FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review

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Section 1

Explanation

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’

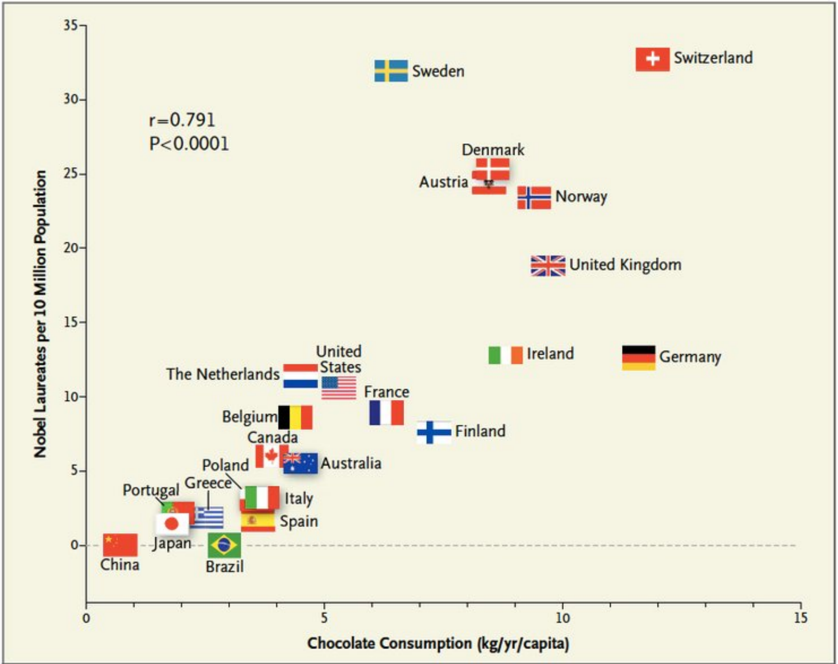

Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

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

Explanation

- Two perspectives on explanation:

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?

Explanation

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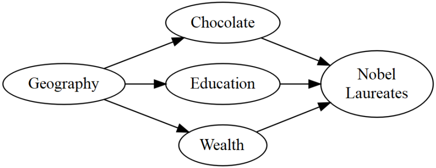

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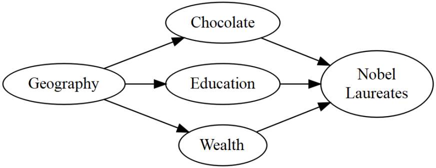

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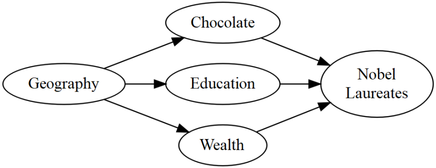

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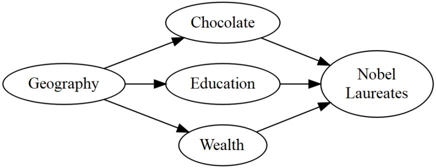

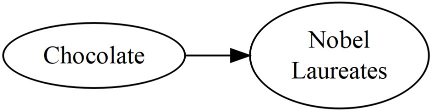

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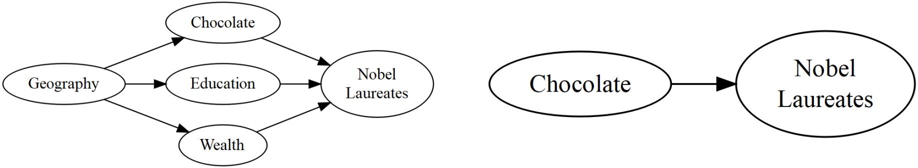

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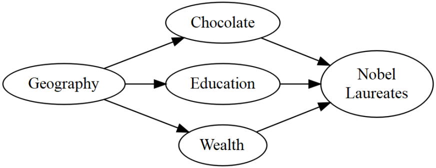

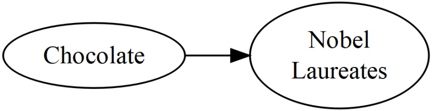

- Identifying the source of **ALL** of the variation in Nobel Laureates
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- Identifying how much **ONE** variable causes variation in Nobel Laureates
- This we can do!

Explanation

- 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:

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

Explanation

- Defining our outcome:
  - Is it the outcome we really care about? Or just what's easy to measure?
  - Tempting to look at many outcomes, but the risk of 'cherry-picking'
    - All outcomes are **probabilistic** (due to all the other factors we haven't accounted for)
    - If we study 20 outcomes, on average one will show a significant effect even with no real causal effect
  - So we also want a **single outcome** usually

Explanation

- What are the **units** of our analysis?
- Countries? Political Parties? Individuals?
- eg. How does electoral system affect attitudes to redistribution?
  - Treatment at the national level
  - Outcome at the individual level
  - Measurement needed at the lowest (individual) level
- Units are **time-specific**: the same person 10 minutes later is a different unit

Explanation

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Probabilistic Explanation

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- Treatment effects are a distribution, not a single value

Section 2

Causal Inference

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- The **causal effect** of treatment is how each unit's outcome differs when it is treated and not treated

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- This means comparing the **Potential Outcomes** for unit i:

$$Y_{Di} = \begin{cases} Y_{1i} & \text{Potential Outcome if unit i treated} \\ Y_{0i} & \text{Potential Outcome if unit i NOT treated} \end{cases}$$

- Individual Treatment Effect for unit i: $\alpha_i = Y_{1i} - Y_{0i}$

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$$Y_{Di} = \begin{cases} Y_{1i} \text{ GDP Growth of Brazil in 2010 if a Democracy} \\ Y_{0i} \text{ GDP Growth of Brazil in 2010 if NOT a Democracy} \end{cases}$$

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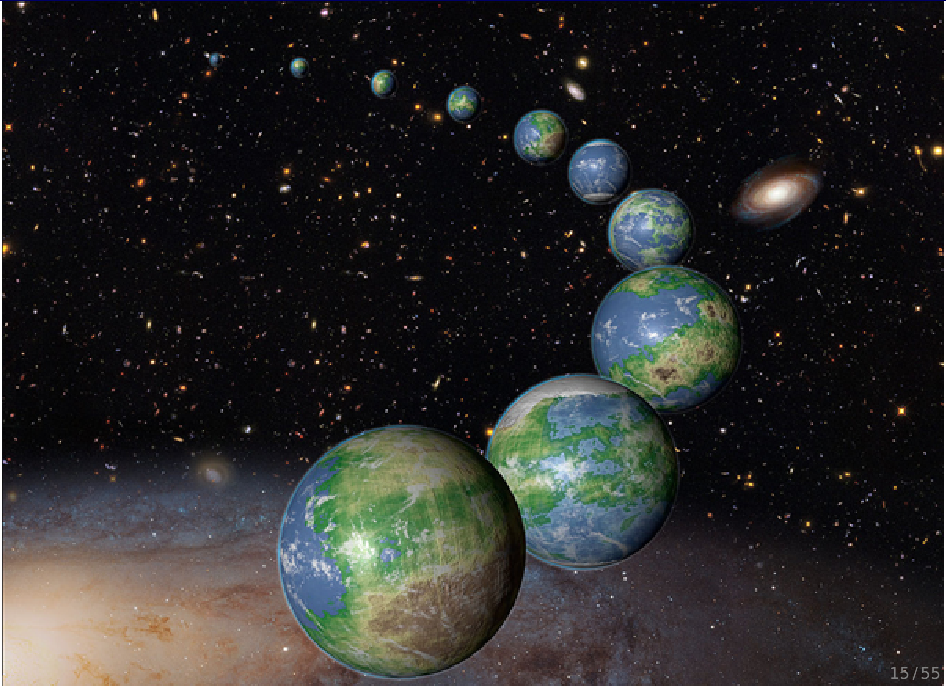

Causal Inference

Potential Outcomes are just another Variable

	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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Average Treatment Effect

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Average Treatment Effect

We want to calculate an **Average Treatment Effect**

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

Causal Inference

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

Causal Inference

The Fundamental Problem of Causal Inference

- No units can receive **both** treatment and control
- So we can never observe both Y_1 and Y_0 for the same unit
- *Individual* Treatment Effects are **Impossible to Estimate**

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

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

Causal Inference

Potential Outcomes Example

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

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	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
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Bolivia	1	2	?	?
Colombia	0	?	7	?
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

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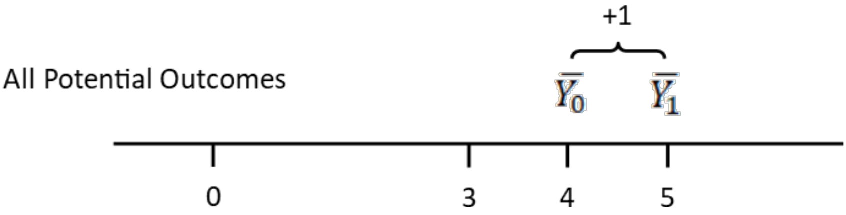

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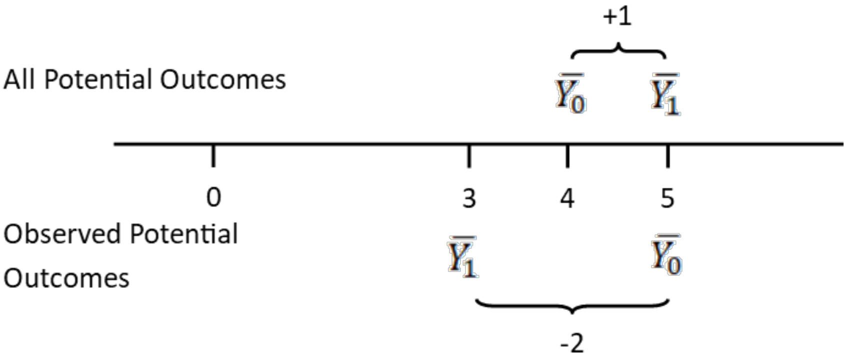

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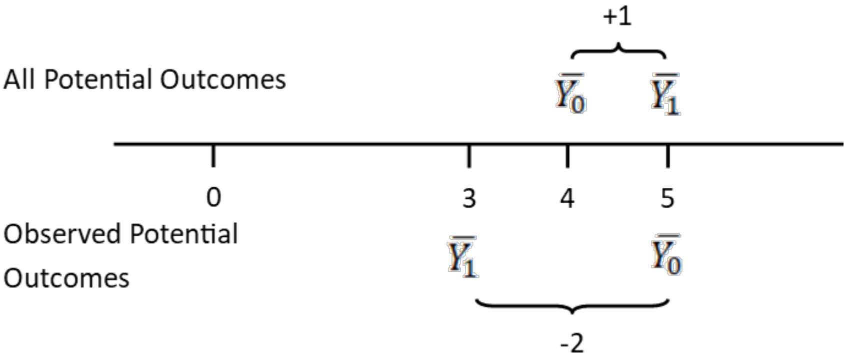

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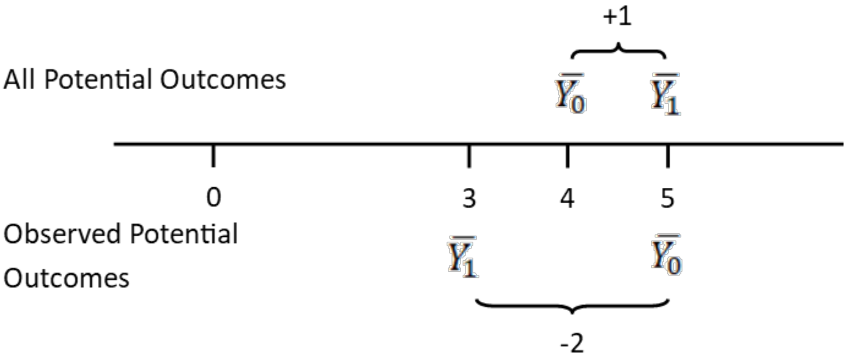

- $E(Y_1)$ values are **biased lower** in the observed data
- $E(Y_0)$ values are **biased higher** in the observed data
- So $E(Y_1) - E(Y_0)$ is **biased**

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  - Causal effects are biased

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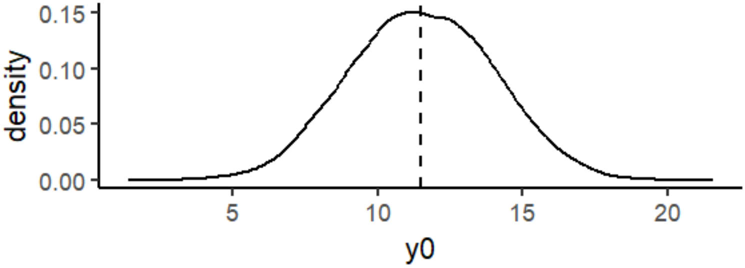

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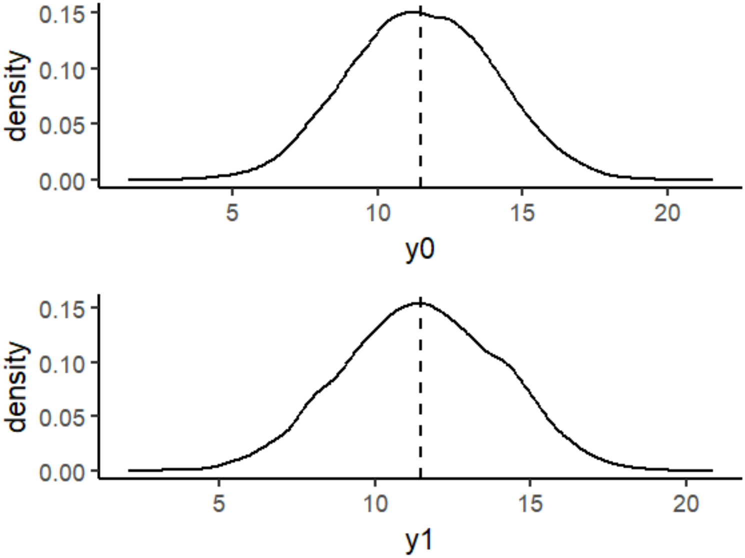

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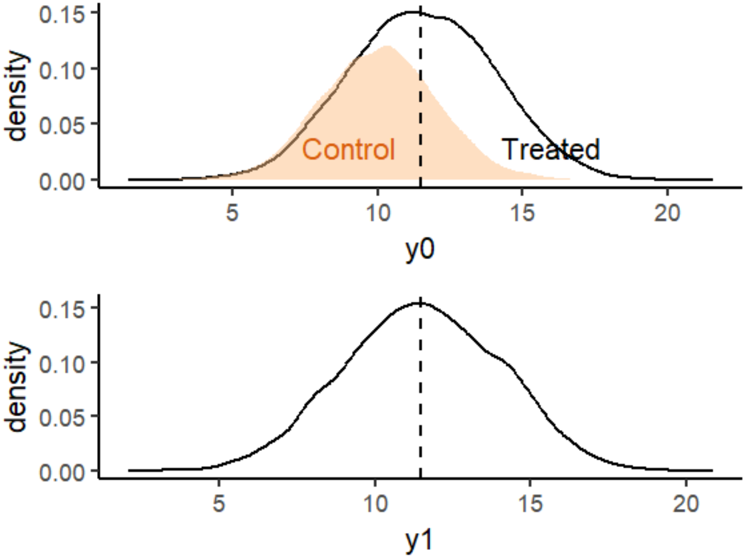

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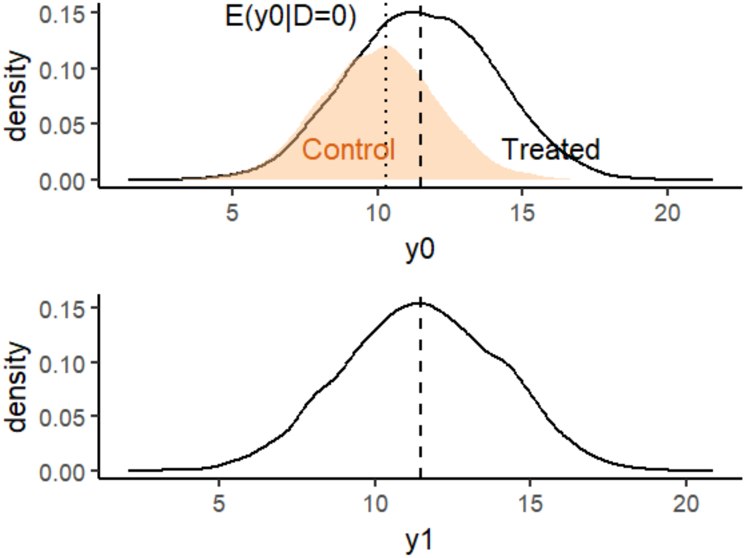

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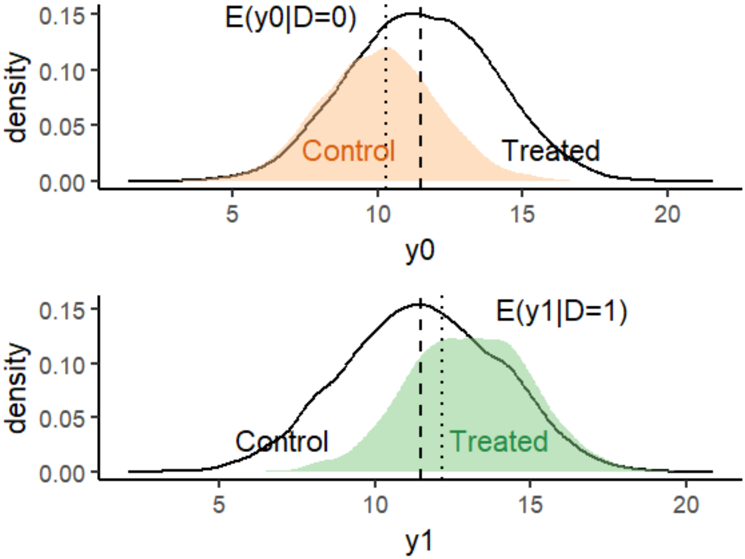


Causal Inference

- Contrasting the averages of the hypothetical variables and the observed variables:

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

Causal Inference

- All our causal estimates are **averages**
  - We cannot distinguish the null hypothesis of no average effect from the sharp null hypothesis of no individual effects

	No Average Effect $(Y_1 - Y_0)$	"Sharp null": No individual effects $(Y_1 - Y_0)$
Brasil	2	0
Argentina	-1	0
Bolivia	1	0
Colombia	0	0
Peru	-2	0
Average	**0**	**0**

Section 3

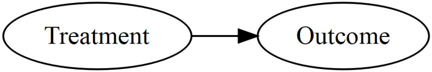
Why Observational Data is Biased

Bias

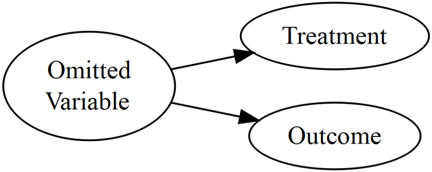
- Why are potential outcomes biased in our data?
  1. Omitted Variables
  2. Reverse Causation
  3. Selection Bias
- **In all of these cases the potential outcomes are distorted so basic regression is biased**

Omitted Variable Bias

A real causal relationship:



Being misled by omitted variable bias:



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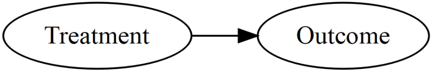

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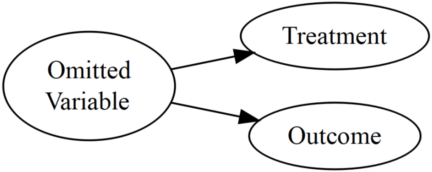

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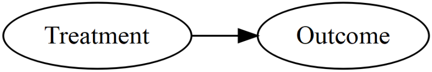

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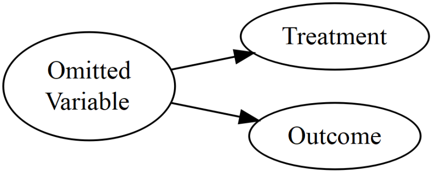

- A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- So treated units have non-representative Y_1
- And control units have non-representative Y_0

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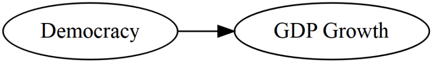

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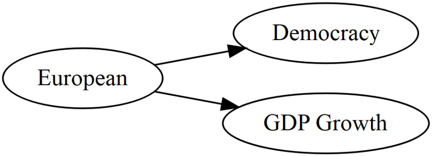

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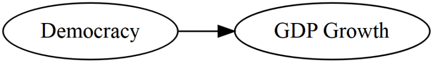

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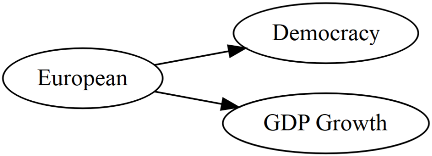
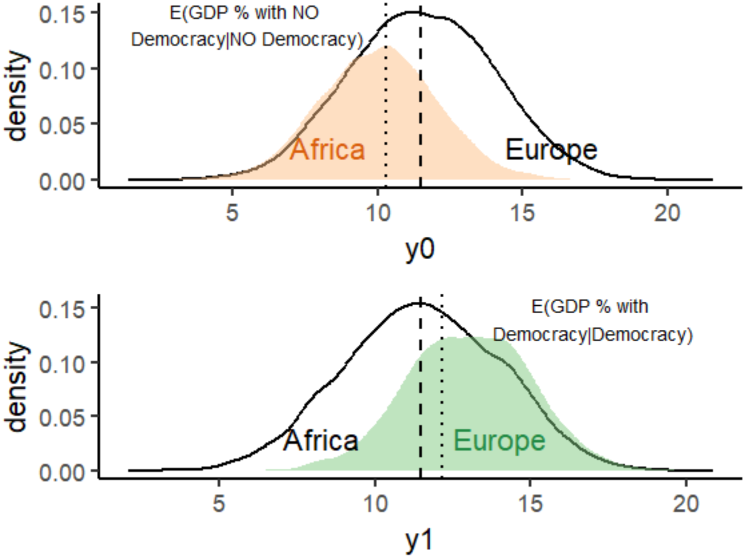


- European countries faced conditions that encouraged both democracy and rapid GDP growth

Omitted Variable Bias



Omitted Variable Bias

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

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

Omitted Variable Bias

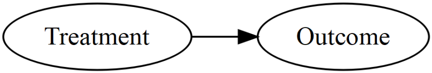
- Let's say that $Y_{1i} = Y_{0i} + \alpha$, where α is the real constant treatment effect

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

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

Reverse Causation

A real causal relationship:



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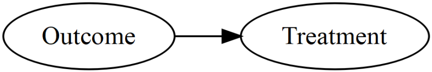

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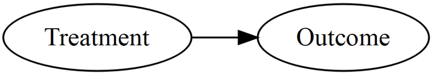

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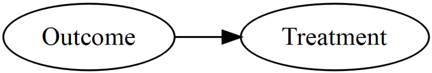

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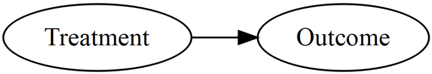

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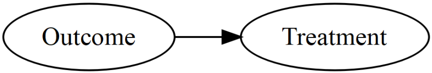

- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are correlated

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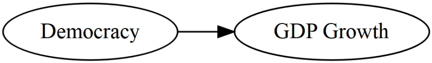

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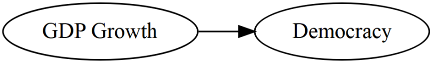

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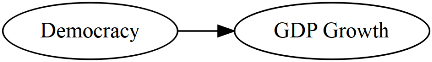

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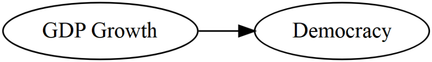
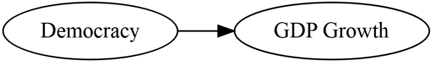


- GDP Growth encourages democratization

Reverse Causation

A real causal relationship:



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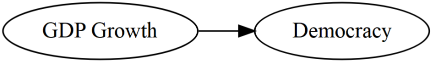
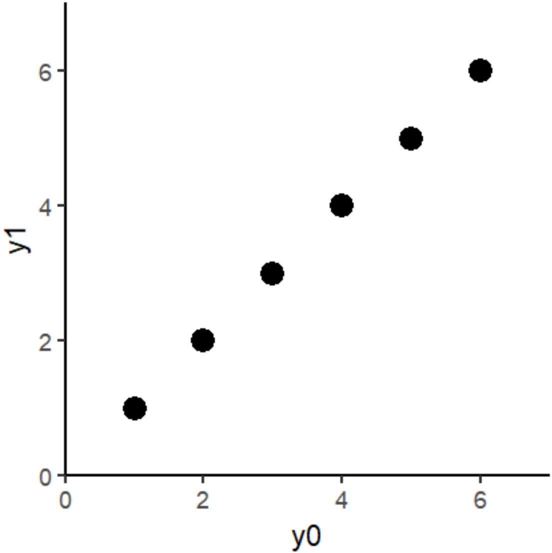


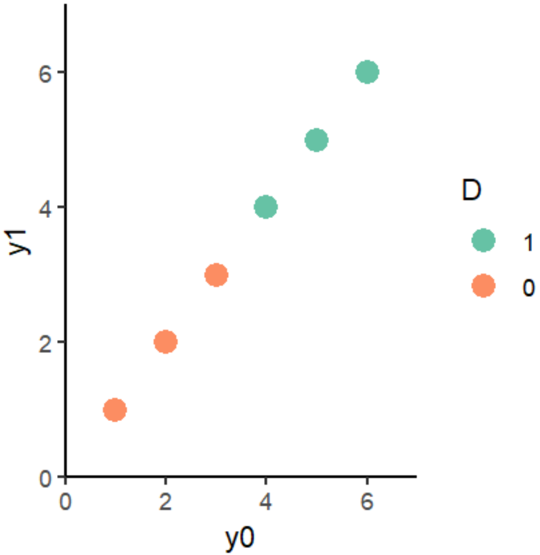
- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Reverse Causation



- $E(Y_1 - Y_0) = 0$

Reverse Causation



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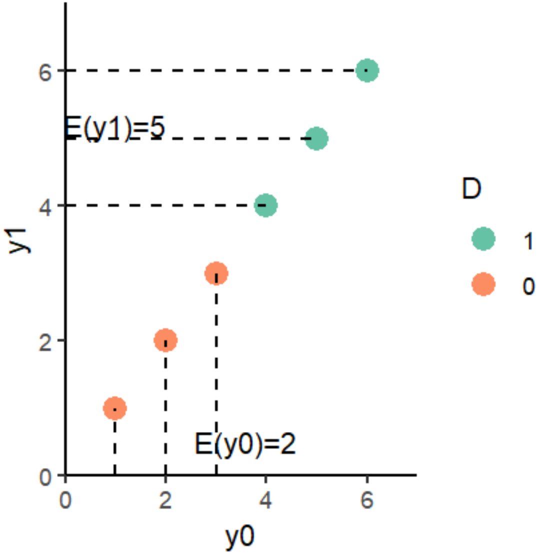

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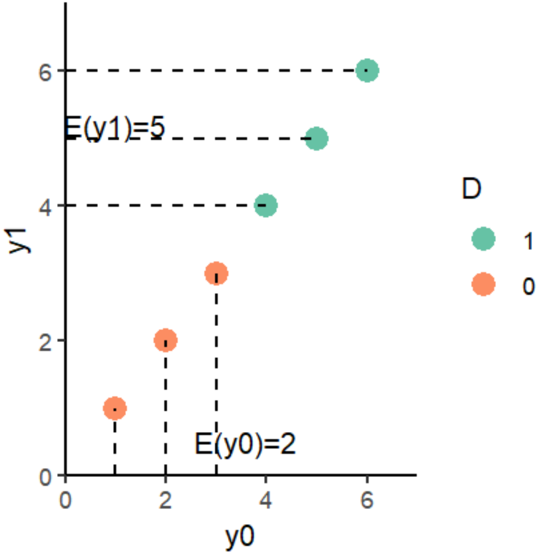
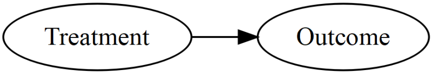


- $E(Y_1|D=1) - E(Y_0|D=0) = 5 - 2 = 3$

Selection Bias

A real causal relationship:



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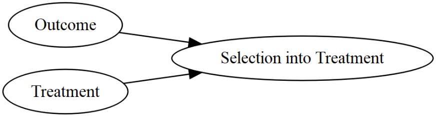

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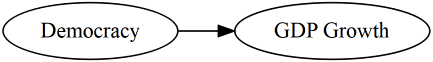

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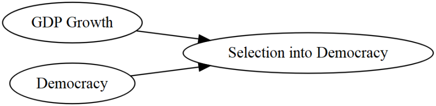

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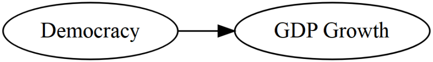

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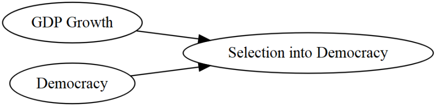

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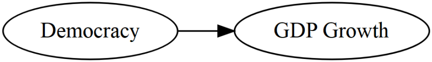

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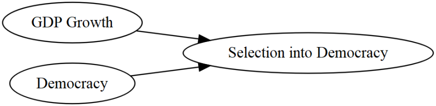
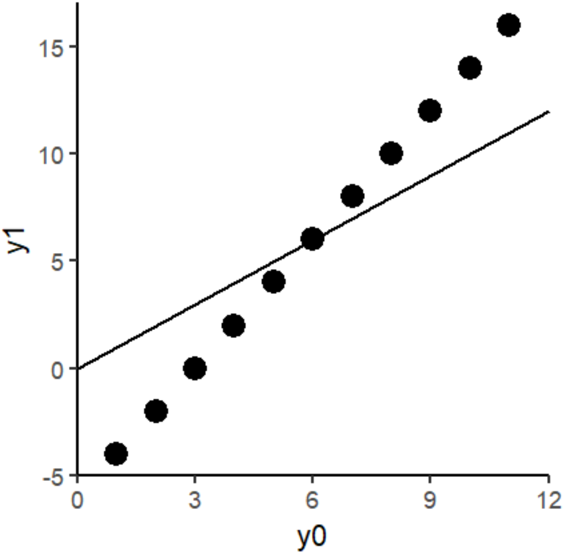


- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment

Self-Selection Bias



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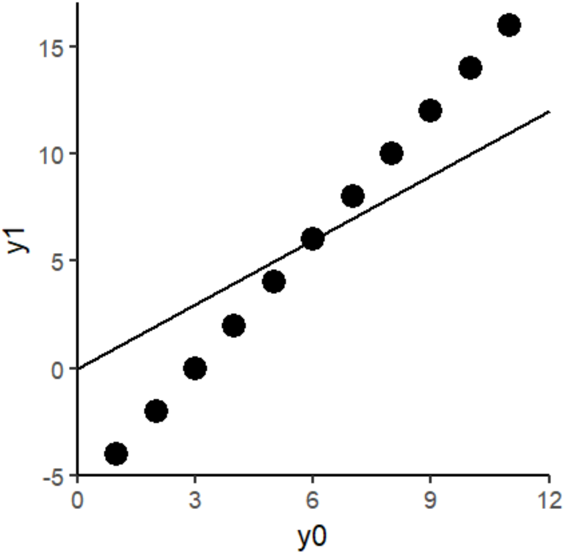

- Countries which can boost their GDP growth by becoming a

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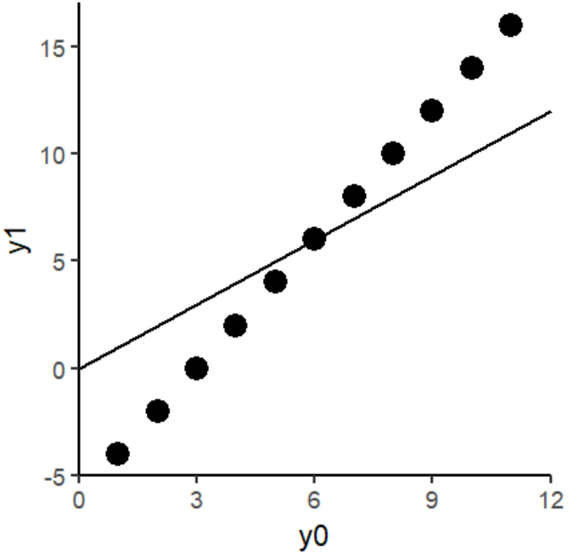

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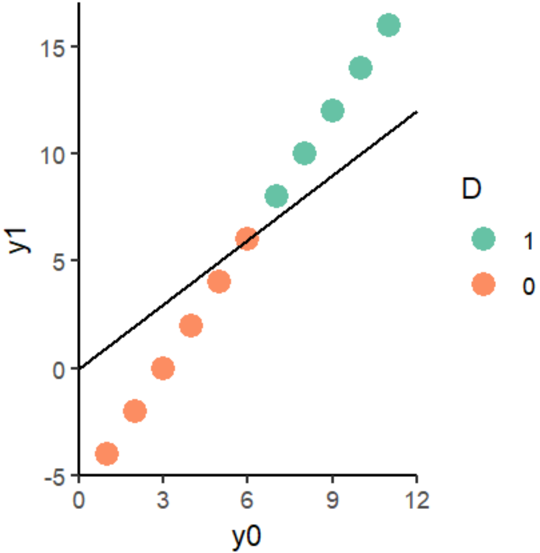

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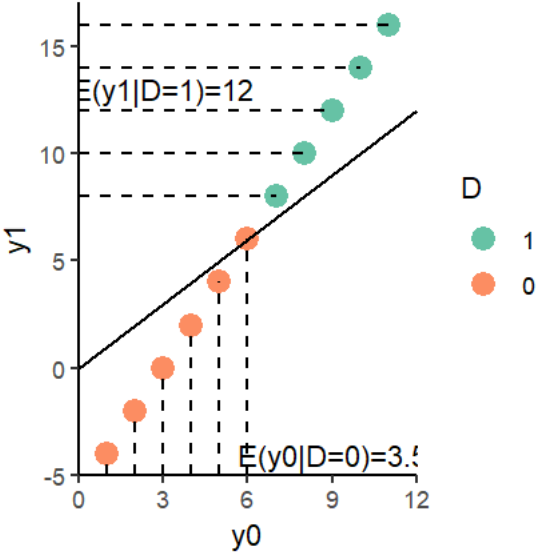
Self-Selection Bias



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

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NB: For equal-sized treatment and control groups

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Treatment Assignment Mechanism

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

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  1. What are the treatment and outcome variables?

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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

* 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.

World Politics 53 (April 2001), 325–61

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Section 4

Rest of the Course

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  - **Design-Based Solutions:** Which treatment assignment mechanisms **avoid these biases** and provide plausible counterfactuals

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  - **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		