

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'

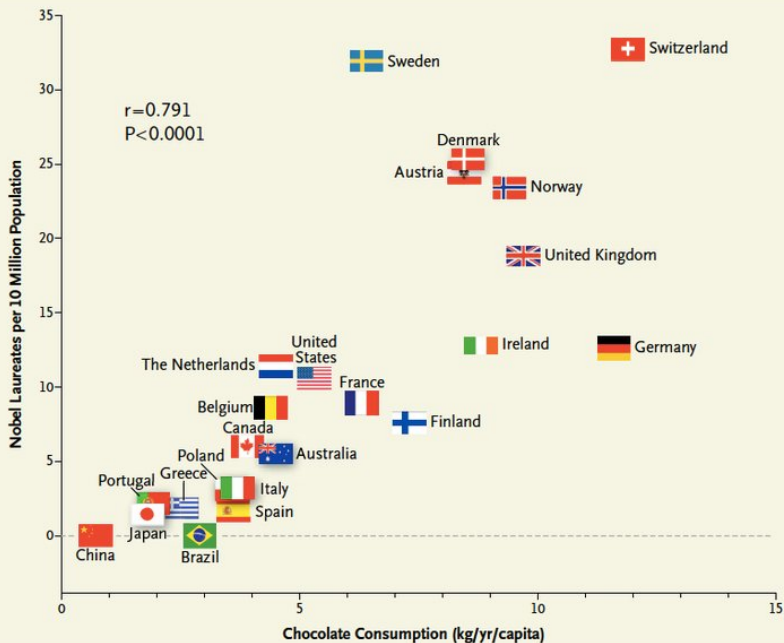


Figure 1 Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

Explanation

- 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

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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:

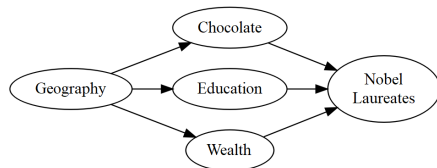
Explanation

- 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?

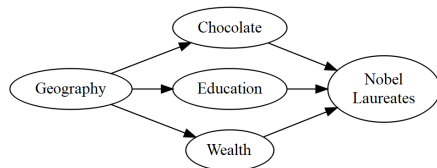
Explanation

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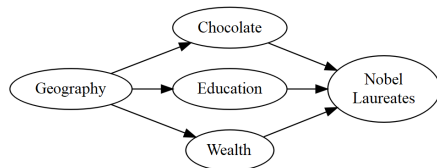
- Two perspectives on explanation:



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

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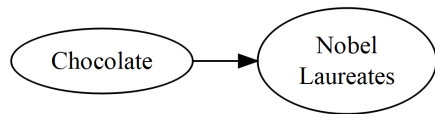
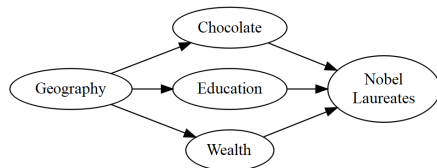
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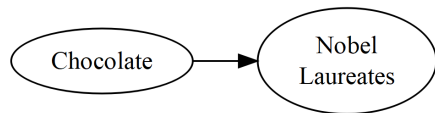
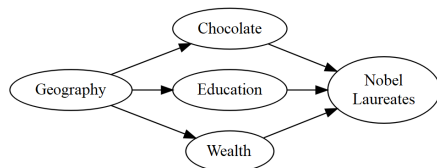
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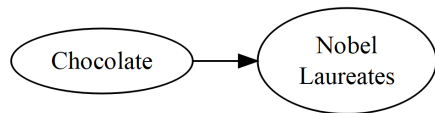
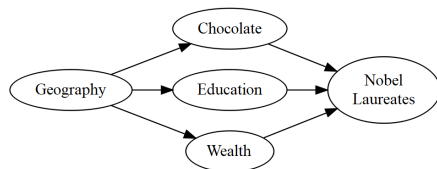
- ▶ Two perspectives on explanation:



- ▶ Identifying the source of **ALL** of the variation in Nobel Laureates
- ▶ An infinite task!
- ▶ Identifying how much **ONE** variable causes variation in Nobel Laureates

Explanation

- ▶ Two perspectives on explanation:



- ▶ Identifying the source of **ALL** of the variation in Nobel Laureates
- ▶ An infinite task!
- ▶ 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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- ▶ This means comparing the **Potential Outcomes** for unit i :

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

- ▶ Individual Treatment Effect for unit $i = Y_{1i} - Y_{0i}$

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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 Democ- racy	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

Causal Inference

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Average Treatment Effect

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

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

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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**

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
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Causal Inference

Potential Outcomes Example

	Democracy?	GDP Growth if Democracy	GDP Growth if NOT Democracy	Treatment Effect
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Brasil	1	4	?	?
Argentina	0	?	4	?
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
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

Causal Inference

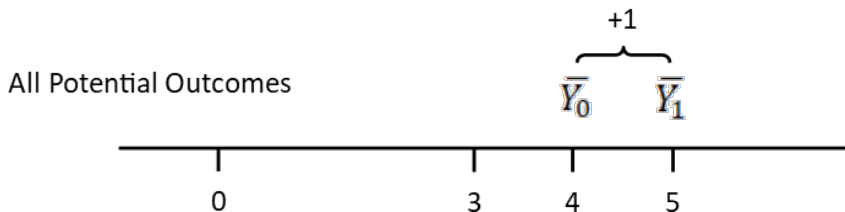
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Causal Inference

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- ▶ The potential outcomes we **observe** are a **biased representation** of the potential outcomes of all the units

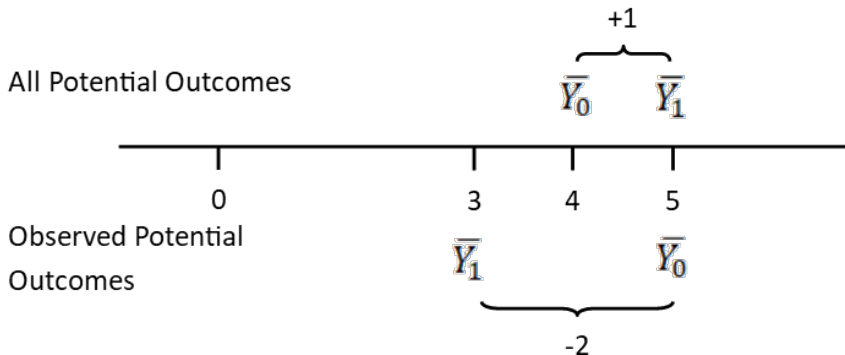
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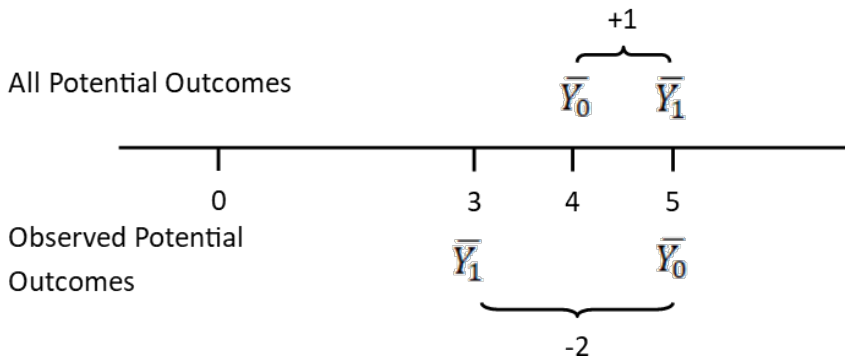
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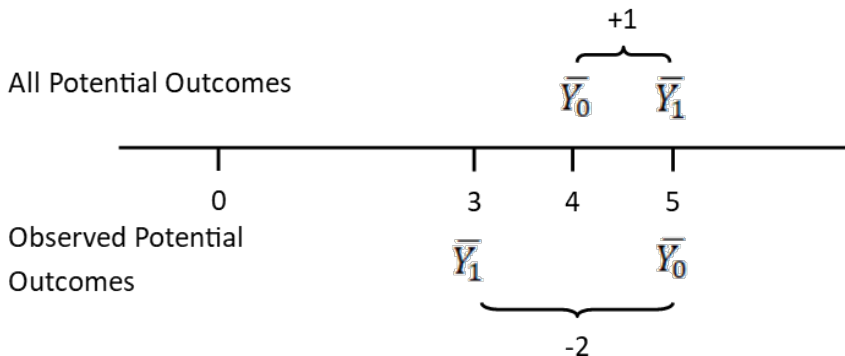
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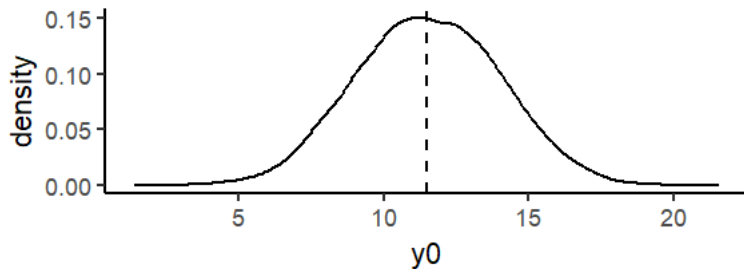
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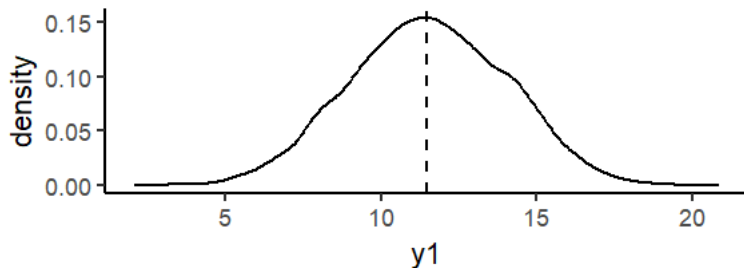
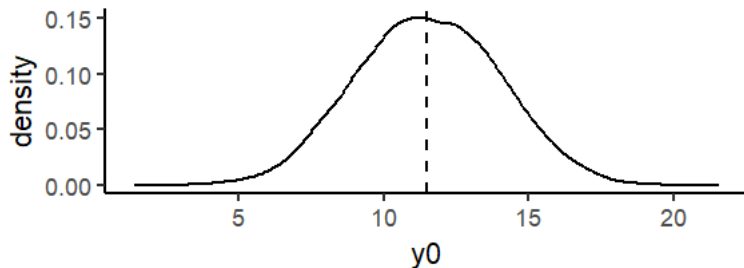


- ▶ $E(Y_1)$ values are **biased lower** in the observed data
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- ▶ So $E(Y_1) - E(Y_0)$ is **biased**

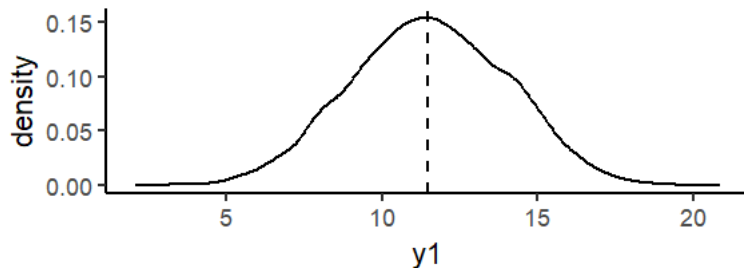
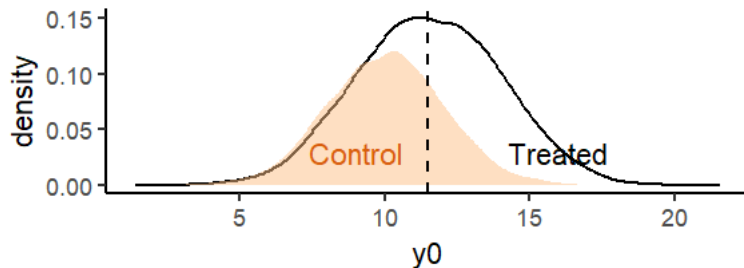
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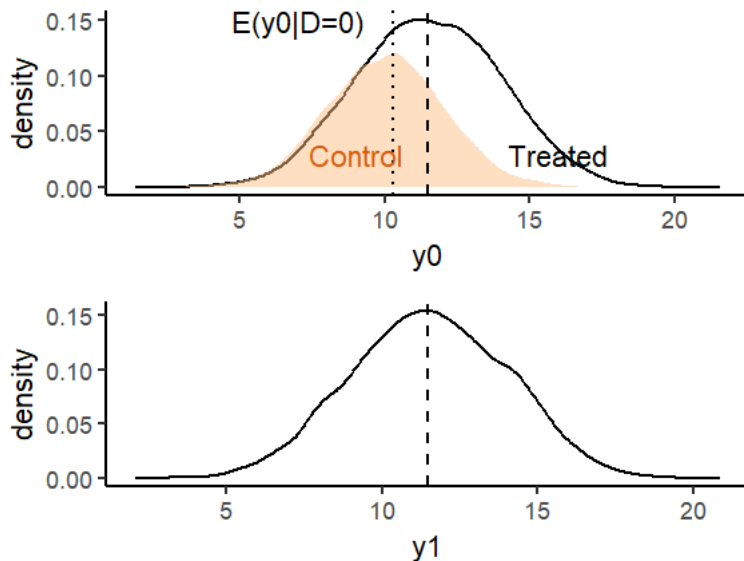
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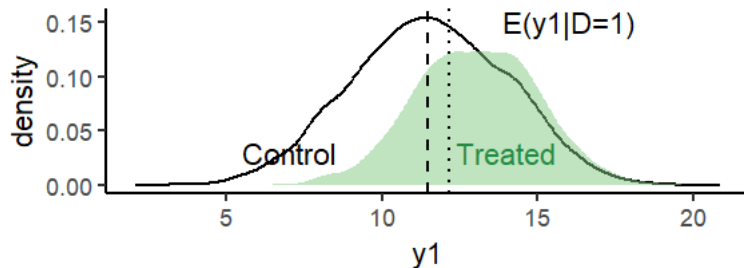
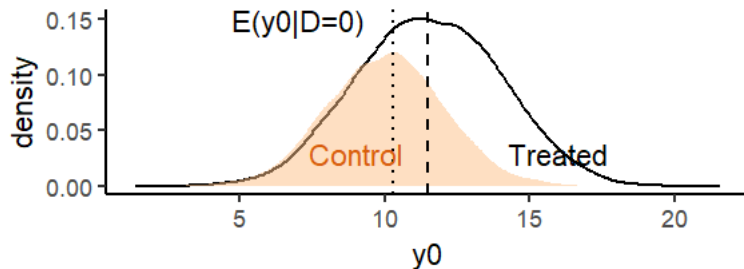
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Causal Inference



Section 3

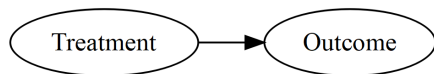
Why Observational Data is Biased

Bias

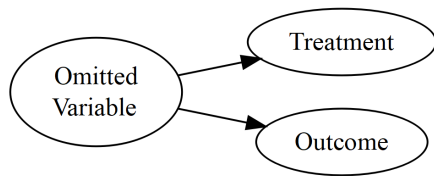
- ▶ Why are potential outcomes biased in our data?
 1. Omitted Variables
 2. Reverse Causation
 3. Selection Bias
- ▶ **In all of these cases the potential outcomes are distorted so basic regression is biased**

Omitted Variable Bias

A real causal relationship:

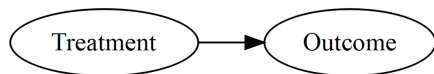


Being misled by omitted variable bias:

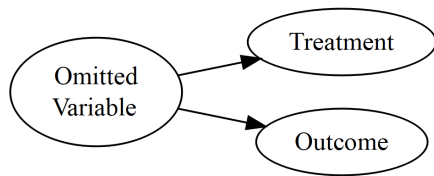


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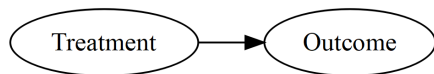
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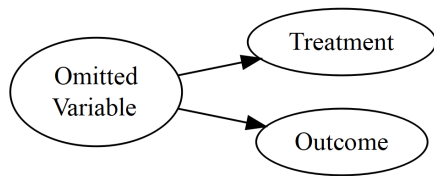
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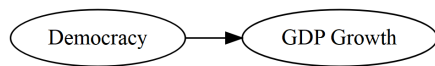
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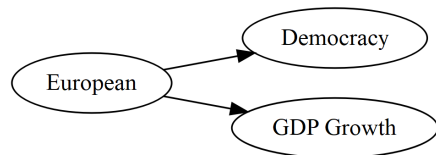
- ▶ A third variable causes some units to have **different values of potential outcomes**, AND for those **same units to be treated**
- ▶ So treated units have non-representative Y_1
- ▶ And control units have non-representative Y_0

Omitted Variable Bias

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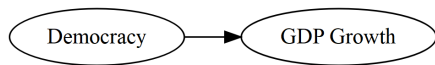


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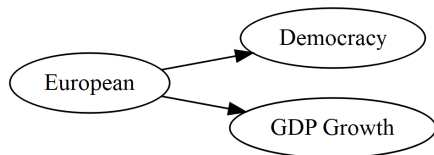


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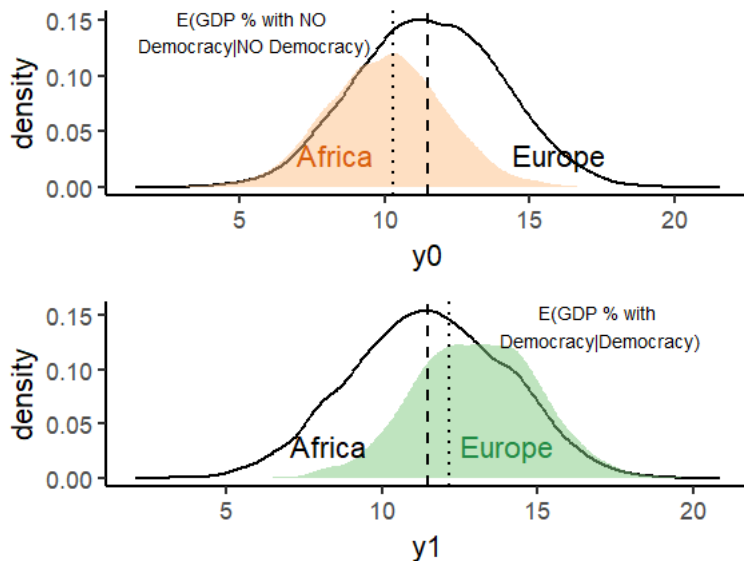


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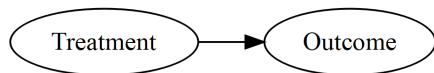
- ▶ European countries faced conditions that encouraged both democracy and rapid GDP growth

Omitted Variable Bias

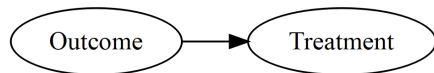


Reverse Causation

A real causal relationship:

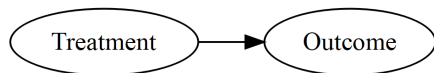


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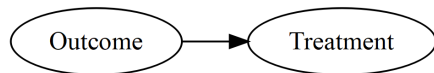


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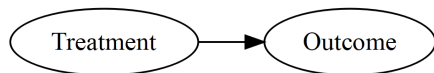
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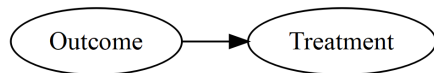
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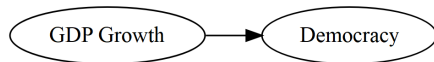
- ▶ D does not affect Y , but higher Y makes treatment (D) more likely
- ▶ So the two variables are correlated

Reverse Causation

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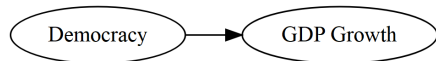


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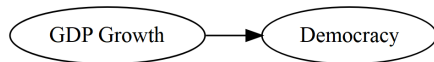


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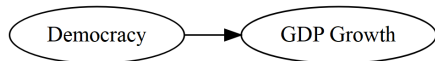
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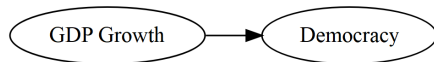
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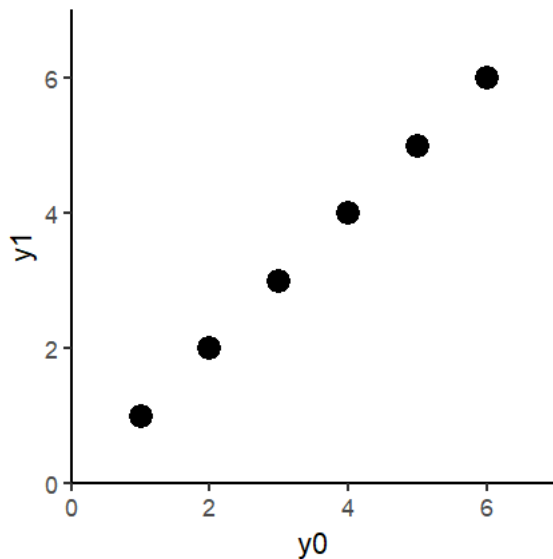


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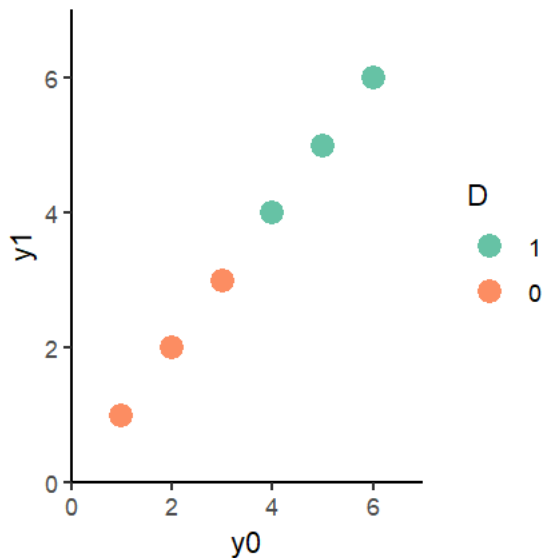
- ▶ GDP Growth encourages democratization
- ▶ So democracies are more likely to have experienced high growth rates

Reverse Causation

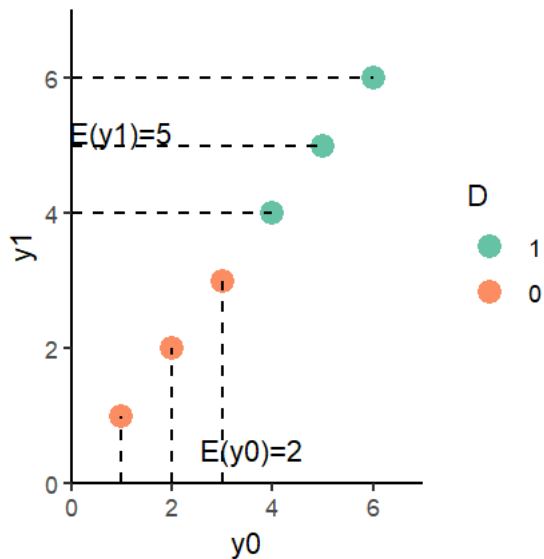


► $E(Y_1 - Y_0) = 0$

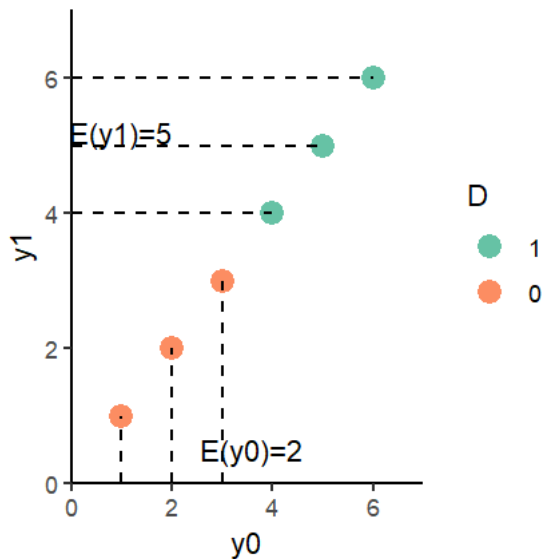
Reverse Causation



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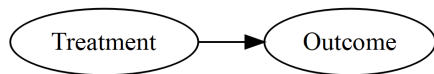
Reverse Causation



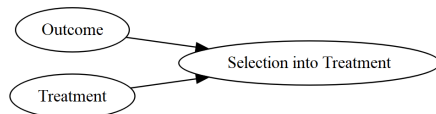
► $E(Y_1|D=1) - E(Y_0|D=0) = 5 - 2 = 3$

Selection Bias

A real causal relationship:



Being misled by Selection Bias:

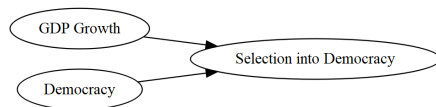


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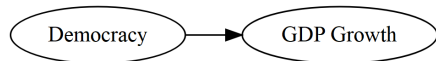


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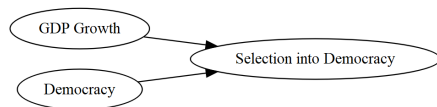


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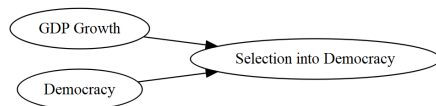
- The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**

Selection Bias

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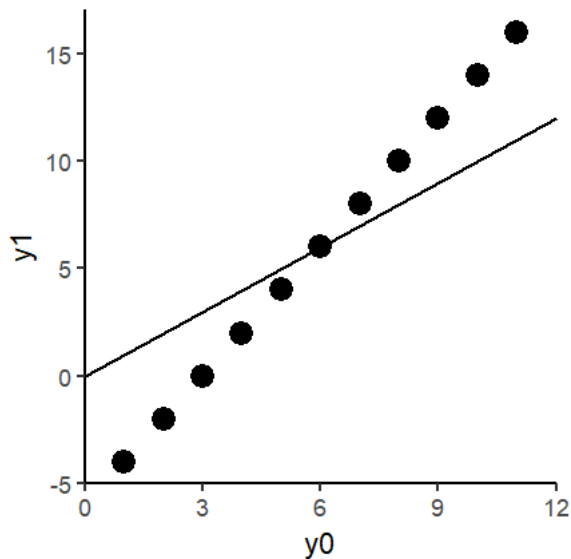


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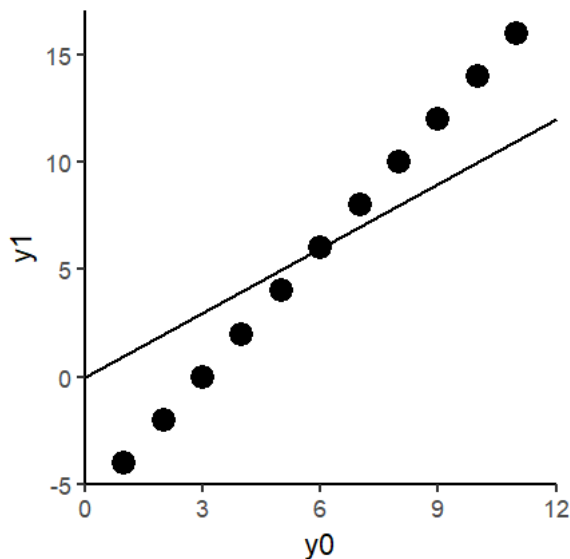


- ▶ The units which benefit most from treatment (largest $y_1 - y_0$) **choose treatment**
- ▶ We don't see any of the low y_1 's of units which avoid treatment

Self-Selection Bias

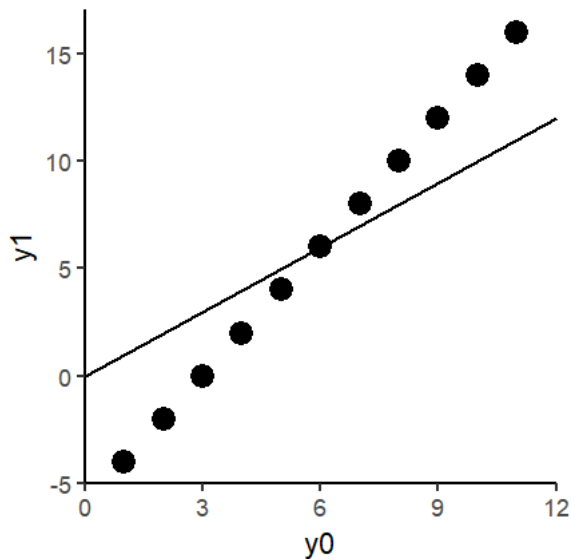


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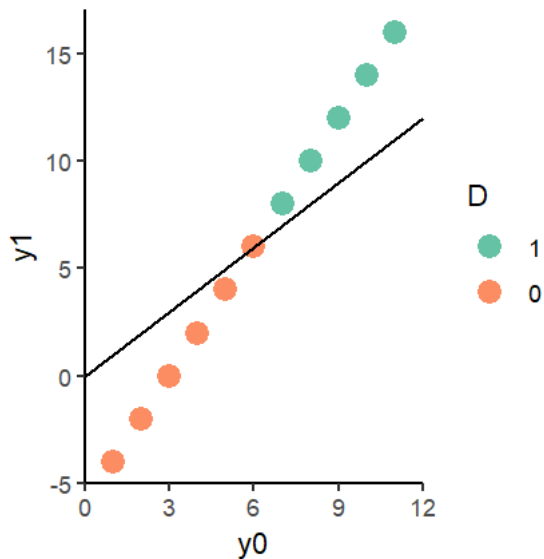
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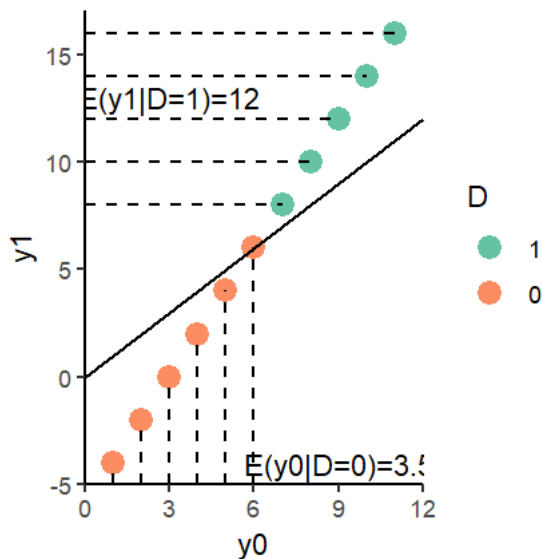
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Self-Selection Bias



► $E(y_1) - E(y_0) = 0$

Self-Selection Bias



► $E(y_1|D=1) - E(y_0|D=0) = 8.5$

Causal Inference

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 - ▶ Y_0 for Malaysia is not a good guide to the Y_0 for Switzerland
 - ▶ 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

Treatment Assignment Mechanism

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

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 - ▶ $Pr(D|(Y_1, Y_0)) = Pr(D)$
 - ▶ 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 confounding 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

Causal Inference

- ▶ Examples of Causal Mechanisms:
 - ▶ Citizens
 - ▶ Electoral Accountability
 - ▶ Client Power
 - ▶ Collective Action
 - ▶ Social Trust/Sanctioning
 - ▶ Wealth Effects
 - ▶ Elites
 - ▶ Violence/Coercion
 - ▶ Brokerage/Patronage
 - ▶ Persuasion/Framing
 - ▶ Incumbency Power
 - ▶ Institutions
 - ▶ Power Devolution/Median Voter
 - ▶ Network Effects
 - ▶ Evolutionary Selection
 - ▶ Conversion/Layering/Drift/Replacement

Causal Inference

► Examples of Causal Mechanisms:

► Citizens

- Electoral Accountability - [Class 5](#)
- Client Power - [Class 6](#)
- Collective Action - [Class 11](#)
- Social Trust/Sanctioning - [Class 4](#)
- Wealth Effects

► Elites

- Violence/Coercion - [Class 8](#)
- Brokerage/Patronage - [Class 9](#)
- Persuasion/Framing
- Incumbency Power - [Class 7](#)

► Institutions

- Power Devolution/Median Voter - [Class 3](#)
- Network Effects
- Evolutionary Selection
- Conversion/Layering/Drift/Replacement - [Class 12](#)