Control’**
  - What is the opposite of investing $1bn in education?
  - No investment, or investing it elsewhere?
- Define treatment:

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

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- Units are **time-specific**: the same person 10 minutes later is a different unit

Section 2

Causal Inference

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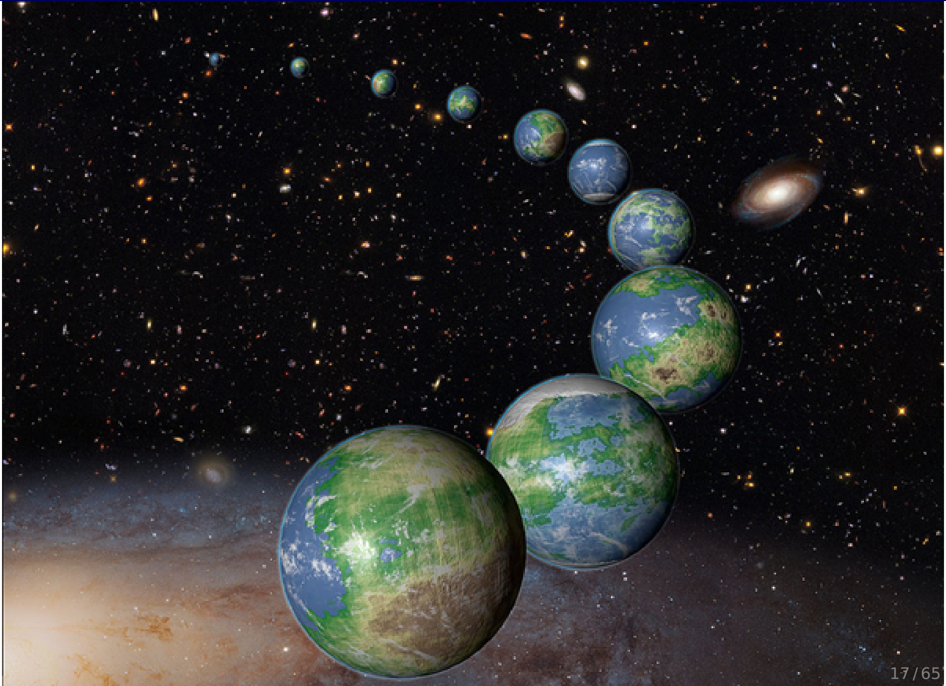

Causal Inference

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

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Average Treatment Effect	**5**	**4**	**1**

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

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Average Treatment Effect on the Untreated (Control)

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- The three effect estimates are usually different
  - The effect democracy has had in Europe is different to the effect if it were introduced in Africa

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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ATU	**0**	**6.3**	**5**	**1.3**

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

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

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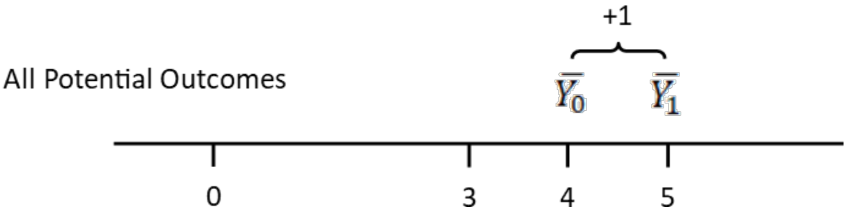

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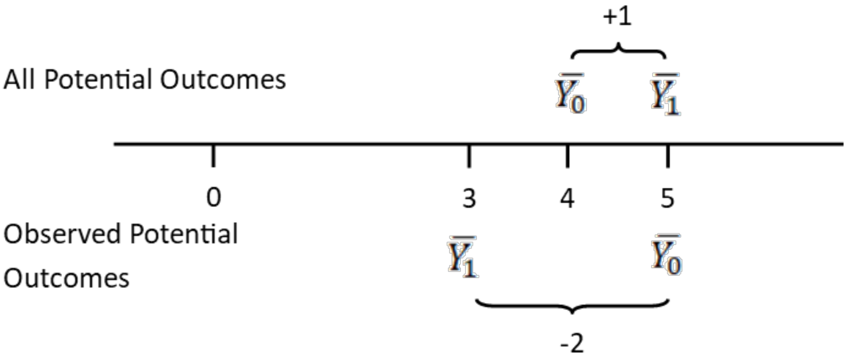

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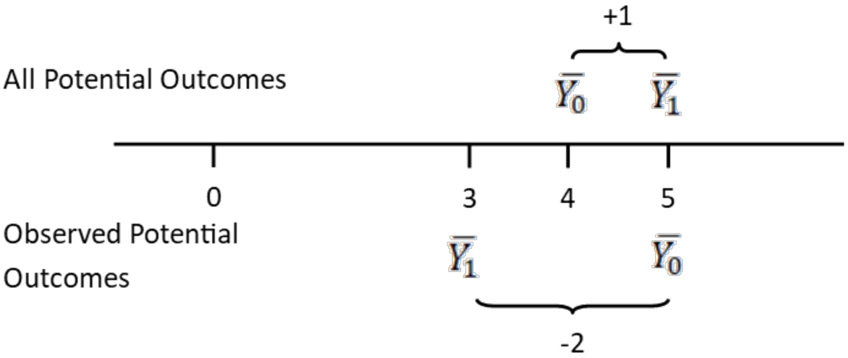

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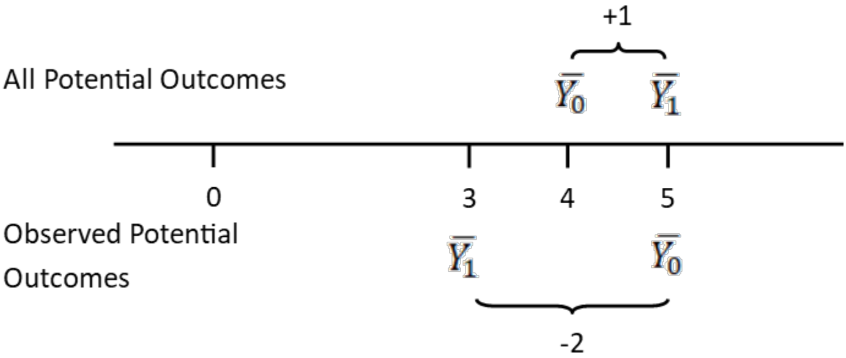

- $E(Y_1)$ values are **biased lower** in the observed data
- $E(Y_0)$ values are **biased higher** in the observed data
- So $E(Y_1) - E(Y_0)$ is **biased**

Causal Inference

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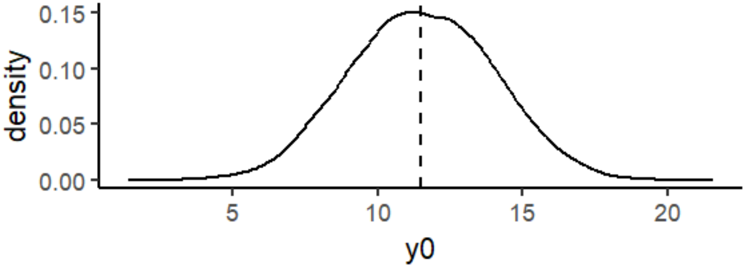
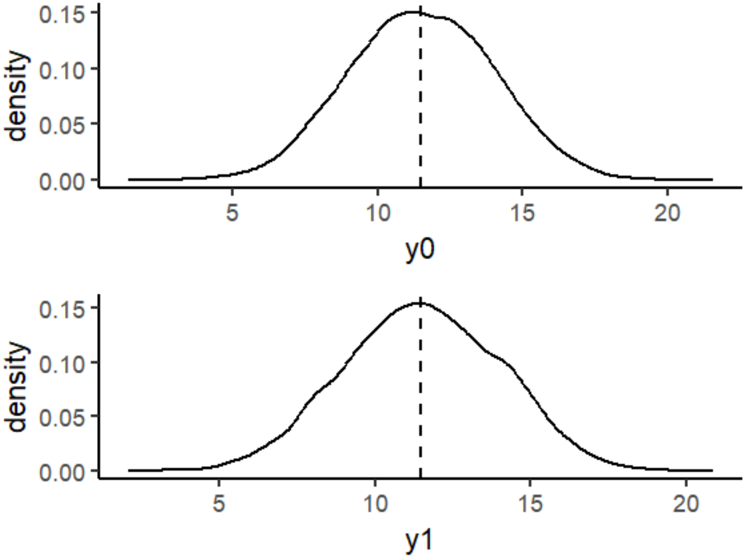
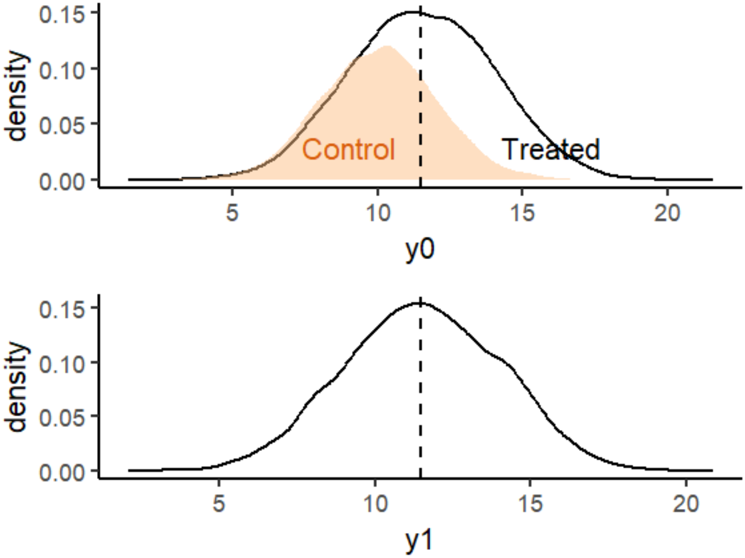
Causal Inference



Causal Inference



Causal Inference



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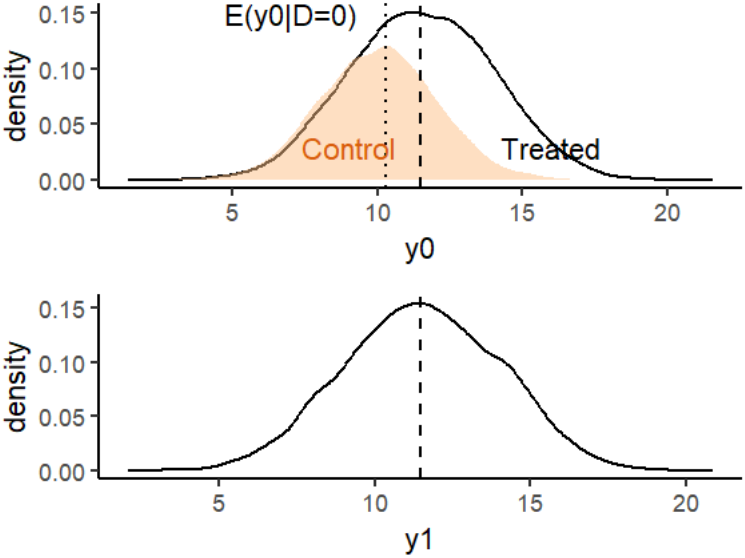

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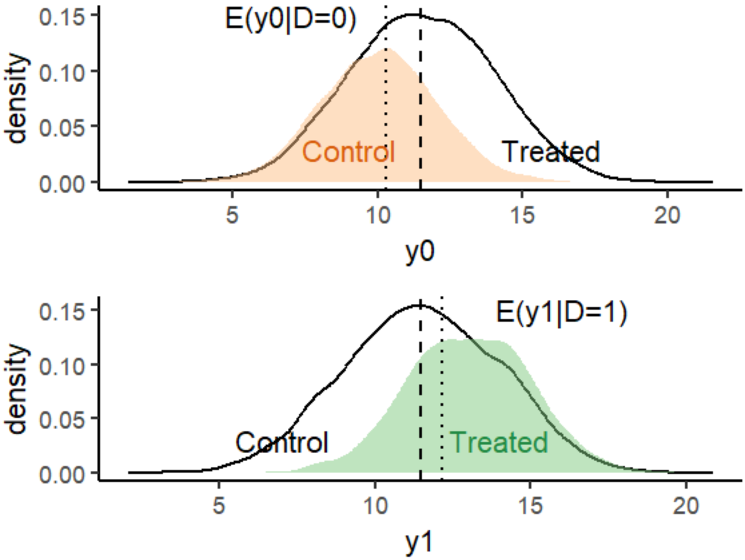

Causal Inference

- Lots of averages:

		Hypothetical outcome	
		$Y0$	$Y1$
Actual Treatment	$D = 0$	$E(Y_{0i}\|D = 0)$	$E(Y_{1i}\|D = 0)$
	$D = 1$	$E(Y_{0i}\|D = 1)$	$E(Y_{1i}\|D = 1)$

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	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?

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  1. Omitted Variables

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Bias

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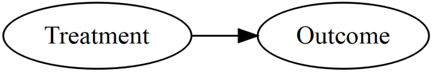
- In all of these cases **the potential outcomes are distorted**
- So basic regression is **biased**

Omitted Variable Bias

A real causal relationship:



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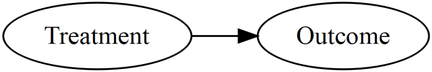
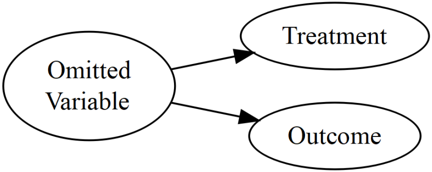


Being misled by omitted variable bias:



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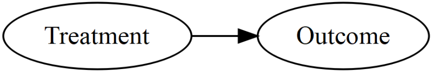

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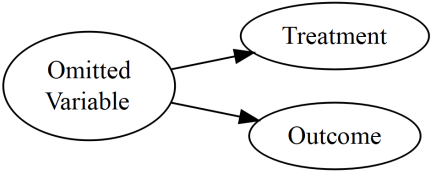

- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**

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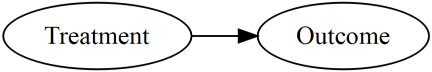

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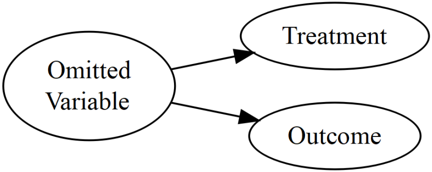

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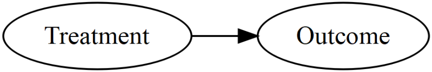

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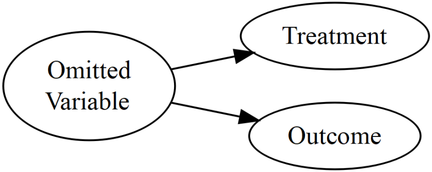

- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1
- And control units have non-representative Y_0

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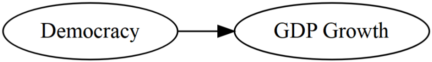

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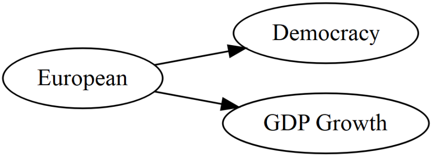

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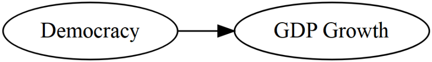

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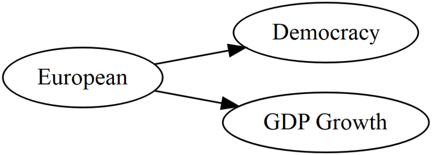
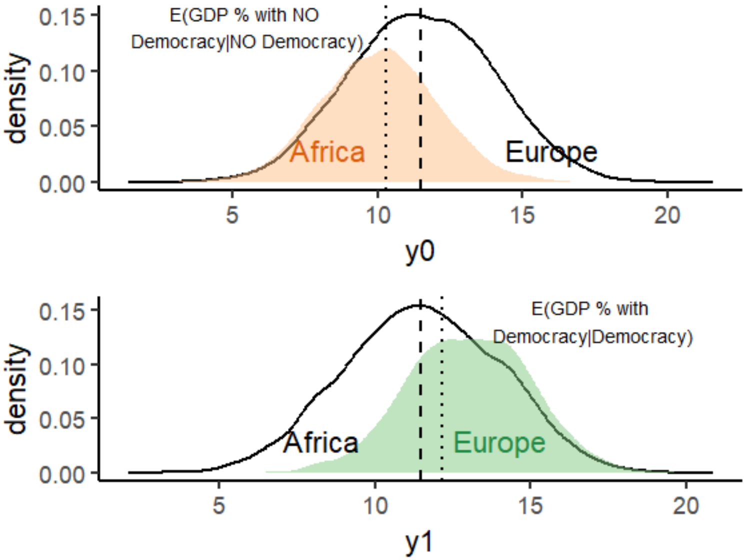


- European countries faced conditions that encouraged both democracy and rapid GDP growth

Omitted Variable Bias



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

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

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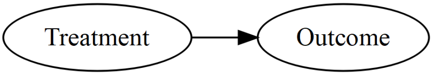
$$\hat{ATE} = E(Y_1|D=1) - E(Y_0|D=0)$$

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

Reverse Causation

A real causal relationship:



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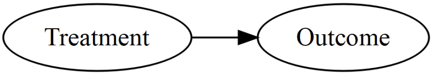

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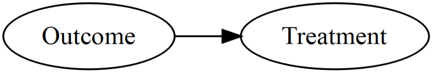

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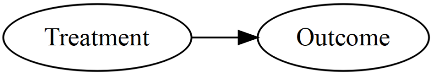

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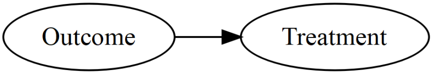

- D does not affect Y, but higher Y makes treatment (D) more likely

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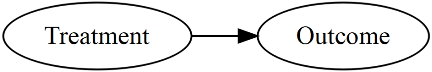

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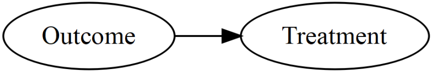
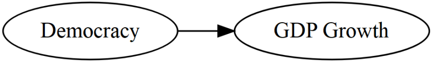


- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are **correlated**

Reverse Causation

A real causal relationship:



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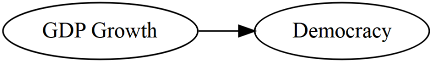

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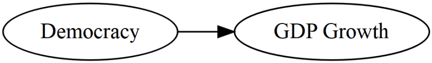

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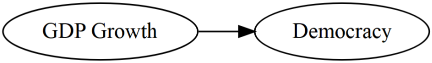

- GDP Growth encourages democratization

Reverse Causation

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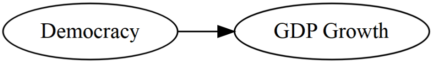

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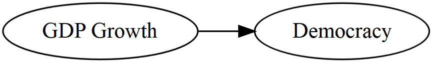
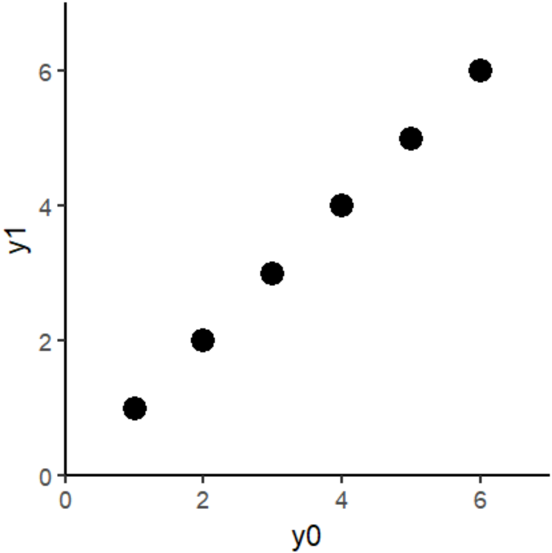


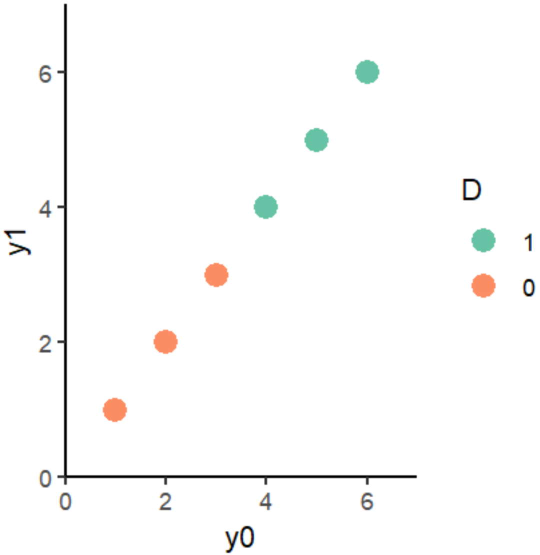
- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Reverse Causation



- $E(Y_1 - Y_0) = 0$

Reverse Causation



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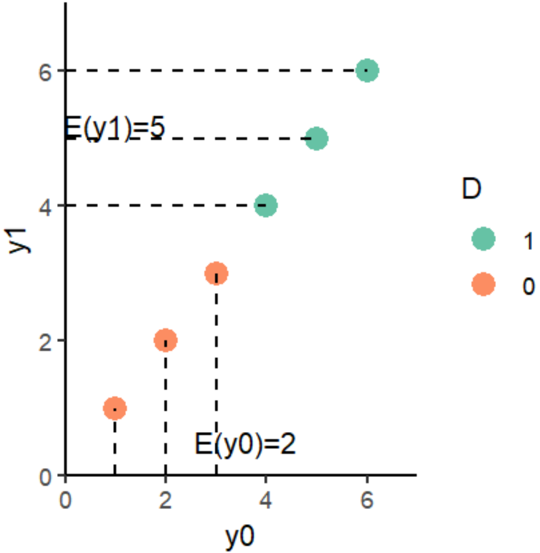

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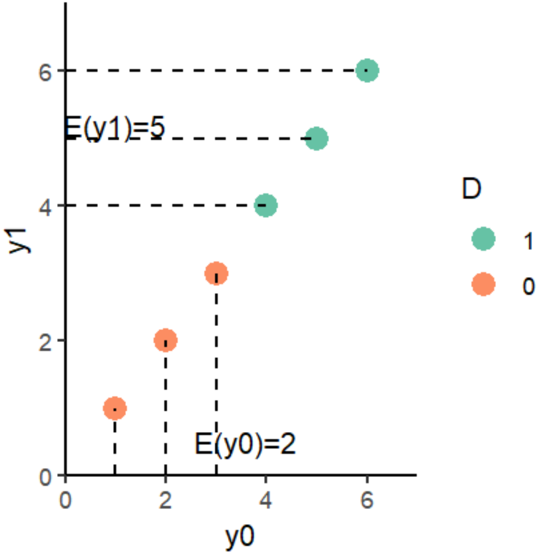
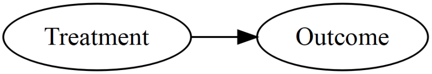


- $E(Y_1|D=1) - E(Y_0|D=0) = 5 - 2 = 3$

Selection Bias

A real causal relationship:



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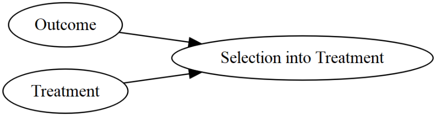

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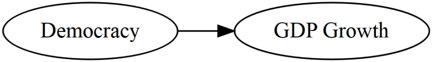

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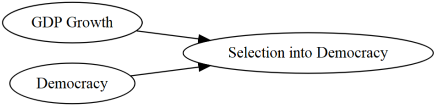

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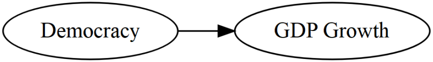

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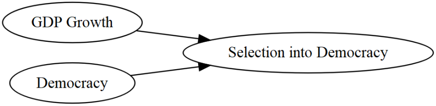

- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**

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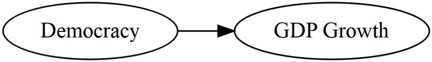

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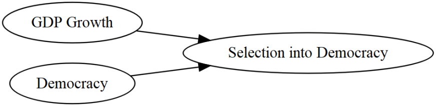

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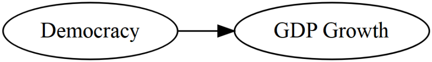

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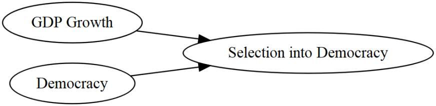

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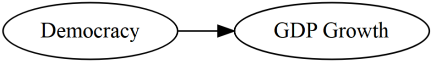

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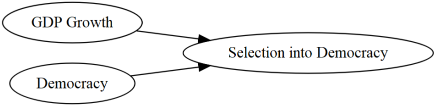

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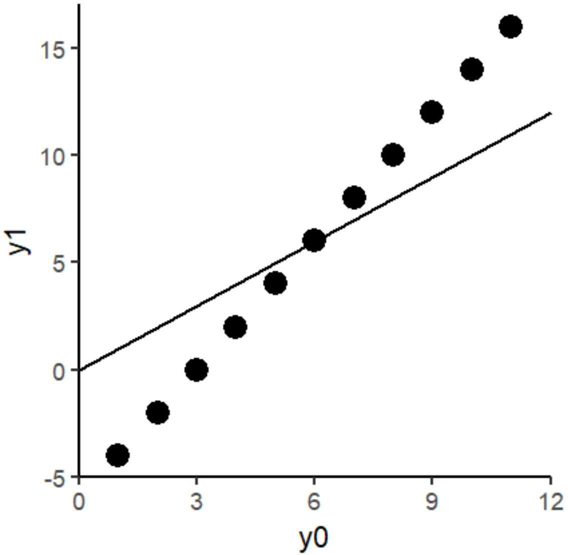
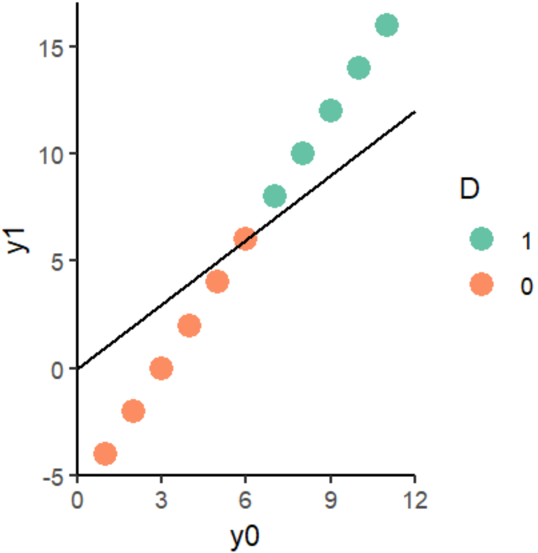
  - Ex. Mexico? Myanmar?

Self-Selection Bias

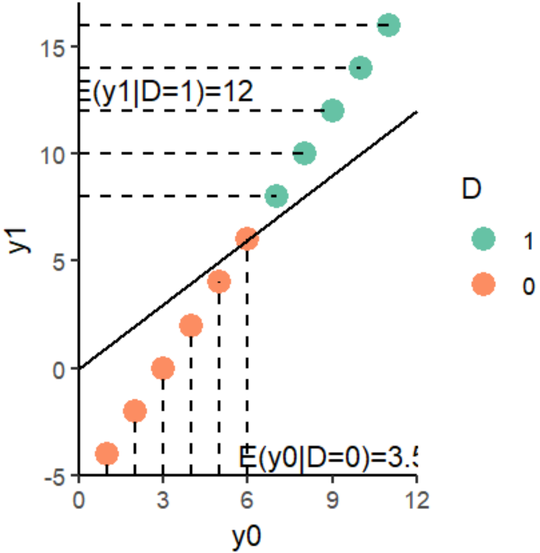


Self-Selection Bias



- $E(y_1) - E(y_0) = 0$

Self-Selection Bias



- $E(y_1|D=1) - E(y_0|D=0) = 8.5$

Self-Selection Bias

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

Self-Selection Bias

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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

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World Politics 53 (April 2001), 325–61

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- 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 Controls Treatment Assignment?**
Controlled Experiments	Field Experiments	✓	✓
	Survey and Lab Experiments	✓	✓
Natural Experiments	Randomized Natural Experiments	✓	
	Instrumental Variables	✓	
	Discontinuities	✓	
Observational Studies	Difference-in-Differences		
	Controlling for Confounding		
	Matching		
	Comparative Cases and Process Tracing		