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’

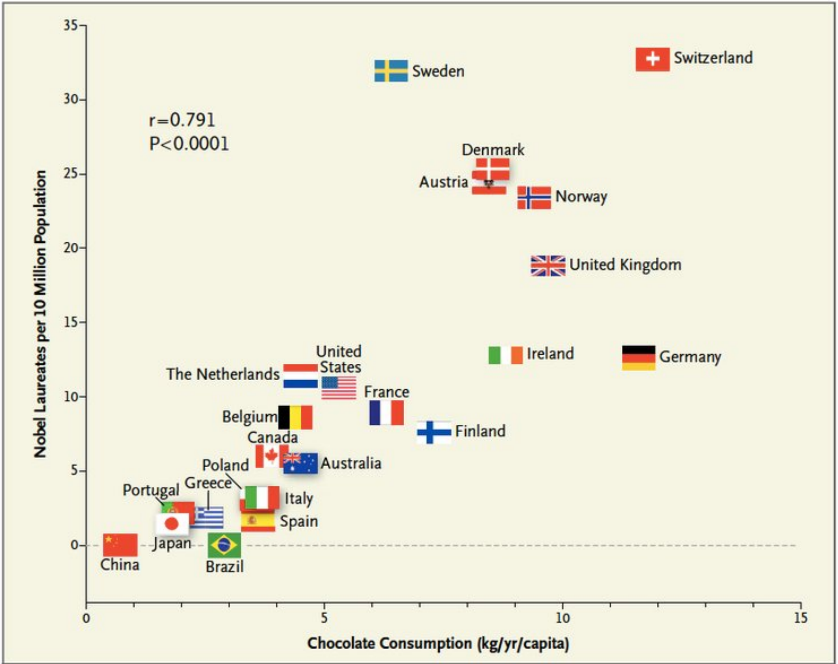

Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

Explanation

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  - 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

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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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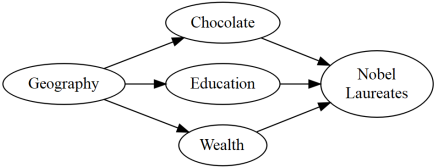

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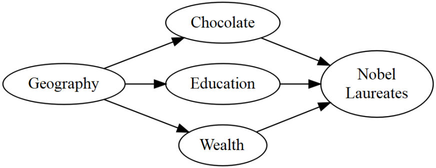

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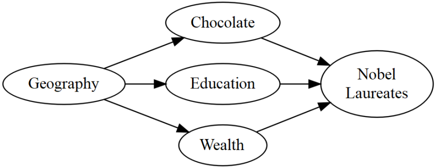

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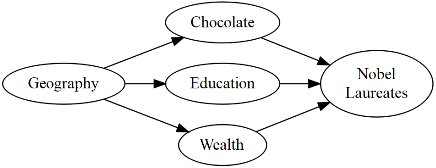

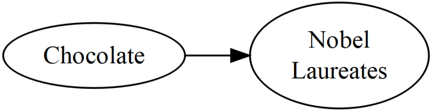

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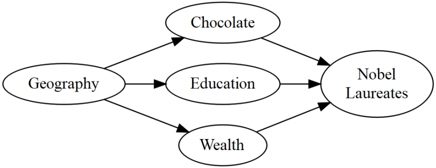

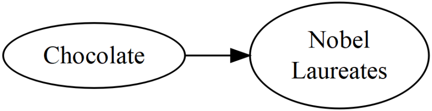

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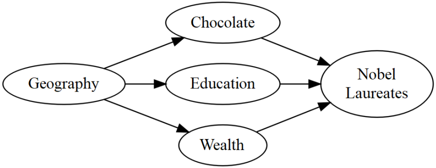

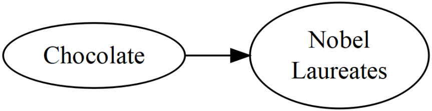

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- Identifying how much **ONE** variable causes variation in Nobel Laureates
- This we can do!

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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Proababilistic Explanation

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- Treatment effects are a distribution, not a single value

Section 2

Causal Inference

Causal Inference

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

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

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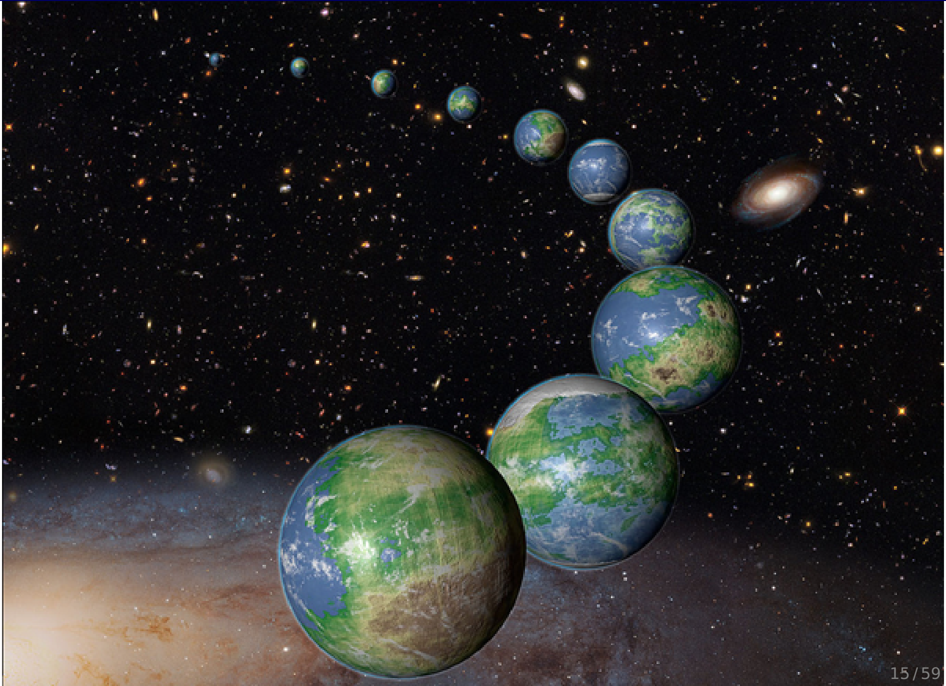

Causal Inference

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

Potential Outcomes are just another Variable

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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

Causal Inference

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Average Treatment Effect		**3**	**5**	**-2**

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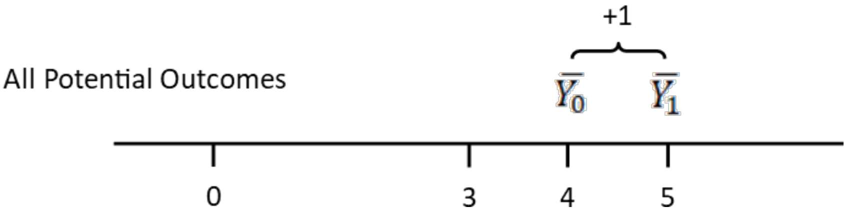

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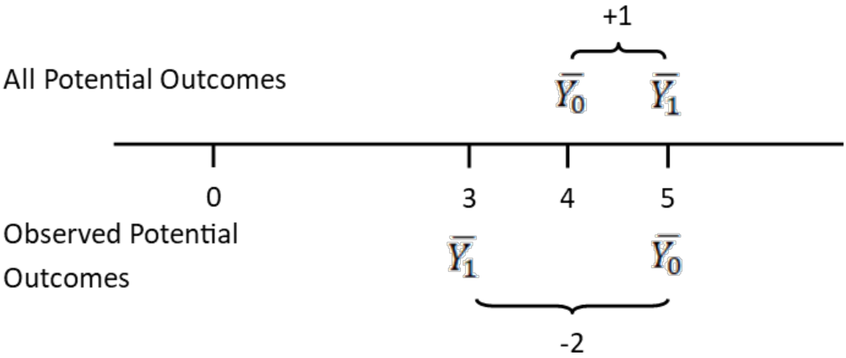

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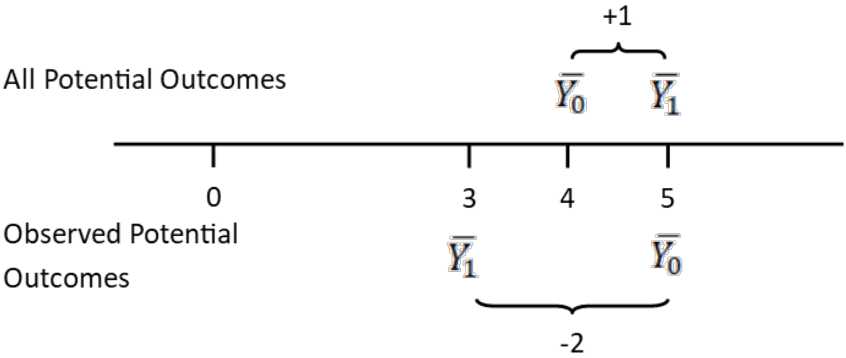

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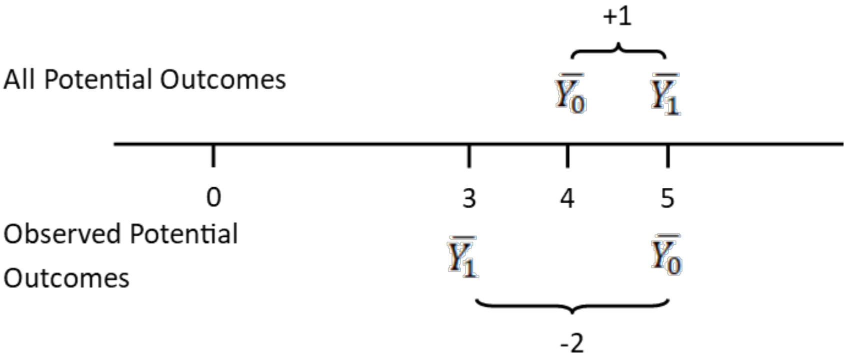

- $E(Y_1)$ values are **biased lower** in the observed data
- $E(Y_0)$ values are **biased higher** in the observed data
- So $E(Y_1) - E(Y_0)$ is **biased**

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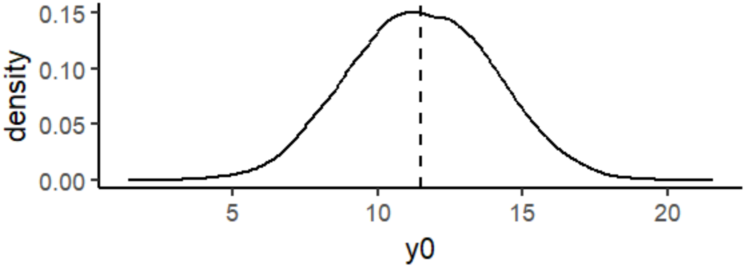

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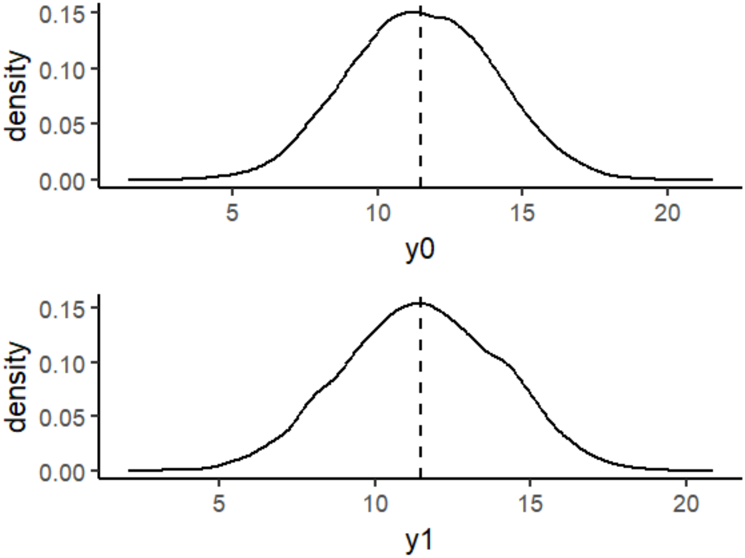

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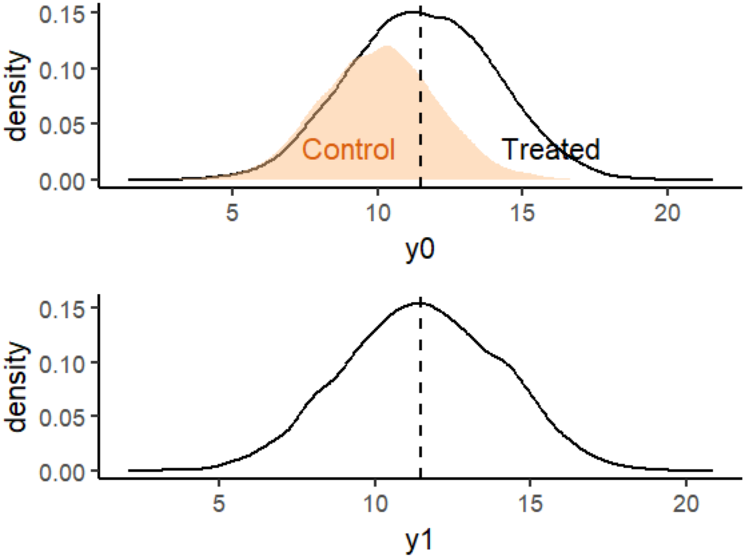

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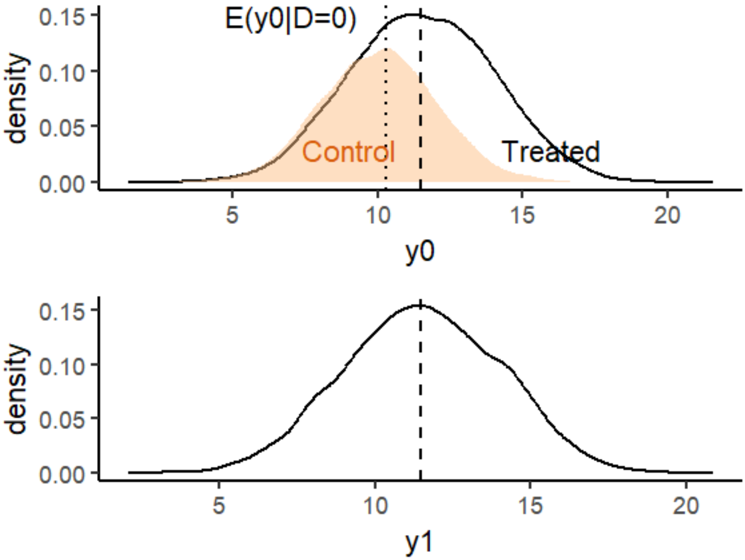

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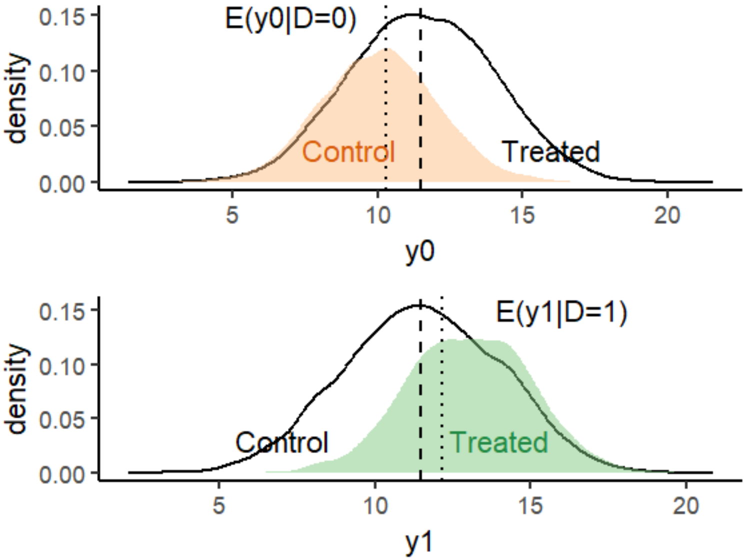


Causal Inference

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

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

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

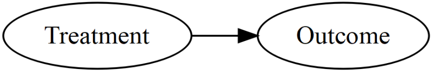
Why Observational Data is Biased

Bias

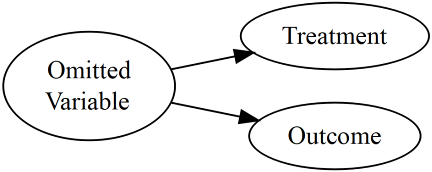
- Why are potential outcomes biased in our data?
  1. Omitted Variables
  2. Reverse Causation
  3. Selection Bias
- **In all of these cases the potential outcomes are distorted so basic regression is biased**

Omitted Variable Bias

A real causal relationship:



Being misled by omitted variable bias:



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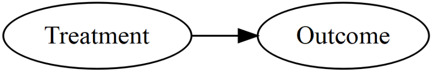

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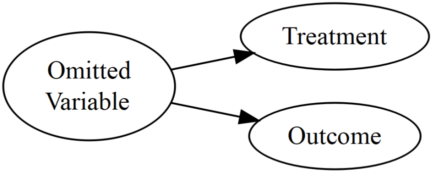

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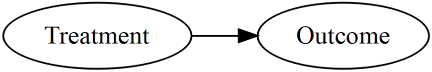

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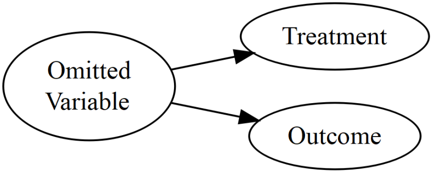

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- So treated units have non-representative Y_1
- And control units have non-representative Y_0

Omitted Variable Bias

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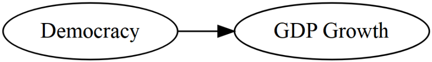

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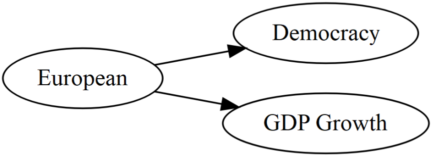

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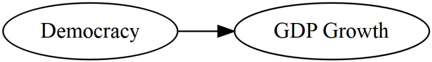

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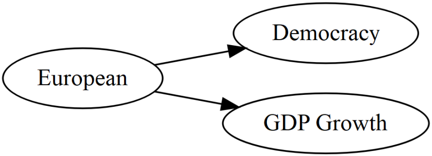
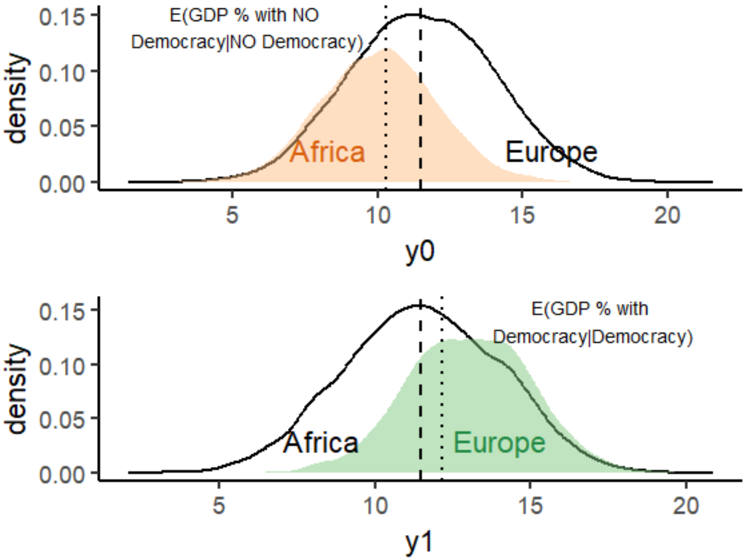


- European countries faced conditions that encouraged both democracy and rapid GDP growth

Omitted Variable Bias



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

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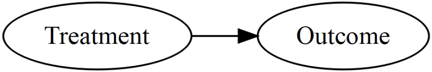
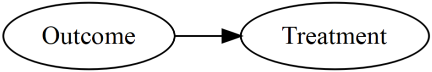
$$A\hat{T}E = \text{Real ATE} + \text{Bias}$$

Reverse Causation

A real causal relationship:

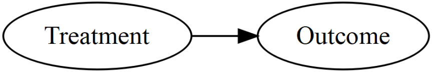


Being misled by reverse causation:



Reverse Causation

A real causal relationship:



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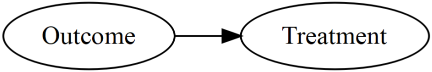

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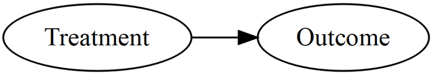

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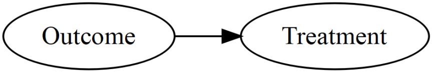
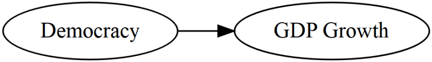


- D does not affect Y, but higher Y makes treatment (D) more likely
- So the two variables are correlated

Reverse Causation

A real causal relationship:



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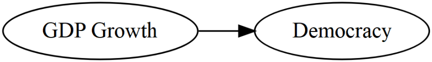

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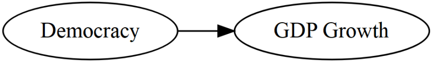

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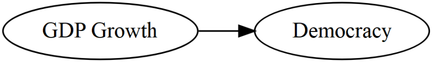

- GDP Growth encourages democratization

Reverse Causation

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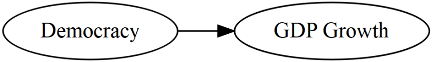

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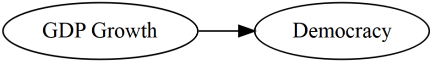
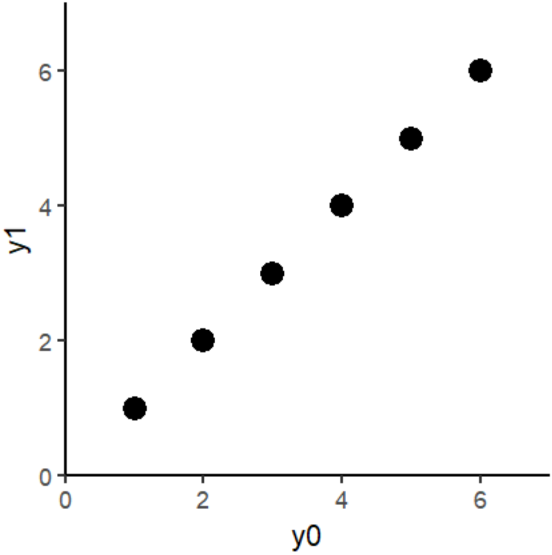


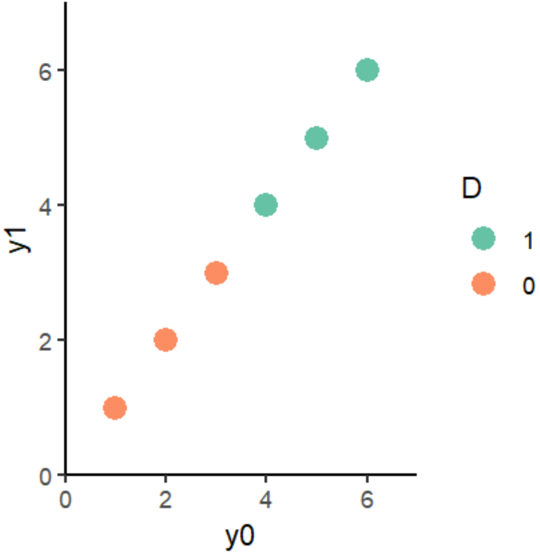
- GDP Growth encourages democratization
- So democracies are more likely to have experienced high growth rates

Reverse Causation



- $E(Y_1 - Y_0) = 0$

Reverse Causation



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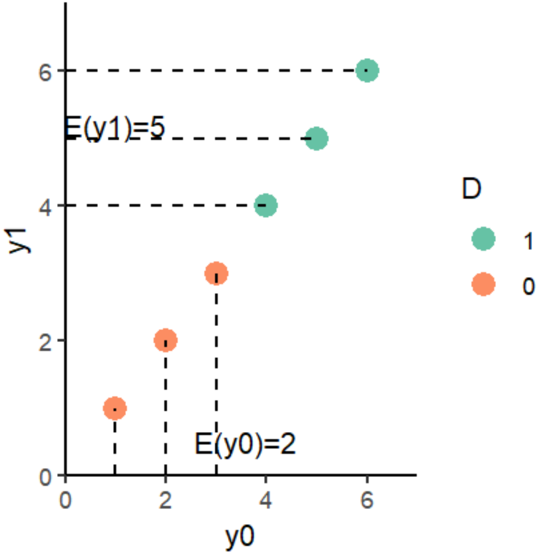

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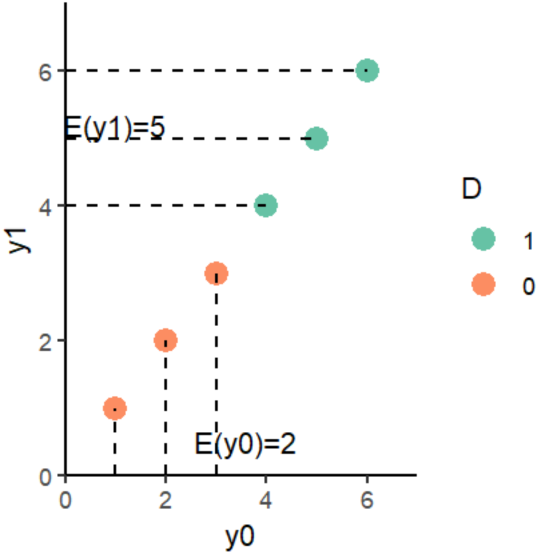
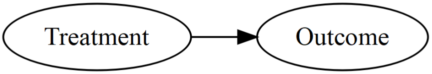


- $E(Y_1|D=1) - E(Y_0|D=0) = 5 - 2 = 3$

Selection Bias

A real causal relationship:



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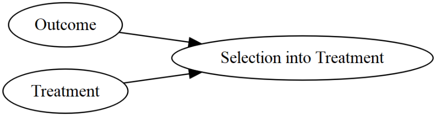

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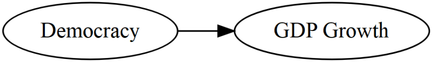

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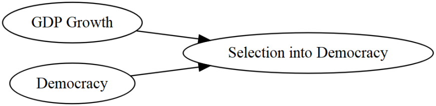

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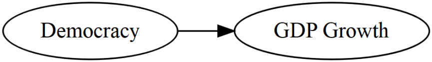

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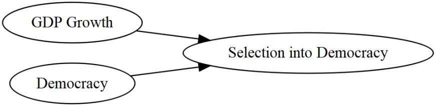

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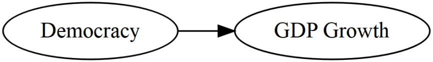

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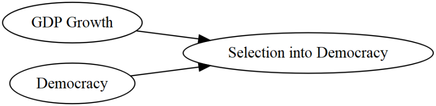
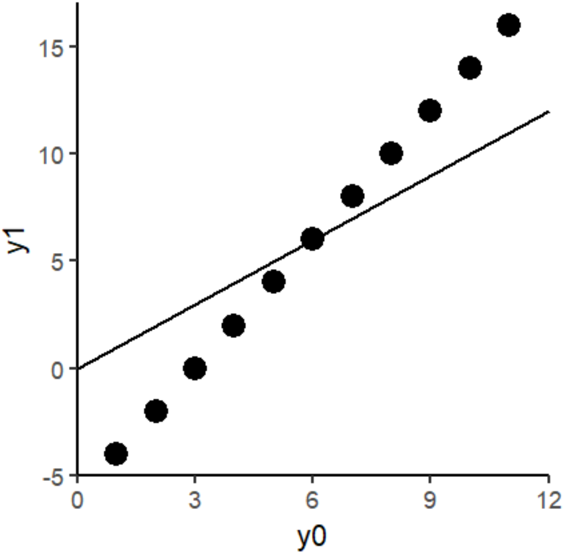


- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- We don't see any of the low y_1's of units which avoid treatment

Self-Selection Bias



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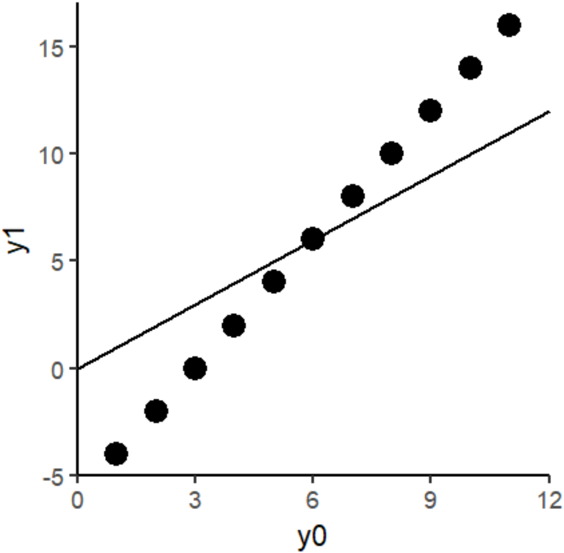
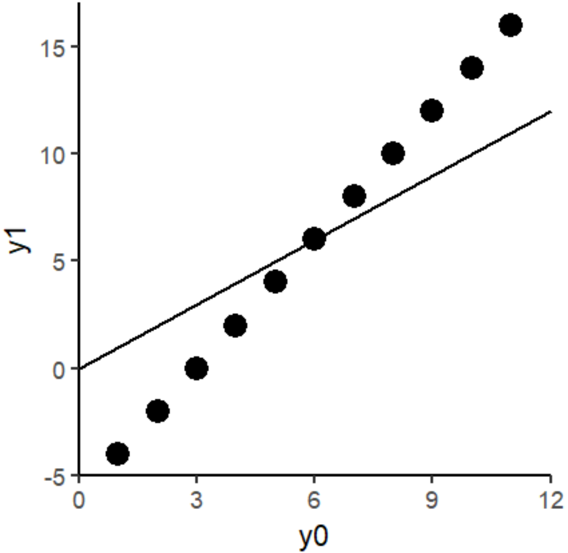


- Countries which can boost their GDP growth by becoming a

Self-Selection Bias



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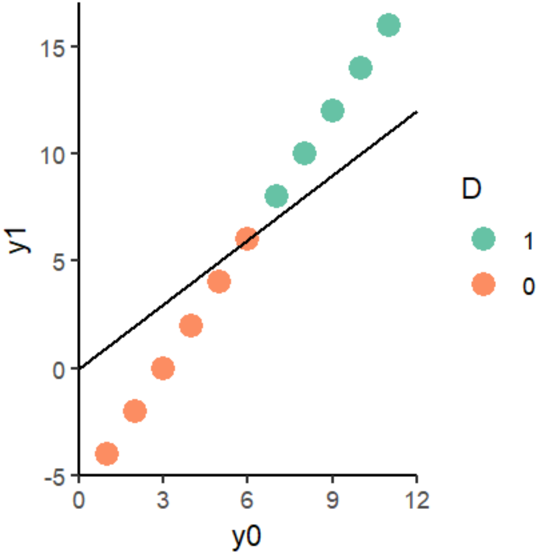
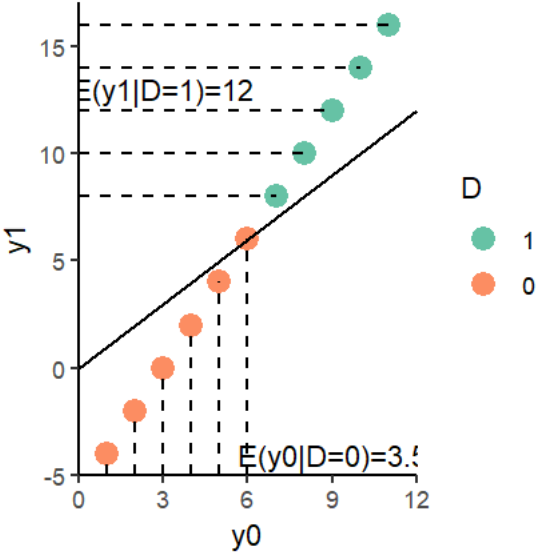


- $E(y_1) - E(y_0) = 0$

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

$$\underbrace{E(Y_i|D=1) - E(Y_i|D=0)}_{\text{Observed Effect}} = \underbrace{E(Y_{1i} - Y_{0i})}_{\text{Real ATE}} + \underbrace{\frac{1}{2}\Big[E(Y_{1i}|D=1) - E(Y_{1i}|D=0)\Big]}_{\text{Imbalance on } Y_1} + \underbrace{\frac{1}{2}\Big[E(Y_{0i}|D=1) - E(Y_{0i}|D=0)\Big]}_{\text{Imbalance on } Y_0} \quad (1)$$

NB: For equal-sized treatment and control groups

Causal Inference

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  - It means our comparison control cases are really misleading
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  - What would happen if the 'untreated' units got treated?

Causal Inference

- The comparability of treatment and control units depends on how they got to be treated

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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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  - $E(Y|D = 1) = E(Y|D = 0)$
  - Potential outcomes are 'balanced' across control and treatment groups

Section 4

Rest of the Course

Causal Inference

- The rest of the course is mostly about the types of treatment assignment mechanisms that **avoid these biases** and provide plausible counterfactuals

Causal Inference

1. **Controlled Experiments** where we **control** the treatment assignment
    - Field Experiments
    - Survey Experiments
    - Lab Experiments

Causal Inference

2. **Natural Experiments** where the assignment mechanism creates balanced potential outcomes
    - Randomized natural experiments
    - Regression Discontinuities
    - Instrumental Variables

Causal Inference

3. **Observable Studies:** What if no suitable treatment assignments are available?
    - No historical examples of natural experiments
    - Not feasible or ethical to run a field experiment

- Remember the purpose of using these specific treatment assignment mechanisms is to achieve **comparable potential outcomes**
- One alternative way of making potential outcomes comparable is to **selectively use Observable Data**
    - Difference-in-Differences
    - Controlling for confouding variables
    - Matching

Causal Inference

Analysis Types and Assumptions

Week	Assumption:	Researcher Controls Treatment Assignment?	Treatment Assignment Independent of Potential Outcomes	SUTVA	Additional Assumptions
	Controlled Experiments				
1	Field Experiments	✓	✓	✓	
2	Survey and Lab Experiments	✓	✓	✓	Controlled Environment for treatment exposure
	Natural Experiments				
3	Randomized Natural Experiments	X	✓	✓	
4	Instrumental Variables	X	✓	✓	First stage and Exclusion Restriction (Instrument explains treatment but not outcome)
5	Regression Discontinuity	X	✓	✓	Continuity of covariates; No manipulation; No compounding discontinuities
	Observational Studies				
6	Difference-in-Differences	X	X	✓	No Time-varying confounders; Parallel Trends
7	Controlling for Confounding	X	X	✓	Blocking all Back-door paths
8	Matching	X	X	✓	Overlap in sample characteristics

Causal Inference

4. **Small-N studies:** Some research questions have few units available

- How do we learn about the political economy of development with few units?
- We can at least avoid some key biases:
  - Comparative Case Studies
  - Process Tracing

Causal Inference

- But **how much** can we learn from a causal analysis?
- Is this an accurate representation of what would happen in the real-world?
    - What was the policy problem (/academic question) you were trying to solve?
    - What details differ? Eg. context of how treatment was applied
- Generalizability to other units (External validity)
    - Would the same thing happen in another country? Next year?
    - Look out for variation in treatment, context, spillovers, learning etc.
- Any generalization requires assumptions

Causal Inference

- We will try to identify abstract, portable processes
  - **Causal Mechanisms**
- **Portable:** If the weather affects election turnout ONLY in Acre, is that a useful causal mechanism?
- **Abstract:** If unions are good at mobilizing support, but so are churches, the mechanism is collective action, not union organization
- We still need to define the **scope conditions** in which we think this causal mechanism will operate as expected